FCN | Future Energy Consumer Needs and Behavior

E.ON Energy Research Center

RWTH AACHEN UNIVERSITY

FCN Working Paper No. 15/2019

Get Ready for Take-Off: A Two-Stage Model of Aircraft Market Diffusion

Xueying Liu and Reinhard Madlener

October 2019

Institute for Future Energy Consumer Needs and Behavior (FCN)

School of Business and Economics / E.ON ERC

FCN Working Paper No. 15/2019

Get Ready for Take-Off: A Two-Stage Model of Aircraft Market Diffusion

October 2019

Authors' addresses:

Xueying Liu, Reinhard Madlener
Institute for Future Energy Consumer Needs and Behavior (FCN)
School of Business and Economics / E.ON Energy Research Center
RWTH Aachen University
Mathieustrasse 10
52074 Aachen, Germany
E-Mail: XLiu@eonerc.rwth-aachen.de, RMadlener@eonerc.rwth-aachen.de

Publisher: Prof. Dr. Reinhard Madlener
Chair of Energy Economics and Management
Director, Institute for Future Energy Consumer Needs and Behavior (FCN)
E.ON Energy Research Center (E.ON ERC)
RWTH Aachen University
Mathieustrasse 10, 52074 Aachen, Germany
Phone: +49 (0) 241-80 49820
Fax: +49 (0) 241-80 49829
Web: www.fcn.eonerc.rwth-aachen.de
E-mail: post_fcn@eonerc.rwth-aachen.de

Get Ready for Take-Off: A Two-Stage Model of Aircraft Market Diffusion

Xueying Liu[1,*] and Reinhard Madlener[1,2]

[1] Institute for Future Energy Consumer Needs and Behavior (FCN), School of Business and Economics / E.ON Energy Research Center, RWTH Aachen University, Mathieustraße 10, 52074 Aachen, Germany

[2] Department of Industrial Economics and Technology Management, Norwegian University of Science and Technology (NTNU), 7491 Trondheim, Norway

October 2019

Over the past decades, the aviation sector has seen an unprecedented technology advancement as well as rise in global air traffic. In this paper, we establish a two-stage model, combining an epidemic diffusion model and a regression analysis to analyze and predict the diffusion process of modern commercial aviation aircraft models before they are launched into the market. For the estimation of the first-stage epidemic diffusion model, a total of 19,768 delivery records covering 52 widely used aircraft models are used and a non-linear least squares method is applied. For the second-stage regression analysis, we collect aircraft specific technical parameters including range, maximum take-off weight and emissions. We find that, at present, pollutant emissions are not of key significance in determining the success of market diffusion of aircraft models, while conventional parameters, such as range, takeoff weight, and bypass ratio of the engine, are comparably more significant. In terms of projection into the future, our model is relatively good at predicting the rate of diffusion but less so at predicting the market size. This naturally points to further research avenues in terms of the prediction of market potentials.

Transportation economics; Technological diffusion; Epidemic Diffusion Model; Aircraft

[*]Corresponding Author: Tel: +49 241-80 49839, Xueying.Liu@eonerc.rwth-aachen.de (X.Liu).

1 Introduction

Air transportation plays an important role in enabling global mobility. Between the years 1990 and 2014, global scheduled flights increased by 80%. Meanwhile, emissions of carbon dioxide also increased by about 80%, and the nitrogen oxides emissions doubled (EASA, 2016). The projections into the future show that, from 2014 to 2035, global scheduled flights are likely to see a 45% further growth while emissions could increase by 43% (EASA, 2016). As a result, the considerable existing impact of air transportation emission on atmospheric climate change (Berntsen and Fuglestvedt, 2008) is likely to face an even more staggering growth. As a response to both increasing air traffic demand and environmental concerns, various aircraft innovations are under way to enable sustainable growth in aviation. It is therefore paramount to study how past aircraft models have been adopted and have diffused into the market, which would in turn advise the design and the diffusion forecast of newer aircrafts as well as the estimation of their potential emission impact.

Numerous previous studies on technology diffusion have been conducted. A significant proportion of such studies focus on adopter behaviors, and attempt to find the reasons and the characteristics that drive heterogeneous entities in different environments to adopt a certain new technology at different rates. Regarding the diffusion processes of products, various modifications have been proposed since the seminal paper by Bass (1969), for instance with a modified functional form using the Gompertz distribution (Martino, 1972), or to include multiple generations of products (Mahajan and Muller, 1996; Norton and Bass, 1987). However, while the studies on adopter behaviors have deepened our understanding regarding the diffusion rate heterogeneity on the consumer side, they usually focus on single-product diffusion and, therefore, often remain silent about the reasons behind the difference in the diffusion rates *between* different products. Similarly, while the class of epidemic diffusion models, including the Bass model, can typically explain the diffusion process of existing products quite well by using historical data, the prediction of new product diffusion is usually done via guessing by analogy, or by using survey data from potential consumers on intentions (Bass et al., 2001). This interest usually stems from a lack of historical sales data for generating meaningful parameter estimates for the Bass model. As Massiani and Gohs (2015) note, the estimates of diffusion parameters vary greatly for various types of cars, which is why an analogy approach leaves much to be desired. A more recent general approach for pre-launch new product diffusion prediction is proposed by Lee et al. (2014), in which several statistical and machine learning methods are examined. In their approach, expert judgment is required to estimate parameters such as the 'degree of newness' or the 'necessity of repurchase' of the new product.

In this paper, our goal is to examine the historical diffusion process of fixed-wing aircraft in the world market. More specifically,we aim to answer the questions: Which characteristics of an aircraft enable it to diffuse faster and which are associated with slower diffusion processes? In addition, we aim to develop a model that allows pre-launch prediction of new aircraft model diffusion. We employ a two-staged approach combining regression analysis with the Bass Model (Bass, 1969) applied to global data and estimated by using non-linear least squares (NLS). We build upon previous studies on diffusion modeling as well as the more recent approach by Lee et al. (2014), and establish a model that depicts the relation between aircraft model characteristics and their respective diffusion patterns, which can then be applied to new aircraft models with known product-level parameters in order to predict their future diffusion.

The remainder of this paper is arranged in the following way. In section 2, we present an overview of the related literature on aggregate diffusion models, such as the Bass model, pre-launch diffusion model methods and selected relevant literature for our own modeling approach. Section 3 introduces our model specifications, explains the methodology used, and pins down the estimation approach adopted. Section 4 describes the dataset for the empirical analysis. Section 5 reports on the results and substantiates some of the findings. Finally, section 6 concludes and provides some avenues for further research.

2 Literature Review

Starting from the pioneering work on innovation and new product diffusion by Fourt and Woodlock (1960), Mansfield (1961), and Bass (1969), the topic has gathered considerable interest for both theoretical and empirical researchers. Three main elements influence the diffusion process: the characteristics of the new products, the social and market systems (including the actors in such systems) into which the new products are diffused, and the time frame of the diffusion process (Rogers, 2003).

These three elements have consequently been examined in detail in the literature. A majority of studies focuses on the social and market systems, the individuals in this system as well as their interactions. A rich set of empirical research examines historical innovation adoption behaviors and aims to find the characteristics that drive heterogeneous actors to adopt a certain new technology at different rates. Such individuals could be aggregated to different levels, e.g. countries (Caselli and Coleman, 2001), industries and firms (Greve and Seidel, 2015; Mansfield, 1961), or households (Islam, 2014). Various aggregate models are also derived based on the social interaction between these actors and aim to create a representation of the system in which new products are adopted. This includes the external influence model first proposed by Fourt and Woodlock (1960), in which a constant proportion of potential adopters adopts in each time period, the internal influence model which reflects the interaction between prior adopters and potential adopts, and the mixed influence model by Bass (1969). Meade and Islam (2006) provide an excellent review of a myriad of alternative diffusion models. A more recent approach employs agent-based modeling (ABM) using computer simulations (Macal and North, 2005; Bonabeau, 2002; Palmer, Sorda, and Madlener, 2015; Liu and Madlener, 2019). These models incorporate individual decision-making processes of each actor in the system, detailed interaction patterns between actors as well as various system-wide parameters, such as the interest rate or government policy parameters. The diffusion process is then derived from simulation results.

In contrast, the study of characteristics of the new products is limited. Some work has been done regarding successive generation of a product (Norton and Bass, 1987). Even so, the focus is mostly put on the different needs and behaviors of repeaters and adopters. In other analyses, one or a few product-level pieces of information are included. These, however, usually serve as controlling factors or as a proxy for the performance of rival products (Greve and Seidel, 2015). A more recent study by Lee et al. (2014) focuses on pre-launch diffusion and product-level information using the Bass model and several machine-learning methods. Nevertheless, in their approach, the product-level information is again collected from relatively general expert judgment rather than technically quantifiable parameters. As a result, this approach requires more effort in its application and is more prone to subjective judgment and thus biases compared to modeling methods that require only product-specific technical parameters.

The existing literature on innovation and new product pre-launch diffusion relies heavily on expert judgment and not so much on objective parameters. This could potentially lead to a lack of objectivity, difficulty with implementation, and systematic biases that are sometimes associated with opinions or judgment, albeit stemming from experts. As such, based on insights gathered from previous studies, we aim to establish a two-staged model combining the aggregate Bass diffusion model with regression analysis to analyze the impact of product-specific information and that focuses on the social and the market system of diffusion as well as on the more objective technical parameters of the new product.

In addition, although the existing literature on diffusion modeling covers a wide range of products such as consumer electronics (CD players, VCR players, fax machine, cellular phones) (Talukdar, Sudhir, and Ainslie, 2002), conventional and electric cars (Massiani and Gohs, 2015), renewable energies (Lee and Huh, 2017), very few diffusion studies have been conducted regarding the diffusion of aircraft models, and specifically airlines' choice of aircraft purchase. Given the rapid growth of global air traffic, the increase in emission associated with it, and the substantial effort invested into new technology development, it is essential to investigate the diffusion behavior in the aviation sector. In our study, we also consult previous work in the aviation sector. Husemann, Schäfer, and Stumpf (2018) sent surveys to airline managers in order to find out more about their preferences regarding aircraft characteristics. Greve and Seidel (2015) examine the diffusion pattern of two rival aircraft models and how the diffusion process is influenced by competition. Kar (2010) explores the diffusion of carbon dioxide emission mitigating measures in the aviation sector using system dynamics. We build upon these studies and examine quantitatively the parameters that are significant in adoption behavior using an aggregate diffusion model and regression analysis.

3 Model Specification and Methodology

In order to characterize the diffusion process and take into consideration the heterogeneity between different aircraft vehicles, we follow a two-stage approach combining the Bass model used as the first stage and regression analysis in the second stage. Figure 1 presents the model setup. We choose the Bass model for the first stage because it provides a good fit to our data available at hand, namely the historical sales data, and in order to preserve generality. Hall (2004) points out that the mixed information models, which include the Bass model, are used most widely due to their larger generality. Section 3.1 further elaborates on the first-stage process.

In the second stage, the regression analysis, aircraft-model-specific characteristics that are known pre-launch, such as range, maximum take-off weight (MTOW), fuel efficiency, noise level, and emission level, are included. These parameters, represented by X in the equation, are selected as they are deemed to be important in the purchase decision of airliners (Husemann, Schäfer, and Stumpf, 2018). Certain other parameters, such as maintenance cost, or number and severity of accidents, may also play a significant role in the diffusion of aircrafts. However, these statistics are usually unknown, very vaguely known before launch, or dependent on airline idiosyncrasies, and are thus not included in this study. Section 3.2 provides more information regarding the second-stage process.

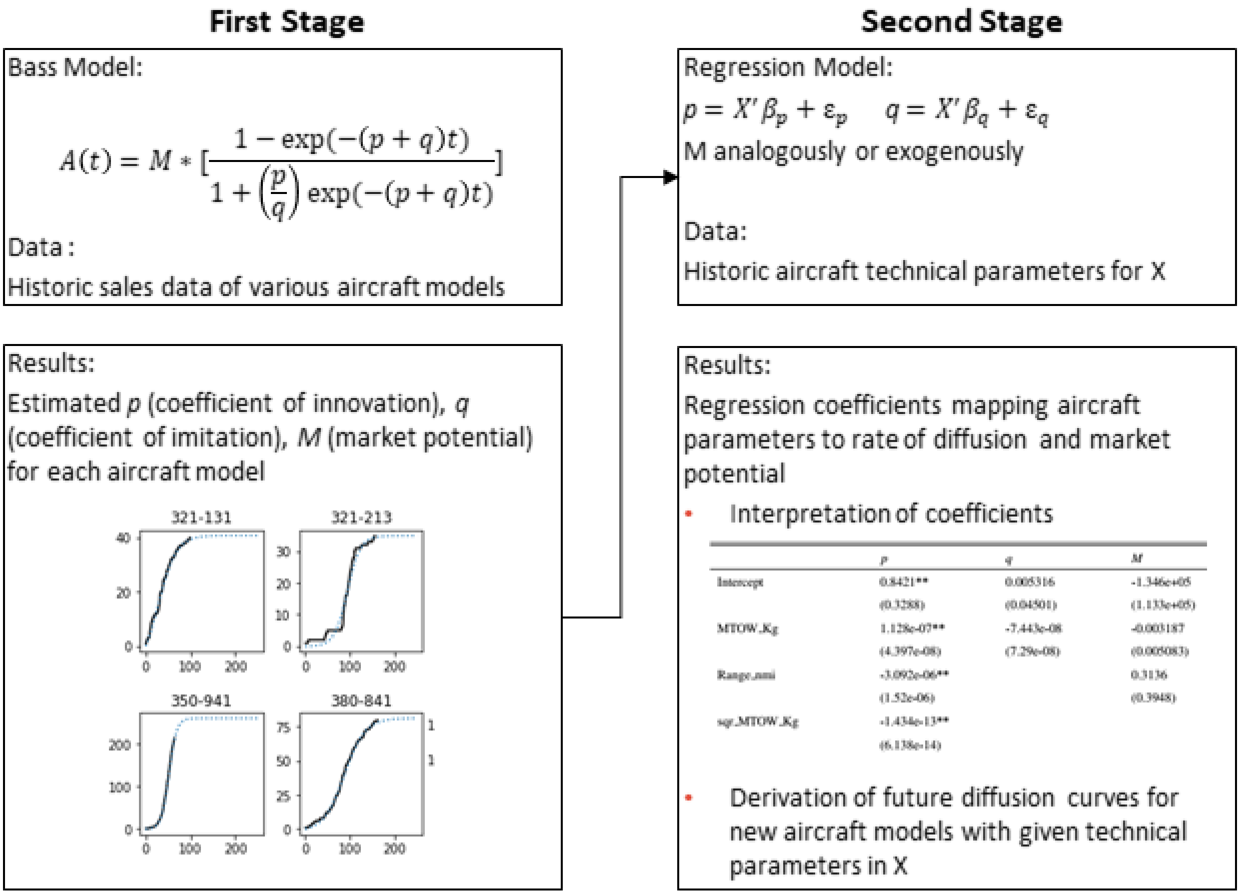

Figure 1: Model Setup

3.1 First-Stage Data Processing

In the first stage, raw historical sales and delivery data, i.e. records of airplanes delivered from manufacturers to airlines or other customers, are processed using the Bass model (Bass, 1969) in order to generate aircraft-model-specific coefficients that depict the diffusion process.

For the aggregated epidemic diffusion model, the general form can be expressed by the following differential equation:

$$\frac{dA(t)}{dt} = g(t)[M - A(t)], \tag{1}$$

where $A(t)$ is the cumulative adoption, i.e. cumulative delivery of an aircraft model up until time period t. M represents the total market potential, which is the ceiling of total deliveries, and $g(t)$ is a function that describes the diffusion rate. This equation states that the number of adoptions per period is a function of the remaining potential adopters and the rate of diffusion.

As the Bass model represents a mixed information model (Kijek, 2010) for single adoption (the number of adoptions is equal to the number of adopters), in which innovation is spread in two ways: via imitators endogenously adopting through word-of-mouth and via innovators exogenously adopting; the rate of diffusion function $g(t)$ takes on the specific form:

$$g(t) = \left(p + q \cdot \frac{A(t)}{M}\right), \tag{2}$$

where p and q are the Bass innovation and imitation coefficients, respectively. The imitation coefficient q represents the process of endogenous diffusion that occurs from the interaction between existing adopters and potential adopters. This process is therefore also influenced by the proportion of existing adopters in the population. The innovation coefficient p represents the influence of external sources, e.g. marketing, government policies on adoption, and it assumes that this external source, and thus the rate of diffusion, are constant throughout the process.

Combing the Bass rate of diffusion function and the general form, we obtain the following equation:

$$\frac{dA(t)}{dt} = \left(p + q \cdot \frac{A(t)}{M}\right)[M - A(t)]. \tag{3}$$

Solving the above equation yields the following closed-form solution:

$$A(t) = M \cdot [\frac{1 - exp(-(p+q)t)}{1 + (p/q)exp(-(p+q)t)}], \tag{4}$$

which is also shown for the first stage in Figure 1. This is the equation that describes the accumulative adoption at each time period t, depicted by the graph for the first stage in Figure 1.

Four main methods can be used for the estimation of the parameters p, q, and M in the above equation: ordinary least squares (OLS), maximum likelihood estimation (MLE), non-linear least squares (NLS), and algebraic estimation. We chose to apply the NLS method for the following reasons. Firstly, despite the relative ease of implementation provided by the OLS method, the results can be unstable or with the wrong signs when only few historical data points are available, and time-interval bias can exist (Kijek, 2010). Secondly, for MLE, computation is expensive due to the lack of explicit formula (Kijek, 2010). As such, NLS is proposed to overcome some of the shortcomings of OLS and MLE (Srinivasan and Mason, 1986). Lastly, algebraic estimation requires knowledge of the time of the inflection point of the diffusion curve, which we do not want to assume in our study *a priori* in order to preserve generality. For a detailed explanation of the above methods, see Weiss (2014) and (Kijek, 2010).

3.2 Second-Stage Regression

While the innovation and imitation coefficients p and q can be considered as time-invariant, as Massiani and Gohs (2015) noted, they vary greatly even between similar products (e.g. different types of cars). Therefore, in the second stage, we use regression analysis to examine how the rate of diffusion varies with different aircraft model parameters. To do so, we estimate the following equations:

$$p = X\beta_p + \varepsilon_p; \tag{5}$$

$$q = X\beta_q + \varepsilon_q, \tag{6}$$

where X is the matrix of regressors that include various aircraft model parameters such as MTOW, range or bypass ratio. For a set of aircraft configurations, a set of regression coefficients β can be estimated based on eqs. (5) and (6), with ε_p and ε_q being the residual from the regression.

We maintain that in our interpretation of the regression results, a causal relationship between the above regressors and the diffusion parameters can be established. The aforementioned product-level parameters are fixed before any aircraft is delivered and has diffused into the market. The entry-into-service date marks the start of the diffusion and therefore is not influenced by the speed of diffusion. As such, one can rule out the possibility of reverse causality. There could be a risk of omitted variable bias, especially since that price information is not used in this model. However, based on the study by Husemann, Schäfer, and Stumpf (2018), where airlines indicated the aircraft model parameters they prioritize in their decision to purchase, we hold that omitted variable bias is not a major concern here.

3.3 Diffusion Curve Estimation for New Aircraft Models

Predictions of future diffusion processes for similar technologies can then be formed based on aircraft configuration parameters using eqs. (4) to (6). Optimistic and pessimistic diffusion scenarios can also be constructed based on the range of estimated β values.

4 Data

Data for 52 aircraft models were collected for this study, with the first aircraft launch dating back to 1963 and the last delivery being at the end of 2018. A total of 19,768 delivery records are collected for all aircraft models. The daily historical aircraft delivery data, range, and MTOW are collected from the official Boeing and Airbus websites and archives, as well as open source online database. Engine data are collected from the European Aviation Safety Agency's (EASA) certification noise levels data sheet for the respective aircraft model. The emission data is obtained from the International Civil Aviation Organization's (ICAO) Aircraft Engine Emissions Databank. All data are publicly available online and the sources are presented in Table 1. It is worth noting that price data for each aircraft are not included, as price data is generally agreed privately between manufacturers and buying airlines, and may vary significantly from the online listed price data. As such, it is omitted to ensure authenticity. However, if such data become available, they can also be easily incorporated into our model.

4.1 Range

The range for an aircraft varies with payload. For instance, Figure 2 shows the payload range diagram of a Boeing 737-300. In our analysis, due to the limited access to data and in order to ensure general comparability across all models, we use the design range given by manufacturers. There could be minor discrepancies in terms of measurement and definition of design range. They are, however, tolerated in this study.

Table 1: Data Description

Categories	Data	Sources
Historical Sales Data	Daily Aircraft Deliveries	Manufacturers' website(1) https://www.airfleets.net/
Aircraft Model Specific Parameters	MTOW, Range	Manufacturers' official or archived official websites (2)
	Engine	EASA website (3)
	Bypass Ratio(4)	ICAO (2018)
	Date (Entry-into-Service date)	Derived from aircraft delivery data
	Emission of CO (Carbon Monoxide), Hydrocarbon, NO_x (Nitrogen Oxides)	ICAO (2018)
Time Range of Data	1963 to 2018	
Number of Observations	52 Aircraft Models, 19,768 Delivery Records	

[1] http://www.boeing.com/commercial/#/orders-deliveries [2] Manufacturers' official websites such as https://www.boeing.com/company/about-bca/startupboeing.page, archived Airbus website containing Aircraft Characteristics and Airport and Maintenance Planning documents for each aircraft model [3] Jet aeroplanes noise database on https://www.easa.europa.eu/easa-and-you/environment/easa-certification-noise-levels
[4] Bypass Ratio data collected as the value for the corresponding engine of each aircraft.

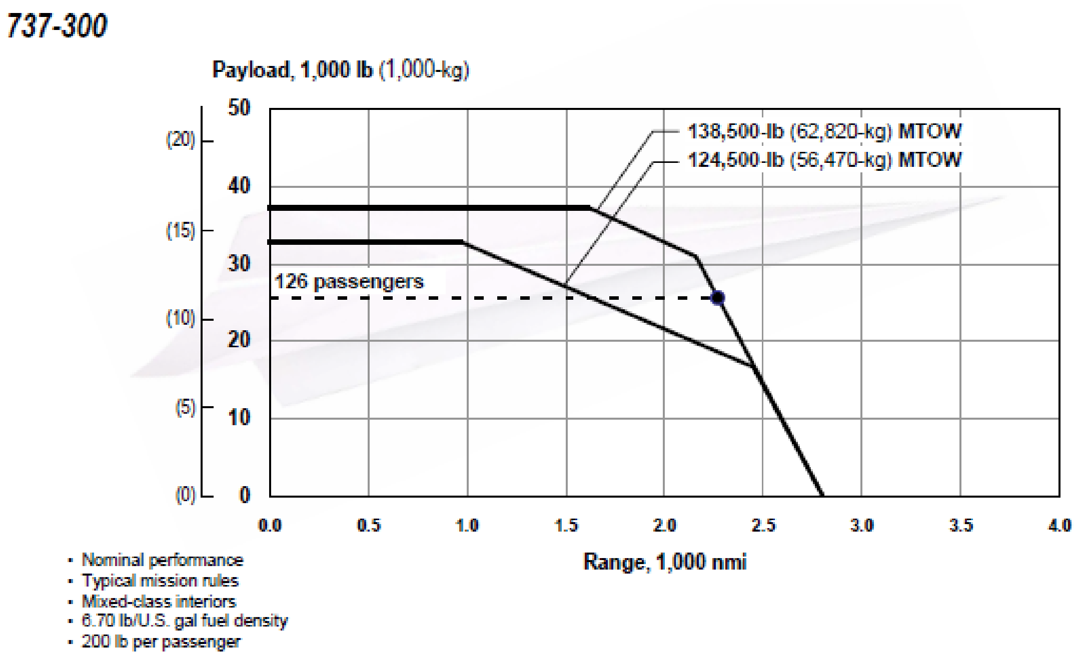

Figure 2: Payload Range Diagram of a Boeing 737-300
Source: Boeing Company, Startup Boeing, Airplane Selection 737 (737-300/-400/-500)
https://www.boeing.com/resources/boeingdotcom/company/about_bca/startup/pdf/historical/737-classic-passenger.pdf

4.2 Maximum Take-Off Weight (MTOW)

Commonly, aircraft manufacturers report the number of passengers (PAX) of a particular aircraft. This is also the parameter of concern for most airliners, since the revenues are generated from payload and not from the total weight. Nonetheless, in this study, we chose to focus on MTOW for a number of reasons. Firstly, the number of passengers could vary due to different seating arrangements. Although a typical seating arrangement is used in some reports, there could still be discrepancies between different manufacturers and different aircraft models (e.g. the typical seating arrangement varies for aircrafts of different seat and range classes). Secondly, MTOW is reported by the aforementioned sources for all aircraft models considered in this dataset, whereas PAX is not. As such, to ensure overall comparability, MTOW is used instead of PAX.

4.3 Pollutant Emissions

In terms of pollutant emissions, hydrocarbon, carbon monoxide (CO) and nitrogen oxides (NO_x) are included in this study. The reasons behind this are three fold. First of all, these three parameters contribute significantly to air pollution and phosphoric climate change, and are therefore of great concern. Secondly, these are the main emissions apart from carbon dioxide that are generated per flight. Lastly, because of their importance, they are also measured and reported by the authority and are thus available. It is worth noting that while NO_x, CO, and hydrocarbons are influenced by the amount of fuel consumed and by the aerodynamics of the aircraft design, data for specific aircraft are only available to us in terms of the respective engine type used. This is denoted for instance as "CO Dp/Foo (g/kN) average" (ICAO, 2018). On the other hand, carbon dioxide emissions, also highly correlated to the amount of fuel consumed, is not reported here because of a lack of data for specific aircraft models. To resolve this issue, we use the so-called Bypass Ratio as an indicator for carbon dioxide emissions (see the following section on Bypass Ratio).

4.4 Entry-into-Service Date (EIS)

EIS date for each aircraft model is the year that the first airplane from this aircraft model is delivered to the customer's fleet and entered into service, i.e. flight operation. The parameter is named as $Date$ in the regression analysis. This parameter is included here in order to account for the possibility that the diffusion rate may change over time. For instance, during the early years in aviation, the existing fleet size was small, and the available aircraft model choices were limited, while the demand was burgeoning, which might lead to a strong demand for airplanes and thus a faster diffusion process when new aircraft models are introduced.

4.5 Bypass Ratio

The Bypass Ratio is a measure that broadly indicates how energy-efficient the engine is. Generally, the higher the Bypass Ratio, the more fuel-efficient the engine is. Commercially, high bypass dominates the aircraft design in civil aviation. It is therefore used here as a proxy measure for fuel efficiency of an aircraft model. Ideally, a more direct and precise measure of fuel efficiency should be used, which also takes into account the aerodynamics of the aircraft design and other design features. This is, however, limited by the availability of data.

5 Results and Analysis

5.1 First-Stage Data Processing

In the first stage of our analysis, historical sales data of each aircraft model are processed to obtain the Bass model parameters p, q and M which describe the diffusion process for each aircraft model. A summary of the estimation results is shown in Table 2. The statistics reported here are: the mean, the standard deviation (std), the minimum (min), the 25, 50, and 75 percentiles, and the maximum (max) values of all estimated parameters, respectively. The diffusion curve for each aircraft model constructed from its individually estimated p, q and M is also plotted against each aircraft model's actual historical sales data in Figure 3, with the x-axis showing the number of time period (months) after diffusion starts and the y-axis showing the number of airplanes adopted globally.

From Table 2, we see that the average rate of innovation, p at 0.00639, is much slower than the average speed of imitation, q at 0.048115 (see Table 2, row 2), which is consistent with the general observation in the literature. Moreover, the market size M of 1078 is also consistent with the industry delivery records of aircraft sold. One valuable takeaway result from this analysis would be the average values of p, q, and M (Table 2, row 2), which can be used as a simplified 'rule of thumb' in the industry for forecasting new aircraft model diffusion. Similarly, the diffusion curves predicted by p, q, and M in Figure 3 also fit the historical data very well.

However, within each parameter, we did observe a high degree of variation, for instance the standard deviations for p, q, and M are relatively large (Table 2, row 3). Similarly, the values for the 25, 50, and 75 percentiles of each parameter p, q, and M also differs greatly e.g. the 75 percentile value for p at 0.008645 (Table 2, row 7, column 1) is almost 10 times larger than the 25 percentile value at 0.000875 (Table 2, row 5, column 1). This suggests that the values of p, q and M for a single aircraft model could differ greatly from another aircraft model. This result substantiates the need for a deeper analysis in our second stage regarding the estimation of individual p, q, and M values, rather than simply using the value of a different model by analogy principle used in prediction.

It is also worth taking a closer look at the estimated market size M. We see that the mean value of M at 1078 (Table 2, row 2, column 4) is actually even much larger than the 75 percentile value of M at 556. This could be an indication that among all commercially successful aircraft models, there exist a few extremely successful ones with significantly larger market potentials than all the other aircraft models, hence pulling up the average value of M substantially. These few extremely well sold aircraft models should be highly relevant for researchers, aircraft manufacturers and policy makers.

Table 2: Summary statistics for p, q, M from first-stage analysis using all aircraft models delivery data

Parameters	p	q	M
Number of Observations	52	52	52
Mean	0.006319	0.048115	1078
Standard Deviation	0.008527	0.038483	2497
Minimum	0.000100	0.002232	29
25 percentile	0.000875	0.021518	84
50 percentile	0.004026	0.042198	232
75 percentile	0.008645	0.066421	556
Maximum	0.054198	0.169908	10000

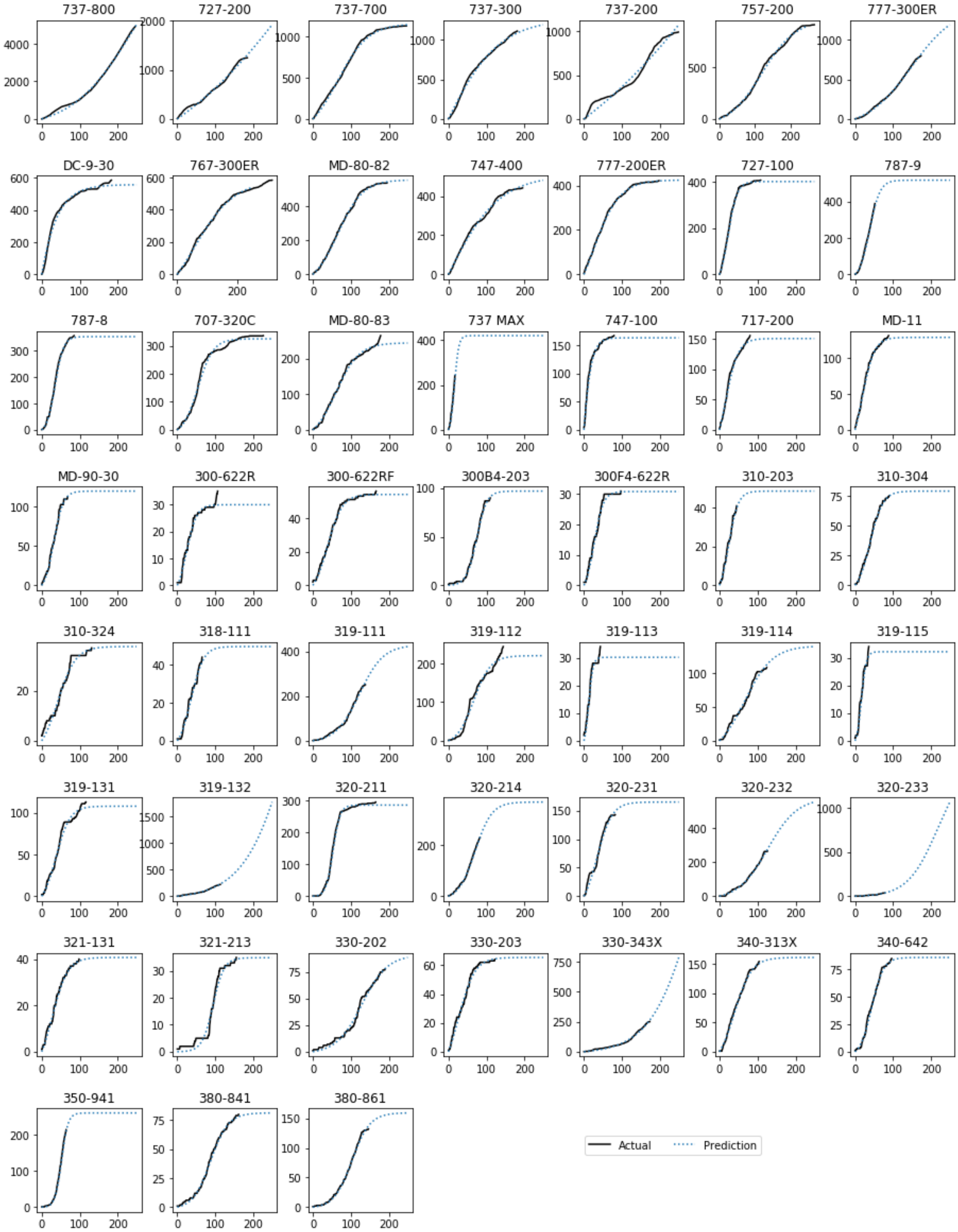

Figure 3: Actual vs. predicted diffusion based on prediction of p, q regression and original Bass parameter M

5.2 Second-Stage Regression Analysis

In the second stage, we use the estimated diffusion coefficients p and q and the market potential M of each aircraft model from the first stage as dependent variables and regress them on a set of regressors, which represent certain pre-launch aircraft model-specific technical parameters (e.g. range, MTOW, see eqs. (5) and (6)). The aim is to see how p, q and M are correlated with these technical parameters and if we could use such correlations to predict future diffusion patterns of new products whose technical parameters are known pre-launch. An overview of the descriptive statistics of the 52 aircraft models' technical parameters used in the model are shown in Table 3.

Table 3: Technical Parameter Description of the 52 Aircraft Models in the Estimation

Parameters	mean	std	25 Percentile	50 Percentile	75 Percentile
MTOW (Kg)	160978	127039	75500	90907	233000
Range (nmi)	4363	1986	3176	3750	5713
Bypass Ratio	5.2	2	4.8	5.1	6
Hydrocarbon	13	41	1	4	10
CO	51	54	15	36	52
NO_x	50	11	45	50	58
Entry-into-service Date	1992	13	1987	1995	2000
Total Deliveries	380	715	77	191	393

Our regression results are shown in Table 4. The regressors for each regression are selected through backward elimination, i.e. all regressors are used and the ones with the lowest partial correlation are removed sequentially. Therefore, not all technical parameters are featured in all three regressions. Note that the values of the coefficients are considerably small for certain regressors (e.g. the coefficient for sqr_MTOW_Kg is -1.434$\times 10^{-13}$) because the estimated values of p are very small (the mean value of all estimated p is 0.0063) while the values of certain technical parameters used as regressors can be very large in contrast (e.g. sqr_MTOW_Kg for the aircraft model 737-800 is around 6×10^{9}). The result shows that various parameters have different impact on the diffusion coefficients p and q and the market potential M.

For the rate of innovation coefficient p, the coefficients for MTOW ($MTOW\_Kg$), Range ($Range\_nmi$), bypass ratio of the engine ($BypassRatio$), squared MTOW (sqr_MTOW_Kg), and entry-into-service date ($Date$) are all significant at the 5% significance level. The positive coefficient for MTOW and the negative coefficient for squared MTOW may suggest the existence of a MTOW for the maximum p (3.9×10^5 kg or 390 t for the highest p value. Note that A380's MTOW is 575 t and Boeing 787 Dreamliner's MTOW is 254 t). Moreover, the negative coefficient for *Range* suggests that extra long haul aircraft may not be desirable, hence negatively affecting the p value. The Bypass Ratio as an indicator for engine fuel efficiency has a positive coefficient for p, indicating fuel efficiency consciousness in adoption behavior. Lastly, the negative coefficient of *Date* suggests slower diffusion through the innovation channel represented by p for more recent aircraft models. This could be due to the fact that the fleet has been built up already, and that further needs of airplanes are only for replacement and further expansion which are both rather gradual processes. Note that the parameters for pollutant emission are not featured here because they are removed in the regressor selection process due to weak correlations with the dependent variable p.

For the rate of imitation coefficient q, only the *BypassRatio* is significant. Again, the positive coefficient value here could be an indicator of fuel efficiency consciousness in adopting decisions. Note that similar to the regression of p, emission variables i.e. hydrocarbon, CO, and NO_x are insignificant. This lack of correlation between emission parameters and the rate of diffusion may suggest the need for policy actions to increase the weight given to emission in the adoption behavior. In addition, the relatively high level of the goodness of fit, indicated by the high R-squared value ($R2$, last row in Table 4) implies that the prediction of q using technical parameters is feasible.

For the market potential M, the 5% significant negative coefficient of *BypassRatio* suggests that higher fuel efficiency is correlated with lower market size, which is puzzling. One explanation could be that the aircrafts with higher bypass ratios are generally the newer models that have only recently entered the market, whose market size estimate are relatively unstable. Moreover, the regression coefficients for CO and hydrocarbon shows conflicting signs. One explanation is that hydrocarbon, as a major contributor to smog, is taken more into consideration during the adoption decision, hence negatively affecting M, whereas CO, a very weak direct greenhouse gas, is not so. This observation again calls for action to increase the weight of emission performance in the aircraft adoption decision and to internalize the environmental impact of flying. Lastly, the goodness-of-fit indicated by the R-squared value is relatively low, which can be observed later in Figures 4 and 5. This reveals a need for further research on the market potentials of the aircraft models investigated.

One obvious limitation of our research is data availability. First of all, our dataset is relatively small, since it only contains 50 different aircraft models. However, these 50 models cover a total of 19,768 airplanes delivered and the majority of the commercially successful aircraft models, i.e. those with more than 30 deliveries each. Globally, a total of 43,000 commercial airplanes, excluding freighters, have been delivered so far by all major manufacturers (Boeing, 2019). The lack of data, however, is not unusual in many such applications where substitute products or product variants are limited. Secondly, because each airline may choose to negotiate for customization of their purchased aircraft, the product-level data are not fully representative of each product. This analysis is thus the best possible given the data available.

Table 4: Regression results for p, q, M from second-stage analysis using all aircraft models' technical data

	p	q	M
Intercept	0.8421**	0.005316	-1.346e+05
	(0.3288)	(0.04501)	(1.133e+05)
MTOW_Kg	1.128e-07**	-7.443e-08	-0.003187
	(4.397e-08)	(7.29e-08)	(0.005083)
Range_nmi	-3.092e-06**		0.3136
	(1.52e-06)		(0.3948)
sqr_MTOW_Kg	-1.434e-13**		
	(6.138e-14)		
sqr_Range_nmi		-4.807e-10	
		(4.899e-10)	
BypassRatio	0.00271**	0.01446***	-740.8*
	(0.00133)	(0.004161)	(397.4)
CO		-0.0001438	37.93*
		(0.000294)	(20.57)
NOx		-0.0001232	
		(0.0005379)	
Hydrocarbon		0.0003331	-44.07*
		(0.0003262)	(23.18)
Date	-0.0004259**		68.95
	(0.0001674)		(57.34)
N	52	52	52
R2	0.24	0.34	0.19
R2 Adjusted	0.16	0.25	0.09

[1] Standard errors in parentheses [2] * p¡.1, ** p¡.05, ***p¡.01 [3] N: size of regression dataset [4] R2: R-squared value.

5.3 Estimation of Expected Future Diffusion

Figures 4 and 5 show the prediction of diffusion plotted against actual historical diffusion data. The prediction in Figure 4 is constructed from the predicted p, q, and M using regression results in the second-stage and technical data of each aircraft model. Figure 5, however, uses the actual total number of deliveries found in historical sales data, while p and q values are the same as in Figure 4. The y-axis shows the total number of planes adopted for each aircraft model while the x-axis shows time period, i.e. months after the diffusion process starts.

We observe that our prediction results in Figure 4 are very weak, i.e. the deviation from actual historical data is rather large. In some cases, for instance, aircraft model 320-231 or 340-642, the predicted market size M is even negative, which is clearly problematic. However, the predictions are much closer to actual data when we only use regression analysis to predict p and q, while incorporating the actual M from delivery data for each aircraft model in Figure 5. Using the example from before to illustrate this, we see that the prediction of the diffusion curves for aircraft model 320-231 or 340-642 are very close to the actual historical delivery data. This suggests that our method is more suitable for predicting p and q, and less so for M. Consequently, this naturally points to further research in the area of market potential prediction, which might also come from exogenous sources (e.g. expert judgment, survey, or clustering with similar products).

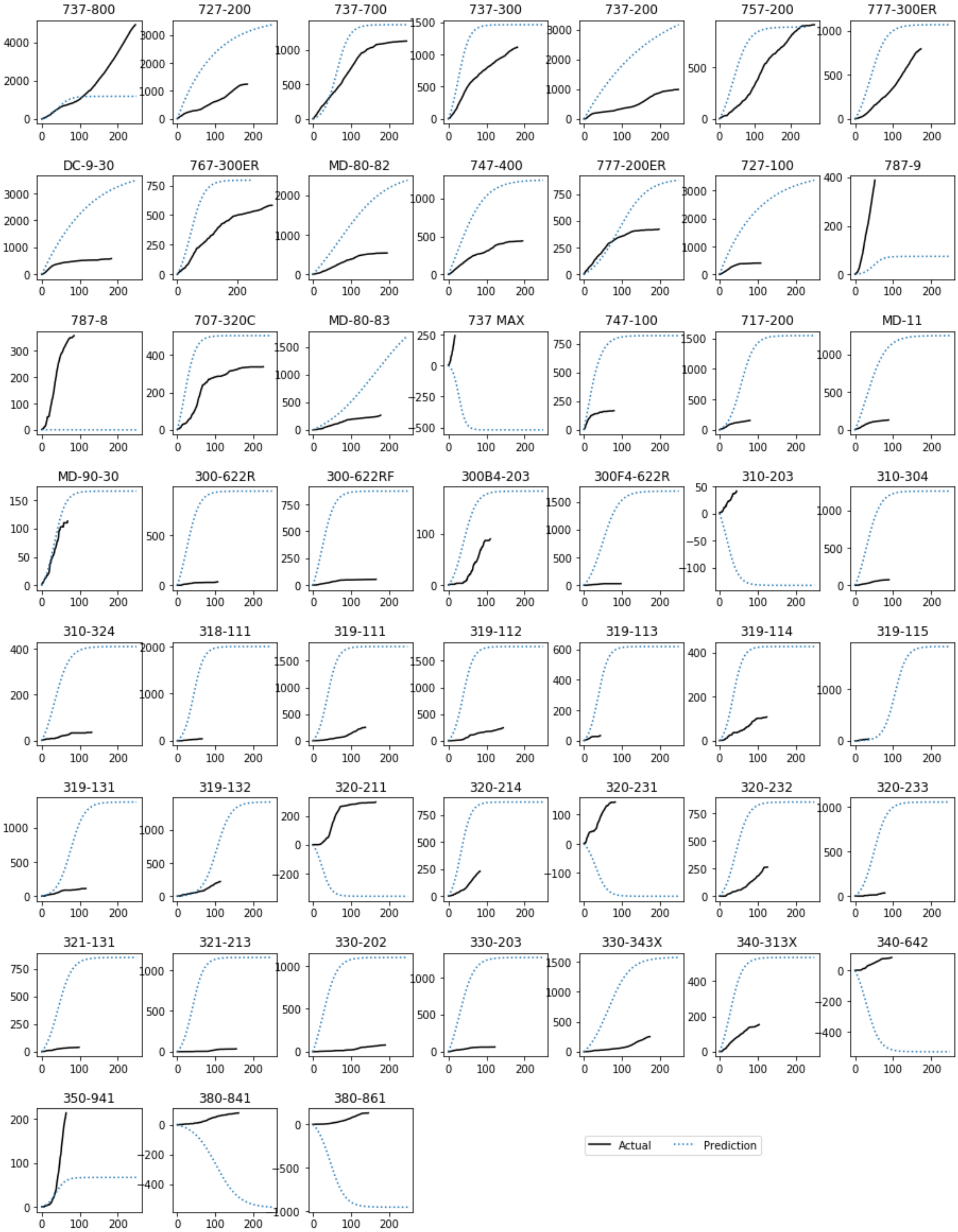

Figure 4: Actual vs. predicted diffusion based on prediction of p, q, M from second stage regression

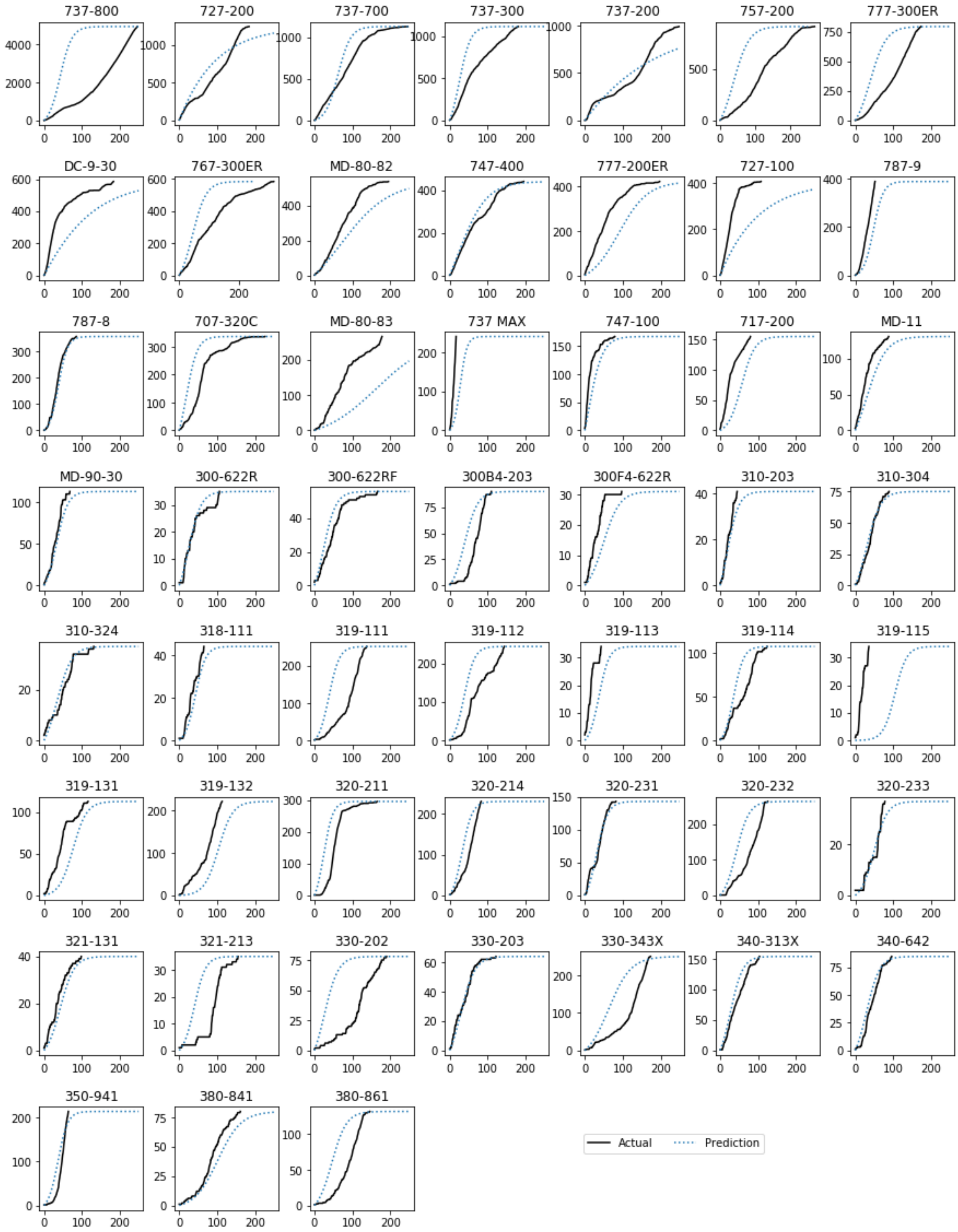

Figure 5: Actual vs. predicted diffusion based on prediction of p, q from second stage regression and actual market size from sales data

6 Conclusion

In this study, we aim to explore how different aircraft models are diffused into the market. In doing so, we collected daily delivery data of 52 major aircraft models, which was transformed into monthly data for the analysis. We also collected corresponding technical data of these aircraft models, including *Range*, *MTOW*, *BypassRatio*, *CO*, *Hydrocarbon*, and NO_x. Entry-into-service date for each aircraft model is calculated from the delivery data. A two-stage analysis combining the Bass model as the first stage and an OLS regression analysis as the second stage is used. In the first stage, we use the monthly delivery data to calculated the Bass model parameters p, q, and M for each aircraft model. We observe that the Bass model provides a very high goodness-of-fit level. In addition, the average parameter values of p, q, and M can be used as a 'rule of thumb' in the industry for a quick estimate of new aircraft diffusion. However, we also find that the estimates for each parameter varies greatly for different aircraft models, which necessitate for the second-stage analysis to further explore how p, q, and M vary with the technical characteristics of the aircraft model. Our second-stage results yield a better understanding with regard to how different aircraft models are adopted and, therefore, can inform and guide policymakers and other decision makers in the design and development of newer and more sustainable aircraft technologies. Our analysis shows that despite much heated discussion on the environmental impact of aviation, emissions such as CO and hydrocarbon are still of minor influence only in the adoption process. However, the bypass ratio as a measure of fuel efficiency as well as of carbon dioxide emission is of great concern, likely due to the cost pressure in the highly competitive airline business. Our attempt at market diffusion prediction by using product-level data and historical sales data shows mixed results. Our method produces relatively good estimates of the Bass parameters p and q; however, more research is needed for the prediction of market potential M.

Acknowledgments

We would like to acknowledge the fruitful discussions with researchers and scientists from the Institute of Aerospace Systems (ILR) at RWTH Aachen University, especially Eike Stumpf and Lis Weilandt, as well as with Thomas Zill from the German Aerospace Center (DLR). Also, this research would have never been possible without the generous funding from Horizon 2020 Clean Sky 2 Programme, project TeDiMo (Contract No. 821354 — TeDiMo — H2020-CS2-CFP07-2017-02).

References

Bass, F. M. (1969). “A new product growth model for consumer durables”. *Management Science* 15(1), pp.215–227.

Bass, F. M., K. Gordon, Teresa L., and M. Githens (2001). “DIRECTV: Forecasting diffusion of a new technology prior to product launch”. *Interfaces* 31, pp.S82–S93.

Berntsen, T. and J. Fuglestvedt (2008). “Global temperature responses to current emissions from the transport sector.” *Proc. Natl. Acad. Sci. U. S. A.* 105, pp.19154–19159.

Boeing (2019). *Commercial Market Outlook 2019 – 2038*. URL: `https://www.boeing.com/commercial/market/commercial-market-outlook/` (visited on 06/18/2019).

Bonabeau, Eric (2002). “Agent-based modeling: Methods and techniques for simulating human systems”. *Proceedings of the National Academy of Sciences* 99.suppl 3, pp.7280–7287.

Caselli, F. and W. Coleman (2001). “Cross-Country Technology Diffusion: The Case of Computers”. *American Economic Review* 91(2), pp.328–335.

EASA (2016). “European Aviation Environmental Report”. ISSN: 978-92-9210-197-8. DOI: `10.2822/385503`.

Fourt, L. A. and J. W. Woodlock (1960). “Early prediction of early success of new grocery products”. *Journal of Marketing* 25, pp.31–38.

Greve, H. R. and M. L. Seidel (2015). “The thin red line between success and failure: Path dependence in the diffusion of innovative production technologies”. *Strategic Management Journal* 36(4), pp.475–496.

Hall, B. H. (2004). “Innovation and diffusion”. *Handbook on Innovation. Oxford University*. Press.

Husemann, M., K. Schäfer, and E. Stumpf (2018). “Flexibility within flight operations as an evaluation criterion for preliminary aircraft design”. *Journal of Air Transport Management* 71, pp.201–214.

ICAO (2018). “ICAO Aircraft Engine Emissions Databank”. 26A. electronic updata of ICAO Engine Exhaust Emissions Databank, First Edition 1995, ICAO, Doc 9646-AN943. URL: `https://www.easa.europa.eu/easa-and-you/environment/icao-aircraft-engine-emissions-databank`.

Islam, T. (2014). “Household level innovation diffusion model of photovoltaic (PV) solar cells from stated preference data”. *Energy Policy* 65, pp.340–350.

Kar, Rahul (2010). “Dynamics of implementation of mitigating measures to reduce CO emissions from commercial aviation”. PhD thesis. Massachusetts Institute of Technology, Boston.

Kijek A., Kijek T. (2010). “Modelling of Innovation Diffusion”. *Operations Research and Decisions* No. 3-4, pp.53–68.

Lee, Chul-Yong and Sung-Yoon Huh (2017). “Forecasting the diffusion of renewable electricity considering the impact of policy and oil prices: The case of South Korea”. *Applied Energy* 197, pp.29–39.

Lee, H., S. G. Kim, H. Park, and P. Kang (2014). “Pre-launch new product demand forecasting using the Bass model: A statistical and machine learning-based approach”. *Technological Forecasting and Social Change* 86, pp.49–64.

Liu, X. and R. Madlener (2019). “The Sky is the Limit: Assessing Aircraft Market Diffusion with Agent-Based Modeling”. *FCN Working Paper No. 16/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, October*.

Macal, Charles M and Michael J North (2005). “Tutorial on agent-based modeling and simulation”. *Proceedings of the Winter Simulation Conference, 2005*. IEEE, pp.14.

Mahajan, V. and E. Muller (1996). “Timing, diffusion, and substitution of successive generations of technological innovations: The IBM mainframe case”. *Technological Forecasting and Social Change* 51(2), pp.109–132.

Mansfield, E. (1961). “Technical change and the rate of imitation”. *Econometrica* 29, pp.741–766.

Martino, J. P. (1972). *Technologial Forecasting for Decision Making*. New York, USA: American Elsevier.

Massiani, J. and A. Gohs (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, pp.17–28.

Meade, N. and T. Islam (2006). “Modelling and forecasting the diffusion of innovation – A 25-year review”. *International Journal of Forecasting* 22(3), pp.519–545.

Norton, J. A. and F. M. Bass (1987). “A diffusion theory model of adoption and substitution for successive generations of hightechnology products”. *Management Science* 33, pp.1069–1086.

Palmer, J., G. Sorda, and R. Madlener (2015). “Modeling the diffusion of residential photovoltaic systems in Italy: An agent-based simulation”. *Technological Forecasting and Social Change* 99, pp.106–131.

Rogers, E. M. (2003). *Diffusion of Innovations*. 5th Edition. New York: Free Press.

Srinivasan, V and Charlotte H Mason (1986). "Nonlinear least squares estimation of new product diffusion models". *Marketing Science* 5(2), pp.169–178.

Talukdar, Debabrata, K Sudhir, and Andrew Ainslie (2002). "Investigating new product diffusion across products and countries". *Marketing Science* 21(1), pp.97–114.

Weiss, C. E. (2014). "The Use of Time-Series Methods for Diffusion Modelling: An Evaluation". *PhD First-Year Report (June 2014), Judge Business School, University of Cambridge*.

List of the latest FCN Working Papers

2019

Specht J.M., Madlener R. (2019). Mitigation and Valuation of the Investment Risk in Engineered Geothermal Systems: A Real Options Analysis, FCN Working Paper No. 1/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, January.

Hackstein F., Madlener R. (2019). Sustainable Operation of Geothermal Power Plants: Why Economics Matters, FCN Working Paper No. 2/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, February.

Wolff S., Madlener R. (2019). Charged up? Preferences for Electric Vehicle Charging and Implications for Charging Infrastructure Planning, FCN Working Paper No. 3/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, March.

Höfer T., von Nitzsch R., Madlener R. (2019). Using Value-Focused Thinking and Multi-Criteria Group Decision-Making to Evaluate Energy Transition Alternatives, FCN Working Paper No. 4/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, April.

Glensk B., Madlener (2019). *Energiewende @ Risk*: On the Continuation of Renewable Power Generation at the End of Public Policy Support, FCN Working Paper No. 5/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, May.

Höfer T., Madlener R. (2019). A Participatory Stakeholder Process for Evaluating Sustainable Energy Transition Scenarios, FCN Working Paper No. 6/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, May.

Gimpel-Henning J., Madlener R. (2019). Synthetic Low-Voltage Grid Replication Using Spatial Information and Private Customer Load Profiles, FCN Working Paper No. 7/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, June.

Gimpel-Henning J., Madlener R. (2019). Large-Scale Grid Clustering to Predict Future Electricity Grid Extension Costs, FCN Working Paper No. 8/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, June

Gimpel-Henning J., Madlener R. (2019). Analyzing Actual Low-Voltage Grid Overloads Due to the Diffusion of Electric Vehicles, FCN Working Paper No. 9/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, July.

Schreiner L., Madlener R. (2019). A Pathway to Green Growth? Macroeconomic Impacts of Power Grid Infrastructure Investments in Germany, FCN Working Paper No. 10/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, August.

Schreiner L., Madlener R. (2019). Investing in Power Grid Infrastructure as a Flexibility Option: A DSGE Assessment for Germany, FCN Working Paper No. 11/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, August.

Wintgens L., Madlener R. (2019). Multi-Criteria Decision Analysis of Technological Alternatives to Conventional Expansion of the German Electricity Grid, FCN Working Paper No. 12/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, August.

Schultes G., Madlener R. (2019). Investment Under Uncertainty in a Power-to-Gas Plant in Germany: A Real Options Analysis, FCN Working Paper No. 13/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, September.

Karami M., Madlener R. (2019). Smart Predictive Maintenance Strategy Based on Cyber-Physical Systems for Centrifugal Pumps: A Bearing Vibration Analysis, FCN Working Paper No. 14/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, September.

Liu X., Madlener R. (2019). Get Ready for Take-Off: A Two-Stage Model of Aircraft Market Diffusion, FCN Working Paper No. 15/2019, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, October.

2018

Koenen J., Madlener R. (2018). Predictive Analysis of an Energy Trading Company's Outstanding Receivables Using Markov Chains, FCN Working Paper No. 1/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, January.

Vonsien S., Madlener R. (2018). Cost-Effectiveness of Li-Ion Battery Storage with a Special Focus on Photovoltaic Systems in Private Households, FCN Working Paper No. 2/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, February.

Pereira G.I., Specht J.M., Pereira da Silva P., Madlener R. (2018). Technology, Business Model, and Market Design Adaptation Toward Smart Electricity Distribution: Insights for Policy Making, FCN Working Paper No. 3/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, March.

Heesen F., Madlener R. (2018). Revisiting Heat Energy Consumption: Household Production Theory Applied to Field Experimental Data, FCN Working Paper No. 4/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, April.

Atasoy A.T., Harmsen – van Hout M.J.W., Madlener R. (2018). Strategic Demand Response to Dynamic Pricing: A Lab Experiment for the Electricity Market, FCN Working Paper No. 5/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, April.

Zeng Y., Schmitz H., Madlener R. (2018). An Econometric Analysis of the Determinants of Passenger Vehicle Sales in Germany FCN Working Paper No. 6/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, April.

Specht J.M., Madlener R. (2018). Business Models for Energy Suppliers Aggregating Flexible Distributed Assets and Policy Issues Raised, FCN Working Paper No. 7/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, April.

Ralovski I., Madlener R. (2018). On the Global Diffusion of Desktop 3D Printers and the Case of Total Adoption in the Customized Hearing Aid Industry, FCN Working Paper No. 8/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, May.

Washausen S., Madlener R. (2018). Economic Evaluation of Germany's Strategic Oil Reserves in Comparison With Major Other Industrialized Countries, FCN Working Paper No. 9/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, June.

Schach M., Madlener R., 2018. Economic and Geopolitical Impacts of the LNG Supply-Side Competition Between the USA and Russia, FCN Working Paper No. 10/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, July.

Wolff S., Madlener R: (2018). Driven by Change: Commercial Drivers' Acceptance and Perceived Efficiency of Using Light-Duty Electric Vehicles in Germany, FCN Working Paper No. 11/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, August.

König M., Madlener R. (2018). Conceptualization of a Distributed Energy Storage Community: An Economic Analysis for Germany, FCN Working Paper No. 12/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, September.

Höfer T., Madlener R. (2018). Locational (In-)Efficiency of Renewable Power Generation Feeding in the Electricity Grid: A Spatial Regression Analysis, FCN Working Paper No. 13/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, October.

Sobhani S.O., Sheykhha S., Madlener R. (2018). An Integrated Two-Level Demand-Side Management Game Applied to Smart Energy Hubs with Storage, FCN Working Paper No. 14/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

Karami M., Madlener R. (2018). Business Model Innovation for the Energy Market: Joint Value Creation for Electricity Retailers and their Residential Customers, FCN Working Paper No. 15/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

Colmenares G., Löschel A., Madlener R. (2018). The Rebound Effect and its Representation in Energy and Climate Models, FCN Working Paper No. 16/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, December.

Hackbarth A., Madlener R. (2018). Combined Vehicle Type and Fuel Type Choices of Private Households: An Empirical Analysis for Germany, FCN Working Paper No. 17/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, December.

Zimmermann G., Madlener R. (2018). Techno-Economic Evaluation of Combined Micro Power and Heat Generation Assets: Implications for the Multi-Tenant Building Market in Germany, FCN Working Paper No. 18/2018, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, December.

FCN Working Papers have been published since 2008 and are free of charge. They can mostly be downloaded in pdf format from the FCN / E.ON ERC Website (www.eonerc.rwth-aachen.de/fcn) and the SSRN Website (www.ssrn.com), respectively. Alternatively, they may also be ordered as hardcopies from Ms Sabine Schill (Phone: +49 (0) 241-80 49820, E-mail: post_fcn@eonerc.rwth-aachen.de), RWTH Aachen University, Institute for Future Energy Consumer Needs and Behavior (FCN), Chair of Energy Economics and Management (Prof. Dr. Reinhard Madlener), Mathieustrasse 10, 52074 Aachen, Germany.