Proceedings of the 2019 Winter Simulation Conference
N. Mustafee, K.-H.G. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y.-J. Son, eds.

APPLYING DIFFUSION MODELS TO SEMICONDUCTOR SUPPLY CHAINS: INCREASING DEMAND BY FUNDED PROJECTS

Ines Gold

Philipps University Marburg
Universitätsstraße 25
Marburg, 35037, GERMANY

Hans Ehm
Thomas Ponsignon

Infineon Technologies AG
Am Campeon 1 – 15
Neubiberg, 85579, GERMANY

Muhammad Tariq Afridi

Technical University of Munich
Arcisstraße 21
Munich, 80333, GERMANY

ABSTRACT

The question of the paper is: "How does governmental funded projects influence the demand forecast for semiconductor manufacturing". For Semiconductor Manufacturing an accurate demand is of paramount advantage due to the challenges arising from a mix of high capital cost and short product life cycles. We consider the Bass Model for new technology and product introduction as the most sophisticated model for supporting demand forecast for new products and technologies. In this paper it is described how the boost from governmental funded projects can be parameterized in the Bass Model from a theoretical and practical point of view. From a practical point of view the model is applied for the German funded projects GeniusTex and Productive4.0 on the example of a selected pressure sensor. A perspective is given on how this model can be validated in future research once actual data are available.

1 INTRODUCTION

A project initiated by the German government, called "Industry 4.0" is aimed to strengthen cooperation between companies all along the value chain in order to link production and processes among industrial players (BMWI 2019). This is how a common language is established that allows for the collaborative push towards a digitalized and connected industry. Semiconductor manufacturers take an important part in the transformation towards the Industry 4.0 since they connect the industry through the use of sensors (Deloitte 2018). With this initiative, the opportunity of collaborating on B2B platforms arises (BMWI 2019). Nevertheless, many companies nowadays are aware of the digital transformation but still shy away from the idea of implementing it into their business model (Deloitte 2018). This is why until now, B2C platforms are at the forefront and even constitute a potential threat towards companies of the B2B sector. Amazon, for instance, has recently started to enter the B2B market and is able to benefit from its strong expertise in platform sales (Intershop Communications AG 2015; Lässig et al. 2015). Hence, if B2B actors do not countervail these developments, they could lose important share of the market (Lässig et al. 2015). Due to the named reasons, it can be concluded that there will be potential growth opportunities for semiconductor markets within the upcoming years. Nevertheless, this potential can only be exploited if semiconductor manufacturers are able to promote and offer their products through digital platforms, so that information and products can easily be accessed and reached. This is especially true for semiconductor products since they differ in product characteristics, such as accuracy and energy consumption, which leads to a certain complexity in the buying process (Infineon Technologies AG 2019; Productive4.0 Consortium 2018b). As a response to the depicted aspects, several projects initiated and co-funded by the European Commission H2020 and the ECSEL Joint Undertaking have recently started to evolve (Fraunhofer Institute for Applied Information Technology FIT 2019; Infineon Technologies Austria 2019; Productive 4.0 Consortium 2019). Infineon Technologies AG is part of several of these projects. It is believed that the participation opens up opportunities for the company to promote their products through B2B platforms. Amongst others, the smart textile industry will be a new targeted market segment. One product category that could especially benefit from these developments is the digital pressure sensor family offered by Infineon. The question arises, how demand growth can be quantified for innovative semiconductor products, such as digital pressure sensors, and how EU funded projects impact this demand evolution within future.

The remainder of this paper is structured as follows. Section 2 will provide an elaborated overview for the Bass Diffusion Model and one modified model which allows for the consideration of successive product generations. Section 3 will give insight to the digital pressure sensor portfolio at Infineon, where the Norton & Bass model will be applied to. It will also describe selected EU funded projects at Infineon, which could have an impact on the demand evolution for the digital pressure sensors. The paper closes with a final conclusion.

2 LITERATURE REVIEW

Since this paper is dealing with a situation where the demand of an innovative product is aimed to be forecasted, it is inevitable to provide an elaborated overview of related literature in this field. Therefore, an overview of the Bass Diffusion Model will be presented in order to depict why it is suitable for the scope of this paper.

2.1 Bass Diffusion Model

Until the beginning of the 20th century, diffusion models have been frequently applied in different fields such as epidemiology, sociology or biology (Jaakkola 1996). There are different approaches to forecast demand of innovative technology products, such as the leading indicator method (Uzsoy et al. 2018). In 1969, Frank Bass introduced the Bass Diffusion Model by using three parameters to describe demand effects (Kurawarwala and Matsuo 1998). Bass integrates internal as well as external influences as demand driving factors (Mahajan et al. 1990). The model is based on the principles of innovation diffusion and product life cycle patterns. According to Rogers, adopters of innovations can be categorized into five groups: innovators, early adopters, early majority, late majority and laggards (Bass 1969). The subsumption of one adopter into a group is based on the timing of the adoption. Based on this, Bass conducts a classification of adopters into two groups: innovators and imitators. Innovators (which would be group one according to Roger's classification) are externally motivated by mass media communication to purchase any innovative product or service (Bass 1969; Massiani and Gohs 2015). For instance, this could be the promotion of a product through the medium TV, radio or newspaper (Sahin 2006). On the other hand, there are imitators (that equal adopter classes two to five according to Roger's classification), that only adopt the innovation due to communication to persons that have already adopted the product or service (Bass 1969; Horsky and Simon 1983). Hence, reasons for an imitator to purchase the product could result from social pressure or positive feedback about the product from prior adopters. Over time, due to increasing WoM effects, the number of imitators is getting bigger, while the number of innovators is decreasing (Ismail and Abu 2013). In order to express the demand evolution in a mathematical manner, Bass uses three parameters: p, q and m (Bass 1969). Parameter p reflects the coefficient of innovation, whilst q declares the coefficient of imitation. The third parameter – m – represents the market potential and equals the maximum number of potential adopters that will be reached over time (Decker and Gnibba-Yukawa 2010). The cumulative adoptions, which will follow the shape of an S-Curve, can be described as follows (Bass 1969):

$$Y(t) = mF(t) = \frac{m\left(1 - e^{-(p+q)t}\right)}{\left(1 + \frac{q}{p} e^{-(p+q)t}\right)} \tag{1}$$

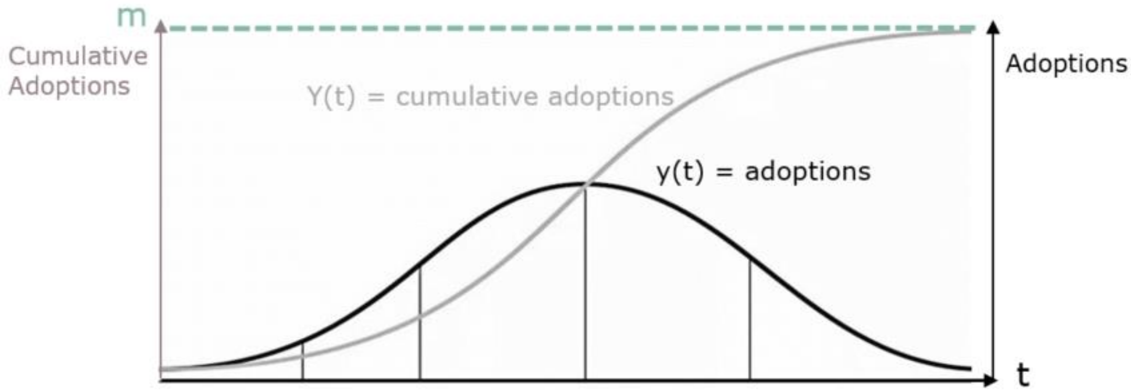


Figure 1: Bass diffusion model as a forecasting tool (own illustration).

The model assumes that one adoption equals to one sales unit (Bass 1969). Thus, when it is used for forecasting reasons, sales figures can be derived from the number of adoptions at time *t*. In literature, different estimation methods for three parameters are applied and discussed (Hong et al. 2016; Massiani and Gohs 2015; Srinivasan and Mason 1986). One of the simplest methods is making use of the Ordinary Least Squares (OLS) estimation (Hong et al. 2016). Bass applies the OLS estimation by constructing a discrete equation that represents sales at time *t*, which can be seen in Equation (2) (Bass 1969).

$$y(t) = pm + (q - p)Y(t-1) - \frac{q}{m} Y^2(t-1) \tag{2}$$

Hence, in order to allow using discrete, historical sales data as input for the subsequent OLS parameter estimation, Equation (2) is reformulated as shown below:

$$y(t) = a_1 + a_2 Y(t-1) + a_3 Y^2(t-1) \tag{3}$$

In Equation (3), $a_1 = pm$, $a_2 = q - p$ and $a_3 = -q/m$ denote the parameters to be estimated. This can easily be done with the help of linear regression (Ganjeizadeh et al. 2017). Nevertheless, this method entails some drawbacks (Hong et al. 2016; Mahajan and Sharma 1986; Schmittlein and Mahajan 1982). For instance, the problem of multi-collinearity occurs for $Y(t-1)$ and $Y^2(t-1)$, standard errors are not appropriately considered and the continuous model is derived from a discrete function, which will lead to time biased results. This is how the Nonlinear Least Squares (NLS) procedure has become the most preferred one to use (Mahajan et al. 1990). Here, parameters can directly be calculated from Equation (1) (Srinivasan and Mason 1986). In addition, it includes an error term that captures both, sampling as well as other errors (Srinivasan and Mason 1986).

2.2 Model Extensions and Modifications

One important model extension of the classical Bass Diffusion Model is the Norton & Bass model. The basic assumption of the model is that new technological generations, such as in the semiconductor industry, will be introduced before the former one has been fully diffused within the social system (Norton and Bass 1987). Consequentially, part of the sales that would have gone to the previous generation will be "stolen" by the newer one. Moreover, they assume that with the introduction of a new generation, additional market potential will unfold. That is, due to technological advancement, products might enter new markets or will be applied in devices that have not been aimed at in the beginning. Nevertheless, some customers might still decide to adopt the older technology. For three generations, for instance, shipments $S_i(t)$ at time *t* can be reflected within the following equations:

$$S_1(t) = F(t)m_1[1 - F(t - \tau_2)]$$
$$S_2(t) = F(t - \tau_2)[m_2 + F(t)m_1[1 - F(t - \tau_3)]$$
$$S_3(t) = F(t - \tau_3)\big[m_3 + F(t - \tau_2)[m_2 + F(t)m_1]\big]$$

where $F(t)$ corresponds to the cumulative density function and m_i denotes the market potential solely related to the respective generation, being caused by the additional use cases and markets. Furthermore,τ_2, for instance, represents the introduction point of time for the second generation and parameters *p* and *q* are kept constant throughout the whole life cycle. To better understand the equations, the adoption process can be described as follows (Bass 2014). Sales for the first generation $S_1(t)$ at time *t* is determined by m_1, but only until the introduction of generation two. Then, generation two is taking over sales from generation one. Sales for generation can be expressed by m_1 plus the incremental potential m_2 that comes with the second generation. However, with the introduction of the third generation, adopters could also purchase this generation instead.

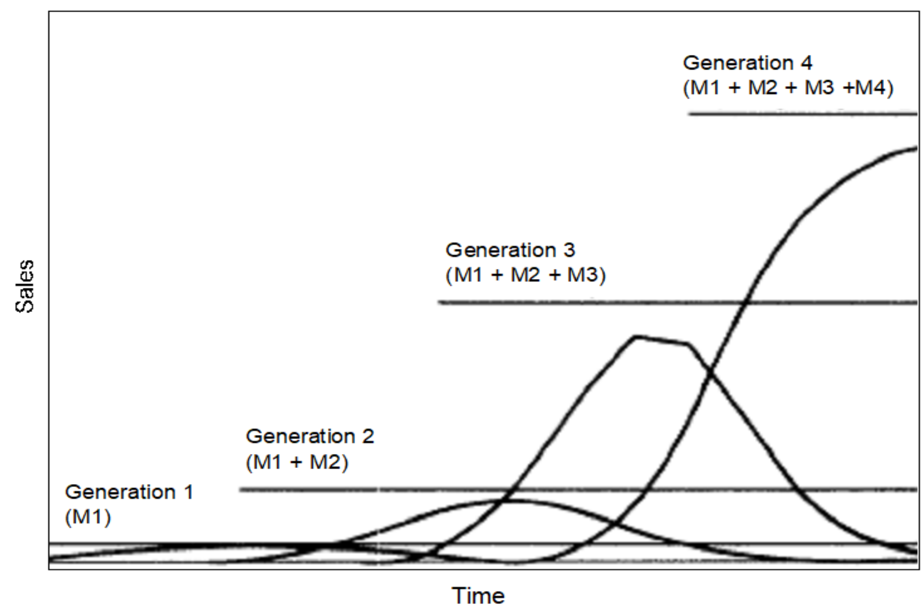


Figure 2: Typical diffusion pattern for different generations (Norton and Bass 1992).

Certainly, there are more extensions of the classical Bass Diffusion Model. Study in (Chien et al. 2010) proposes a multi generation diffusion model for semiconductor product demand forecast combining seasonal factor, price, market growth rate, technology substitution, repeat purchases, in which non-linear least square method is used for parameter estimation. Besides the consideration of successive generations, the impact of marketing activities has gained significant attention within literature. For instance, the impact of marketing and advertising expenditures on the coefficients of innovation and imitation and the market potential has been extensively investigated (Bass et al. 1994; Boehner and Gold 2012; Horsky and Simon 1983). However, these models include marketing activities in terms of quantitative terms, such as expenditures. This work differentiates itself by conducting an in-depth analysis of the impact of EU funded projects on demand which cannot be found in any other research work.

3 CASE STUDY: DEMAND FORECASTING FOR DIGITAL PRESSURE SENSORS AND EU FUNDED PROJECTS AT INFINEON TECHNOLOGIES AG

3.1 Digital Pressure Sensors and EU Funded Projects

The products under investigation in this work constitute the digital pressure sensor (DPS) portfolio that is offered in the PMM department at Infineon. Sensors in this portfolio are able to measure temperature and barometric pressure on a highly accurate scale (Infineon Technologies AG 2019). Currently, Infineon lists three products in its DPS portfolio: DPS310, DPS368 and DPS422. With its launch in October 2015, the DPS310 is the product with the longest life time within the DPS portfolio (Würth 2018). The DPS422 has just been introduced to the market, while the DPS368 will only be launched within the first half of 2019. Due to the small package, high accuracy and very low energy consumption, the pressure sensors can be deployed in several application areas (Infineon Technologies AG 2019). The main target application fields are indoor navigation, health and sports, outdoor navigation, weather stations and drones. Hence, pressure sensors can mainly be found in smart and wearable devices. This could be, for instance, a smart watch that tracks the motion and sports activity of a person (Infineon Technologies AG 2016). In addition, DPS368 stands out with an environmentally protected package that is robust to water, dust and humidity (Infineon Technologies AG 2019). Furthermore, the DPS422 package height is even smaller than the one of the DPS310. On the other hand, it offers excellent temperature stability that enables features such as heat control and micro weather forecasts. The product has been chosen because it offers innovative product characteristics, can be used for IoT solutions and can easily be promoted through EU funded projects. It will be assumed that Norton & Bass model can be applied for this case study. For instance, the three products that the DPS portfolio offers will be considered as different product generations. This is because it is believed that customers could decide to switch from buying the DPS310 to buying the DPS368, for instance. Therefore, DPS310 is going to be considered as generation 1, while the DPS368 and DPS422 are summarized into one further generation, thus generation 2. This is because they are launched approximately at the same time. Additionally, the application of diffusion models has been chosen in this work because they are able to represent "contagion" effects that will lead to rapid increasing sales within a market and allows for a closer look at demand paths.

The selected funded projects being considered in this paper are Productive4.0 and GeniusTex. The mission of the Productive4.0 project is the push of the digitalization and IoT within the European industry (Productive4.0 Consortium 2019). With more than 100 partners participating in the project, expert knowledge from academia and businesses all along the supply chain is brought together. Therefore, manufacturers, Original Equipment Manufacturers (OEMs), suppliers, and several SMEs are collaborating on the three topics digital production, product life cycle management and supply chain networks. Adding to that, several research institutions contribute with their respective domain knowledge. The scope of the project comprises the development of the "Solution Finder" which helps customers to find the right components for their end products. Several review meetings open up opportunities to get in contact with potential new customers.

The GeniusTex project brings together players from different industries such as textile, semiconductor and health care companies (Fraunhofer Institute of Applied Information Technology FIT 2019). Representatives from relevant research institutions are part of the project, as well. The outcome of the project will be a network that links several stakeholders in the smart textile industry such as developers, manufacturers but also end users in one open innovation platform. With the availability of a B2B platform, disruptive innovative ideas can be expressed, discussed and collaboratively developed. With the initiation of GeniusTex, innovation in the smart textile industry will be pushed and a "common language" allows for an effective collaboration between relevant stakeholders.

3.2 Bass Diffusion Model Application at Infineon Technologies AG

In order to model the demand evolution for the two generations, a nonlinear least squares parameter estimation is conducted with the help of the statistical software RStudio. In order to do so, the following equations are used:

$$Min \sum_{I=1}^{n} \sum_{t=1}^{l} [s_i(t) - \widehat{s_i}(t)]^2$$

$$S_1(t) = m_1 F_1(t) * (1 - F_2(t - \tau_2))$$

$$S_2(t) = F_2(t) * (m_2 + F_1(t) * m_1)$$

$$f_i(t) = F_i(t) - F_i(t-1)$$

$$F(t) = \frac{(1 - e^{-(p+q)t})}{(1 + \frac{q}{p} e^{-(p+q)t})}$$

Parameter estimation deliver the following outcome:

Table 1:Parameter Estimation for Norton & Bass model.

	Estimate	*Std. Error*	*t value*	*Pr(>|t|)*
p	0.0076	0.0014	5.447	0.0055 **
q	0.5661	0.0470	12.035	0.0003 ***
R^2		99.14%		
MAPE		4.98%		

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

The high estimation accuracy (R^2 = 99.14 %) and forecasting accuracy (*MAPE* = 4.98%) indicate that the Norton & Bass model is suitable to represent the demand evolution for the digital pressure sensors.

3.3 Impact of Funded Projects on Coefficient of Innovation and Imitation

Funded projects, such as GeniusTex or Productive 4.0 could impact the demand evolution for innovative semiconductor products. Since Infineon has just started to participate in the funded projects, historical data that could help to assess their impact is difficult to obtain. This is why factors that might influence the respective parameter’s value will be outlined with the help of relevant literature. Finally, it has been decided that the potential variation in *p* and *q* values will be examined by taking a closer look at the adoption-decision process, defined by Everett Rogers. There are five stages in this process: knowledge, persuasion, decision, implementation and confirmation and they can be described as follows (Rogers 2010).

- **Knowledge:** At this stage of the process, the adopting unit learns about the product’s existence and its utility (Rogers 2010). Questions about the “what?”, “how?” and “why?” of the innovation will be answered at this first stage.
- **Persuasion:** At the second stage of the process, adopting units will establish a personal opinion about the product (Rogers 2010). Statements made by prior adopters can be influential in this stage.
- **Decision:** The following step is characterized by the adoption or rejection act of the decision-making unit (Rogers 2010). In this step, similarly to the persuasion stage, the impact of statements from prior adopters on the adoption unit’s behavior is believed to be strong.

- **Implementation and Confirmation:** At the last two stages, implementation describes the utilization of the innovation, while confirmation reflects the final attitude towards the adoption that could lead to further adoptions in future (Rogers 2010).

As it has already been mentioned before, the *knowledge stage* mainly focusses on learning about the product. According to Rogers, the use of mass media communication is the most effective way to give potential adopters access to knowledge (Rogers 2010). In the end, the awareness or the knowing of a product could potentially lead to an adoption decision (Rogers 2010). The Bass Diffusion Model is based upon similar assumptions. In this model, innovators are mainly motivated to adopt because they have heard of the innovation through mass media communication (Bass 1969). Since the coefficient of innovation indicates how likely an innovator-driven adoption is, it can be concluded that the knowledge stage is correlated to the coefficient of innovation. Thus it will be investigated in how far the project partners get the chance to learn about the product. When analyzing the Productive4.0 homepage, an article about the DPS310 can be found (Productive4.0 Consortium 2018a). In this article, the multifaceted range of use for the DPS310 due to its high precision is pointed out. This article is not only accessible for project partners, but also for other visitors of the Productive4.0 website. In addition, by illustrating the use of the DPS310 as a virtual racket in a ping pong game at a project meeting last July, the potential use of the sensor in different application areas is exemplified. Thus, it can be concluded that project partners are able to learn about the product via the Productive4.0 homepage but also at regular meetings.

Contrary to the knowledge stage, which is more about getting to know a product, the *persuasion stage* is rather related to developing an attitude. Since in this stage, opinions from other adopters play an important role for the decision-maker (Rogers 2010), it can be concluded that there is a connection to the coefficient of imitation. There are five product characteristics that can affect the attitude that the adopting unit develops about the product (Dodgson et al. 2013). This is why it will be analyzed how strong the respective attributes apply to the DPS series and if the participation in funded projects will affect those characteristics.

- **Relative Advantage:** The relative advantage refers to the additional benefit that is arriving with the new product (Rogers 2010). Superior performance for the digital pressure sensors is present in terms of low energy consumption, high accuracy and the low price that results from the use of capacitive technology (Infineon Technologies 2016). For instance, the DPS310 can reach a 50% reduction of energy consumption compared to competitors who use piezo-resistive technology (Möhrle 2018). In addition, the DPS368 only constitutes 20% of the usual size of waterproofed pressure sensors. Hence, the relative advantage for the DPS portfolio can be stated to be already very high. The participation in funded projects provides important support in promoting the high performance of the DPS series – for instance, through online articles and product demonstrations.
- **Compatibility:** The compatibility describes in how far the new product is in accordance with already existing standards (Rogers 2010). Compatibility in the case of the DPS series can be related to the ease of integration into end devices. The small size of only few millimeters makes it easy to integrate the pressure sensors into end devices such as mobile or wearable device. In addition, flexibility concerning the configuration of parameters such as energy consumption and precision makes the integration of the sensors into end devices very convenient (Infineon Technologies AG 2017). The DPS368 even allows for application areas that demand for robustness concerning humidity and dust. An initiative of the Porductive4.0 project, the so-called “Solution Finder” allows for an online simulation of different product parameters in order to find out if they match with the end product’s requirements (Productive4.0 Consortium 2018b). Thus, compatibility can be tested.
- **Complexity:** The complexity refers to the ease of comprehension and applicability of the innovation (Rogers 2010). Semiconductor product’s complexity is reflected in the huge product variety that are offered nowadays (Productive4.0 Consortium 2018b). Thus, when choosing from a semiconductor manufacturer’s product portfolio, it is difficult for customers to find the perfect matching one to use for their own products. The Solution Finder makes finding the right products

for the customers' individual use cases as easy as possible. Thus, with the help of the Solution Finder, the degree of complexity can be decreased.

- **Trialability:** The trialability indicates how easy or difficult it will be for potential adopters to test and try the innovation in advance (Rogers 2010). Prototyping with the Infineon DPS310 sensor is already possible (Infineon Technologies AG 2018). That is, Infineon offers a combination of hard- and software that makes it easier for engineers to develop their own tailor-made solutions. This prototyping option will also be available for DPS368 and DPS422 and allows for a faster assessment of possible solutions (Möhrle 2018). Thus, trialability is already given. In addition to that, with the introduction of the GeniusTex platform, an open innovation concept is introduced (Fraunhofer Institute for Applied Information Technology FIT 2019). With this platform, it becomes possible for stakeholders of the smart textile industry to test and develop new ideas with the digital pressure sensors.
- **Observability:** The observability characteristic of an innovation states how strong their presence can be found in the potential adopter's environment (Rogers 2010). Promotion for observable products such as fashion goods (e.g. UGGS) or electronics (e.g. iPad) is highly effective and leads to faster diffusion (Boehner and Gold 2012). On the other hand, there are products that are less observable. The slow diffusion of computers, for instance, can to some extent be traced back to their low visibility (Rogers 2010). Semiconductor products are mainly components of end user products (Gupta et al. 2006). Hence, their observability is rather low. Nevertheless, the demonstration of the DPS310 as a ping pong racket can lead to stronger visibility and recognition of the product. Moreover, through the visualization of the DPS310 as a virtual racket, the product becomes more tangible to potential adopters.

The strength of the presented product characteristics is a meaningful indicator for determining the rate of adoption of a product innovation (Rogers 2010). Accordingly, the coefficients of innovation and imitation state how fast a product will be adopted (van den Bulte 2002). At the decision stage, the choice between adoption and rejection will be made (Rogers 2010). If a positive attitude towards the product is developed within the persuasion stage, an adoption act is likely to occur.

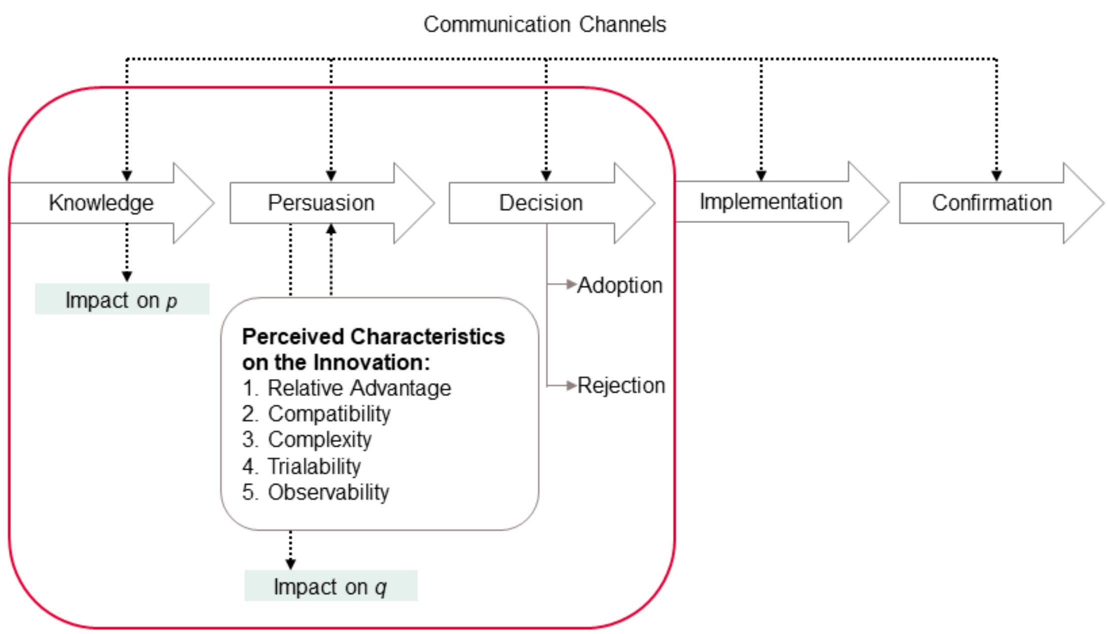


Figure 3: Five stage adoption-decision process (own illustration based on Rogers 2010, p. 163).

3.4 Impact of Funded Projects on Market Potential

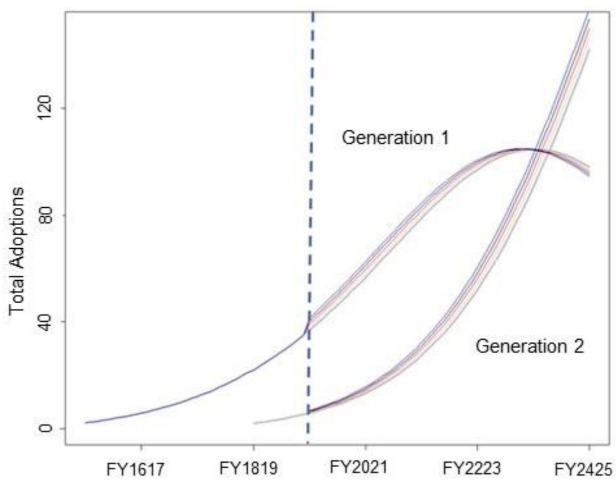
Contrary to the coefficients of innovation and imitation, the market potential is a value that is more tangible and easier to interpret (Sokele and Moutinho 2018). With the support of EU funded projects, new market opportunities might arise. This can be done by determining the market potential in terms of applications that incorporate components (Bass 2001). The market potential is therefore defined by multiplying the number of ultimate applications times an average purchase rate. In the case of the digital pressure sensor portfolio this could be smartphones or smart watches, for instance (Infineon Technologies AG 2019). Hence, if the number of feasible application areas grows, the market potential will grow as well. The GeniusTex project serves as an example for a possible growing number of applications (Fraunhofer Institute for Applied Information Technology FIT 2019). This is owed to the strong focus on enhancing innovation. Within the smart textile industry, most product developments are only at an infancy stage. The GeniusTex project, however, aims to go beyond this stage in order to strengthen the market position within this industry. Thus, the project offers a huge potential for new products that otherwise would not have been developed. With the first use case of developing innovative products, such as smart bands or smart orthoses, the DPS products are likely to be incorporated. This is based on the fact that Infineon is a close project partner and the digital pressure sensors are strongly promoted among project members.

3.5 Implications from Rising Parameter Values

With the execution of a meta-analysis, Sultan et al. discovered that the average value of p is at around 0.03 (Sultan et al. 1990). Compared to that, the coefficient of innovation for the digital pressure sensors (0.0076) is low. For that reason, it can be assumed that only few adoptions will be due to mass media communication (Norton and Bass 1987). A small value for p also indicates that sales will be rather low within the initial stages of the product life cycle (van den Bulte 2002). If the coefficient of innovation increases, sales will rise faster at the beginning but will also lead to a stronger decline afterwards. In the case of the digital pressure sensors, higher p values for generation 1 mainly leads to an increase in adoptions from fiscal year 19/20 to fiscal year 22/23, which can be seen at Figure 4. From then on, rising adoptions can only be reached on a low scale which even leads to a decline in total adoptions. From a practical perspective, this can be interpreted as an indicator for the increasing popularity of generation 2, which slowly takes over sales from generation 1 (Islam and Meade 1997). Moreover, generation 2 undergoes rapid growth. Since it will only be introduced in fiscal year 18/19, it can strongly benefit from an increase in the coefficient of innovation. Thus, marketing activities should be aligned with the respective life cycle stage that the products are positioned at within a certain time period (Society for Public Health Education 2016). Horsky and Simon (1983) take this assumption up by stating that advertising is mainly successful in early life cycle stages. Since generation 1 is situated at an advanced life cycle stage, increasing values of p do not have significant impact on demand. Thus, mass media marketing is not that impactful at this stage. However, generation 2 is only at the introduction stage and can strongly profit from innovator driven adoptions.

Moreover, parameter estimation has produced a value of 0.566 for the coefficient of imitation. According to a meta-analysis by Sultan et al., the average value of q is at 0.38 (Sultan et al. 1990). Hence, imitation effects for the digital pressure sensors are high. Therefore, it can be stated that most adoptions for the digital pressure sensors are imitator-driven. Changes in q will lead to steeper demand curves, which has also been the case for higher p values. Nevertheless, higher q values indicate that demand increases at a much lower scale in the beginning, but then rapidly increase at the take-off phase (van den Bulte 2002). Since generation 1 has already been introduced in fiscal year 15/16, it can profit from an increasing coefficient of imitation. Despite of its main impact in advanced life cycle stages, higher q values still hold strong impact on demand for generation 2. This finding leads back to the fact that imitator effects are much higher than innovator effects from the beginning. Moreover, total adoptions in fiscal year 22/23 – which means adoptions and disadoptions – decline with higher q values. This decrease indicates that there is still potential for adoptions of generation 1, which will nevertheless, migrate to generation 2. In a practical view, that would mean that customers or applications that have been adopters of generation 1 so far, will switch to generation 2 (Speece and Maclachlan 1995). With product demonstrations that become possible through the participation in the funded projects, observability and trialability for the digital pressure sensors will be increased. Moreover, with B2B platforms, such as the Solution Finder, complexity is reduced. Thus, digitalization and IoT related topics offer great opportunities for Infineon and its sales. Hence, marketing activities such as prototyping, product demonstrations and sampling have been identified to be crucial for the digital pressure sensors demand.

With regards to a potential increasing market potential, the GeniusTex B2B platform offers valuable contribution to the German smart textile industry. With the strong focus on collaborative innovation, product ideas can come up that will potentially comprise the use of pressure and temperature sensors. Thus, additional customers and applications can be reached, that would not have been thought of when launching the DPS series to the market. With the help of GeniusTex, Germany could take over the leading edge in the smart textile industry.



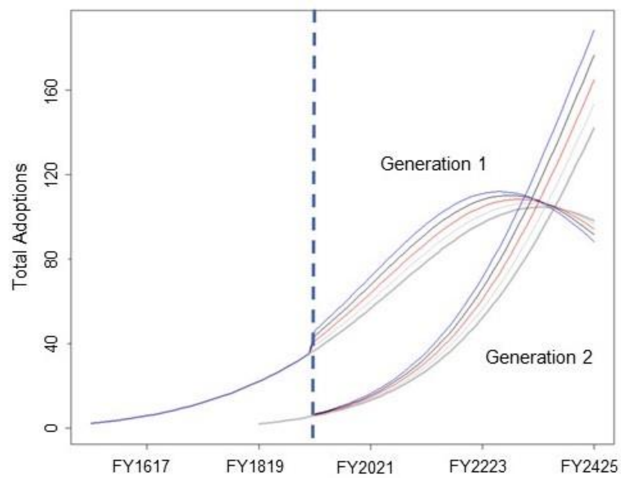


Figure 4: Demand curves for changed coefficient of innovation (left) and changed coefficient of imitation (right) (own illustration).

4 CONCLUSION

In this paper, it has been shown that the use of diffusion models is an appropriate method to conduct a demand forecast for innovative semiconductor products. The Norton & Bass model was able to reproduce demand paths for successive generations of digital pressure sensors by offering high estimation and forecasting accuracy. In addition, it has been found out which role funded projects play for participating companies to strengthen their market position. The changing business environment for B2B companies constitutes several opportunities within this sector. However, if companies do not keep up with the arising chances, they could suffer from the increasing forces that come from the B2C sector. With the participation in EU funded projects, such as GeniusTex or Productive4.0, diffusion speed for innovative products, such as the digital pressure sensors, is likely to increase. Moreover, we have a model where we can model that additional market potential can be created. Hence, it has been shown how governmental support can help the industrial players to exploit the potential that arises from the Industry 4.0 and why it is so important for them to keep up with this development. Further research could be carried out for selected product families, to find appropriate formulation of demand development with the right attributes, e.g., different product generations, cannibalism, competition etc., that could influence this demand development. Also, the implications of demand development on capacity planning such as ramp up demand, readjustment of production flow, and/or linkages between capacity and equipment, could be sought. Idea would be to simulate the formulation of the demand development using system dynamics modeling. Moreover, the validation of the proposed model should be the objective in a long-term perspective.

REFERENCES

Bass, F. M. 1969. "A New Product Growth Model for Consumer Durables". *Management Science* 17(3):215–227.

Bass, F. M., T. V. Krishnan, and D. C. Jain. 1994. "Why the Bass Model Fits without Decision Variables". *Marketing Science* 13(3):203-223.

Bass, P. I. and F. M. Bass. 2001. "Diffusion of Technology Generations: A Model of Adoption and Repeat Sales". In *INFORMS Marketing Science Conference,* November 30th, Catonsville, USA, 79-87.

BMWI 2019. Was ist Industrie 4.0? https://www.plattformi40.de/I40/Navigation/DE/Industrie40/WasIndustrie40/was-ist-industrie-40.html, accessed 1st March.

Boehner, R. and S.C. Gold. 2012. "Modeling the Impact of Marketing Mix on the Diffusion of Innovation in the Generalized Bass Model of Firm Demand". In *Developments in Business Simulation and Experiential Learning* 39:75–91.

Chien, C.-F., Y.-J. Chen, and J.-T. Peng. 2010. "Manufacturing Intelligence for Semiconductor Demand Forecast based on Technology Diffusion and Product Life Cycle". *International Journal of Production Economics* 128(2):496-509.

Decker, R. and K. Gnibba-Yukawa. 2010. "Sales Forecasting in High-Technology Markets: A Utility-Based Approach". *Journal of Product Innovation Management* 27(1):115–129.

Deloitte. 2018. IoT Opportunity in the World of Semiconductor Companies. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/technology/us-semiconductor-internet-of-things.pdf, accessed 1st March.

Dodgson, M., D. Gann, and N. Phillips. 2013. *The Oxford Handbook of Innovation Management*. Oxford: Oxford University Press.

Elektronik. 2018. Drucksensoren von Infineon: Kein Hals- und Beinbruch. https://www.elektroniknet.de/elektronik/messen-testen/kein-hals-und-beinbruch-159374-Seite-2.html, accessed 15th January.

Fertmann, C. I, and D. D. Allensworth. 2016. *Health Promotion Programs: From Theory to Practice*. San Francisco: Jossey-Bass.

Fraunhofer Institute for Applied Information Technology. 2019. GeniusTex. https://websites.fraunhofer.de/SmartStage/, accessed 1st February.

Ganjeizadeh, F., H. Lei, P. Goraya, and E. Olivar. 2017. "Applying Looks-like Analysis and Bass Diffusion Model Techniques to Forecast a Neurostimulator Device with No Historical Data". *Procedia Manufacturing* 11:1916–1924.

Gupta, J. N., Ruiz, R., Fowler, J. W., and Mason, S. J. 2006. "Operational planning and control of semiconductor wafer production". *Production Planning & Control*, 17 (7): 639–647.

Hong, J., H. Koo, T. Kim. 2016. "Easy, Reliable Method for Mid-Term Demand Forecasting based on the Bass Model: A Hybrid Approach of NLS and OLS". *European Journal of Operational Research* 248(2):681–690.

Horsky, D., L.S. Simon. 1983. "Advertising and the Diffusion of New Products". *Marketing Science* 2(1):1–17.

Infineon Technologies AG. 2016. Barometric Pressure Sensor and Use Cases. https://www.infineon.com/dgdl/Infineon-AN510_DPS310-AN-v01_00-EN.pdf?fileId=5546d462584d1d4a015895ac5c0d426a, accessed 15th January 2019.

Infineon Technologies AG 2017. Capacitive Technology in Wearable Devices: Low-Power, High-Accuracy Pressure Sensing for Battery Operated Wearable Devices. https://www.infineon.com/dgdl/Infineon-Capacitive%20technology%20in%20wearable%20devices-WP-v01_00-EN.pdf?fileId=5546d4625d5945ed015da82f1b2b5ccd, accessed 15th January.

Infineon Technologies AG. 2018. Fast, Flexible, and Easy Prototyping for IoT Applications. https://www.infineon.com/dgdl/Infineon-S2Go_MyIoT_Fast_flexible_and_easy_prototyping_for_IoT-ABR-v01_02-EN.pdf?fileId=5546d462647040d10164708e322705c4, accessed 1st February.

Infineon Technologies AG. 2019. Barometric Pressure Sensor for Consumer Applications. https://www.infineon.com/cms/de/product/sensor/barometric-pressure-sensor-for-consumer-applications/, accessed 15th January.

Infineon Technologies Austria. 2019. 2nd European Advances in Digital Transformation Conference. http://www.idev40.eu/news-details/eadtc-european-advances-in-digital-transformation-conference-2019, accessed 5th March.

Intershop Communications AG. 2015. Intershop E-Commerce Report 2015. Grenzen überwinden: Die Digitalisierung des B2B-Commerce. https://www.intershop.de/files/Intershop/media/downloads/de/studies/de_Intershop%20E-Commerce%20Report%202015.pdf, accessed 1st March.

Islam, T. and N. Meade. 1997. "The Diffusion of Successive Generations of a Technology: A More General Model". *Technological Forecasting and Social Change* 56(1):49–60.

Ismail, Z., N. Abu. 2013. "A Study on New Product Demand Forecasting based on Bass Diffusion Model". *Journal of Mathematics and Statistics* 9(2):84–90.

Jaakkola, H. 1996. "Comparison and Analysis of Diffusion Models". In *Diffusion and Adoption of Information Technology,* edited by K. Kautz and J. Preis-Heje, 65–82. London: Chapman and Hall.

Kurawarwala, A. A., and H. Matsuo. 1998. "Product Growth Models for Medium-Term Forecasting of Short Life Cycle Products". *Technological Forecasting and Social Change* 57(3):169–196.

Mahajan, V., E. Muller, and F. M. Bass. 1990. "New Product Diffusion Models in Marketing: A Review and Directions for Research". *Journal of Marketing* 54(1):1–26.

Mahajan, V., and S. Sharma. 1986. "A Simple Algebraic Estimation Procedure for Innovation Diffusion Models of New Product Acceptance". *Technological Forecasting and Social Change* 30(4):331–345.
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* 50:17–28.
Möhrle, T. 2018. Robust and Precise Barometric Pressure Sensor for Wearables in Harsh Environments. https://www.eetimes.eu/wp-content/uploads/2018/11/EETimes-Europe_201811.pdf, accessed 12th March.
Norton, J. A., and F. M. Bass. 1987. "A Diffusion Theory Model of Adoption and Substitution for Successive Generations of High-Technology Products". *Management Science* 33(9):1069–1086.
Productive4.0 Consortium. 2018a. How a Stunning Air Pressure Sensor Explains Productive4.0. https://productive40.eu/2018/08/25/how-a-stunning-air-pressure-sensor-explains-productive4-0/, accessed 1st February.
Productive4.0 Consortium. 2018b. Solution Finder – Inspiring Customers. https://productive40.eu/2018/08/02/solution-finder-inspiring-customers/, accessed 1st February.
Productive4.0 Consortium. 2019. Productive 4.0 is a European Co-Funded Innovation and Lighthouse Program. https://productive40.eu/about/, accessed 1st February.
Rogers, E. M. 2010. *Diffusion of Innovations*. 4th ed. New York: Simon & Schuster.
Roland Berger GmbH. 2015. The Digitial Future of B2B Sales. https://www.rolandberger.com/en/Publications/The-digital-future-of-B2B-sales.html, accessed 1st March.
Sahin, I. 2006. "Detailed Review of Rogers' Diffusion of Innovations Theory and Educational Technology-Related Studies based on Rogers' Theory". *Turkish Online Journal of Educational Technology* 5(2):14–23.
Schmittlein, D. C., and V. Mahajan. 1982. "Maximum Likelihood Estimation for an Innovation Diffusion Model of New Product Acceptance". *Marketing Science* 1(1):57–78.
Sokele, M., and L. Moutinho. 2018. "Bass Model with Explanatory Parameters". In *Innovative Research Methodologies in Management-Volume I: Philosophy, Measurement and Modelling*, edited by Sokele, M., and L. Moutinho, 145–164. Palgrave Macmillan.
Speece, M. W., and D. L. Maclachlan. 1995. "Application of a Multi-Generation Diffusion Model to Milk Container Technology". *Technological Forecasting and Social Change* 49(3):281–295.
Srinivasan, V., and C. H. Mason. 1986. "Technical Note-Nonlinear Least Squares Estimation of New Product Diffusion Models". *Marketing Science* 5(2):169–178.
Sultan, F., J. U. Farley, and D. R. Lehmann. 1990. "A Meta-Analysis of Applications of Diffusion Models". *Journal of Marketing Research* 27(1):70.
Uzsoy R., J. W. Fowler, L. Mönch. 2018. "A Survey of Semiconductor Supply Chain Models Part II: Demand Planning, Inventory Management and Capacity Planning", *International Journal of Production Research* 56(13):4546-4564.
van den Bulte, C. 2002. *Technical Report: Want to Know how Diffusion Speed Varies Across Countries and Products? Try using a Bass model*. Visions Magazine. https://www3.nd.edu/~busiforc/handouts/Other%20Articles/Bass%20model.pdf, accessed 1st February 2019.

AUTHOR BIOGRAPHIES

INES GOLD is a Master of Science student in Business Administration at Philipps University in Marburg. Her major is Innovation and Information. She is currently writing her master thesis in collaboration with Infineon Technologies in Neubiberg, Germany. She holds a Bachelor of Science degree in Business Administration with a major in Supply Chain Management and Information Systems from Otto-Friedrich University in Bamberg. Her email address is goldI3012@hotmail.com.

HANS EHM is Lead Principal Supply Chain heading the Corporate Supply Chain Engineering Innovation department at Infineon Technologies. He has a Master of Science in Mechanical Engineering from Oregon State University. His interest is on Supply Chain Innovation with focus on capacity and demand planning, deep learrning, artificial intelligence, simulation, and block chain applications for traceability. His email address is hans.ehm@infineon.com.

THOMAS PONSIGNON works as a Senior Staff Engineer in the Corporate Supply Chain organization of Infineon Technologies AG in Munich, Germany. He obtained masters degrees in Industrial Engineering from the EPF-Ecole d'Ingénieurs, Sceaux, France and the University of Applied Sciences, Munich, Germany and a Ph.D. in Mathematics and Computer Science from the University of Hagen, Germany. His research interests include production planning and simulation of semiconductor supply chains. His email address is thomas.ponsignon@infineon.com.

MUHAMMAD TARIQ AFRIDI is a Master student in Management at the Technical University of Munich. His major is Logistics and Supply Chain Management. He is currently writing his master thesis in collaboration with Infineon Technologies in Neubiberg, Germany. He holds a Bachelor of Science in Computer Systems Engineering from University of Engineering & Technology Peshawar, Pakistan. His email address is muhammad.tariqafridi@infineon.com.