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Extended Bass Diffusion Model for Meat Substitute Markets

Methodological Challenges and Estimation Results

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December 2025

The project RISC is supported by funds of the Oesterreichischen Nationalbank (Austrian Central Bank, Anniversary Fund, project number: 18757.

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1. Introduction

The Bass diffusion model (Bass, 1969) is the workhorse model for forecasting the adoption of new products and technologies. Originally developed for durable goods where each consumer makes a single purchase, it has been widely applied across industries. However, its application to consumable products like meat substitutes requires extension to account for repeat purchases.

Meat substitute markets present an interesting case: they exhibit characteristics of both innovation diffusion (new consumers trying the product for the first time) and repeat consumption (satisfied consumers repurchasing). The challenge is to decompose observed aggregate sales into these two components and estimate meaningful market parameters.

This paper documents a systematic exploration of this problem using consumption data from Austria (2017-2025, 9 observations) and production data from Germany (2019-2024, 6 observations). Both the methodology and the challenges that led to implausible results.

2. The Standard Bass Diffusion Model

2.1 Origins and Development

The Bass diffusion model (Bass, 1969) has become one of the most influential frameworks in marketing science for understanding and forecasting the adoption of new products. The seminal paper has accumulated over 11,000 citations and was ranked among the ten most frequently cited papers in the 50-year history of Management Science (Bass, 2004).

The model builds on earlier work in the sociology of innovation diffusion, particularly Everett Rogers' Diffusion of Innovations (1962), which described how innovations spread through social systems.

The Bass model rests on a fundamental behavioural assumption: the adoption rate at time t is governed by two forces operating on the remaining potential adopters. Innovators adopt independently of how many others have already adopted. Their adoption decision is driven by external influences such as advertising, mass media coverage, or personal awareness of the innovation. The probability that a potential adopter becomes an innovator is captured by the coefficient of innovation (p).

Imitators adopt due to internal influence —word-of-mouth communication from prior adopters creates social pressure and provides information that reduces uncertainty. The probability that a potential adopter becomes an imitator is proportional to the fraction of the market that has already adopted, captured by the coefficient of imitation (q).

2.3 Mathematical Formulation

The fundamental Bass model expresses the adoption hazard rate as:

$$f(t) / [1 - F(t)] = p + q \times F(t)$$

where p is the coefficient of innovation (external influence), q is the coefficient of imitation (internal influence), and F(t) is the cumulative proportion of adopters by time t. The number of new adopters at time t can be expressed as:

$$n(t) = [p + q \times N(t-1)/m] \times [m - N(t-1)]$$

where m is the market potential (total number of eventual adopters) and N(t-1) is the cumulative number of adopters through time t -1.

2.4 Extension for Repeat Purchases (Preview)

The standard Bass model assumes each consumer purchases exactly once. For consumable products like meat substitutes, this assumption is clearly violated: satisfied customers repurchase repeatedly. Observed sales therefore comprise both first-time purchases (new adopters) and repeat purchases (existing adopters buying again):

$$S(t) = n(t) + R(t)$$

where S(t) is total observed sales, n(t) is first-time purchases, and R(t) is repeat purchases from all prior cohorts.

Repeat purchases are modelled with generational decay. Each cohort of first-time adopters generates repeat purchases that decay linearly over a "cohort lifetime" (T_life), reflecting mortality, preference changes, and generational turnover:

$$r(\tau) = r_0 \times \max(0, 1 - \tau/T\_life)$$

where r_0 is the initial repeat rate (fraction of first-time volume repurchased in year 1), τ is years since first purchase, and T_life is the cohort purchasing lifetime (set to 35 years — approximately one generation).

Total repeat purchases at time t sum over all prior cohorts:

$$R(t) = \Sigma\ n(s) \times r(t-s) \quad \text{for all } s < t$$

2.5 Parameter Interpretation and Empirical Benchmarks

A comprehensive meta-analysis by Sultan, Farley and Lehmann (1990) across 213 applications established empirical benchmarks that continue to guide practitioners. The coefficient of innovation (p) was found to be "fairly stable across the 213 applications, with an average value of 0.03" (Meade and Islam, 2006). This parameter typically ranges from 0.01 to 0.05 for most consumer products.

The coefficient of imitation (q) is "far more variable about its average of 0.38" (Meade and Islam, 2006). Sultan et al. argued that this variability "demonstrates the coefficient's sensitivity to marketing variables." For consumer products, q typically ranges from 0.2 to 0.5.

The q/p ratio indicates the relative importance of imitation versus innovation effects. Ratios of 5-15 are typical for consumer products, reflecting the generally stronger role of word-of-mouth compared to external advertising.

2.6 Estimation Methods

Several approaches exist for estimating Bass model parameters. Meade and Islam (2006) note that "there is a clear consensus that using OLS to estimate the Bass model is non-optimal" since the linearised OLS approach "is prone to wrong signs, implying negative probabilities, and to unstable estimates."

The main alternatives are maximum likelihood estimation (MLE) and nonlinear least squares (NLS). It has been observed that MLE favours higher estimates of market potential and the coefficient of innovation, and a lower estimate of the coefficient of imitation than NLS (Meade and Islam, 2006). However, although most recent works have favoured NLS, Meade and Islam (2006) think that it is too early to disregard MLE.

2.7 Applications to Food Products

While the Bass model was originally developed for consumer durables, its applicability extends to food products. Duval and Biere (2002) provided seminal work integrating Bass diffusion theory with economic demand models for food products, demonstrating that food products exhibit meaningful diffusion patterns amenable to Bass-type modelling.

As Guo (2014) with reference to Du and Kamakura (2011) and Rink and Swan (1979) underlined the existence of word of mouth effect for nondurable product adoptions and that these products also follow the classical diffusion curve. The Bass model is therefore suitable for modelling both durable and nondurable product adoptions including first-purchase modeling.

Horvat, Fogliano and Luning (2020) extended the Bass framework for radical food innovations through their study of edible insect adoption. Key findings included that word-of-mouth was the primary mechanism driving diffusion, sensory quality was critical, and radical food innovations might require decades rather than years to achieve substantial market penetration.

2.8 Limitations for Consumable Products

A critical limitation of the standard Bass model is its focus on first-time purchases only. As Bass (1969) noted, the model is concerned "only with the timing of initial purchases." For consumable products like meat substitutes, observed sales data represent a mixture of first-time trial purchases and repeat purchases, creating parameter estimation bias when standard Bass models are applied.

Guo (2014) emphasises that the classic Bass model is not suitable for long-term sales forecasting due to the exclusion of repeat purchases (see also Kamakura and Balasubramanian, 1987).

This limitation motivated repeat purchase extensions, beginning with Dodson and Muller (1978). Subsequent research includes the Novelty-Loyalty Based Consumer Utility (NLBCU) theory by Guo (2014) and the Generalised Diffusion Model with Repeat Purchases (GDMR) by Jain et al. (2020).

2.9 Cross-Country Considerations

Diffusion varies systematically across countries. Takada and Jain (1991) observed significant differences in the coefficients of imitation between countries with different cultures, such as US and Korea. They also found evidence that a lagged product introduction led to accelerated diffusion" (Meade and Islam, 2006).

Talukdar, Sudhir and Ainslie (2002) found that "market potential was best explained by previous experience in the same country; in contrast, the probability of adoption was better explained by product experience in earlier adoption countries." These findings suggest caution when applying parameter estimates from one market to another.

3. The Data

3.1 Austria: Consumption Data (2017 -2025)

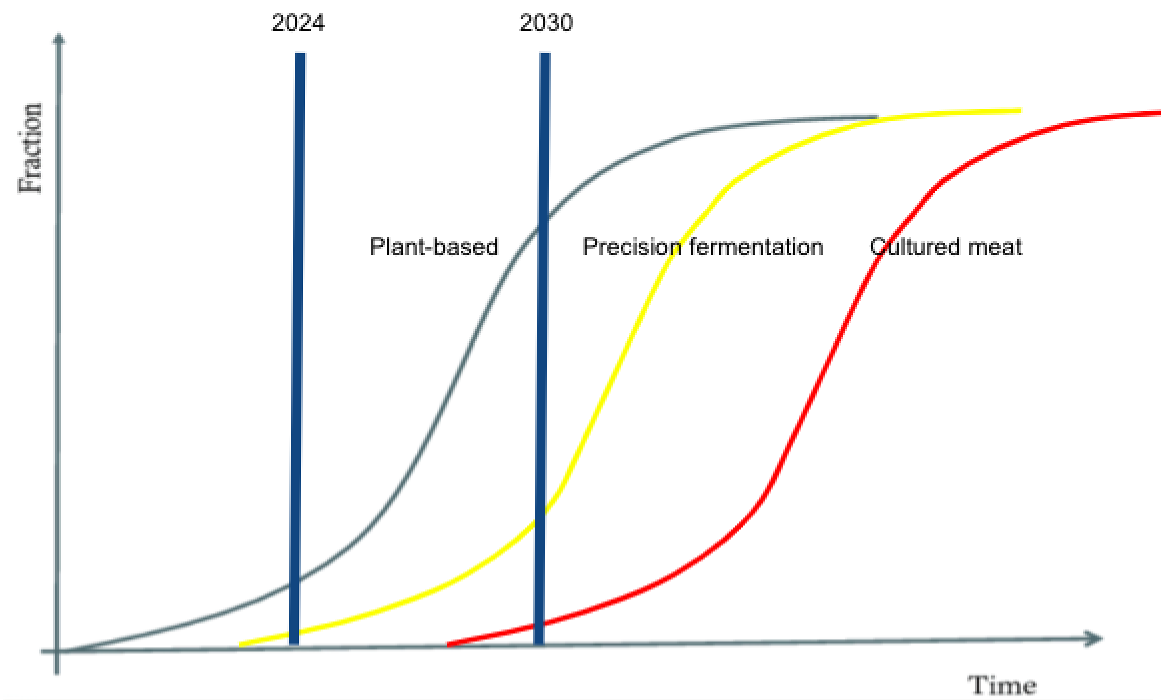
Growth processes in nature and also of new products — insofar as they are successful — usually follow an S-curve (Smil, 2020). In the introductory phase, products grow quickly, but from a very low level and have a negligible market share. After the first inflection point, exponential growth occurs, which in turn flattens out after reaching the second turning point and slowly approaches the maximum.

Currently, practically only plant-based products are available to consumers. Cultured meat and precision fermentation-based products are available in selected markets for a small number of consumers at an elevated price. Plant-based products have grown substantially over the past decade but detailed and comparable information is still sparse.

The typical assumption for the diffusion of these products is that they follow an S-curve, i.e. growing exponentially after a long build-up period, reaching market saturation after beyond the second inflection point. This diffusion curve would portray single buyers of the product which – somewhat simplified – purchase one unit. For products which are bought regularly, the curve would be composed of first time and repeat customers but still follow an S-curve.

The evolution of alternative protein-based products depends on the maturity level of the three base technologies. The general assumption is that plant-based products are being followed by precision-based products once the production infrastructure is scaled up, again followed by cultured meat. The industry consensus is that precision fermentation is about to be scaled up at the time of writing of this paper (end of 2025) while cultured meat will need more time to reach a price point and product features that are attractive for customers. Still, it is generally assumed that even plant-based meat alternatives are at the bottom of the diffusion curve and will see substantial growth in the years to come.

Figure 1: Idealised S-curves for "alt protein" technologies



The available data sets that portray the evolution of alt protein markets with sufficient detail are scarce. Two distinct datasets from Austria and Germany are used for modelling the diffusion of meat substitutes. The Austrian time series is from a survey on behalf of AMA - the public marketing agency for agricultural products – which collects data on the volume and value of meat alternatives sold to Austrian consumers (see Table 1). For the years up to 2022 yearly figures were published in the RollAMA survey thereafter only numbers for the first half of the respective year. These were doubled to arrive at the figures in the table below.

According to the RollAMA survey, Austrians consumed 0.45 kg of meat substitutes in 2025 which is less than 1% of the per capita meat consumption. Still the market share of meat substitutes increased from 0.27% in 2017 to 0.76% in 2024. Interestingly, this also shows that the reduction of the per capacity meat consumption since 2017 is only to a small part explained by meat substitutes.

Table 1: Meat and meat substitute consumption and market share in Austria

Year	Meat substitute (t)	Meat (t)	Per capita meat substitute consumption (kg)	Per capita meat consumption (kg)	Market share meat substitutes (%)
2017	1,510	556,586	0.17	63.3	0.27
2018	1,847	562,332	0.21	63.6	0.33
2019	2,038	556,185	0.23	62.7	0.37
2020	2,574	538,760	0.29	60.5	0.48
2021	3,426	528,027	0.38	59.0	0.64
2022	3,376	531,137	0.37	58.7	0.63
2023	3,588	527,104	0.39	57.7	0.68
2024	4,102	532,338	0.45	58.0	0.76

Source: Statistik Austria, RollAMA, own calculations

3.2 Germany: Production Data (2019 -2024)

The statistical office Destatis collects production volumes of meat substitute producers in Germany. In 2024 68 companies produced about 126000t of meat alternatives which was about twice the level of 2019. The number of producers has also almost doubled in this period from 34 to 68. On a per capita basis, the German alternative meat industry produced 1.5kg per inhabitant.

Table 2: German Meat Substitute Production

Year	Production (tonnes)	YoY growth (%)	Number of producers
2019	60,366	-	34
2020	83,714	38.7	34
2021	97,913	17.0	44
2022	104,300	6.5	51
2023	121,600	16.6	67
2024	126,480	4.0	68

Source: Destatis

While both datasets show significant growth overall, growth rates are particularly high from 2019 to 2020 and 2020 to 2021, they show moderate growth from 2022 to 2023 and are even in negative territory in Austria (-1.5%) but pick up again in the following years. Still growth rates are below the 2019 to 2022 period. In 2025, growth of meat substitutes is flat in Austria. The obvious COVID-19 acceleration of alternative meat products is visible in both time series.

Table 3: Data Overview — Meat Substitute Markets

	Austria consumption				Germany production					
	Volume (tonnes)	% change	Value (mio €)	% change	Volume (tonnes)	% change	mio €	% change	# Companies	% change
2019	2038				60366		272.8		34	
2020	2574	26.3	32.9		83714	38.7	374.9	37.4	34	0.0
2021	3426	33.1	43.2	31.5	97913	17.0	458.2	22.2	44	29.4
2022	3376	-1.5	42.0	-2.8	104300	6.5	537.4	17.3	51	15.9
2023	3588	6.3	46.2	9.9	121600	16.6	583.2	8.5	67	31.4
2024	4102	14.3	48.3	4.7	126480	4.0	647.1	11.0	68	1.5

Source: Source: RollAMA, Destatis, eigene Berechnungen

4. Standard Bass Model Results

The standard Bass model was first estimated (assuming all observed sales are first-time purchases) using both OLS linearization and nonlinear least squares (NLS). These serve as benchmarks.

Table 4: Austria — Standard Bass Model Estimates

Method	p	q	m (tonnes)	R^2
OLS	0.0298	0.2650	49,978	0.9666
NLS	0.0244	0.2539	53,454	0.9998

The NLS estimates suggest a market potential (cumulated) of approximately 53,000 tonnes, with a q/p ratio of 10.4 indicating strong word-of-mouth effects typical of food products.

Table 5: Germany — Standard Bass Model Estimates

Method	p	q	m (tonnes)	R^2
OLS	0.0534	0.3020	1,206,387	0.9719
NLS	0.0424	0.2850	1,341,668	0.9999

Germany shows a market potential of approximately 1.34 million tonnes, with a q/p ratio of 6.7. The excellent fit ($R^2 > 0.99$) indicates the Bass model captures the growth pattern well.

The coefficients in both markets are in the expected range and the model fit is high. The German dataset shows higher coefficients both for innovative buyers and word of mouth effects. The overall size of the market – i.e. the cumulated volumes over time – are in both estimates small. Given that this also includes volumes sold in the past (up to 2024 for German data: 594,373 t, 2025 for Austrian data: 26,581 t), the remaining cumulated market volume is about the same as in the years for which data are available. As there are no signs that plant-based meat alternatives are vanishing from the market anytime soon, the forecasts of the simple Bass model that does not distinguish between first time and repeat customers is out of sync with actual buying behaviour.

Comparison with Related Product Categories

To contextualize these results, Table 17 presents Bass model parameter estimates from the literature across various product categories. This comparison situates meat substitutes within the broader landscape of innovation diffusion.

Table 6: Summary of Bass Model Parameter Estimates Across Product Categories

Product Category / Source	p	q	q/p Ratio	Notes
Meta-analysis average (Sultan et al., 1990)	0.03	0.38	12.7	213 applications
General benchmark (Lilien et al., 2013)	0.035	0.39	11.1	Cross-industry
European markets (Chandrasekaran & Tellis, 2007)	0.01-0.03	0.38-0.53	12.7-53	Higher q than US
Hybrid vehicles, Japan (Park et al., 2011)	0.0037	0.345	93.2	Green technology
Electric vehicles, Germany (Massiani & Gohs, 2015)	0.0001-0.025	0.40-0.87	Variable	Sensitive to m
Meat substitutes, Austria (present study)	**0.024**	**0.254**	**10.4**	**Consumption**
Meat substitutes, Germany (present study)	**0.042**	**0.285**	**6.7**	**Production**

Note: The q/p ratio indicates the relative importance of imitation versus innovation. Higher ratios suggest word-of-mouth dominated diffusion.

Parameter Interpretation

The parameters estimated for European meat substitutes markets fall within established ranges while exhibiting characteristics consistent with sustainable and green innovations. Innovation coefficients ($p = 0.024\text{-}0.042$) are close to the meta-analysis average (0.03), indicating that external influences such as advertising and media coverage drive adoption at typical rates. Imitation coefficients ($q = 0.25\text{-}0.29$) are somewhat below the meta-analysis average (0.38), suggesting that word-of-mouth effects may be weaker than for typical consumer products.

Comparison with Green Technologies

The meat substitutes diffusion pattern shares characteristics with electric and hybrid vehicles, which also exhibit sustainability motivations and require behavioural change from consumers. However, the lower q/p ratios for meat substitutes suggest that social influence may play a smaller role than for visible purchases like vehicles, consistent with food being a less publicly observable consumption category.

Insights from Radical Food Innovation Research

Horvat, Fogliano and Luning (2020) studied edible insect adoption in the Netherlands using an extended Bass framework. Their findings offer relevant insights: (1) Word-of-mouth was the primary mechanism driving diffusion, with external promotion serving mainly to seed initial tasters; (2) Low sensory quality created cumulative rejection, with premature market entry potentially hindering long-term adoption permanently; (3) Radical food innovations require decades rather than years for substantial market penetration, with simulations suggesting 50+ years for complete diffusion. These findings suggest that current plateaus in meat substitute sales may reflect sensory quality limitations rather than market saturation.

5. Extended Model: Estimation Challenges

Various approaches were used to estimate extended models with repeat purchases, i.e. the joint estimation of all parameters, constrained optimisation, using standard Bass p, q, with repeat extension, non-linear least square (NLS) estimation. Each approach encountered fundamental problems that produced economically implausible results.

The dominant results across all estimates for Austrian and German data was that the market peaked around 2024/2025 and then declined. This is mostly due to the growth pattern of both time series which showed – somewhat simplified – high increases up to 2021, then lower growth before they increased again from 2023 to 2024 though at a lower rate than up to 2021/2022. In Austria quantities sold stagnated also between 2024 and 2025.

The models interpreted the market growth pattern as having already peaked and beginning being on the decline. The latter of course is due to the small or missing numbers of first time buyers and the sinking volume of sales from repeat purchases.
The dominant result is that markets for meat substitutes have already peaked. This seems to be highly unlikely but not unknown in the literature. Van den Bulte and Lilien (1997) identified this as a fundamental challenge: "a tendency for the saturation level to be underestimated and close to the latest observed penetration." They demonstrated through simulation that "expecting a handful of noisy data points to foretell the ultimate market size and the time path of market evolution is asking too much of too little data."

There are a number of factors that contribute to the difficulties in properly modelling production data of meat substitutes:

- With only 9 observations for Austria and 6 for Germany, there is not sufficient information to estimate 4+ parameters reliably. The Bass model typically requires observation of the full S-curve, including the inflection point, for stable estimation. The data capture only the early growth phase. This constellation seems to be particularly challenging for the estimation of the repeat purchasing rate where it is not possible to separately identify diffusion and repeat purchasing parameters. Additionally, as this market is still in an early phase consumer behaviour might be much more heterogeneous (i.e. some become loyal quickly while others churn quickly as well as different behaviour in different age cohorts).

- The COVID-19 pandemic (2020-2021) created anomalous demand patterns. Increased home cooking and health awareness drove a temporary spike in meat substitute consumption. This was coupled with supply chain disruptions, inflation and changing consumer sentiment. The Bass model assumes smooth, continuous diffusion, which may not hold in such volatile conditions.

- The subsequent normalization (2022-2023) appears in the data as deceleration. The Bass model interprets this deceleration as approaching saturation, driving market potential estimates downward. In reality, this is likely mean reversion after an anomalous shock, not evidence of market saturation.

- The data for Austria is from RollAMA based on a survey of retailers. The approach of the survey is not described in detail nor is there any information on coverage and weighing procedures to obtain numbers representative of market development. The data was available for 2017-2022 on an annual basis and for 2020-2020 for the first half of the year. Doubling the data for the first half year and comparing them with the annual data for the same year showed some irregularities which seem hard to explain.

- The success of meat alternatives increased the effort of meat producers to ascertain their markets. Given the size difference between meat producers and their competitors in the alternative protein sector, there is a distinct disadvantage for the new entrants with respect to marketing resources and the ability to lobby for their interest. The pending naming ban of alternative meat products (e.g. disallowing naming them "burgers") shows the regulatory capture of European regulators by and the determination of these lobby groups.

6. Decomposition of Sales into First-Time and Repeat Purchases

6.1 Empirical Benchmarks from Industry Data

Attempts to deal with the problems of the Bass with a given low number of observations lead to an approach that replaces some of the variables to be estimated with published findings in the literature. A prime candidate is the initial share of first time and repeat customers at the beginning of the time series. The Bass model suggests that in early stages the number of innovators/first time buyers is higher while imitators and repurchasing buyers take over in later market phases. Industry sources provide s ome information to establish empirically-grounded assumptions about repeat purchase behaviour in the plant-based meat market. The Good Food Institute (GFI) and the Plant Based Foods Association (PBFA) publish annual retail data that includes household-level purchase metrics.

Key findings from U.S. market data:

- Repeat buyer rates: In 2024, among households that purchased plant-based meat, they averaged approximately six purchase occasions and bought about 12 units (Good Food Institute, 2024). Approximately 60% of households who purchase plant-based meat alternatives make repeat purchases (Lusk et al., 2022).
- Historical trend: The percentage of buyers making multiple purchases has remained relatively stable: 63% (2020), 64% (2021), 62.5% (2022), 61.5% (2023), declining to approximately 56% in 2024 as household penetration decreased from a peak of 20% to 13% (Plant Based Foods Association, 2020–2024).
- Category comparison: Plant-based milk shows even higher repeat rates (75.7% in 2022), suggesting that more mature plant-based categories develop stronger repeat purchase patterns (Good Food Institute, 2024).

6.1.1 Translating Buyer Rates to Volume Shares

It is important to distinguish between *repeat buyer rates* (the percentage of households that purchase more than once) and *repeat volume shares* (the percentage of total sales volume attributable to repeat purchases). These are fundamentally different metrics.

Consider a market with 100 purchasing households where 60% are repeat buyers averaging 6 purchase occasions per year, while 40% are one-time triers:

Total purchase occasions = (60 × 6) + (40 × 1) = 400

First-time purchases = 100 (one per household) = 25% of volume

Repeat purchases = 300 (60 households × 5 additional) = 75% of volume

Thus, a 60% repeat buyer rate implies approximately 75% of sales volume comes from repeat purchases in a mature market. This provides the empirical foundation for the decomposition approach used here.

Based on the industry benchmarks and assumed importance of the share of first time and repeat purchases, we attempt to decompose the times series data with respect share of first time and repeat buyers. The decomposition approach assumes either that 75% of first-year observed sales represent repeat purchases from prior cohorts, with 25% representing first-time purchases or vice versa. This addresses the one fundamental limitation that led earlier modelling approaches produce unexpected outcomes. Also the market started some time before the year we have data on. The first observation on our datasets thus comes with a specific but unknown distributions of first time and repurchasing customers. The assumption helps to integrate prior market history.

The decomposition proceeds as follows. For the first observation year:

$$Repeat(t_1) = 0.75 \times S(t_1)$$

$$First\text{-}time(t_1) = 0.25 \times S(t_1)$$

The first -year repeat volume implies a 'prior stock' of cumulative first -time adopters before the observation period. Assuming an average prior cohort age of 3 years and an initial repeat rate r□ = 50%:

$$Prior\ Stock = Repeat(t_1) / [r_0 \times (1 - 3/T\_life)]$$

For subsequent years, repeat purchases are computed from both the prior stock (aging by one year each period) and all observed first -time cohorts, using the generational decay model. First -time purchases are then derived as the residual.

6.1.2 Model Assumptions for Decomposition

Before proceeding to the decomposition algorithm, it is important to clarify the assumptions underlying the approach. The decomposition does not use the Bass diffusion model. Instead, it relies on three key assumptions about repeat purchase behaviour:

Assumption 1: Base Repurchase Rate (r0 = 50%). In the year immediately following their first purchase, adopters repurchase 50% of their initial volume. This parameter reflects the probability that a first -time buyer becomes a repeat customer.

Assumption 2: Generational Decay (T_life = 35 years). The repurchase probability decays linearly over a purchasing lifetime of 35 years. This captures the reality that early adopters eventually reduce or cease purchasing as they age, change dietary prefere nces, or exit the market. The decay function is: r(tau) = r0 x (1 - tau/T_life), where tau is years since first adoption. After 35 years, the repurchase probability reaches zero.

Assumption 3: Initial Repeat Share (25% or 75%). Since the market existed before our observation period began, the first year of data contains both first -time and repeat purchases. Two scenarios are examined: (a) Early-stage market: 25% repeat, 75% first -time – appropriate if the market was still nascent; (b) Mature market: 75% repeat, 25% first -time – appropriate if the market was already established. See the annex for an in depth explanation of how this was implemented.

Crucially, the decomposition algorithm treats first -time purchases as a residual. Given these assumptions, repeat purchases are calculated deterministically from the accumulated stock of prior first-time buyers. Whatever remains of observed sales must be n ew (first-time) purchases. The Bass model enters only later, when the extracted first -time series is fitted to validate that it follows diffusion dynamics.

6.2 Decomposition Results: Late stage market

Applying the 75% initial repeat assumption with r□ = 50% yields an implied prior stock of 2,477 tonnes of cumulative first-time purchases before 2017. Table 7 presents the year-by-year decomposition.

Table 7: Austria — Decomposition with 75% Initial Repeat (r□ = 50%)

Year	Observed	First-time	Repeat	Rep %	Cumul. 1st
—	(prior)	2,477	—	—	2,477
2017	1,510	378	1,132	75.0%	2,855
2018	1,847	567	1,280	69.3%	3,421
2019	2,038	523	1,515	74.3%	3,945
2020	2,574	854	1,720	66.8%	4,798
2021	3,426	1,348	2,078	60.7%	6,146
2022	3,376	712	2,664	78.9%	6,858
2023	3,588	666	2,922	81.4%	7,523
2024	4,102	954	3,148	76.7%	8,478
2025	4,120	616	3,504	85.0%	9,094
Total	26,581	6,617	19,964	75.1%	—

The decomposition maintains an average repeat share of 75.1% across the observation period. The repeat share fluctuates between 61% (2021) and 85% (2025), reflecting year-to-year sales volatility. Notably, 2021 shows the lowest repeat share, coinciding with the pandemic-driven surge in trial purchases.

For Germany, the 75% initial repeat assumption implies a prior stock of 99,038 tonnes of cumulative first-time purchases before 2019.

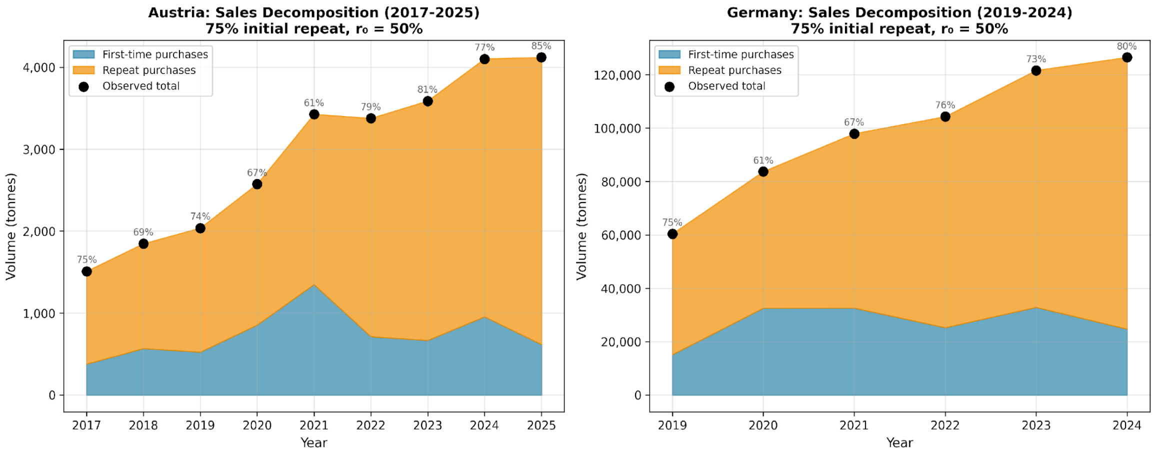
Table 8: Germany — Decomposition with 75% Initial Repeat (r□ = 50%)

Year	Observed	First-time	Repeat	Rep %	Cumul. 1st
—	(prior)	99,038	—	—	99,038
2019	60,366	15,092	45,274	75.0%	114,129
2020	83,714	32,524	51,190	61.1%	146,654
2021	97,913	32,556	65,357	66.7%	179,210
2022	104,300	25,225	79,075	75.8%	204,435
2023	121,600	32,833	88,767	73.0%	237,268
2024	126,480	24,686	101,794	80.5%	261,954
Total	594,373	162,916	431,457	72.6%	—

Germany shows an average repeat share of 72.6%, slightly lower than Austria. The pandemic years (2020-2021) exhibit reduced repeat shares (61-67%), consistent with elevated first-time trial during this period.

Figure 2 shows the stacked decomposition for both countries. The percentages above each bar indicate the repeat share for that year. Blue areas represent first-time purchases; orange areas represent repeat purchases.

Figure 2: Austrian consumption and German production data decomposition



A key question is whether the decomposed first-time series can be reconciled with Bass model dynamics. Fitting the Bass model to the first-time series yields:

- Austria: $p = 0.055$, $q = 0.402$, $m = 7{,}498$ tonnes (additional potential), $R^2 = 0.46$
- Germany: $p = 0.103$, $q = 0.400$, $m = 202{,}700$ tonnes (additional potential), $R^2 = 0.40$

The R^2 values of 0.40-0.46 indicate that the Bass model explains less than half the variance in the decomposed first-time series. This limited fit reflects the fundamental challenge: *the year-to-year volatility in observed sales propagates directly into the first-time series*, creating fluctuations that do not conform to the smooth S-curve assumed by the Bass model.

There are – again – specific challenges that are responsible for the limited fit of the Bass model. The pandemic distortion 2020-2021 resulted in elevated first-time purchases (854 tonnes and 1,348 tonnes for Austria), followed by compression in 2022-2023 (712 and 666 tonnes). This boom-bust pattern violates Bass's assumption of smooth, monotonic diffusion dynamics. The first-time series rises, falls, rises again — behaviour inconsistent with classical Bass, which predicts first-time adoptions should rise to a peak and then decline monotonically. With only 6-9 data points, there is insufficient statistical power to reliably estimate Bass parameters, particularly given the structural breaks induced by COVID-19.

While the empirically-calibrated decomposition represents a methodological improvement over approaches that ignore prior market history, the fundamental challenge remains. Aggregate annual sales data, particularly when distorted by structural shocks like the pandemic, cannot cleanly separate diffusion dynamics from repeat purchase behaviour. The decomposition should be interpreted as providing *indicative magnitudes* rather than precise point estimates.

6.3 Alternative Scenario: Early-Stage Market

The preceding analysis assumed 75% initial repeat share, implying the market was already mature by the first observation year. However, for an emerging product category, it is more plausible that first-time purchases dominate initially, with repeat share growing as the customer base accumulates.

Therefore an alternative scenario with 25% initial repeat / 75% first-time in year 1 was implemented. This allows the repeat share to grow organically thereafter.

With 25% initial repeat, the implied prior stock is only 826 tonnes — substantially smaller than the 2,477 tonnes implied by the mature market assumption. The repeat share then grows from 25% toward mature levels.

Table 9: Austria — Early-Stage Decomposition (25% initial repeat, r_0 = 50%)

Year	Observed	First-time	Repeat	Rep %
2017	1,510	1,132	378	25.0%
2018	1,847	931	916	49.6%
2019	2,038	698	1,340	65.8%
2020	2,574	936	1,638	63.6%
2021	3,426	1,385	2,041	59.6%
2022	3,376	727	2,649	78.5%
2023	3,588	670	2,918	81.3%
2024	4,102	953	3,149	76.8%
2025	4,120	613	3,507	85.1%
Total	26,581	8,046	18,535	69.7%

For Germany, the early-stage assumption implies a prior stock of only 33,013 tonnes, compared to 99,038 tonnes under the mature market assumption.

Table 10: Germany — Early-Stage Decomposition (25% initial repeat, r□ = 50%)

Year	Observed	First-time	Repeat	Rep %
2019	60,366	45,274	15,092	25.0%
2020	83,714	47,104	36,610	43.7%
2021	97,913	39,542	58,371	59.6%
2022	104,300	28,514	75,786	72.7%
2023	121,600	34,321	87,279	71.8%
2024	126,480	25,294	101,186	80.0%
Total	594,373	220,049	374,324	63.0%

Figure 3 compares the early-stage (25% initial repeat) and mature market (75% initial repeat) decompositions. The left panels show repeat share growing from low initial levels; the right panels show relatively stable repeat shares throughout.

Figure 3: Comparison of different initial first buyer/repeat buyer scenarios

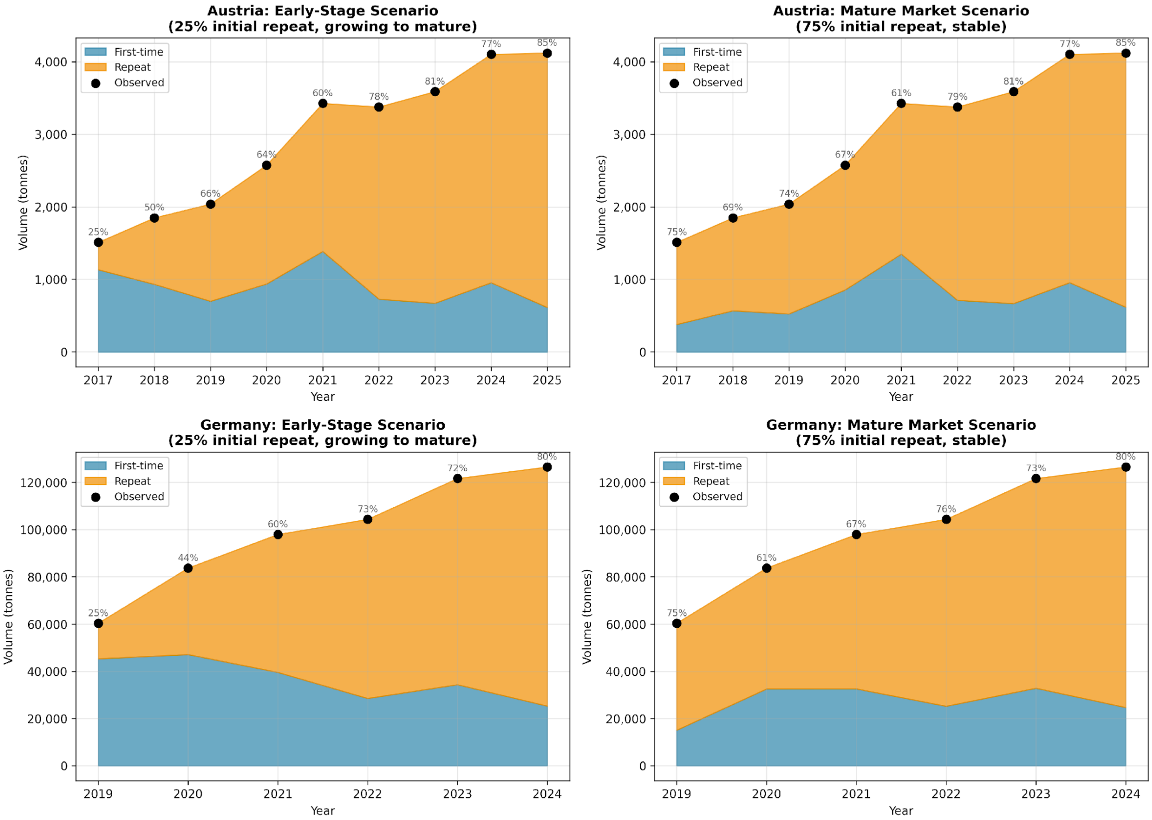


Table 11: Summary Comparison of Decomposition Scenarios

Metric	Early (25%)	Mature (75%)	Difference
AUSTRIA			
Prior stock (tonnes)	826	2,477	-67%
Total first-time (tonnes)	8,046	6,617	+22%
Average repeat share	69.7%	75.1%	-5.4pp
Final year repeat share	85.1%	85.0%	≈0
Bass R² (first-time series)	0.22	0.46	-0.24
GERMANY			
Prior stock (tonnes)	33,013	99,038	-67%
Total first-time (tonnes)	220,049	162,916	+35%
Average repeat share	63.0%	72.6%	-9.6pp
Final year repeat share	80.0%	80.5%	≈0
Bass R² (first-time series)	0.84	0.40	+0.44

The main finding of this analytical step are the following:

1. Both scenarios converge to similar repeat shares by the final observation year (80-85%). The choice of initial assumption primarily affects the *path* rather than the *destination*.
2. The early-stage scenario implies 22 -35% more first -time purchases during the observation period, as less volume is attributed to repeat purchases in early years.
3. For Germany, the early-stage scenario produces a dramatically better Bass fit (R^2 = 0.84 vs 0.40). The first-time series under the early-stage assumption shows a cleaner pattern of initial growth followed by moderation — consistent with diffusion dynamics. For Austria, neither scenario produces a strong fit, likely due to the pandemic -induced volatility.
4. The early-stage scenario implies a much smaller market existed before observation (826 vs 2,477 tonnes for Austria; 33,013 vs 99,038 tonnes for Germany). This is more plausible if meat substitutes were truly a nascent category in 2017/2019.

Given that (a) the early-stage assumption is more theoretically consistent with an emerging product category, and (b) it produces substantially better Bass model fit for the larger German market, the early-stage scenario (25% initial repeat) appears more defensible.

6.4 Bass Model Fit as Validation – Sensitivity Analysis

To validate that the decomposition produces sensible results, the extracted first -time series is fitted to the standard Bass diffusion model. If the decomposition correctly isolates first -time purchases, the series should exhibit the characteristic S -curve dynamics of innovation diffusion.

Germany (early-stage scenario): The Bass fit yields p = 0.143, q = 0.080, m = 328,154 tonnes, with R - squared = 0.84. This strong fit indicates that the decomposed German first -time series follows clean diffusion dynamics. The high innovation coefficient (p) and relatively low imitation coefficient (q) are consistent with an emerging market where external influences (media coverage, marketing) drive adoption more than word -of-mouth.

Austria (early-stage scenario): The Bass fit yields p = 0.079, q = 0.087, m = 69,821 tonnes, with R - squared = 0.22. This weak fit indicates that the Austrian first -time series does not follow typical diffusion dynamics. The pandemic -induced boom (2020 -2021) and subsequent decline obscure any underlying diffusion pattern. Forecasts for Austria should therefore be interpreted with considerable caution.

These validation results have important implications for forecasting. For Germany, the strong Bass fit provides confidence that Bass-based projections will be meaningful. For Austria, the weak fit suggests that alternative forecasting approaches may be more appropriate, and results should be presented as scenario bounds rather than point predictions.

Throughout this analysis, an annual repurchasing rate of r_0 = 50%. This parameter has a specific interpretation: in the year immediately following their first purchase, adopters repurchase 50% of their initial volume. The rate then decays linearly over a 'purchasing lifetime' of T_{life} = 35 years.

This 'generational decay' model captures the reality that early adopters eventually reduce or cease purchasing as they age, change dietary preferences, relocate, or exit the market for other reasons. The 35-year horizon approximates a generational cycle.

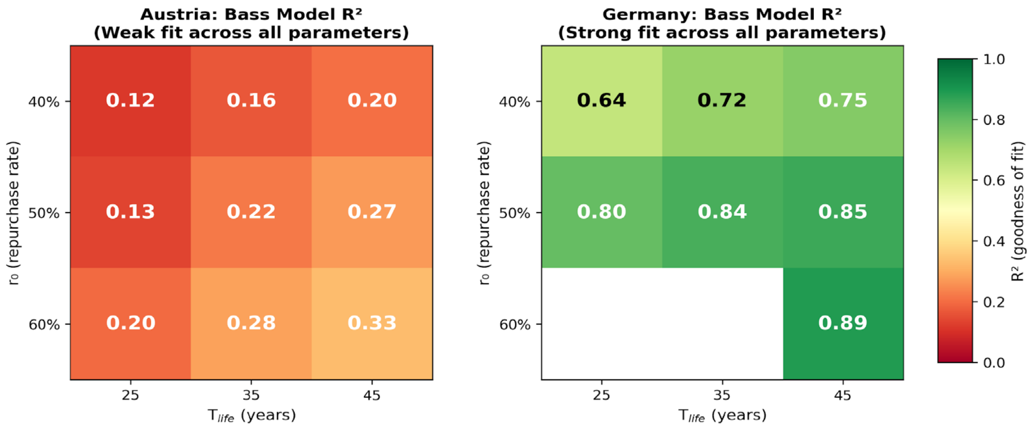
The decomposition depends on three key parameters: the annual repurchase rate (r_0), the purchasing lifetime (T_{life}), and the assumed age of prior cohorts. The robustness of these results is tested across a grid of plausible values.

Table 12: Sensitivity to r_0 and T_life (Early-Stage Scenario, prior age = 3 years)

r□	T_life	Prior Stock	Total 1st	Avg Rep%	Bass R²	Country
40%	25	1,072	9,924	62.7%	0.12	Austria
50%	35	826	8,046	69.7%	0.22	Austria
60%	45	674	6,744	74.6%	0.33	Austria
40%	25	42,874	261,810	56.0%	0.64	Germany
50%	35	33,013	220,049	63.0%	0.84	Germany
60%	45	26,949	188,697	68.3%	0.89	Germany

Key finding: Germany shows consistently high Bass model fit (R^2 = 0.64–0.89) across all parameter combinations, suggesting robust diffusion dynamics. Austria's fit remains weak (R^2 = 0.12–0.33) regardless of parameters, reflecting pandemic-induced volatility that obscures underlying diffusion patterns.

Figure 5: Bass model R^2 across parameter combinations (green = better fit)



7. Forecasting to 2040

The decomposition algorithm described above works only for historical data where actual sales are observed. To project market development beyond the observation period, an assumption must be made about future first-time purchases. Two fundamentally different approaches are possible:

(1) Bass-based projection: Uses the fitted Bass parameters (p, q, m) to project first-time purchases. This assumes a finite market potential that eventually becomes exhausted, causing first-time purchases to decline toward zero as the market saturates.

(2) Arbitrary decay projection: This approach makes no assumption about market potential. Instead, it assumes first-time purchases decay exponentially from recent levels: First-time(t) = recent_average x exp(-decay_rate x years_ahead). The parameters used are: recent_average = mean of last 3 observed years, decay_rate = 5% per year, floor = 50 tonnes. First-time purchases decline gradually but never reach zero - new adopters continue entering indefinitely. This represents a scenario where new customers continue entering the market indefinitely, perhaps due to product innovation, price reductions, or expanding cultural acceptance.

Both approaches use the same generational decay model for repeat purchases (r0 = 50%, T_life = 35 years). They differ only in how first-time purchases are projected.

The forecasts presented below (Tables 13-16) use the arbitrary decay approach. This approach assumes continued inflow of new customers and produces an UPPER BOUND on market projections. The Bass-based approach, which produces a LOWER BOUND due to market saturation, projects (persistently) a market that has already peaked and is in decline up to the year 2040 (see figure 4).

Table 13: Austria — Market Development Forecast (Early-Stage Scenario)

Year	Total	First-time	Repeat	Rep %	Cumul. 1st
2017*	1,510	1,132	378	25%	1,958
2020*	2,574	936	1,638	64%	4,524
2025*	4,120	613	3,507	85%	8,871
2030	4,982	581	4,401	88%	12,087
2035	5,231	452	4,779	91%	14,592
2040	5,056	352	4,704	93%	16,543

** Observed period. Cumul. 1st includes prior stock of 826 tonnes.*

Table 14: Germany — Market Development Forecast (Early-Stage Scenario)

Year	Total	First-time	Repeat	Rep %	Cumul. 1st
2019*	60,366	45,274	15,092	25%	78,287
2024*	126,480	25,294	101,186	80%	253,062
2030	171,661	21,763	149,899	87%	401,563
2035	184,700	16,949	167,751	91%	495,453
2040	181,803	13,200	168,603	93%	568,575

** Observed period. Cumul. 1st includes prior stock of 33,013 tonnes.*

Table 15: Austria — Bass-Based Forecast to 2040

Year	Total	First-time	Repeat	Rep %	Cumul. 1st	YoY
2025*	4,120	613	3,507	85%	8,871	+0.4%
2030	4,533	375	4,158	92%	11,362	+0.1%
2035	4,187	172	4,015	96%	12,577	-2.5%
2040	3,488	73	3,415	98%	13,110	-4.3%

** Last observed year.*

Table 16: Germany — Bass-Based Forecast to 2040

Year	Total	First-time	Repeat	Rep %	Cumul. 1st	YoY
2024*	126,480	25,294	101,186	80%	253,062	+4.0%
2027	136,047	14,327	121,719	89%	308,413	+1.0%
2030	132,946	7,303	125,644	95%	334,613	-1.5%
2035	115,248	2,184	113,064	98%	353,470	-3.5%
2040	91,779	628	91,151	99%	358,974	-5.1%

** Last observed year. By 2040, the market exhausts 99% of its first-time potential.*

Austria's weak Bass fit ($R^2 = 0.22$) indicates a fundamental data quality problem. The pandemic-induced boom (2020-2021) followed by compression (2022-2023) creates a non-monotonic pattern that violates the smooth S-curve dynamics the Bass model assumes. This is not a model failure — it reflects that the underlying data cannot reliably distinguish diffusion dynamics from noise. The following projections should therefore be interpreted as *scenario bounds* rather than point forecasts.

The fitted parameters (p = 0.079, q = 0.087, m = 12,660 tonnes) imply a total market potential of approximately 13,500 tonnes, but these estimates are unreliable given the poor fit.

With $R^2 = 0.84$, Germany's first-time series follows Bass diffusion dynamics well. The fitted parameters are: p = 0.143 (innovation coefficient), q = 0.080 (imitation coefficient), m = 328,154 tonnes (market potential during observation period). Including prior stock, total market potential is approximately 361,000 tonnes.

For Germany, Bass-based predicts peak in 2027 at 136,047 tonnes declining to 91,779 tonnes by 2040. Arbitrary decay predicts peak in 2036 at 185,270 tonnes with 181,803 tonnes in 2040.

The divergence between the two models stems from their treatment of market potential: (1) Bass predicts saturation – the pool of first-time buyers is finite and gets exhausted by approximately 2030; (2) Arbitrary decay predicts indefinite slow decline – new adopters keep coming forever; (3) Generational decay amplifies the difference - under Bass, when first-time purchases collapse, there are no new cohorts to replace aging ones.

The Bass-based projections predict earlier peaks and steeper declines than the arbitrary decay assumption – see table 15 and figure 6 for a comparison of model outcomes. Here are the main differences:

- The Bass model implies Germany's plant-based meat market approaches saturation by the late 2020s, with first-time purchases falling from ~45,000 tonnes (2019) to under 1,000 tonnes by 2040.
- By 2040, repeat purchases account for 99% of sales volume. Market health becomes entirely dependent on retention, making the repurchase rate r□ and generational decay T_{life} critical parameters.
- Without external shocks (new product innovations, price reductions, policy support), the model predicts the market will contract after peaking, as generational attrition outpaces new adoption.
- Austria's weak fit ($R^2 = 0.22$) means its projections should be treated with substantial caution. Germany's stronger fit ($R^2 = 0.84$) provides more confidence, though extrapolating diffusion models beyond the observation window always carries risk.

The Bass-based approach is theoretically grounded but assumes fixed market potential. This may be unrealistic for emerging technology where the addressable market could expand through product innovation, price reductions, policy interventions, or cultural shifts. If market potential itself is growing, the Bass model will systematically underestimate future volumes. The other model arbitrarily regulates the inflow of new customers and does set an upper boundary for the market size. While this is one plausible scenario, the rate of new customer acquisition should be set based on empirical evidence and not by pure assumptions as done in this case.

Figure 6: Comparison of Bass-based (solid) vs arbitrary decay (dashed) projections

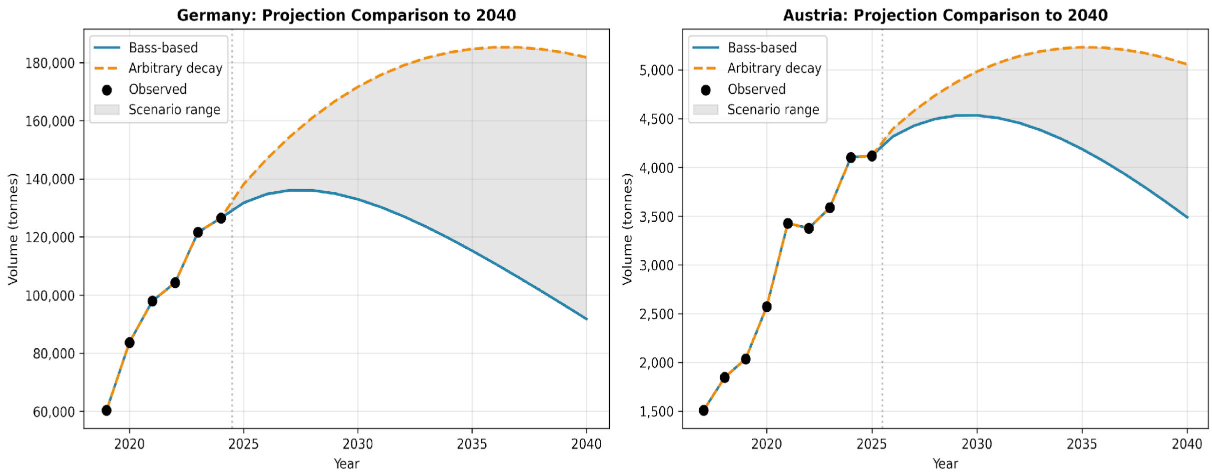


Table 17: 2040 Projection Comparison — Bass vs Arbitrary Decay

Country	Method	2040 Total	Peak Year	Peak Volume
Germany	Bass-based (R^2=0.84)	91,779	2027	136,047
Germany	Arbitrary 5% decay	181,803	2036	185,270
Austria	Bass-based (R^2=0.22)	3,488	2030	4,533
Austria	Arbitrary 5% decay	5,056	2035	5,231

9. Conclusions

Data availability constrains useful forecasts. Given the available data, the Bass model consistently estimates that the market has peaked or is close to peaking for both Austrian and German data series and will decline through 2040. This is clearly not a plausible outcome.

The second model, based on an arbitrarily set parameter that keeps the inflow of new customers at a high level, produces somewhat higher but not exponential market forecasts. This is also not seen as a realistic depiction of future sales or production, as the parameter was set arbitrarily and should instead be calibrated based on empirical evidence.

Future analysis would benefit from several improvements. Individual-level purchase histories would allow direct observation of first-time versus repeat purchases, eliminating the identification problem. Consumer survey data might provide the right source to calibrate first-time and repeat customer parameters. Longer time series would help stabilise estimation and allow explicit accounting for pandemic effects through regime-switching or intervention analysis.

The arbitrary decay model highlights that the evolution of meat substitutes demands a continuous high inflow of new consumers which demands innovation to offer products that are attractive to a larger share of the population as well as behavioural change if the market is to grow. Consequently, governments are called upon to foster innovation in this sector and to communicate effectively in order to increase the share of innovators and imitators as well as the repurchasing rate. The latter may be particularly important: given that word-of-mouth effects dominate innovation effects, marketing and communication strategies should prioritise trial generation and positive experience sharing.

The repeat purchase dynamics highlight the importance of customer retention. The decay effects observed suggest that maintaining consumer interest also requires ongoing product innovation and quality improvement.

The comparison with other radical food innovations suggests that plant-based meat markets may require decades rather than years to reach maturity. Current market plateaus may represent temporary pauses in a longer-term diffusion process rather than permanent saturation.

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Annex

Decomposition Algorithm

To ensure transparency and reproducibility, the decomposition algorithm is described in detail. The Python implementation follows these exact steps:

Step 1: Year 1 Split. For the first observation year, apply the assumed initial repeat share directly: Repeat(t1) = initial_repeat_share x Observed(t1); First-time(t1) = Observed(t1)- Repeat(t1). With a 25% initial repeat assumption (early-stage scenario), this means 75% of Year 1 sales are attributed to first-time purchases.

Step 2: Calculate Implied Prior Stock. The Year 1 repeat volume implies that customers must have adopted the product before the observation period. This prior stock of cumulative first-time adopters is calculated as: r_prior = r0 x (1 - avg_prior_age / T_life); Prior Stock = Repeat(t1) / r_prior. With r0 = 50%, T_life = 35 years, and avg_prior_age = 3 years: r_prior = 0.50 x (1 - 3/35) = 0.457.

Step 3: Subsequent Years. For each subsequent year, repeat purchases are computed from two sources: (A) Repeat from prior stock, aging by one year each period; (B) Repeat from all observed first-time cohorts, where for each prior cohort s: tau = t - s (years since adoption), r(tau) = r0 x max(0, 1 - tau / T_life), and rep_from_cohort_s = First-time(s) x r(tau). Total Repeat(t) = rep_from_prior + rep_from_observed.

Step 4: First-time as Residual. First-time(t) = max(0, Observed(t)- Repeat(t)). The max(0, ...) constraint ensures first-time purchases cannot be negative, though this constraint was never binding in the data.

Interpretation: This algorithm treats first-time purchases as the residual after accounting for all repeat purchases from prior cohorts. The key insight is that repeat purchases are deterministic given the model parameters (r0, T_life) and the history of first-time adoptions. The decomposition essentially asks: Given how many first-time buyers have accumulated, how much repeat volume should be expected? Whatever remains must be new adopters.