Modeling and Forecasting the Diffusion of Unicorn Startups

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Abstract

Unicorn startups have become symbols of entrepreneurial success and fundamental drivers of innovation and wealth creation. This study examines the diffusion process of unicorns across eight countries (the US, China, India, the UK, Germany, France, the Netherlands, and Sweden) and three industries (Fintech, Health, and Transport). The aim of this research is to model and forecast the diffusion of unicorn startups using three- and four-parameter Logistic and Gompertz sigmoid growth models, leveraging data from the Dealroom database. By addressing this research gap, the study seeks to provide valuable information for policymakers and investors regarding the ultimate potential number of unicorns and the time to saturation. The findings indicate that the Gompertz model generates highly optimistic estimates of unicorn saturation levels, while the Logistic model produces more realistic projections for both fitting existing data and forecasting future trends. Specifically, the three- parameter Gompertz model is suited for analyzing unicorn diffusion in China. The three-parameter Logistic model is appropriate for analyzing unicorn diffusion in the USA, the UK, and all studied sectors. Meanwhile, the four-parameter Logistic model is the best model for explaining unicorn diffusion in India, Germany, France, the Netherlands, and Sweden. The results also reveal that India has the highest estimated speed of unicorn diffusion (97%), while the US exhibits the highest saturation level (6,241 unicorns). Sectoral analysis shows that Fintech has the lowest estimated diffusion speed (43.1%), but the highest saturation level (1,630 unicorns). Our forecasting analyses suggest that all selected countries and sectors — except the US and Fintech — are likely to reach unicorn saturation by around 2030. These findings provide critical insights for planning, regulation, policy formulation, and portfolio decision-making.

Keywords: unicorn startups; innovation diffusion; forecasting; entrepreneurial performance; Logistic model; Gompertz model

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Introduction

Over the past decade, the term "unicorn startup", referring to privately held companies valued at over $1 billion, has become a symbol of entrepreneurial success and technological innovation. Since its introduction by Aileen Lee in 2013,[1] the global number of unicorns has increased exponentially, from just 38 in 2013 to over 2,600 by early 2023.[2] Despite this rapid expansion, unicorns remain rare phenomena. In Europe, for instance, only one in 100 seed-funded startups achieves this valuation milestone[3].

Unicorns typically emerge at the nexus of disruptive technologies and highly scalable business models, reshaping traditional industries by offering more efficient, accessible, and often digital solutions (Stadler, 2016; Meek, Cowden, 2023; WIPO, 2023). Their rise was particularly accelerated in the wake of the COVID-19 crisis: 472 new unicorns were created in 2021 alone, fueled by global digitization, abundant venture capital, and increasingly supportive regulatory frameworks. This surge translated to nearly one new unicorn per day in the United States, approximately every ten days in India and China, almost every 15 days in Germany and the UK; every month in France; and every two months in the Netherlands and Sweden.

While most unicorns take at least five years on average to reach this valuation (Venâncio et al., 2023), a subset — including ClickHouse (US), Gorillas (EU), and iCarbonX (China) — achieved unicorn status in in less than a year, highlighting the exceptional agility of certain ventures during periods of systemic disruption (Kuckertz et al., 2020; Rodrigues, 2021).This rapid emergence raises an important question: **Is the unicorn phenomenon sustainable or is it approaching a saturation point?**

Despite the high failure rate of startups and growing macroeconomic volatility, the proliferation of unicorns represents both a strategic challenge and a major opportunity for innovation-driven economies. The concept of creative destruction (Schumpeter, 1943) remains particularly relevant for understanding the disruptive force of these firms. Yet the scale, speed, and uneven distribution of unicorn emergence remain poorly understood and insufficiently theorized.

A growing body of literature has attempted to identify the key drivers of unicorn success. For instance, Guo and Zhang (2021), using fuzzy set qualitative comparative analysis, highlight the role of emerging industries, enabling ecosystems, platform-based business models, and access to capital in unicorn development in China. Venâncio et al. (2023), analyzing 766 unicorns across 39 countries, emphasize the importance of innovation capacity, infrastructure, and resource availability. Kutsenko et al. (2022) add an important dimension by examining founder mobility, showing that nearly 40% of unicorns involved foreign entrepreneurial talent.

While these studies offer valuable insights, they often fall short of providing analytical frameworks capable of systematically modeling or forecasting unicorn diffusion across countries and industries. Although some scholars acknowledge the non-linear and abrupt nature of unicorn growth, analyses often rely on anecdotal evidence or descriptive analyses of individual business models (Urbinati et al., 2018; Trabucchi et al., 2019). Consequently, they offer limited guidance for anticipating future trends or for benchmarking national innovation ecosystems.

This research aims to address this gap by modeling the diffusion dynamics of unicorn startups across eight countries — namely the United States, China, India, the United Kingdom, Germany, France, the Netherlands, and Sweden — and three major sectors: fintech, healthtech, and transportation. Drawing on data from the Dealroom database, which tracks the cumulative number of unicorns from 2000 to 2022, we apply three- and four-parameter Logistic and Gompertz growth models to estimate the diffusion trajectories of unicorn startups. This methodological approach represents an advance over previous studies by offering a robust, quantifiable framework for capturing non-linear growth and forecasting saturation points.

The study is guided by the following research questions:

1. Can unicorn growth be effectively modeled using S-curve diffusion models?
2. Which model variant — logistic vs. Gompertz, three- vs. four-parameter — best captures the diffusion dynamics of unicorns across countries and industries?
3. How do diffusion trajectories differ across national and sectoral contexts?
4. What explains these differences?
5. What are the projected saturation points or upper limits of unicorn creation in each country or sector?
6. What strategic insights can be derived for investors, policymakers, and innovation ecosystem stakeholders?

This study makes several key contributions to the literature. First, to our knowledge, it is the first to apply Logistic and Gompertz growth models — tradition-

[1] https://techcrunch.com/2013/11/02/welcome-to-the-unicorn-club/, accessed 12.09.2024.

[2] https://dealroom.co/, accessed 18.01.2025.

[3] https://2020.stateofeuropeantech.com/chapter/state-european-tech-2020/, accessed 06.02.2025.

ally used in technology adoption studies — to the diffusion of unicorn startups. Grounded in Rogers' (1962) innovation diffusion theory, our study extends the applicability of S-curve models from product-level to firm-level valuation phenomena. Contrary to critiques regarding the incompatibility of sigmoid curves with rapid, exponential startup growth (Urbinati et al., 2018), our results show that these models effectively capture the core dynamics of unicorn proliferation with Logistic models outperforming Gompertz in most national and sectoral contexts

Second, by employing both three- and four-parameter specifications, we improve the precision and flexibility of diffusion modeling. Prior studies (e.g., Akin et al., 2020; Korkmaz, 2020) indicate that four-parameter models provide more accurate forecasts in scenarios characterized by delayed take-off or early saturation. Our results support this conclusion, showing that four-parameter models most effectively capture the unique growth dynamics of unicorn startups.

Third, the study offers a comparative, cross-country, and cross-sectoral perspective. By linking estimated diffusion trajectories to contextual variables such as venture capital intensity, regulatory landscape, and entrepreneurial mobility, we identify why certain countries (e.g., the US and China) and sectors (e.g., fintech) exhibit faster unicorn proliferation. The comparative lens also enables us to identify countries and industries approaching saturation, versus those with untapped growth potential.

From a practical standpoint, our findings yield actionable insights for investors, policymakers, and entrepreneurs. Reliable forecasting of unicorn emergence can inform venture capital allocation, guide innovation policy formulation, and scaling strategies for high-growth ventures. For instance, our results indicate that fintech unicorns are likely to reach saturation more gradually than those in the health tech and transportation sectors — suggesting differentiated approaches for public support and investment strategy. Entrepreneurs can benchmark their growth trajectories against diffusion curves, optimizing their scaling approaches, while corporate strategists can use these insights to anticipate market disruptions and refine acquisition or partnership strategies.

Although some scholars caution against overemphasizing unicorns as representative of entrepreneurship (Aldrich, Ruef, 2018), there is strong evidence that unicorns play a critical role in advancing innovation, creating jobs, and driving economic dynamism (Shane, 2009; OECD, 2021; Testa et al., 2022; Shahid, 2023). In 2021 alone, Europe's unicorns generated over 135,000 jobs (Huebl et al., 2022). Furthermore, unicorn density has become a core indicator in global innovation rankings (WIPO, 2023). Supporting their emergence is thus a matter of strategic importance for national development agendas (Kuratko, Audretsch, 2021; Kuckertz et al., 2020, 2023).

In an increasingly competitive and innovation-driven global economy, the ability to model and forecast unicorn diffusion is of critical strategic value. By bridging innovation diffusion theory with the empirical realities of startup ecosystems, this study offers a novel, data-driven framework for understanding and anticipating the trajectories of high-growth firms.

Theoretical Framework and Hypothesis Development

This study is anchored in the Diffusion of Innovation (DoI) theory and utilizes the logistic and Gompertz diffusion models as its principal analytical frameworks for modeling the growth trajectories of unicorn startups.

The conceptualization of innovation diffusion was first systematically articulated by Rogers (1962). According to Rogers, diffusion is defined as the process by which an innovation — understood as a new idea, practice, or technology — is communicated over time through specific channels among members of a social system. He identifies five core elements that shape this process: the innovation itself, communication channels, time, the social system, and the adoption decision process. Rogers also proposed a classification of adopters into five groups — innovators, early adopters, early majority, late majority, and laggards — laying the foundation for understanding how and why innovations spread unevenly within populations.

Building on this theoretical base, subsequent research has introduced quantitative models to capture the temporal dynamics of innovation diffusion. Among the most prominent are the Logistic and the Gompertz models, both of which exhibit the characteristic S-shaped curve of cumulative adoption. This curve typically unfolds in three phases: (1) a slow initial uptake, (2) a rapid acceleration phase as the innovation gains legitimacy and traction, and (3) a deceleration as the market approaches saturation.

Originally rooted in 19th century biological and demographic studies, the Gompertz and the Logistic model have been widely adopted in fields ranging from marketing and technology forecasting to epidemiology. Their empirical relevance was notably reaffirmed during the COVID-19 pandemic, where they were extensively employed to simulate the spread of infection (Pelinovsky et al., 2022; Satoh, 2021).

While these models have proven robust in many contexts, their suitability for modeling digital-era, high-velocity innovations, such as unicorn startups, has been the subject of scholarly debate. Unicorns often embody unique dynamics: platform-based scalability, global scalability, and substantial venture capital infusion — factors that may generate diffusion patterns deviating from traditional S-curves (Urbinati et al., 2018; Trabucchi et al., 2019).

However, historical evidence shows that even paradigm-shifting innovations — such as the automobile, electricity, or television — can be effectively modeled using growth-based frameworks when appropriately parameterized (Meade, Islam, 2015). This underscores the adaptability and enduring relevance of these models, even in the face of disruptive technological change.

As previously noted, unicorn startups share key features of transformative innovations: they are digitally native, disruptive, and rapidly adopted, often reshaping entire industries. These characteristics make them particularly well-suited for empirical modeling through non-linear diffusion curves, especially the Logistic and Gompertz functions.

By leveraging both models, this study conducts a comparative analysis of diffusion patterns across countries and sectors, enabling the estimation of critical parameters such as maximum market potential (M), growth rate (α), and inflection point (β). The Logistic model, which assumes a symmetrical S-curve, is optimal for contexts with balanced early and late adoption, while the Gompertz model — characterized by an asymmetrical S-curve — is better suited to scenarios where early adoption is gradual but followed by a rapid acceleration in later stages.

Recent studies (e.g., Akin et al., 2020; Korkmaz, 2020) have shown that four-parameter extensions of the Gompertz and Logistic models often outperform their three-parameter counterparts in terms of fit and forecasting accuracy. The three-parameter model (Logistic or Gompertz) constrains the curve to start at zero, which may not accurately represent the data. In reality, some countries might already have a baseline level of entrepreneurial activity or an existing tech ecosystem. The four-parameter model, with its lower asymptote, accounts for this non-zero starting point. This model offers greater flexibility in fitting the data, even if the initial data points are not perfectly accurate.

Accordingly, following the methodologies of Jha & Saha (2020) and Akin et al. (2020), this study employs both three-parameter and four-parameter versions of the Logistic and Gompertz models, as detailed in the subsections below.

Logistic Model

The Logistic curve is symmetrical about its inflection point. The three-parameter logistic model (LM3P) is as follows:

$$U(t) = \frac{M}{1+e^{-\alpha(t-\beta)}}, \quad (1)$$

M, β and α, are all positive parameters.

M is the market potential or the maximum number of possible unicorns, α is the growth rate or the pace of unicorn adoption and β is the inflection point, which indicates the point at which the growth of unicorn adoption reaches its peak and begins to decline. This is generated when the diffusion of unicorns has reached half of its maximum level (*M / 2*).

The Logistic model with four parameters (LM4P) is as follows:

$$U(t) = A + \frac{B}{1+e^{-\alpha(t-\beta)}}, \quad (2)$$

Where *A* is a location parameter and acts as the lower asymptote, *B* is the asymptotic amount of unicorn growth that occurs as *t* increases, and *A+B=M.*

Gompertz Model

The Gompertz curve has the property of being asymmetric about the inflection point. The three parameter Gompertz model (GM3P) is:

$$U(t) = Me^{-e^{-\alpha(t-\beta)}}, \quad (3)$$

M is the market potential or the maximum number of possible unicorns, α is the growth rate or the pace of unicorn adoption, and β is the inflection point, which indicates the point in time at which the growth of unicorn adoption peaks and begins to decline. This occurs when the diffusion of unicorns reaches the share *1/e* ≈ 36.8% of its maximum level (*M/e*).

The Gompertz model with four parameters (GM4P) is as follows:

$$U(t) = C + De^{-e^{-\alpha(t-\beta)}}, \quad (4)$$

Where C is a location parameter and acts as a lower asymptote, *D* is the asymptotic amount of unicorn growth that occurs as *t* increases, and *C+D=M.*

Research Hypotheses

By operationalizing unicorn diffusion through established growth models, this study empirically evaluates the extent to which Logistic and Gompertz functions can capture the cross-national and cross-sectoral trajectories of unicorn startup proliferation. The following hypotheses are proposed and tested :

H1: The diffusion of unicorn startups follows an S-shaped growth trajectory that can be effectively modeled using either the Logistic or Gompertz function, consistent with classical innovation diffusion theory.

H2: The Gompertz model provides a superior fit in contexts characterized by rapid early-stage growth followed by premature saturation, often influenced by regulatory or structural constraints.

H3: The Logistic model is better suited for countries where structural, economic, and institutional conditions support balanced, sustained scaling, aligning with its assumptions of symmetrical growth around an inflection point.

H4: Unicorn diffusion patterns differ significantly across countries, driven by heterogeneity in institutional frameworks, innovation capacity, access to venture capital, and national entrepreneurship ecosystems.

H5: Sector-specific factors — such as regulatory barriers, technological maturity, and product lifecycle dynamics — significantly influence the shape, speed, and ultimate ceiling of unicorn diffusion trajectories.

Methodology and Data

Our analysis begins with a descriptive examination of the dataset (detailed in the following subsection) to provide a preliminary assessment of our first hypothesis concerning the applicability of the Logistic and Gompertz diffusion models to the context of unicorn startups. Following this, we adopt a three-stage methodological approach.

*Stage 1: Model Estimation***.** We estimate the parameters of the diffusion models outlined in Equations (1) through (4) for each country and industry in the sample using Nonlinear Least Squares (NLS) regression. For each case, the model with the highest adjusted R^2 and the lowest Root Mean Square Error (RMSE) is selected as the best-fitting model for historical data.

Stage 2: Forecasting and Validation. Using the estimated parameters, we forecast the diffusion of unicorns by country and industry for the period 2023–2033. To evaluate forecasting accuracy, we rely on two primary error metrics: the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE). The model exhibiting the lowest MAE and MAPE is considered the most reliable for projection purposes.

Stage 3: Comparative Analysis of Diffusion Dynamics. To explore heterogeneity in diffusion patterns, we compare the fitted parameters — such as growth rate, inflection point, and market potential — across countries and sectors. This comparison enables us to assess the influence of institutional frameworks, digital infrastructure, and innovation ecosystems on unicorn diffusion by country, and the role of technological maturity, regulatory complexity, and innovation cycles at the sectoral level.

Data and Descriptive Analysis

This paper focuses on assessing the goodness of fit and predictive ability of the Logistic and Gompertz models for the diffusion of unicorns. To this end, we use time series data on cumulative unicorns from the Dealroom database, specifically the so-called "Unicorn Club". Launched in 2013, the Dealroom database provides information on technology companies founded since 1990, with a particular focus on the EU market. Dealroom is recognized as a leading data provider for high-growth companies, offering detailed funding round histories, valuation milestones, and investor networks (Veugelers, Amaral-Garcia, 2025). It is one of the most widely cited and used databases for tracking startups, scaleups, and unicorns, making it highly relevant for studying their diffusion process. Several previous studies have relied on this database, such as (Burstrom et al., 2023; El-Dardiry, Vogt, 2023; Testa et al., 2022). Furthermore, its transparent methodology for identifying unicorns — defined as privately held startups exceeding a $1 billion valuation — ensures consistency in firm classification, making it well-suited for analyzing the diffusion patterns of these companies across different geographies and industries.

The Unicorn Club is particularly well suited for research as it is updated daily and is structured in an accessible way (Retterath, Braun, 2020). It enables near real-time tracking of new unicorns, exits, and funding activities. Unlike traditional data sources, Dealroom provides up-to-date information, minimizing delays in data availability (van Meeteren et al., 2022). Dealroom offers granular data on the number of new and cumulative unicorns by continent, country, and industry since 2000. Compared to other databases (e.g., CB Insights, Crunchbase, PitchBook), Dealroom stands out for its global scope, particularly on emerging markets, and its integration of proprietary and publicly available data sources. It gathers information using multiple methods including automated harvesting of public data (e.g., press releases, VC reports, job boards, domain registries), partnerships with government agencies to supplement startup records, and manual verification to ensure data accuracy (El-Dardiry, Vogt, 2023). Furthermore, Dealroom provides broader sectoral tags and deeper coverage of European ecosystems (Burstrom et al., 2023; Leendertse et al., 2022).

Despite its strengths, Dealroom — like other venture capital databases — has limitations. As with many commercial startup data providers, its datasets can be incomplete due to the private nature of many investment deals, inconsistent reporting by some investors, or selective reporting of certain deal types (Testa et al., 2022). Moreover, while Dealroom offers extensive global coverage, regional gaps persist, particularly in the Asia-Pacific ecosystem. However, van Meeteren et al. (2022) validated Dealroom's coverage by comparing it with Crunchbase. Their findings revealed similar sectoral and geographical distribution patterns in both datasets, with most companies concentrated in North America and Europe. This suggests that while some limitations exist, Dealroom remains a reliable source for studying unicorn diffusion on a global scale.

According to the Dealroom database, there are currently 2,615 unicorn companies worldwide, 90% of which are in just 15 countries. Among these countries, the US and China alone account for 54% and 12.42% of the total number of unicorns, respectively. The most represented industries are fintech, with 517 companies in this category, healthcare with 433 unicorns and transportation with 234 unicorns.

The dataset used for this paper was downloaded in December 2022. It covers the period 2000-2022 and includes information on the number of cumulative unicorns in eight countries (US, China, India, UK, Germany, Sweden, France and the Netherlands) and three industries (fintech, health, and transport). Our database represents 80% of the world's unicorns. The size of this database is consistent with diffusion and forecasting studies such as (Armstrong, 2001; Michalakelis et al., 2008; Lee et al., 2011).

Figures 1 and 2 describe the growth paths of the unicorns in the eight countries and three sectors selected during the study period. As can be seen from these figures, the shapes of the unicorn curves follow an S-curve pattern. Therefore, using forecasts based on linear extrapolation may lead to under- or overestimation. The distribution of unicorns varies considerably across countries and sectors. As noted above, Figure 1 shows that most unicorns are concentrated in the US and China, with the former leading the pack. Among European countries, the UK has the most unicorns, followed by Germany, the Netherlands, Sweden, and France. However, India seems to outperform the EU27 countries in terms of the number of unicorns, especially from 2020 onwards. Figure 1 also shows that the number of unicorns has increased continuously since 2014 in all the countries examined.

The largest increase in unicorns came in 2021, when all countries except China, the Netherlands, Sweden, and the UK saw the highest rate of unicorn growth. However, it appears that the growth rate of European and Indian unicorns in 2021 outpaced that of their US and Chinese counterparts. The same patterns are observed for the growth rate of unicorns in the three sectors examined (Figure 2). Figure 2 shows that most unicorns are active in the health and fintech sectors followed by unicorns active in the transportation sector. A continuous increase in the number of unicorns has been observed since 2014, reaching a peak in 2021.

Results and Discussions

Logistic and Gompertz models with three and four parameters are used as growth models in this research. We use the non-linear least squares (NLS) and STATA 15 software to estimate the parameters in (1), (2), (3), and (4), after providing appropriately chosen initial values, since the two curves are non-linear in the parameters of interest. The estimated parameters can then be used to obtain forecasts of the variable *U*.

The quality of the fit to the data is excellent for each model. All models show a high accuracy with an adjusted coefficient of determination (Adj_R^2) greater than 95%. All the parameters of the models are almost statistically significant at the 1% level. In the following sections, we detail our results by country and by sector.

Analysis of Unicorn Diffusion by Country

The results of the analysis for the eight countries are summarized in Table 1. The models obtained for all countries in the study are statistically significant and all the parameters of the models are statistically significant at the 1% level, except for the saturation point parameter in the case of the USA, UK, and Germany (Table 1). From Table 1, we can conclude that the Logistic model is suitable for analyzing the diffusion of unicorns in the USA, India, Germany, the UK, France, the Netherlands, and Sweden. Indeed, this model yields a lower RMSE and a higher adjusted R^2 than the Gompertz model. In the case of China, however, the Gompertz model is more appropriate to describe unicorn diffusion.

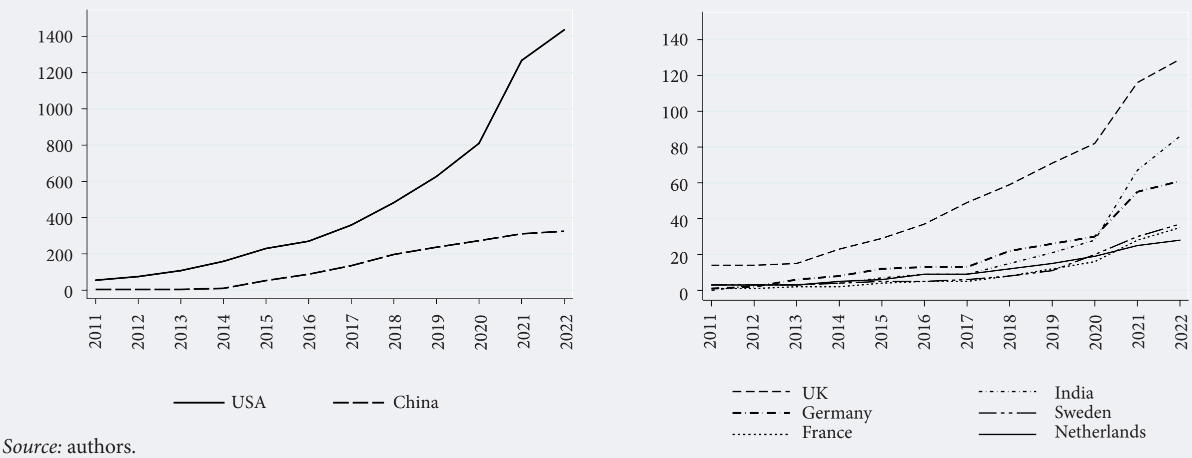
Our Logistic model results for unicorn diffusion in the USA indicate a maximum level of 6,241.574. The speed of convergence to the saturation level is 0.322, and half of the maximum level will be reached in 2026. Using the Logistic model with four parameters, we find almost the same results as those reported above. The results of the Gompertz model indicate an overestimation of the potential maximum number of unicorns and a very low speed of diffusion (0.017). The values of adjusted R^2, RMSE, MAE, and MAPE indicate that the three-parameter Logistic model is the best to describe and forecast unicorn diffusion in the USA. Our forecasting analysis shows that the saturation of unicorn diffusion in the USA, generated by the Logistic model, is predicted to be reached in 2052.

The results of the Logistic model for the diffusion of unicorns in China indicate a maximum level of 335.796, with a convergence speed to the saturation level of 0.694. According to the model, unicorn diffusion reached half of its maximum level in 2018. The Gompertz model results suggest a maximum diffusion level of 380.713, a diffusion speed of 0.378, and that 36.8% of the maximum level was achieved in 2017. Based on the values of adjusted R^2, RMSE, MAE, and MAPE, the three-parameter Gompertz model demonstrates superior performance in both describing and forecasting unicorn diffusion in China. Our forecasting analysis predicts that the saturation of unicorn diffusion in China, as estimated by the Gompertz model, will be reached in 2032.

For the UK, our results from the three-parameter Logistic model for unicorn diffusion show a maximum level of 545.113 (but not statistically significant). The speed of convergence to the saturation level is 24.5% (significant at 1%) and half of the maximum level will be achieved in 2027. Using the Gompertz model, we find similar results to the USA case. The potential maximum number of unicorns is also overestimated, while the speed of diffusion is underestimated. The values of adjusted R^2, RMSE, MAE, and MAPE indicate that the Logistic model is the best to describe and forecast unicorn diffusion in the UK. Our forecasting analysis shows that the saturation of unicorn diffusion in the UK, as generated by the Logistic model, is predicted to be reached after 2032.

For India, the results of the four-parameter Logistic model for unicorn diffusion indicate a maximum

Figure 1. **Growth Path of Unicorns by Country**



Source: authors.

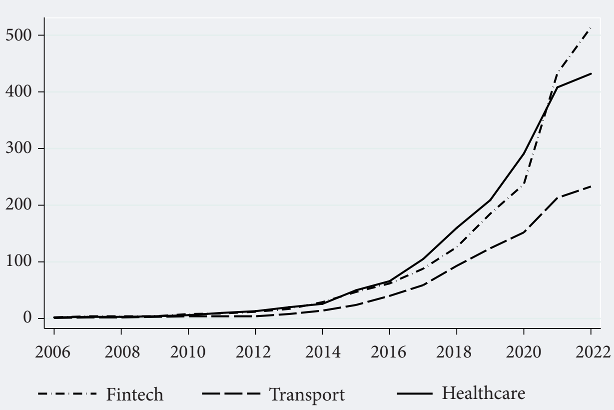
level of 139.889 and the speed of convergence to the saturation level is 97%. Unicorn diffusion reached half of its maximum level in 2021. The results of the Gompertz model indicate a maximum diffusion level of 313.211 (but not statistically significant), the speed of diffusion is 0.298 and 36.8% of its maximum level was achieved in 2022. From Table 1, we can conclude that the four-parameter Logistic model provides more accurate results in describing and forecasting the unicorn diffusion in India, which is reflected in its high adjusted R^2 and low RMSE, MAE, and MAPE. Our forecasting analysis shows that the saturation point of unicorn diffusion in India, as generated by the Logistic model, is predicted to be reached in 2030.

The results of the four-parameter Logistic model for the diffusion of unicorns in France show a maximum level of 91.9 and the speed of convergence to the saturation level is 0.496. Unicorn diffusion achieved half of its maximum level in 2023. The Gompertz model strongly overestimates the ultimate potential number of unicorns and underestimates the speed of diffusion. The four-parameter ogistic model is found lto be suitable for describing the process of unicorn diffusion in France, while the Gompertz model is the best for predicting unicorn diffusion. However, given that the predictive performance of the Logistic and Gompertz models is not significantly different and considering that the ultimate market potential estimate of the Logistic model is more realistic (91.9), we choose the Logistic model over the Gompertz model to forecast the unicorn diffusion in France. According to our forecast results generated by the Logistic model, the saturation of unicorn diffusion in France will be reached in 2032.

The four-parameter Logistic model also performs well in describing and forecasting the diffusion process of unicorns in Sweden and the Netherlands. In Sweden, the maximum potential number of unicorns is 48 and half of this number was reached in 2021. In the Netherlands, it took a year longer to reach half of the maximum potential number of unicorns, which is 57. Our results also show that unicorns in Sweden are diffusing at 2.4 times the speed of unicorn diffusion in the Netherlands. Regarding our forecasting results, we find that while Sweden will achieve its saturation point of unicorn diffusion in 2027, the Netherlands will need five more years to reach its maximum potential number of unicorns.

For the case of Germany, the performance analysis of non-linear growth models based on adjusted R^2 and RMSE shows that the three-parameter Gompertz model is more suitable for describing and forecasting the diffusion of German unicorns. However, the saturation value is strongly overestimated, while the speed of growth is underestimated, and these values do not seem plausible with the German data. This estimation problem has also been identified by several previous researchers such as (Gamboa, Otero, 2009; Jha, Saha, 2020) in the telecommunications industry.

Figure 2. **Growth Path of Unicorns by Sector**



Source: authors.

Table 1. **Estimated Parameters of the Unicorn Diffusion Models by Country**

Parameter	**Country**							
	USA (n=23)		**China (n=12)**		**UK (n=13)**		**India (n=13)**	
Model	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**
M_3P	6241.574	8.94e+09	335.796 *	380.713*	545.113	452195.2	196.359*	6.94e+08
M_4P	5 545,489	-	342,582*	378,268*	381.833	2 358,319	139.889*	313.211
_3P	0.322 *	0.017*	0.694*	0.378*	0.245*	0.024	0.678*	0.028*
_4P	0.331*	-	0.637*	0.385*	0.276**	0.066	0.97*	0.298**
_3P	2025.629*	2182.154*	2017.603*	2016.996 *	2026.676*	2109.214*	2021.719*	2121.446*
_4P	2025.065*	-	2017.574*	2017.007*	2024.435*	2038.416*	2020.835*	2022.305*
In-sample								
Adj R^2_3P	0.995	0.995	0.998	0.999	0.997	0.996	0.987	0.985
Adj R^2_4P	0.993	-	0.996	0.998	0.991	0.991	0.988	0.983
RMSE_3P	34.047	34.978	8.122	5.119	3.683	3.727	4.532	4.849
RMSE_4P	34.825	-	7.583	5.304	3.853	3.841	3.685	4.386
Out-of-sample								
MAE_3P	15.412	16.437	5.898	3.791	2.252	2.339	3.227	3.309
MAE_4P	15.685	-	5.194	3.6	2.181	2.151	2.37	2.745
MAPE_3P	0.132	0.135	0.415	0.238	0.063	0.068	0.465	0.373
MAPE_4P	0.417	-	0.467	0.19	0.055	0.052	0.451	0.483

Parameter	**Country**							
	Germany (n=13)		**France (n=13)**		**Sweden (n=13)**		**Netherlands (n=14)**	
Model	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**
M_3P	2648.196	3.59e+08	15139.13	4.64e+08	81455.96	1.82e+08	186.937	1.26e+08
M_4P	301,384	1.08e+08	91.9**	1.11e+08	48,308*	88,65***	56,765**	236,871
_3P	0.285*	0.017*	0.355*	0.021*	0.319*	0.021*	0.236*	0.013*
_4P	0.349	0.020*	0.496*	0.024*	0.834*	0.295**	0.347*	0.091***
_3P	2035.042*	2182.009*	2039.03*	2157.377*	2046.163	2153.066*	2029.22	2224.1 *
_4P	2025.92 *	2154.355 *	2022.98*	2132.8*	2020.632*	2021.679*	2022.15*	2030.601*
In-sample								
Adj R^2_3P	0.982	0.984	0.991	0.991	0.983	0.985	0.995	0.996
Adj R^2_4P	0.955	0.960	0.991	0.990	0.990	0.985	0.992	0.991
RMSE_3P	3.557	3.408	1.117	1.124	1.982	1.865	0.837	0.82
RMSE_4P	4.138	3.888	0.950	0.980	1.131	1.39	0.776	0.794
Out-of-sample								
MAE_3P	2.48	2.461	0.817	0.894	1.456	1.488	0.603	0.618
MAE_4P	2.59	2.594	0.546	0.572	0729	0.937	0.523	0.541
MAPE_3P	0.4	0.344	0.338	0.399	0.246	0.306	0.108	0.112
MAPE_4P	0.235	0.226	0.143	0.123	0.260	0.301	0.084	0.086

Note: Significance level: *, $p < 1\%$; **, $p < 5\%$; ***, $p < 10\%$. Some values are not reported since the modeling failed to achieve the convergence criteria even after thousands of iterations..

Source: authors.

Furthermore, we find that the NLS estimation procedure requires more than two thousand iterations to reach the convergence criteria, in contrast to the Logistic model, which requires only a few iterations. Since the maximum potential number of unicorns estimated with the Logistic model is more realistic, we chose the Logistic model over the Gompertz model to describe and forecast the diffusion processes of unicorns in Germany. For the choice between a Logistic model with three or four parameters, we refer to Figure 3. We find that the Logistic model with four parameters best fits the real adoption curve. Therefore, we consider this model to be the most suitable for describing and predicting the diffusion of unicorns in Germany. The results show that the growth rate is 34.9%, the saturation level is 301.384, and half of this saturation level will be reached in 2026. According to our forecasting analysis results, generated by the four-parameter Logistic model, unicorn diffusion in Germany will reach 128 in 2025.

Comparing the estimated parameters of the best fitted models for our sample of countries, the results show that India has the highest estimated speed of diffusion (97%), followed by Sweden (83.4%) and China (37.8%). As for the maximum diffusion of unicorns, our results show that the US has the highest level (6,241.574), followed by the UK (545.13) and China (380.713). Therefore, the US will continue to be the top country for unicorns. We also find that China, India, France, Sweden, and the Netherlands have already reached half of their maximum diffusion of unicorns. Conversely, the US, UK, and Germany still need one to two years to reach this level. Furthermore, we find that all the countries selected in our analysis, except the US, will reach their maximum level of unicorn diffusion around 2030.

Results of the Unicorn Diffusion Analysis by Sector

In this section, we report the results of our analysis of the unicorn diffusion process by sector. The results of the analysis, for the three selected sectors, are summarized in Table 2.

The models obtained for all the sectors in the study are statistically significant and almost all the parameters of the models are statistically significant at the 1% level. From Table 2, we can conclude that the Logistic model is suitable for analyzing the diffusion of unicorns in all three sectors, as it provides a lower RMSE and a higher adjusted R^2 than the Gompertz model.

For the fintech sector, our Logistic model results indicate a maximum level of 1,630.231. The speed of convergence to the saturation level is 0.431 and half of the maximum level will be reached in 2024. Using the Logistic model with four parameters, we find similar results. The Gompertz model results indicate an overestimation of the potential maximum number of unicorns and a very low speed of diffusion (0.022). The adjusted R^2 and RMSE values indicate that the three-parameter Logistic model is well-suited for describing unicorn diffusion in the fintech sector, while the Gompertz model performs better for predicting diffusion. However, given the Logistic model's more realistic estimate of the ultimate market potential (1,630.231), as illustrated in Figure 4, we have chosen the three-parameter Logistic model for forecasting unicorn diffusion in the fintech sector. According to our analysis, unicorn diffusion in the fintech sector is expected to reach saturation by 2040.

For the health sector, the three-parameter Logistic model results indicate a maximum level of 619.390 unicorns, with a convergence speed to the saturation level of 50.8%. Unicorn diffusion reached half of its maximum level in 2020. The Gompertz model results indicate a maximum diffusion level of 1,440.596, a diffusion speed of 15.9%, and 36.8% of the maximum level reached in 2023. Based on the adjusted R^2, RMSE, MAE, and MAPE values, we find that the three-parameter Logistic model performs best in describing and forecasting unicorn diffusion in the health sector. Our forecasting analysis predicts that the saturation of unicorn diffusion in the health sector will be reached in 2030.

For the transport sector, the three-parameter Logistic model results indicate a maximum level of 318.955 unicorns, with a convergence speed to the saturation level of 50.4%. Unicorn diffusion reached half of its maximum level in 2020. The Gompertz model results indicate a maximum diffusion level of 615.22, a diffusion speed of 17.6%, and 36.8% of the maximum level reached in 2022. From Table 2, we can conclude that the three-parameter Logistic model provides more accurate results in describing and forecasting unicorn diffusion in the transport sector, as reflected in its high adjusted R^2, low RMSE, MAE and MAPE. Our forecasting analysis predicts that the saturation of unicorn diffusion in the transport sector will be reached in 2030.

Comparing the estimated parameters of the best-fit models for our selected sectors, the results show that the fintech sector has the lowest estimated speed of diffusion (43.1%) but the highest saturation level (1,630). We also find that selected sectors have already reached half of their maximum diffusion of unicorns. Furthermore, the transportation and health sectors are expected to reach their maximum unicorn diffusion in seven years, while the fintech sector will need ten more years to reach this level.

Discussion

This study is the first to systematically apply Logistic and Gompertz models to analyze the diffusion of unicorn startups across major countries and sectors. The findings provide several key insights into growth trajectories, ecosystem maturity, and the influence of institutional environments on entrepreneurial success.

Validation of S-Curve Dynamics. First, we confirm H1: the diffusion of unicorns follows an S-shaped curve, consistent with established patterns in product and technology adoption. Contrary to earlier concerns (e.g., Urbinati et al., 2018), S-curve models effectively capture the early acceleration and eventual saturation of unicorn creation. In line with previous studies (Akin et al., 2020; Korkmaz, 2020), four-parameter models improve forecasting accuracy, particularly in cases of delayed take-off or early saturation.

Model Performance: Logistic vs. Gompertz. Consistent with H2 and H3, the Logistic models generally outperform Gompertz, especially in market-oriented ecosystems such as the US, India, and most European nations. These environments are characterized by steady access to venture capital and organic entrepreneurial growth, making the symmetric nature of the Logistic curve an appropriate fit. In contrast, the Gompertz model is better suited for China, where unicorn creation is front-loaded due to state-driven initiatives like "Made in China 2025," followed by a sharp decline owing to regulatory constraints. This explains China's early saturation point (2032) and lower ceiling (381 unicorns), as supported by recent analyses on the revival challenges of Chinese unicorns (Jian et al., 2024). Conversely, the United States exhibits consistent annual growth of 32.2%, progressing toward a saturation ceiling of 6,241 unicorns — a pattern well aligned with Logistic dynamics.

Country-Level Diffusion Patterns. As predicted by H4, unicorn diffusion dynamics vary significantly across countries. The US leads in saturation (6,241 unicorns), with the highest saturation ceiling, supported by mature financial markets, extensive R&D networks, and robust startup ecosystems. India demonstrates the fastest annual growth rate (97%), driven by a large market and rapid tech adoption (Startup Genome, 2022), though its ultimate ceiling is lower

Table 2. **Estimated parameters of the unicorn diffusion models by sector**

Parameter	Sector					
	Fintech (n=21)		Healthcare (n=19)		Transport (n=17)	
Model	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**
M_3P	1630.231***	3.11e+09	619.390*	1440.596**	318.955*	615.22*
M_4P	1 373,545**	239 642,95	599,396*	1 179,559**	315,394*	541,338*
_3P	0.431*	0.022*	0.508*	0.159*	0.504*	0.176*
_4P	0.459*	0.052	0.532*	0.184*	0.512*	0.196*
_3P	2023.707*	2148.927*	2020.128*	2022.922 *	2019.911*	2021.68 *
_4P	2023.045 *	2056.553*	2020.007*	2021.828 *	2019.87*	2021.032*
In-sample						
Adj R^2_3P	0.992	0.992	0.996	0.994	0.998	0.997
Adj R^2_4P	0.989	0.988	0.995	0.993	0.996	0.996
RMSE_3P	14.75	15.026	9.925	12.301	4.598	5.098
RMSE_4P	14.967	15.639	9.986	12.062	4.750	4.905
Out-of-sample						
MAE_3P	6.961	6.538	5.457	7.447	2.674	3.210
MAE_4P	6.678	6.732	5.191	6.814	2.5	2.501
MAPE_3P	0.334	0.295	0.302	0.492	0.249	0.392
MAPE_4P	0.474	0 .415	0.402	0.768	0.154	0.219

Note: Significance level: *, p < 1%; **, p < 5%; ***, p < 10%.

Source: authors.

due to limitations in capital, depth, and infrastructure. This contrast illustrates a classic trade-off: rapid diffusion may come at the cost of long-term scalability. European countries exhibit moderate diffusion patterns and mid-range saturation potential. While their capital markets are more fragmented, stable institutional environments provide a foundation for sustained, but slower, unicorn development (Testa et al., 2022).

Sectoral Dynamics and H5 Validation. H5 is also validated. The fintech sector demonstrates the slowest diffusion rate but the highest projected long-term potential (1,630 unicorns), reflecting persistent regulatory hurdles and trust concerns (CB Insights, 2023). By contrast, health and transportation sectors display faster adoption, fueled by clear demand signals and fewer institutional constraints. These differences underscore the need for sector-specific policy and investment strategies.

*Theoretical Contributions and Diffusion Mechanisms***.** These findings affirm Rogers' diffusion of innovations theory, emphasizing the role of social systems and institutional factors in shaping S-curve trajectories. In market-oriented environments (e.g., the US, India, Europe), unicorn diffusion typically proceeds through the classic phases of slow initiation, rapid acceleration, and eventual saturation. These patterns align with the Logistic model. Conversely, in state-led ecosystems such as China, diffusion is asymmetric, with strong early-stage support followed by regulatory constraints — well captured by the Gompertz model.

Implications for Policymakers and Investors. This study offers practical implications for both policymakers and investors. For investors, understanding cross-country saturation levels and sectoral adoption speeds is critical for timing entry and exit strategies. In China, regulatory volatility presents a key risk, whereas in the US, market saturation could limit future returns. Geographic diversification — balancing high-growth potential in China and India with the stability of the U.S. and Europe — can help mitigate these risks.

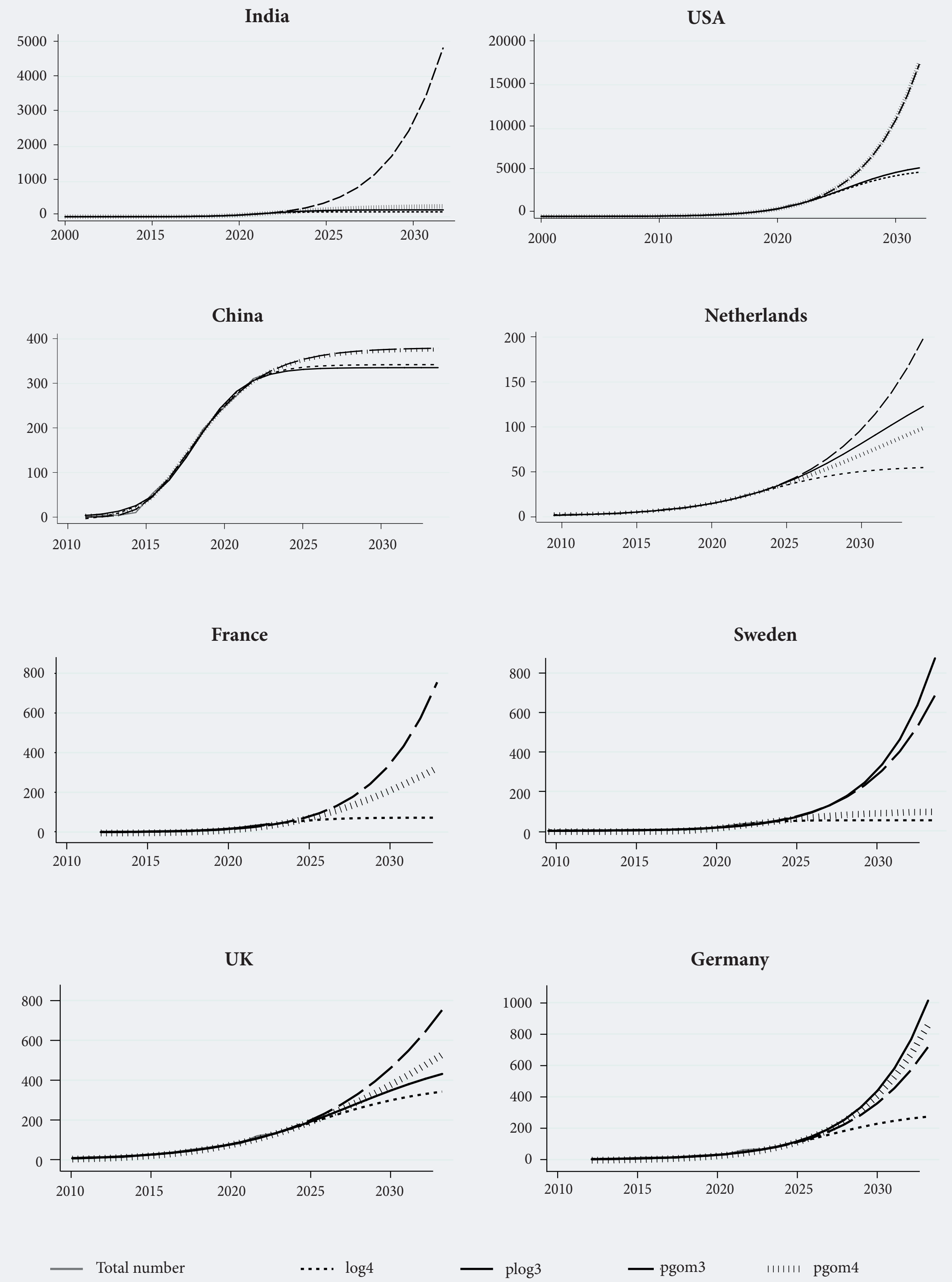
Policymakers should anticipate market saturation and support unicorn scaling through targeted reforms. In the US, continued investment in venture capital infrastructure and innovation leadership is essential. China must transition toward more market-oriented policies to enable long-term scaling, beyond the initial growth push. Its lower saturation ceiling (estimated at 335–380 unicorns) underscores the need for sectoral deregulation and deeper capital markets. Europe, meanwhile, must address its scale-up gap by harmonizing policies, improving cross-border investment flows, and supporting regional innovation clusters.

To accelerate unicorn diffusion, governments should focus on sector-specific enablers — such as regulatory reform in fintech, increased R&D investment in health, and risk-sharing mechanisms for early-stage ventures in all high-potential sectors.

Conclusion

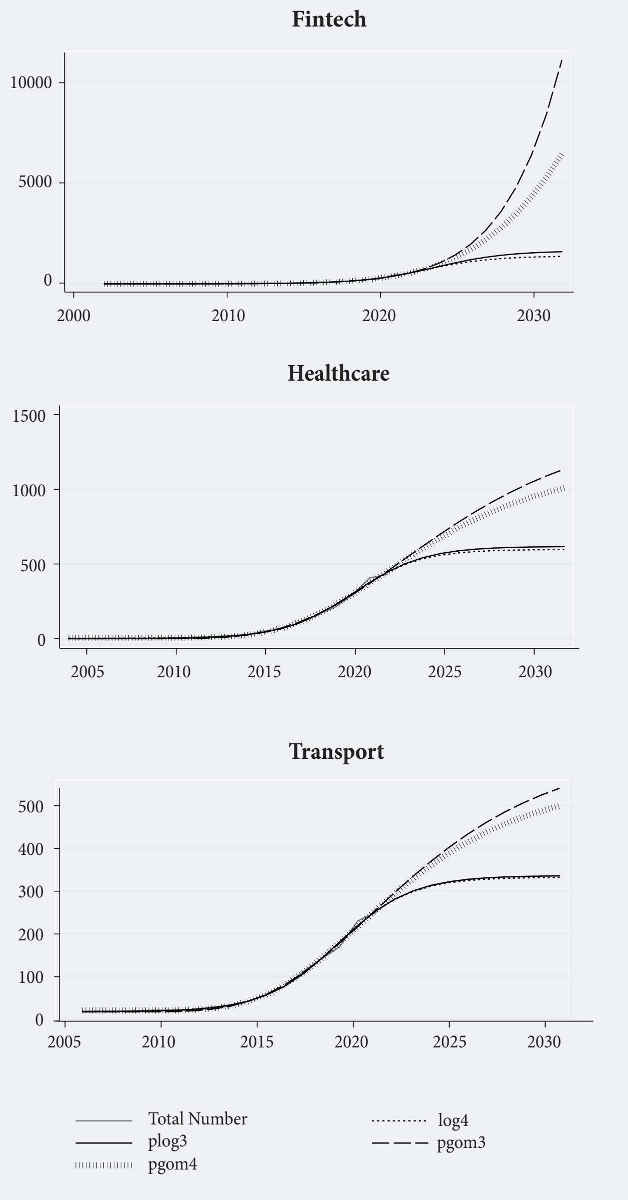
This study investigates the global diffusion of unicorn startups through the lens of Logistic and Gompertz models, offering a novel application of innovation diffusion theory to the startup ecosystem. By analyzing cross-country and sectoral trends — particularly

Figure 3. **Unicorn Diffusion and Forecasting by Country**



Note: plog4= forecasting by LM4P, plog3 = forecasting by LM3P, pgom3= forecasting by GM3P, pgom4 = forecasting by GM4P.
Source: authors.

Figure 4. **Unicorn Diffusion and Forecasting by Sector**



Note: plog4= forecasting by LM4P, plog3 = forecasting by LM3P, pgom3= forecasting by GM3P, pgom4 = forecasting by GM4P..
Source: authors.

in the United States, China, India, and key European countries, as well as in the fintech, health, and transportation sectors — the research uncovers significant insights into the dynamics shaping unicorn emergence and growth.

The results demonstrate that Logistic models outperform Gompertz models in market-driven ecosystems such as the US, India, and most European nations, where organic entrepreneurial activity and venture capital access are prominent. Conversely, China's diffusion pattern aligns more closely with the Gompertz model, reflecting early saturation due to centralized policy controls and regulatory constraints. The use of four-parameter models further improves forecasting accuracy, particularly in contexts with delayed take-off or premature saturation.

Country-specific findings reveal pronounced heterogeneity. The United States remains the global leader in unicorn creation, supported by deep financial markets, a robust innovation infrastructure, and sustained startup scaling. India exhibits remarkable growth velocity but faces a lower saturation threshold. Europe presents a more fragmented landscape — while countries such as Germany, France, and Sweden show solid growth trajectories, fragmented capital markets, regulatory heterogeneity, and limited cross-border scaling hinder broader continental convergence.

Sectoral analysis confirms that diffusion dynamics vary significantly. Fintech lags in adoption speed due to regulatory complexity and trust barriers but holds the highest long-term potential. In contrast, the health and transportation sectors benefit from strong demand drivers and relatively streamlined institutional environments, leading to faster uptake.

These findings carry meaningful implications. For policymakers, tailored interventions are essential: market-driven economies should focus on reinforcing venture capital ecosystems and nurturing regional innovation hubs, while state-led economies may need to adopt regulatory reforms that support entrepreneurial scaling. Sector-specific strategies, such as reducing barriers in fintech or investing in R&D for health and transportation, are also vital.

For investors and startup founders, understanding the interplay between sectoral adoption speeds and country-specific saturation levels can help optimize strategic decisions. Identifying inflection points in growth trajectories enables better timing for market entry, scaling, or exit.

While this study breaks new ground by modeling unicorn diffusion globally, several limitations suggest directions for further research. First, although Logistic and Gompertz models capture broad patterns effectively, they could be extended — for example, through five-parameter or hybrid models — to account for more nuanced dynamics. Second, incorporating a longitudinal dimension by categorizing unicorns based on the year they attained unicorn status could offer deeper insights into cohort-specific behaviors and lifecycle patterns. Third, future research could develop a more comprehensive framework integrating macroeconomic variables, institutional quality, digital infrastructure, and policy environments to better explain cross-country and cross-sector diffusion differences.

By advancing both the theoretical and empirical understanding of how unicorns emerge and scale, this study lays the groundwork for more data-driven and context-sensitive policy and investment strategies aimed at fostering inclusive and sustainable innovation ecosystems globally.

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