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Tesla's Robotaxi network: A quantitative analysis of adoption, economic impact, and implications

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Abstract

Self-driving technology has the potential for disrupting the transportation industry, specially autonomous ride-hailing, which is part of the new paradigm of Mobility-as-a-service. Companies involved in autonomous technology have received billions of dollars in funding and they are deploying the capital in research and development as fast as possible. Analysts and industry experts are starting to realise the potential, an example of this is Tesla's stock, which has gone up more than +1000% in the last two years. Technological convergence and declining cost curves play a big role in the current state of the technology and its readiness in the next years. An overview of the literature on potential implications of this technology has been conducted, identifying that urban planning will play a big role in designing the evolution of cities as parking and other transportation behaviours heavily change. There are important potential benefits for people in terms of economic and time savings, health improvements, avoidance of accidents. The environment will benefit tremendously for this transition towards less and cleaner cars. The Robotaxi network is Tesla's approach for autonomous ride-hailing has been analysed because of the state of its technology and its ability to be deployed and scale fast. The Monte-Carlo simulation model developed in Python shows that the potential adoption rate and revenue, which could be hundreds of billions of dollars per year, it has the capacity for capturing a significant share of the total vehicles' miles travelled and some of the possible effects for this technology depicted in the literature have been validated by the model.

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1. Introduction

Self-driving technology will revolutionize the transportation industry, reshape cities, and impact the life of billions of people. The more society knows about the potential effects that this technology will have, the more prepared it will be to tackle the challenges that the rapid changes that this disruption will bring. One important application for this technology is autonomous ride-hailing, where users of the service will order a customised ride, in this case without a driver, making the cost so low that it has the potential of displacing the car ownership for a significant part of the population.

For these reasons this master thesis aims to analyse and research what are the most relevant possible effects that this radical change in the transportation system will have in cities, people's lives, environment, and potential further uses of this technology. In order to achieve this, research has been conducted on the most relevant literature on the topic.

How the technology came to be and relevant history has been researched too for better understanding of the context and background on the topic. This includes the current state of the technology and main players in the industry, as well as some of the potential challenges that will need to be overcome before of the mass adoption of this technology, like regulation.

According to experts on the industry, analysts and the stock market, Tesla is one of the companies with the most potential for solving the remaining technical challenges for achieving full self-driving capabilities. They are also the only one in a good position for deploying a service at scale and fast, thanks to their millions of cars currently driving on roads, their current production growth and demand for their cars.

This is why a Monte Carlo simulation model has been developed in order to quantify what is the potential rate of adoption, economic impact, and repercussions on other relevant areas like the environment in the coming decades. The model does not predict the future, but it is tool where the user can input his own judgment on some key variables using their probability distribution. The output is computed through statistical analysis of thousands of simulations, which is a methodology commonly used for complex and indeterministic models like this one.

2. Aim, objectives, and limitations

In this section the aim, the main objectives of this master thesis will be detailed as well as the limitations of the research.

2.1 Aim

The general aim of this thesis is to understand the impact that autonomous ride-sharing technologies will have on the world. The focus of the simulation model will be Tesla's Robotaxi network because it is probably going to be one of the first players in the industry, so assessing their rate of adoption and economic impact it is key for understanding the potential of this technological revolution that will take place, most probably, this decade.

2.2 Objectives

The more specific objectives that this master thesis want to achieve are:

- Research the history and some of the factors and trends that are making autonomous driving possible.
- Study the competitive landscape of autonomous driving technology, identifying key players and milestones in their path towards achieving autonomous driving capabilities.
- Develop a simplified flexible simulation model which allows for the study of the potential adoption rate of the Robotaxi network.
- Develop a simplified flexible simulation model which allows for the study of the economic impact of the Robotaxi network.
- Analysis of the results and output from the simulation models.
- Research of the most relevant implications that the autonomous driving and autonomous ride-hailing may have on society based on relevant literature and current data.

2.3 Limitations

The reach of the project has been influenced by the following factors:

- Because of the study nature of this study, it is limited to the public available information on the different topics covered in the thesis. Some companies may be more or less advance on their technological development than it is disclosed. There may be projects and technologies on "stealth mode" which would invalidate some of the claims made in this thesis.
- There are big differences in many areas like infrastructure, culture, economics, customer preferences, etc… in different regions of the world. This study is more oriented, in terms on data and implications, towards a western urban society, mainly the United States, but the results are still useful for other areas if those differences are considered.
- Predicting the future, especially for a complex model like the one analysed in this thesis, is impossible, this thesis project aims to give provide a tool with which to roughly estimate the most probable scenario. Nevertheless, there are many factors that are not taken into account because, at the moment of developing the model it was considered, based on the information available, that those were not relevant enough.

2.4 Benefits of the project

The achievement of the objectives exposed previously would provide benefits to the following stakeholders on the topic

2.4.1 Competitors

In the recent years more companies have started to understand the potential of autonomous vehicles and how close this futuristic technology is, but most traditional automakers realised quite late the potential of EVs and self-driving cars. This thesis may be a valuable data point on the opportunity that this technology represents and why it is worth to spend the necessary resources in its development.

2.4.2 Regulators

This stakeholder will play a crucial role for the industry, both federal and local governments will need to adapt at a very rapid pace to the technologies developments as they occur. It is essential for each region to prepare in advance for the coming changes to be able to take advantage of the potential benefits, which are both economical and for people's lives. It is also crucial to put the necessary measures in places to mitigate some of the negative aspects of such transformation in the transportation system.

2.4.3 Individuals

This may help the public understand how their lives will change in the near future. People can use this information to take a more informed decision for the purchase of vehicles, houses, or financial instruments. The learnings for identifying technology convergence, declining cost curves and the potential impact of some technologies may be useful for identifying new opportunities both for investing and entrepreneurial activities.

3. Background

3.1 EVs

At the start of 20th century, the main way of transport was still the horse, the industrial revolution brought changes in the available technologies, which combined with the higher wages allowed for innovation to take place in the transportation industry. Electric vehicles are not new, their origins date even earlier that the internal combustion engine cars. In 1834, the inventor Thomas Davenport made the first electric vehicle, which worked with direct current and non-rechargeable batteries, it was only capable of short distance trips, but the history of electric vehicles had started (Zhao, 2017).

In 1837 the Scottish inventor Robert Davidson invented the first electric car available to the public, which was almost half a century before Gottlieb Daimler and Karl Benz would invent the gasoline engine in 1886. Davidson's vehicle had a battery made out of iron, zinc and mercury and sulfuric acid; this battery was non rechargeable so it was quite impractical (Zhao, 2017).

This changed in 1859 with the first rechargeable electric battery, the lead-acid battery developed by the French physicist Gastón Planté (Pavlov, 2017). In spite of this development, until 1880 it was not considered efficient or reliable enough to be used in an electric vehicle, in this year the chemistry engineer Camille Alphonse Faure improved the design and efficiency of this kind of battery covering the lead plaques with and paste of lead oxides, sulfuric acid and water, which also allowed for the industrialization of manufacturing of such batteries (Guarnieri, 2011).

Gustave Trouvé saw the potential of this new technology and in 1881 created an electric tricycle using a Siemens engine on a conventional tricycle, this is considering the first electric vehicle in history(Zhao, 2017). On the following years the electric vehicle market grew and it was the technology with the most sales between 1890 and 1900.

At the start of the 20th century there were three main technologies competing in the industry, steam, electric and internal combustion engines. In 1910 the market share for each one these technologies in the automobile industry were: 40% for steam engine, 38% for electric and the rest, 22% for diesel and gasoline.

Electric vehicles entered the century with a mature product and well positioned in the market. It had the advantage against the internal combustion engine that it did not have vibration, noise, or gearbox, making an easier and more comfortable rise. The reason more the lack of mass adoption was the lack of extensive electric infrastructure, because the range was no issue since the main use case the urban, which where the roads in better condition (Zhao, 2017).

The internal combustion engine ended up dominating the market, starting in 1908 with the release of the Ford Model T, the first car manufacture in series, which made the car much more affordable that the alternatives. In 1912 the cost of Model T was around $650 while an electric vehicle was around $1.750, almost three times the price (McFadden, 2020). On top of that, Charles F. Kettering solve one of the main inconveniencies of gasoline cars, the manual starter, whit his electrical starting motor, the long-distance roads were also improved, which made range a more relevant factor in the buying decision process.

It was not until 1973, with the Petroleum Crisis, where a conflict in the middle east created a heavy increase in oil prices and the United States realised the heavy dependency they had on oil. This was combined with the heavy increase in the ecologist movement, with the creation of WWF in 1968 and Greenpeace in 1971. With the objective of reducing the energy dependency and CO_2 emissions, the US passed the Electric Vehicle Research, Development, and Demonstration Act, which gave a heavy push on development and research of electric engines and batteries (McFadden, 2020).

In 1990, the state of California, trying to improve their air quality, approved the Zero Emissions Mandate, which made mandatory that 2% of vehicles sold in the state would not emit greenhouse gasses by 1998 and 10% by 2003. In response to this, General Motors presented their electric prototype, the Impact, in the Los Angeles Auto Show. The car came into reality in 1996 with the General Motors EV1, over 1000 cars were produced and leased to drivers in California and Arizona. In 2003 the state of California modified the Zero Emissions Mandate becoming much more permissive; therefore, General Motors decided to cancel their EV1 program and destroyed most the cars, some were donated to museums or other educational institutions (Shahan, 2015). Other brands like Honda, Nissan or Toyota had similar programs in place during this time.

This year, 2003, Tesla was founded, but this topic will be discussed in another next section.

3.2 Autonomous driving

Self-driving is a technological advancement that promises to greatly change people's lives and the transportation industry. Its history could be considered to have started at 1925, when Houdina Radio Control showed their "American Wonder", a radio-controlled car which made a trip through Broadway in New York City (TIME, 1925). The next relevant event was the Futurama exhibition by General Motors and design by Normal Bel Geddes, which was presented in the New York World Fair in 1939, the scale model of a city of the future featured radio-controlled electric cars driving through electromagnetic lanes. These visions of the future inspired different prototypes like the GM Firebird II (GM Heritage Center, 2017), another wire-controlled car by RCA Labs , and the DS 19 by Citroen. All of these cars relied on external infrastructure to the car so the use cases were limited and the scalability was difficult because of the high cost.

This is why in 1986 the first self-driving prototypes which did not relied on other infrastructure were presented, thanks to the Carnegie Mellon University Navlab team and Erst Dickmann's team from the Budeswehr University of Munich (Thorpe et al., 1987). In 1995 the Navlab team drove from Washington D.C. to San Diego, California in the "No hands across America" tour, where the car was able to drive autonomously 98% of the way thanks to the use of imitation learning with a small neural network (Pomerleau, 1987). Their European counterparts participated in the European PROMETHEUS project driving From Munich, Germany to Odense, Denmark driving autonomously around 95% of the way.

These successes in the field inspired other researchers to dive into the topic, like Frank et al. (Franke et al., 1998), who studied the urban aspect of autonomous driving, which had not been researched previously because the focus was on highway driving. Their research pointed out that computational capabilities were increasing rapidly allowing for good object detection and recognition but there were some visual challenges like tunnels, reflections, or shadows, therefore it was recommended to use of enhanced sensors. These are right now an important element in the industry, specially LiDAR.

Another important project was the races organised by the Defense Advanced Research Project Agency (DARPA) by the US Department of Defense (DARPA, 2014). The first one took place in 2004, with a prize of $1 million to the first team to cross the finish line after a 240 kilometres route from California to Nevada through the desert. None of the participants were able to finish the race, but in the second edition, one year later, 5 vehicles were able to complete the race successfully (Buehler et al., 2007), which shows the rapid advancements in the technology. The last race, in 2007, was the Darpa Urban Challenge (Buehler et al., 2009), were the participants had to drive a 96 kilometres route in a mock-up town, encountering situations usually found in cities. The successful teams heavily relied on LiDAR technology, which would shape the future of most the industry for the coming years.

In 2013 the National Highway Traffic Safety Administration developed a 4-level framework for vehicle automation (NHTSA, 2013b), but one year later, the Society for Automotive Engineers International (J. Shuttleworth, 2019), introduced their 5-level automation which is currently the industry standard and depicts the role of human and operational functions of the automated driving system.

Figure 1: SAE Autonomy levels (J. Shuttleworth, 2019)

3.3 Tesla

3.3.1 History and strategy

The company was founded in 2003 by two engineers, Marc Tarpenning and Martin Eberhard in San Carlos, California under the name Tesla Motors (Vance, 2015). It got its name after Nikola Tesla a Serbian inventor from the 19th century, best known for his discoveries in alternating current and rotating electromagnetic fields.

The founders got inspired by the public reception of the EV1 by General Motors, where the lucky individuals that got their hands on the vehicles had express their excitement about the product. The EV1 project validated the technology and gave a new life to the electric vehicles industry (Shahan, 2015), and Eberhard and Tarpenning wanted to take advantage of the momentum built.

Elon Musk joined the company in 2004 investing $30 million and becoming chairman at its Board of Directors (Tesla Motors, 2010). In 2006 their first electric vehicle prototype was unveiled, the Tesla Roadster, they sold about 2450 units, starting the production in 2008 (Reed, 2020) . The car's chassis was built by Lotus and it is heavily inspired in the Lotus Elise. Their objective was to build a zero compromises high performance electric sports car, in order to show the world that electric cars were a viable option and could work even as a sports car (Musk, 2006).

In 2008 a big restructure in the company took place, 25% of the workers had to be laid off, Elon Musk became the new CEO and the original founders left the company (Tesla Motors, 2010). This transition brought some controversy, as the founders alleged that their exit from the company was not completely voluntary and there were some legal actions taken on the matter, which were dropped shortly after (Tesla, 2010a).

After the launch of the Roadster, the financials of the company were not ideal, they had less than $10 million in cash to produce the ordered cars, which could cost more than that. At that time Daimler decided to buy a 10% stake in the company for $50 million, which combined with a $465 million loan from the Department of Energy helped the company survive this difficult period. Next year, in 2010, the company decided to go public through an IPO, raising $226 million (Squatriglia, 2010).

This first car was not intended for the masses, the car costs were over $100.000, being the battery the main costs, because at the time the cost of Li-ion batteries was around $1000 per kWh, 10 times higher than it is right now (Bullard, 2020; Curry, 2017). As Tesla stated, their plan was to use the profits of the Roadster to build a more affordable car (Musk, 2006), which was later revealed as the Model S, and finally, as part of their first phase, build an even more affordable car, the Model 3.

The Model S prototype was revealed in 2011 (Tesla, 2011), a luxury sedan three times cheaper than their previous model, their entry point in the consumer market. The deliveries of the cars started in 2012 and the reception by user and media was great, winning multiple “Car of the Year” prices and even “Car of the Century” by Car and Driver (Sherman, 2015). This same yar the company started building their Supercharging network for charging the cars, which is now a global network of fast chargers, right now there are more than 30.000 chargers in 3.240 stations all over the world (Tesla, 2021e).

Tesla new that battery production would be one of the main bottlenecks in the supply chain in the coming years, this is why they announced in 2013 the project to build their first Gigafactory in Nevada. It would be of the largest buildings in the world and with plan of producing more batteries than it was being produced at the time in the whole world. One use case people were not aware was energy storage, and in 2015 the company announce their solar energy products and energy storage solutions for homes and businesses (Tesla, 2016). Tesla had become more than a car company and this is why in 2017, the name of the company changed from “Tesla Motors” to “Tesla, Inc.”, which was a better name considering their new lines of products and future projects.

In order to make their mission a reality, “accelerating the world's transition to sustainable energy” (Tesla, 2021a), they needed to go to the mass consumer market, for this reason, in

2016 Tesla announced their Model 3 sedan (Tesla, 2019a). The production started in 2018, and the ramp up in production was a very difficult task, which combined with overpromising, resulted in what was known as “production hell”, where the company had a lot of manufacturing difficulties to achieve set goals, which was combined with financial and stock market issues.

They were able to exit “production hell” after many months of hard work, the ramp up was achieved and Tesla started their winning streak. Starting with the announcement of the Cybertruck in November 2019, a polarizing pickup truck which surprised the world because of its design, features and pricing (Tesla, 2010b). At the same time Tesla’s profitability started to be apparent, and they have been profitable and growing the net income rapidly since Q3 2019 (Tesla, 2021d). The stock reacted accordingly increasing a more than 1500% since then (Nasdaq, 2021), and a lot of analysts started understanding some of the potential, strategy, and technology of the company.

The company have plans for growing their car production approximately 50% every year for the foreseeable future in order to manufacture 20 million cars in 2030 (Tesla, 2021c). In 2022 they will probably start deliveries of their pickup truck and semi-truck, and they have plans to enter every vehicle for factor, delivery vans, smaller cars, etc… Their energy business should grow to a similar size, according to musk it should be as big as their automotive business.

But Tesla has even more ambition, their autonomous driving technologies is one of the most advanced in the industry, they have developed their own battery technology, solar panels, and neural network training supercomputer. Building a humanoid robot ,leveraging their existing technologies, is in their roadmap. This robot would be able to do some of the dangerous, repetitive, or boring manual tasks that humans perform nowadays (Tesla, 2021b).

3.3.2 Robotaxi Network

The idea for Tesla to build a ride-hailing autonomous network had been brewing for several years. Elon Musk knew that in order to achieve their mission for "accelerating the world's transition to sustainable energy" they needed to displace cars at higher rate than just substitution, Even producing 20 million units per year it would take decades considering the small replacement rate.

It was first shared with the world by Elon Musk in Tesla's blog (Musk, 2016) expressing their objective of enabling their cars to make money for its owner when he did not need it. Just tapping a button in the app would allow for your car to generate income for the owner. In cities where demand would probably exceed what the private owners can offer, Tesla would operate their own fleet to ensure the availability of the service.

More details on the service were shared during Autonomy Day (Tesla, 2019b), first by introducing the idea that the car could be share with friends or co-workers if desired, but also through a ride-sharing app.

Figure 2: Tesla Robotaxi app concept (Tesla, 2019b)

The first phase would be to use the Model 3 as a Taxi, Tesla express their plans of buying back all the cars which have been leased to individuals in order to use them exclusively to the ride-hailing service, this would help them generate more revenue and manage the demand better. They also revealed their plan for having a longevity of the cars of 1 million miles and higher efficiency than current models. According to their calculation the approximate gross profit for each Robotaxi would be around $30.000 dollars and last 11 years.

3.4 Big picture

Disruptions are very difficult to predict, as shown in the image below the rate of adoption for different technologies have been increasing in the last century. The economic progress played a big role in this, as well as the increase efficiency in the manufacturing and logistic industries.

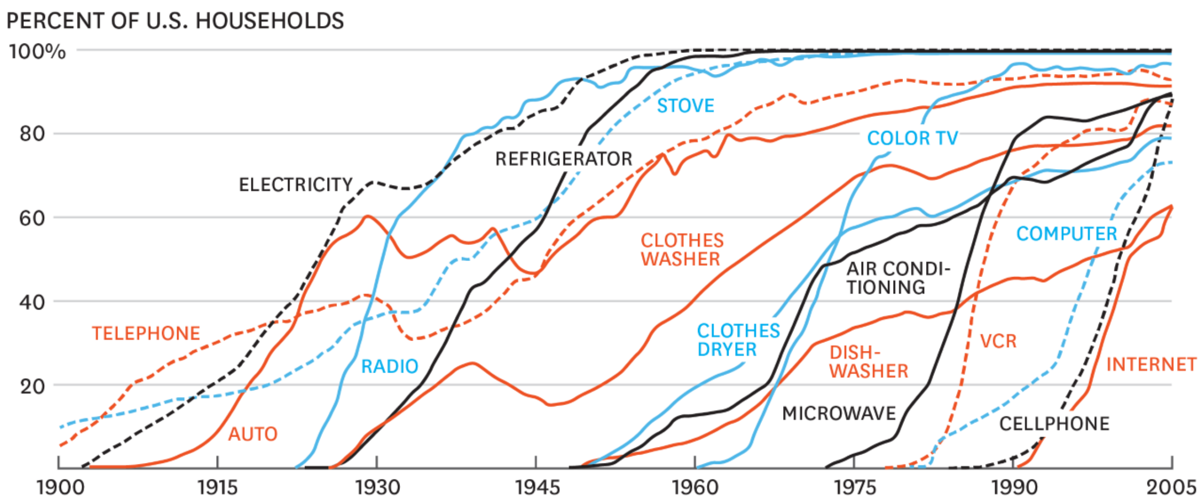


Figure 3: Adoption of technologies since 1900 (McGrath, 2013)

There is an opposite flywheel effect for the new and old technology that makes the transition very fast and follow an S curve, usually opposite S curves, as one grows exponentially the other one plummets. The reasoning behind this opposite flywheel effect can be found in the diagram below.

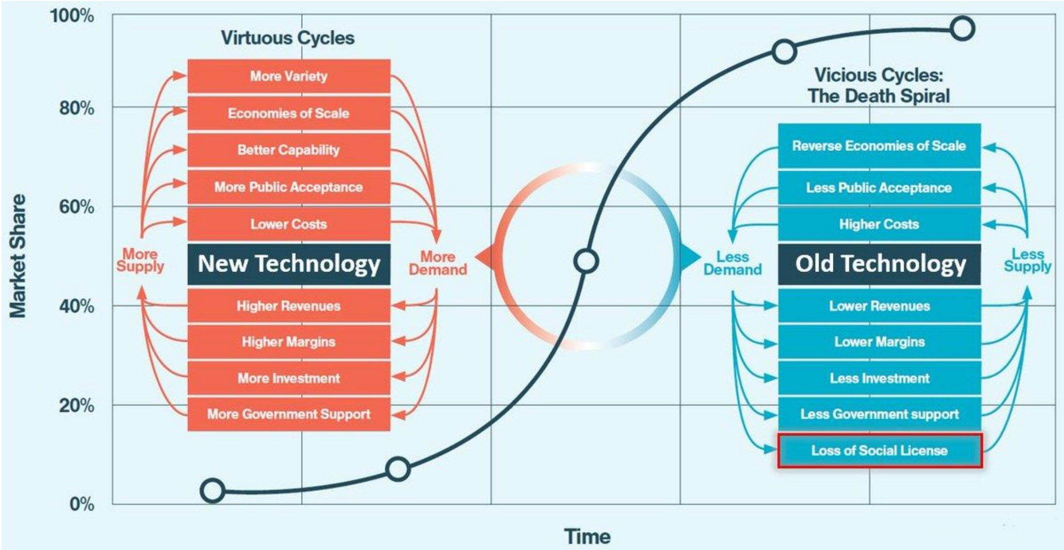


Figure 4: Opposite flywheels for old and new technologies (Arbib & Seba, 2017)

The Robotaxi network presented by Tesla is part of the transportation system knows as Shared Autonomous Vehicles, which is the next iteration in the shared-use transportation systems.

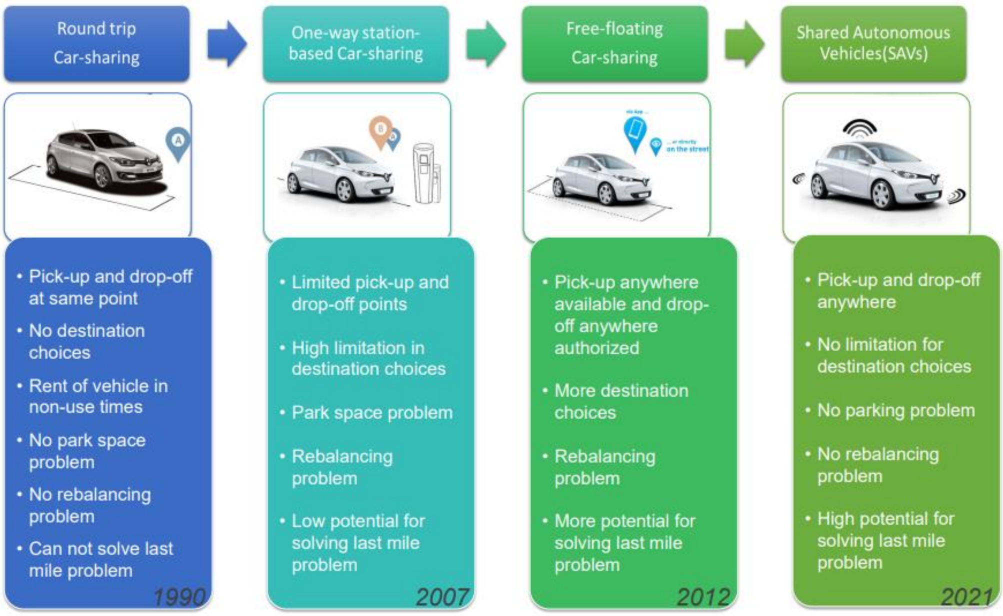


Figure 5: Evolution of shares-use transportation systems (Reza, 2017)

The Mobility-as-a-Service is a new paradigm is the transportation system where user of such service can plan, book, and pay via digital channels for multiple types of mobility, making easier to shift away from the necessity of owning a car to fulfil transportation needs (Jittrapirom et al., 2017). In the near future autonomous ride-hailing will play a big role in this disruption, it will continue the groundwork that companies like Uber or Lyft started.

The main reasons why autonomous ride-hailing has the potential for having a tremendous impact are economic. The upfront cost for the user for using the service is cero, this really helps the user to interact with the service and discover the benefits. The capital expenditure is done by the owner of the fleet, the user only needs to pay for the temporal utilization, which would be a lower price than other competitor services. A lot of the behavioural barriers that some users express, like waiting time, fares, sharing vehicle with other users (Krueger et al., 2016) have been broken down by services like Uber, Lyft or Blablacar.

The price advantage of the service is going to be its main advantage against other mainstream methods of transportation, specially traditional ride-hailing or owning the vehicle itself. In comparison with ride-hailing the lack of driver will drive the cost down tremendously, as this is one of the biggest costs of this services. In regard to owning a car, the significant difference in utilization rate for these vehicles will make it a very attractive proposition. These autonomous cars will be electric which will also play a relevant role, as the lower operating costs will lower the cost even more, helping to displace internal combustion engine and traditional model of transport.

Because of these reasons, once the technology is ready the transition towards autonomous ride-hailing in the context of Mobility-as-a-service will be quick and inevitable. This is even more accurate if Tesla is able to be one of the first to achieve level four or five autonomy, because of the millions of cars they have currently in the roads. The higher utilization rate means that each autonomous car can displace more than one traditional car, making this transition fast. The process would start in cities, where the demand and density will be positive factors for this transition, but over the years it will keep expanding outwards capturing more of the total addressable market. There will be always use cases where autonomous ride-hailing is not the best solution, but these will be small minority.

3.5 Technology convergence

For every technology of innovation that changes radically people's lives or an industry, usually there is a convergence of different technologies and cost curves of other technologies that takes place. For the electric autonomous ride-hailing revolution that it is being discussed, the main technologies involved where: batteries, computer hardware and AI.

There were clear trends in all of these industries for many years, but Tesla was one of the few companies that devised a plan to capitalise on this opportunity. In 2006, Elon wrote a blog post detailing their plan "The Secret Tesla Motors Master Plan (just between you and me)" (Musk, 2006), where they laid the short-term plan, which has already come to fruition. The plan took into account the cost declining curves, as stated in the blog post "Almost any new technology initially has high unit cost before it can be optimized and this is no less true for electric cars.". The plan was to build an electric car "without compromises", this was the Tesla Roadster, using the profits to build a more affordable car, the Tesla Model S, and then use that money to build an even more affordable ca, the Tesla Model 3.

Ten years later he publishes the "Master Plan, Part Deux" (Musk, 2016), where he revealed the real plan, expanding their product line of electric vehicles to all major segments, develop a self-driving technology which was at least ten times safer that humans and finally the main topic of this thesis, ride-hailing, their Robo-Taxi network. This plan was no surprise to anyone who had been following Tesla's steps, all their cars built since September 2014 had the Autopilot Hardware 1.0 for starting to train their autonomous driving AI.

3.6 Wright's law

One of the most famous technology predictions in history was Moore's law, where Gordon Moore's forecasted that the density of transistors on integrated circuits would keep doubling every two years, which would mean a consequent halving of computational costs (Schaller, 1997). But the issue is that computational costs have begun to plateau in recent years as the growth in production of transistors have stagnated. The reason for this is that Moore's law did not take into account another very powerful factor into the equation, the production volume, which is according to Wright's Law the main mechanic behind the cost reductions that has happened in the recent years in industries like solar or batteries.

Theodore Paul Wright was an American aeronautical engineer. In his paper "Factors Affecting the Costs of Airplanes" (Wright, 1936), while studying the production costs of the airplane manufacturing industry in the 1920s, he determined that for every doubling in production, the costs would be reduced by a stable amount, around 10-15%. Modern research validates his theory, like the Santa Fe Risk Institute (Nagy et al., 2013), where a comparison between Wright's Law and Moore's Law across over 60 different technologies of the last century was performed. The result of this study was that Wright's Law was 15% more accurate in predicting the cost decline curves of these technologies, even in semiconductor production the results pointed to a 40% higher accuracy for Wright's Law.

Nonetheless, Wright's Law is far from perfect and faces multiple challenges, the main one is that it needs many years of cost data points in order to come up with a good estimation. Another important challenge is that even though it may predict the costs of the product depending on production volume it is not able to predict the demand and therefore the costs in the future, this is something that must be forecasted separately, taking into account both qualitative and quantitative factors into consideration. A good example of this would be the Lithium-Ion batteries, where the production growth was diminishing every year from 2000 to 2012 (Bullard, 2020; Placke et al., 2017), until the costs justified the production of electric cars. This year the Model S was released and the production growth have been accelerating ever since.

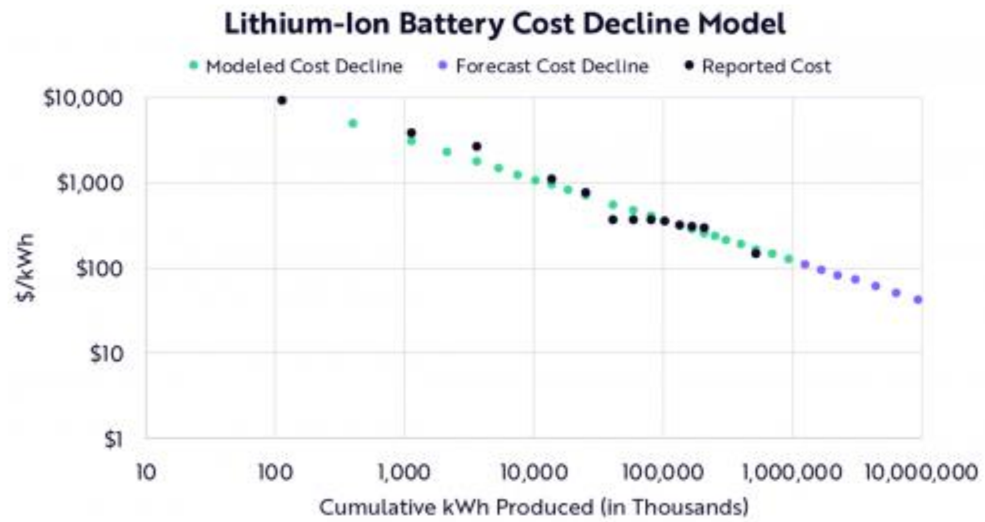


Figure 6: Lithium-Ion battery cost decline (ARK Invest, 2021)

As it has been explained with the example of electric cars, these cost reductions open the door for more demand, which lower the costs, which ends up opening the door to new products or business models which will adopt the technology, in this case Lithium-Ion Battery. Electric cars production is growing exponentially and the next product to adopt this battery technology may be utility-scale storage, which will positively influence the battery production-costs flywheel.

3.7 Competitive landscape

Tesla Robotaxi network relies on two different technological revolutions that are taking place right now, the rapid transition to electric vehicles and the shift toward self-driving cars. Tesla has competitors in both areas, but this thesis will focus on autonomy competitors because the manufacturing cost of the car is not such a big relevant factor, because this figure is small in comparison with the revenue potential for each car.

3.7.1 Autonomous cars

One very important factor to achieve full autonomy is the real-world miles driven for training the neural networks that take the decisions while driving. This data point is a very good indicate, but obviously does not tell the whole picture, of the level of each companies' technology. Unfortunately, this information is not always available or is not necessarily up to date, Tesla has over 3 billion miles (Karpathy, 2021), Comma.ai over 40 million miles (comma.ai, 2021), Waymo over 20 million (Waymo, 2021b), and Cruise over 2 million for example. The difference with Tesla was their strategy, while other companies had to use their own vehicles and drivers to acquire data, Tesla was selling the cars and getting the data for free, this is why there is such a big difference in the amount of miles driven.

But total miles driven are not the only factor, the technology used for understanding the world is key. Almost all companies rely heavily on LiDAR technology, which stands for Light Detection and Ranging, which user a laser to measure distances for generating a precise, three-dimensional representation of its surroundings (Collis, 1970). Other companies make also use of high-definition maps, which contain information related to road shape, markings, traffic signs and other relevant information accurate to the centimetre level. This is the reason why some companies allow their cars to drive autonomously on certain roads or areas of a city. Tesla approach relies on camera vision and a neural network, just like their human counterparts, which allows it to be a more generalised solution and less dependent on infrastructure or external data.

Another reason why total miles are not enough is that correctly annotating the data is also crucial, you need to correctly identify in the most efficient manner every object and agent in the driving situation. You also need to be able to gather and find the edge cases, those non common situations that your neural network is not able to handle at the moment and you need to train on. These two processes required a lot of talent and technological development in order to digest efficiency the millions of miles of data that each company is acquiring.

A good data point regarding the different companies is the Disengagement Report published by the California Department of Motor Vehicles (California Department of Motor Vehicles, 2021b) (see Appendix A), which is an annual survey that the DMV required from all companies licensed to test their autonomous cars on California's public roads.

Not all companies are represented here, like Tesla or comma.ai, who have a different business model and they are testing their systems with real costumers using the products they've purchased, either the Tesla car or openpilot device by comma.ai. From this survey several conclusions can be drawn:

- Many companies are involved in the space and are testing in real life conditions.
- There are big differences in miles driven, being Waymo, Cruise, Pony.ai, Baidu, Nuro and Zoox the main companies, the ones over 50.000 miles driven in either 2019 or 2020.
- There is a big variance in the miles per disengagement, which points to big differences in the maturity between technologies.
- Most companies improved their miles per disengagement metric heavily between 2019 and 2020, which points on a rapid development of the technology.

Table 1: Rate of disengagement improvement California 19/20

Company	*Improvement*
Waymo	+126%
Cruise	+133%
Pony.ai	+65%
Nuru	+149%
Zoox	+2%

A lot of the big players in the self-driving industry are start-ups, and almost all of them are not related to traditional automakers. One of the possible reasons for this is that the technology stack is very different and the rate of innovation is completely the opposite. The traditional automakers were used to subcontracting most of their software needs, so they lack the talent and corporate culture to tackle the autonomous driving technological challenges.

3.8 Total Addressable Market

In order to understand the potential economic opportunity that this innovation would mean some easy calculations have been made using the United States as an example. This is just for autonomous ride-hailing use, the self-driving technology will also generate billions for goods transportation. Some of the numbers are conservative rough estimations based on the technology and its potential benefits and advantages like convenience, lower cost, safety, etc.

Table 2: TVM in the US (U.S. Department of Energy, 2021)

TVM per year	3.2 trillion miles

Table 3: Distribution and Penetration of trips for autonomous ride-hailing

Trips use case	*Distribution miles*	*Penetration*
Commuting	33%	80%
Shopping	29%	40%
Social	26%	60%
Other	12%	40%

Table 4: Results of TAM miles in the US for autonomous ride-hailing

US TAM Miles penetrated	1,874,022,400,000.00
Total Penetration	58.56%

Table 5: Results of Revenue TAM in the US for autonomous ride-hailing

Price per mile	$0.8
Platform cut	30%
Revenue Platform	450 billion

The revenue for the platform would be almost pure profit, since the economic model is based on people owning the cars and operating them through the Robotaxi network platform. According to Tesla they would own some cars in big cities to balance the demand, when necessary, but the capital required for the initial investment on the cars was, is and will be done by people purchasing the cars from Tesla.

The price sensitivity is very complicated to predict, because the lower the price is, the higher the demand it will be, so there should be a sweet spot which would create the highest returns. The price model will, most probably, dynamic like Uber, in order to balance the demand properly.

The TAM addressable market globally is more difficult to calculate, but only considering United States, Canada, Europe, Japan and China, the passenger miles that can be disrupted are over 10 trillion, which would mean trillions of dollars of revenue per year.

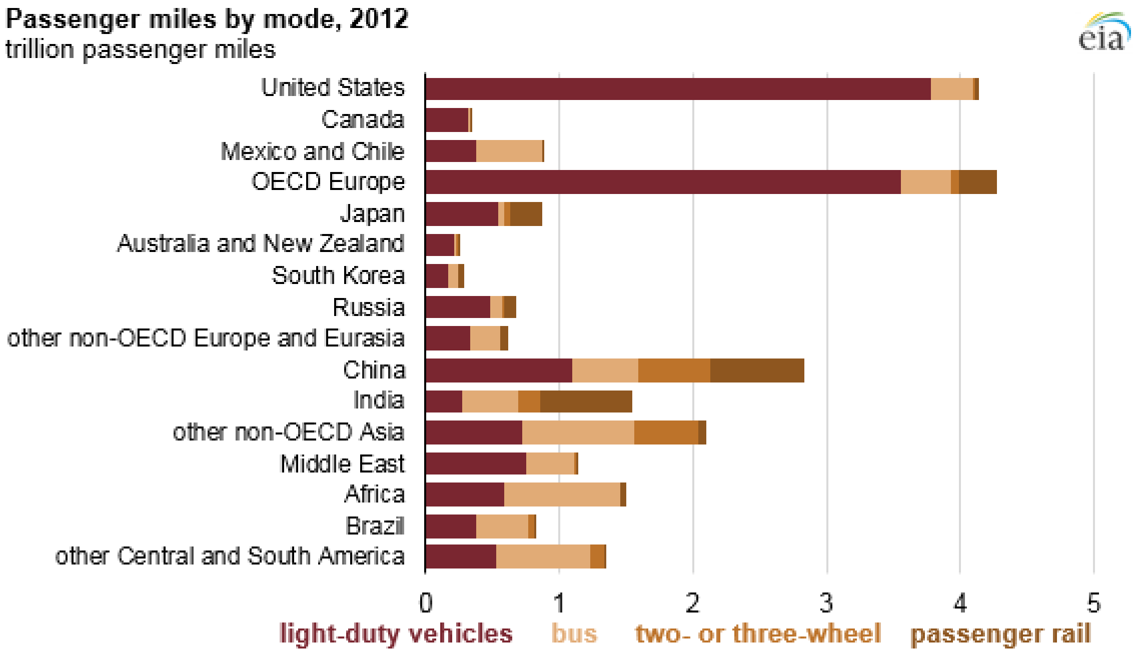


Figure 7: Passenger miles by region (U.S. Energy Information Administration, 2016)

3.9 Regulation

This is a very controversial topic, some people think that even if autonomous driving is ready, the regulators will not allow the technology to be deployed and it will significantly delay the autonomous ride-hailing revolution. In this section some of the regulation which have been passed in the U.S. already will be analysed and discussed.

Regulators are taking seriously the autonomous vehicles issue, this is why they are enacting bills on the topic, according to the NCLS (National Conference of State Legislatures, 2021), these are the bills introduced related to the commercial use and operation on public roads, but even more bills are being introduced on related topics like cybersecurity of vehicle, licensing and registration, insurance and liability, privacy of collected vehicle data or vehicle inspection requirements. Just in the last 5 years 47 out of 50 states have enacted a total of 513 bill related to autonomous vehicles.

Table 6: Total bills related to autonomous vehicles passed per year

Year	*Total States*	*Total Bills*
2017	21	35
2018	30	58
2019	27	49
2020	21	40

Nevada was the first state that authorised the operation of autonomous vehicles in 2011 (Nevada Legislature, 2011), when they passed a law that allowed the testing of autonomous vehicles, at that time, it required a person behind the wheel and passenger's seat but it was an important first step in the regulation of the industry. As of February 2020, (National Conference of State Legislatures, 2021), 29 states had passed legislation allowing autonomous vehicles on the road.

Some Tesla Robo-Taxi competitors like Waymo and Cruise are already operating driverless ride-hailing vehicles in some states. Waymo operates their Chrysler Pacifica Hybrid minivans in Phoenix metropolitan area, 24 hours per day, seven days a week, and also running a test program in San Francisco using Jaguar I-PACE (Waymo, 2021a).

The conclusion from this section is that meaningful effort is being put by political actors into passing the necessary regulation to make autonomous cars possible, they are aware of the positive aspects like being safer and reduction of fatalities, as these are common talking points in the hearings. There are already commercial players operating in several states or cities, and this number is only going to increase as the technology improves. California alone, the largest state in the United States, according to the DMV (California Department of Motor Vehicles, 2021a), as of 19th October 2021, 55 companies to test autonomous vehicles with a safety driver, 8 have been permitted to do driverless testing and 3 have obtained deployment permits.

Even considering all this, the United States is not even close to the most advance country in terms of regulation according to the study by KPMG (KPMG, 2018) where the readiness for each country was analysed. The main factors studies where: policy and legislation, technology and innovation, infrastructure, and consumer acceptance. The top ten for Policy and legislation was the following: Singapore, New Zealand, The Netherlands, United Kingdom, Germany, United Arab Emirates, Canada, Sweden, Austria, and United States.

Nonetheless there is still a lot of work to be done, but it is in the best interest of the regulators to pass the necessary regulations to be able to take advantage of the potential economic and social benefits that this technology will bring. The positive aspect of this technology is that it generates, because of its technological nature, a tremendous amount of data which will be used to convince both the public and politicians.

4. Autonomous technology and ride-sharing implications

The implications will focus mainly on the bigger picture, in the effects of Autonomous EVs Transportation as a Service. These effects would take place once most conventional cars have been replaced by autonomous fleet of cars that are not necessarily owned by the user, opening a new whole set of possibilities and use cases. According to Heinrichs (2016) , the autonomous vehicles will be used both as private and commercial vehicles, but shared autonomous vehicles could offer a service with huge potential, combining car-sharing and taxi services (Fagnant & Kockelman, 2014), which results in convenience and, cost and time savings without precedents.

The effects will mostly use US data because it is going to be one of the first countries, other than China, where Autonomous TaaS will most likely be introduced because is where Tesla has the most data and where their Full Self-Driving technology is the most advanced. According to KPMG (2018), it is also the third most ready country in the world for autonomous driving, considering regulation, technology, infrastructure, and consumer acceptance. The only countries above it are Singapore and The Netherlands, but the big difference in population makes it more relevant to study how it will affect the US and also higher priority markets for the self-driving companies.

Another very relevant factor for the implications of autonomous vehicles is the adoption rate in the area, the total share of the vehicle fleet or of the vehicles miles travelled (Litman, 2015). For this implications research it will be supposed that this adoption is high, some studies conclude that shared autonomous driving cars like the Robo Taxi network could replace about eleven cars (Fagnant & Kockelman, 2014) Some authors even believe that private would not even be needed at all in the future (Levin & Boyles, 2015).

4.1 Methodology

With the objective of answering the research question of “What are the implications of wide adoption of autonomous ride-hailing networks?” a qualitative literature review has been conducted. The academic databases used were Scopus and Google Scholar because the topics in the scope of the research were well covered on them. Accessibility also played a decisive factor, with the student credentials from TUM (Technische Universität München) access all required literature was possible.

Considering the literature research objective following keywords were used in the search process. For the search process several variants of the words were used, such as hyphenation or plural and singular variants. The main keywords used where “Autonomous” combined with “vehicles”, “ride-hailing” and “ride-sharing”, in addition “effects”, “implications” and “consequences” where used to. On the relevant implications found in this research further analysis of their existing literature was carried out to find more relevant information.

Other than research papers some reading on book publications on relevant topics present in the literature was conducted in order to gather data to support claims or expand on ideas and concepts. For the same reasons data was search by public institutions and reputable sources for providing context and figures for the arguments presented.

The following criterion were followed to select what research papers:

- Title and abstract contain desired keywords
- The language of the paper must be English
- The publication must be recent considering the context for the topic.
- On the last stage a quality criterion based on the relevance to the topic was applied.

4.2 Urban planning

In the early 20th century, the cities were redesign once cars started to become mass produced (Brown et al., 2009), most public spaces became primarily road and parking space, leaving a small percentage of the street for people. Streets used to be places of public congregation, where people could walk, talk, shop, eat, etc.

Nowadays a big part of cities is used for parking, for example, one third of the land mass of American cities is currently used for parking spaces (Baldwin & Rehler, 2021), in some cities is even higher, like Los Angeles where 40% of the city has this use (Fraser et al., 2016).

Once autonomous cars are driving people around, the concept of a parking space will become unnecessary. The car the brings you to the destination, and after that it can go pick up another user nearby, it does not need to wait for you occupying useful and scarce space.

In the book "ReThinking a Lot" by Eran Ben-Joseph (Ben-Joseph, 2012), some very interesting figures about the parking culture in society are analysed, which helps to understand better the problem and the scale of the possibilities ahead. There are over 500.000.000 surface parking spaces in the US, which using a conservative 250 square feet size means that there is over 2800 squares miles of surfaced parking space. In the US there are more than 100.000 shopping centres, where the parking requires more space than the actual mall. There is also an average of 8 parking spaces per car.

The COVID situation gave us a glimpse of how fast and beneficial the transformation of public spaces can be, car lanes and parking spaces were transformed into restaurants outdoor areas (ReasonTV, 2021). As closed spaces posed a risk to people, city governments removed some regulations and allowed restaurants to occupy room previously reserved for cars, both suspending minimum parking requirements and allowing to use part of the sidewalk or even car lanes in some cases . The restaurants adapted fast to the new regulations and were able to transform their new available space into dining areas, which was greatly appreciated by customers and the local economy.

Autonomous vehicles have the potential of disrupting the parking industry, they will change how people interact with the city (Millard-Ball, 2019), a lot of new space will become suddenly available where new green spaces, affordable houses, community gardens and much more could be built. This is the biggest opportunity society has had to redesign the cities to their needs for centuries, and now more data, research, and information is available about what society needs than ever. The result would be a reduction of parking demand at urban core locations, reusing those spaces for boosting the economic activity and increasing the urban density in locations that may benefit from it (Bagloee et al., 2016).

On the other hand, the benefits from autonomous vehicles like comfort, convenience, reliability, and increased time utilization could incentivise longer commuting routes, which would contribute to people moving away from cities, also known as urban sprawl, which would have a significant impact in prices and urban planning both in the city centres and areas close to centre of economic activity (Rubin, 2016).

4.3 People's lives

4.3.1 Traffic

According to the Texas A&M Transportation Institute report (2019), the average commuter in the US spends 42 hours per year stuck in traffic, which amounts to 6.9 billion hours totally each year. The worst part is that since 1980 it has gotten worse, it has increase around 20% in the last 40 years.

There are four main causes for traffic, people looking for parking is the reason of 30% of traffic, after that, the high volume of vehicles on the roads. Another relevant factor is the lack of communication and slow human reaction times, which causes events like the phantom intersection, where cars come to near standstill even though there was no major accident. And finally, accidents, which obviously cause traffic, because in many instances they close lanes or people slow down to see what is happening.

Autonomous cars would help with all these issues because parking would be less necessary as explained previously. The communication between the cars would be more efficient, either through vehicle-to-vehicle (V2V) communication or faster response times for road events. These two factors combined would mean that the rate of accidents would radically decrease, since most accidents are cause by the human factor (McKenna, 1982).

According to Anderson et al. (2014) some of the technological advantages and capabilities that may have the biggest impact on the way people drive and interact with roads would be: agent detection, valet parking, crash avoidance, platooning, lane changing, traffic sign and signal identification, safe manoeuvring at intersections and lane keeping.

4.3.2 Accidents

Road traffic is the leading cause of death for young people, between 5 and 29 years old, in the world (World Health Organization, 2021). In the U.S. in 2015 there was 6.76 million car accidents with 2.74 million serious injuries requiring medical attention as a result of these (NHTSA, 2020). Autonomous cars have the potential of changing this. Around 1.3 million people die every year, and around 50 million people is injured or disabled (World Health Organization, 2021).

Both the fatalities and fatality rate in the US had been in declined for decades, as depicted in Figure 7, but in 2015 the trend changed and for a couple years started growing again. A possible reason for this is that drivers are more distracted than ever because of smartphones, a relevant metric about his issue is that around 660.000 US drivers are using their phone while driving at every moment of the day (NHTSA, 2013a). The National Safety Council (Williams-Bergen et al., 2011), reported that 1.6 million crashes are caused by cell phone use, and 387.000 injuries occur because of texting while driving.

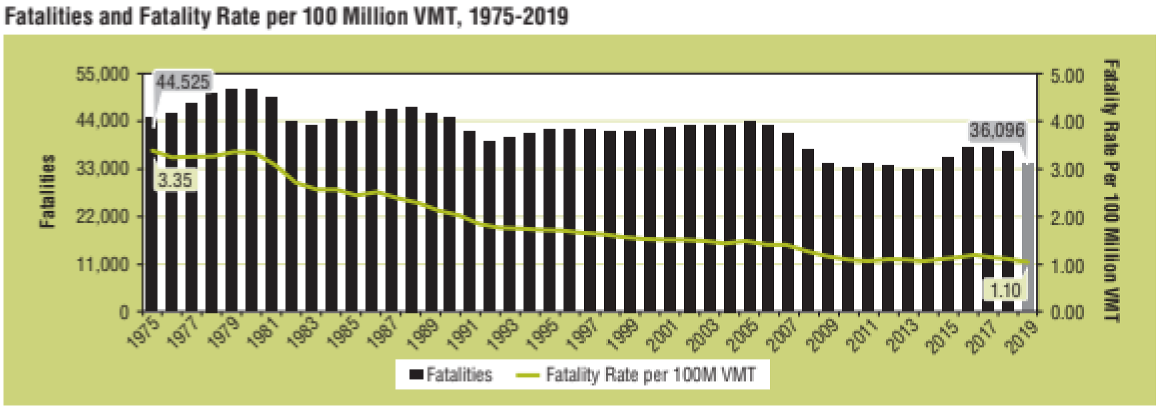


Figure 8: Fatalities and Fatality rate per Million VMT in the US (NHTSA, 2020)

The human factor is key for accidents, The NHTSA determined (2015), that 94% of all accidents are caused by human errors. Autonomous driving could solve this issue and save the lives or avoiding injuries of millions of people. Even low levels of automation have the potential of avoiding around one third of current traffic accidents (Bagloee et al., 2016).

Autonomy technology is already saving lives and has been doing it for several years already, in the Tesla Vehicle Safety Report (Tesla, 2021f) data is presented on how driving with Tesla Autopilot results in nine times less accidents than the average rate in the United States. Obviously, this metric is not perfect because it is not controlling for driver profile, routes, etc. but it is definitely a promising data point.

4.3.3 Cost savings

According to ARK Invest (Keeney, 2017), the cost per mile of TaaS could get as low as $0.25, which is significantly lower than owning a personal car, which has an approximate cost per mile of $0.70. These costs include vehicle depreciation, fuel, parking, financing, insurance, maintenance & repair, registration & taxes, and tires. Other studies (Milakis et al., 2017) get to similar conclusions, shared autonomous vehicles would decrease both the fixed and operations costs associated with transport and therefore reducing the rate of car ownership.

This is the first real reduction in cost per mile (adjusted for inflation) since the Model T was released. An average driver in the US drives, according to the U.S. Department of Transportation's Federal Highway Administration (2018), around 13.500 miles every year, so even being conservative the average citizen will save several thousand dollars each year.

The number of accidents that could be avoided have been analysed, but the total cost of these accidents considering medical expenses, productivity loses, legal costs, insurance administrative costs, congestion, property damage and emergency service costs is over 242 billion dollars (304 billion dollars adjusted for inflation) according to a report by the National Highway Traffic Safety Administration (Blincoe, L. J., Miller, T. R., Zaloshnja, E., & Lawrence, 2015).

Considering the trend in the industry and the clearly declining cost curves discussed previously, the future of autonomous mobility is electric, this will result in other indirect savings. Pollution in cities is a known issue, and it is very difficult to quantify, but accordingly to the American Lung Association (Holmes-Gen & Barret, 2016), for every gallon of gasoline used in the U.S. there is an associated $1.15 in health damage costs, like heart attacks, lung cancer and societal damage related to climate change. Considering that in 2020 123.73 billion gallons of driving gas were consumed in the United States (U.S. Energy Information Administration, 2021b), the potential savings according to the American Lung Association are in the tens of billions of dollars per year once the transition has happened.

In terms of public costs and potential tax savings, another source of reduction in capital investment it would be existing plans of road expansion and improvements, because the platooning feature could increase by a factor of five the road capacity (Fernandes & Nunes, 2012) this would definitely reduce the necessary investment in infrastructure.

There are many other costs that are not being taken into account or that are difficult to calculate, but it is clear that people will have more disposable income which they will use to buy products on other industries, boosting these industries in a very significant way.

4.3.4 Time savings

Not everything in life is about economic savings, the most relevant non-renewable resource people have is time, and driving takes a lot of time of people's lives. Not only that, but it also requires focus, energy and in many instances creates frustration. The average US citizen spends around 230 hours commuting every year (United States Census Bureau, 2021), that is more than 9 full days just commuting.

A study by Daniel Kahneman & Alan Kruger (2006), revealed that for women commuting was the least pleasurable activity in their daily lives right after housework and childcare. A negative correlation has also been found between commute time and people's wellbeing (Hilbrecht et al., 2014), where people with longer commutes tended to have lower satisfaction in life. But there are other studies (Dyck & Gimpel, 2005; Humphreys et al., 2013; Sandow, 2019; van Ommeren & Gutiérrez-i-Puigarnau, 2011), also link long commutes to high blood pressure, back and neck pain, depression, divorce, obesity, high cholesterol, death, being less likely to vote, being more likely to be absent from work, less likely to get out of poverty and kids being more likely to have emotional problems.

In the near future most of these issues will be mitigated thanks to autonomous driving because commuting will no longer be a high focus activity but a relaxed one where entertainment is the main activity. Driving may go from generating frustration to becoming working or social time. This will also be amplified with the growing adoption of remote work, fully or partial. The new time available will result in productivity gains to the economy, as some of this time is devoted to productive activities.

4.3.4 Employment

A lot of the benefits detailed previously come at a cost, the job of a lot of individuals whose jobs nowadays consist of the transportation of people of goods, both short and long distances. This people would lose their livelihood during the process of mass adoption of autonomous vehicles. Even more people would lose their jobs because there are indirect jobs created because of the numbers of cars, mainly in manufacturing and maintenance (Crayton & Meier, 2017)

Nonetheless other industries would experience an opposite fate and grow significantly, according to Godsmark et al, (2015) the sectors of IT product and services, conversion parking construction and roads modification would be highly benefited from this transformation in the economy. Training of people from one industry to another will be crucial to ensure their wellbeing and that enough skilled workers are available to carry out the jobs needed to adapt cities to the new reality.

4.4 Environment

Right now, there are around 238 million cars and light trucks in the United States alone (United States Department of Transportation, 2021), and according to the Union of Concerned Scientist (2014) it is the largest single source of carbon monoxide and the second largest source of hydrocarbons and nitrogen oxides. In 2013 transportation accounted for half of the carbon monoxide and nitrogen oxides and a quarter of hydrocarbon (Union of Concerned Scientist, 2014). Each gallon of gasoline emits 18.74 pounds of CO_2 into the atmosphere (U.S. Energy Information Administration, 2021a). Which seems contra intuitive because it is producing more mass in emissions than the mass of the fuel itself, the reason for this is because during combustion each carbon combines with oxygen from the air (U.S. Energy Information Administration, 2021c). The total fuel consumption savings could be up to 45% in an optimistic scenario and around 30% savings in a pessimistic one (Chen et al., 2019).

Another important factor in car related pollution, especially in cities, is PM 2.5 particles, which are fine particulate matter that are two and half or less microns in width. According to the World Health Organization (2013), these particles are directly related with respiratory and cardiovascular morbidity, aggravation of asthma, respiratory symptoms, increase in hospital admissions and increased mortality from cardiovascular and respiratory diseases and lunch cancer. Even more worrisome is the fact that there is no evidence of a low level of exposure or threshold where no negative effects on health occur (Kelly & Fussell, 2015).

The effect that these particles have on the human body is not negligible, according to (Correia et al., 2013), epidemiological evidence was found about the damage of PM 2.5 particles on human respiratory system. The conclusion of the 7-year study was that for every 10 µg/m3 decrease of concentration in the year the average lifespan is extended by 0.35 years. Another study, to (Center for Disease Control and Prevention, 2019), also stated that reducing by 10% the PM 2.5 emissions in the United States could save up to 13.000 deaths per year.

A study done in 1996 (Gillies et al., 2001), on The Sepulveda Tunnel in Los Angeles revealed that approximately an average vehicle emits 0.052 grams of PM 2.5 particles per kilometre. Only that year, 1996, in the United States, 125.840 tons of PM 2.5 particles were emitted considering the 2.42 trillion miles driven that year (U.S. Department of Transportation, 2021)

Obviously, the emissions per car are lower nowadays thanks to better technology and regulation, but people are driving 33% more (U.S. Department of Transportation, 2021), and is not possible to make everyone comply with the rules. According to (Anenberg et al., 2017), excess emissions from diesel vehicles which were exceeding certification limits were associated with the death of 38.000 people globally in 2016 alone.

The transition to electric vehicles will therefore mitigate a lot of the negative aspects of the current transportation system, especially considering the growth and current investment in renewable energy. This growth is mainly driven by the fast decrease in costs in the recent years, following the previously explained Wright's law.

4.4.1 Tesla's role

Tesla publishes every year their Impact Report (Tesla, 2021c) where they share some of their contribution for helping to "accelerate the world's transition to sustainable energy", as their mission states. Thanks to their cars being electric and their solar panels they have avoided the emission of 5 million metric tons of CO_2 into the atmosphere in 2020 alone. This figure is undoubtedly small in comparison to the 36.44 billion tons which is the total global emissions, but Tesla is aware of this and therefore they have much higher goals in mind. Their goal in 2030 is to produce 20 million cars annually, compare to the 0.5 million in 2020, and deploy 1500 GWh of energy storage, compared to the 3GWh in 2020.

Their approach is to create an ecosystem, a flywheel where every element supports the others, as depicted in Figure 8. In order to achieve their goal, they need to continue excelling in areas like material science, manufacturing, and software. Improvements in these areas not only make sense for the product and the planet but also economic sense.

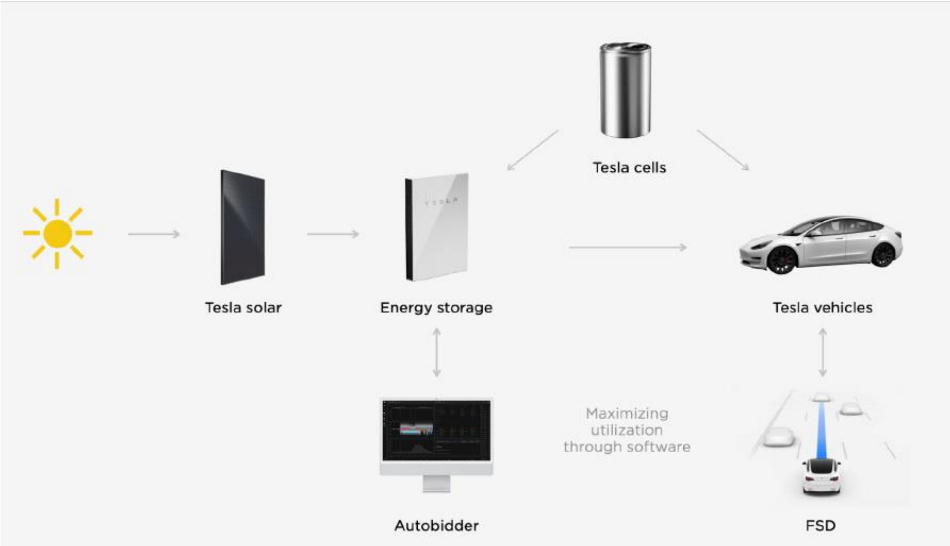


Figure 9: Tesla's ecosystem (Tesla, 2021c)

The improvements in battery technology must focus on cost, recyclability, low degradation so they can build more energy storage, with the objective that renewable energy can become a higher percentage of the energy grid. On the cars side Tesla knows that the replacement rate of cars is very low, so in order to disrupt the industry and transition as soon as possible to EVs they knew they had to make autonomous ride-hailing more attractive than using your own existing car. Users will mainly use it because of a mix of convenience, lower cost and doing the right thing for the environment.

Tesla’s cars are already much better for the environment that the current internal combustion engine competition, as shown in Figure 9, this is considering the entire lifecycle of the product, considering manufacturing and use phase. It is very interesting than the ridesharing version has a much lower manufacturing costs, this is because it would be substituting multiple personal use cars.

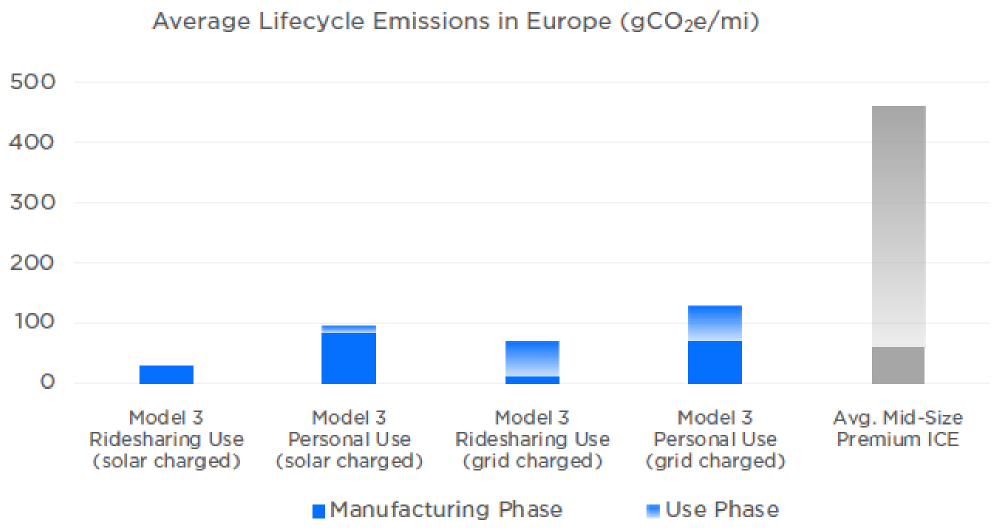


Figure 10: Average lifecycle emissions in Europe Tesla Model 3 vs ICE (Tesla, 2021c)

Manufacturing is another big element in the equation, first because for EVs the manufacturing phase represents a big part of the total emissions of the car if the standard grid is used, or all of the emissions in the case the car is being charged by solar. Therefore, Tesla have been improving the efficiency of their plants and are focused on production and supply chain localization. They are now finishing their factory in Berlin for Europe and the factory for Asia in Shanghai already started production in 2019.

4.5 Real World AI

The AI technology developed for the purpose of autonomous driving may have even more impact in people's lives in the future if it is applied to other industries. The main building block of this technology is their image recognition neural network. The first step for AI to interact in the real physical world is to understand it, the world is visually very complex, there are many agents on every situation, both humans, objects, and machines, being able to differentiate and understand that will be key for kickstarting the next revolution in Real World AI.

Tesla is already doing an important part of what it is understood as intelligence, as they show in the "AI Day" (Tesla, 2021b), their technology is already perceiving the real world, but the simpler context of a road, planning the possible options to achieve its goal, evaluating the different alternatives, and executing, all this is happening hundreds of times each second, allowing the car to react and adapt to changes in the environment. As Elon stated *"A major part of real-world AI has to be solved to make unsupervised, generalized full self-driving work"* (Musk, 2021), and they are quite close to solve this, which means that a big part of the work is done already.

The combination of their neural networks, their Full Self Driving computer, sensors, batteries, actuators and Dojo, their supercomputer designed for AI training, can be what finally unleashes AI into the real world. This is why their humanoid robot was presented in "AI Day", and a prototype may be ready at the end of 2022. The requirements for this robot would be the ability to navigate the world and carry out boring, dangerous, or repetitive tasks. Their presentation had the main objective of attracting even more talent to the company in order to bring this idea into reality.

This first use case of "Real World AI" would improve productivity tremendously, the impact it would have on the economy is difficult to predict, but it could be bigger than the internet. Thanks to the industrial revolution many tasks passed from humans to machines, increasing the productivity and lowering the costs like never before, which resulted in the increase of human well-being all over the world. There were some tasks that machines were not able to automate, but this technology has the potential of automating a significant percentage of the physical tasks that humans perform nowadays. This revolution and the technology adoption will take some decades, it is not happening next year or this decade but it is inevitable if the technology and cost curve trends are analysed. The same happened with electric vehicles in the last decade, it was unstoppable, no amount of media or politicians' manipulation could stop it, and anyone who analysed the issue from an objective point of view saw it coming.

5. Adoption and economic impact model

The practical part of this master thesis consists of a simulation model for the rate of adoption and economic impact that the deployment of the Robotaxi network may have. The model is flexible and the user can edit the input variables of the model, this is crucial because there is a wide range of opinions on many of the most relevant variables, and it is important for the model to be able to adapt to the different possible scenarios.

The objective it is not to predict the future but creating a model where everyone can input their predictions and get the potential results in return. Nevertheless, for analysing the output of the model conservative input data will be used, this data is based on Tesla's projections, electric vehicle experts, the current state of the technology and the industry's competitive landscape.

5.1 Methodology

5.1.1 Monte Carlo simulation

Stanislaw Ulam and John von Neumann developed a mathematical technique for estimating the probability of outcomes of an uncertain event in the context of World War II (IBM Cloud Education, 2020). The name for this multiple probability simulation approach derives from the city of Monaco, famous for its casino, mainly because both the casino and the technique rely on the introduction of random variables to achieve their objective (Johansen, 2010)

Monte Carlo simulations have been implemented in many different industries such as finance, sales, engineering, science, logistics, etc. (Amar, 2006; Banomyong & Sopadang, 2010; Kalkhoran & Glantz, 2015; Manly, 2018). There is uncertainty, ambiguity, and variability in every aspect of life and work, and simulation of the different possible outcomes, based on a predefined set of input variables with a probabilistic distribution, gives a very useful outlook on the potential risks and opportunities to take better decisions.

It is a very appropriate tool for model with complex structures, where there are many variables that influence each other and also outside factors which are difficult or impossible to predict. For this type of model traditional techniques are not capable of estimating to the same degree the infinite range of possible outcomes.

The model created requires that assumptions are developed about the probability distribution of the relevant variables which have an inherent uncertainty. There are many kinds of probability distributions, in the Wikipedia (2021) page for "List of probability distributions" there are over 180 distributions listed. The most common one, which is the one used in this model, is the normal distribution, also known as Gaussian or "bell curve". The user simply defines the mean and standard deviation for the distribution. It is symmetric, and many things in nature and society follows this distribution.

For each input variable also maximum and minimum have been introduced as a safeguard to make sure that each simulation is inside the realm of possibilities. There are also variables that have clear limits because of their nature, for example prices can't be negative, Robotaxi deployment date can't be in the past, or there are some values that are so unlikely that should not be considered.

A very important advantage of the Monte Carlo simulation over other modelling techniques is that not only outputs what is possible but how likely it is to happen. Since the whole model is represented in numerical data structures it is very easy to generate a visual representation of the results, which is very useful for sharing the insights generated with other stakeholders in the project.

This is out of the scope of the current project, but a sensitivity analysis can be carried out on the input variables, this way it is possible to identify which ones have the biggest influence, which is a very important insight for better decision making.

There are some known disadvantages of the Monte Carlo simulation method, one significant aspect is that it is computationally inefficient, this is relevant for big and complex models, where the large amount of variables may require a lot of time to output the results. It should also be considered that the input variables and their relationships must be carefully developed because the technique is very sensitive, the quality of the output relies heavily on the quality of the input.

5.1.2 Python model

The programming language chosen to carry out the simulation is Python after careful research considering both the interests of the project and personal. The reasons for the selection of this language as the basis for the model are the following.

It is one of the most used programming languages in the world (Stack Overflow, 2020), this means that the ecosystem builds around it is mature, the documentation is of very high quality and there is a huge community of developers that have written tutorials, answered questions, created courses, etc.

It is a very high-level programming language, which means that it is easy to read. This is relevant in the context of a master thesis, since this will help other people to build on top of this project and also understand, use, or edit the model itself. The significant indentation forces the developer to keep the code tidier, which combined with the simple syntax makes it a very good choice for the project.

There are a seemingly infinite number of libraries, but the ones for data science and data manipulation are very robust and have a proven track record. The module for Statistical functions from the library *SciPy* has been used is used in this project to generate the random probability distribution for the input data. The main data structure use for the model is DataFrame by the library *pandas*, which is a two-dimensional tabular data object, made for data manipulation and includes indexing out of the box. This library has also been used to read the input data from CSV files. The other relevant library used is *Matplotlib,* a very powerful plotting library, which generates the necessary graphs to visualize the output of the model in order to draw insights from them. All these libraries have a very large set of tools and functions, only a tiny fraction of those, the necessary ones for the project have been used.

Python can be used for multiple applications, not only data science or data analytics, but it is also very powerful language for web development, with the use of frameworks like Django or Flask state of the art web applications can be developed. This also would allow to easily replicate the Monte Carlo simulation model in an interactive website, which would be beneficial for sharing purposes. Other relevant applications for python include artificial intelligence, game development, automation, software development, etc.

Interactive computing is a very powerful tool for any data exploratory project, it helps with the visualization, sharing and editing of the executable code for rapid testing and prototyping. The software chosen for this was *Jupyter Notebook*, where the model was developed, allowing for a step by step run of the model for visualizing and understanding how it was developed. The software consists of a shareable web application which supports executable code, visualization, and comments.

5.2 Model description

The Monte Carlo simulation has been used before in the finance industry for modelling complex systems with high uncertainty before (Mcleish, 2005) this is why it was a good fit for this project

5.2.1 Variables

Number of simulations

The first variable which will be discussed is the number of simulations; the more simulations the better results because of the Monte-Carlo technique, but it must be considered that simulation time is not linear because of the data structure and calculations. Therefore, it is advisable to use a lower number of simulations to test multiple situations and set a high number once you find a configuration that you want to analyse in detail.

Years to simulate

The next variable explained is the timespan simulated, so the years**,** the farther into the future the less accurate the results will be because more unexpected events or changes in the industry may occur. This is why up to 2030 is a good timespan, this is even the last year where guidance has been given by Tesla regarding their production goal.

Regions or areas

Only relevant “regions” will be considered for this analysis: USA, China, Europe, Canada & APAC excluding China. This are the areas with the most potential in the short to medium term because of purchasing power and current factories developed or being developed in the area.

Price per mile

Regarding the economic repercussions of the Robotaxi network, the price will pay a big role, so the price per mile must be chosen carefully considering the competitive environment, expected demand and pricing power of Tesla. The price per mile for China & APAC is independent because this market is much more competitive, it has different regulations and most importantly, lower salaries for drivers, so in order to be stay competitive the service will most probably need to have a significantly lower price. Europe, USA, and Canada have a very similar market; therefore, the Price/Mile can be supposed to be the same in order to simplify the model. The price will adapt to offer and demand, just like the current system that Uber has, but the average expected price must be estimated.

Cost per mile

In order to know what is the expected profit that the car owners may have once the service is deployed, it is necessary to try to estimate what will their costs be, which would include the depreciation of the car, electricity, and maintenance. These costs are much lower than the equivalent for an internal combustion engine car, but they are relevant and must be taken into account. According to Tesla (2019b) the average cost to run a Robotaxi should under $0.18 dollars including the necessary overhead.

Platform fee

Tesla will take a cut out of the price of the service; this platform fee will directly impact the revenue of the company. This number will heavily depend on the demand and competitors in the areas of operation, because it represents a significant portion of the final price. Most probably it will be similar to the cut that platform like app stores take currently from the apps, which is around 30%, but it could be higher, especially in the first years of operation.

Operation time

The service will not operate 24 hours per day, because there is no demand for it and cars needs time for charging for instance. Therefore, the expected average hours of operation per day for cars in the network must be estimated. Personal use of the car by the owner and the time of low demand should be considered. Some users may not put their cars into the network to the network for various reasons, travelling, emergencies, busy day, etc. So, the days per week is another variable to take into account.

Miles per hour

The amount of miles that the cars will do during operation needs to be calculated, in order to achieve this, a simple but accurate way is to use the average miles/hour that the Robotaxis will have during the service. It needs to be taken into account how much of the traffic will be in inner cities and between cities because this would radically change the result.

Occupancy rate

Uber is taking clients approximately 40% of the time, the rest is what it is called “deadheading” (California Air Resources Board, 2019), when the car is circulating but without any client on board, waiting for the next ride to be booked. Tesla Robotaxi network will have the same issue, it is impossible for the car to be used by clients 100% of the time. Obviously with their expertise on artificial intelligence they will most likely develop an algorithm which will greatly optimise routes and balance offer and demand, but it will never be one hundred percent occupancy rate.

Network participation

Allowing strangers to use your car is not a common practise nowadays, in spite of the positive trend of similar services like carpooling, short-term rentals of main residence, it is far from mainstream. Not all Tesla owners will want to participate in the network, for this above-mentioned reason, or maybe just because they don’t need the money and prefer to have their car available 100% of the time for themselves. Taking these facts into consideration the variable network participation is being use.

Average car lifespan

Cars have a finite service life, according (Held et al., 2021) the average lifespan of cars in Western Europe is 18,1 years. ICE cars are complex machines with thousands of moving pieces, whereas electric cars car very few moving pieces. The battery is anyway, most probably, the main point of failure because of degradation. Currently the average capacity retention after 200.000 miles rounds the 90% (Tesla, 2021c), which is optimistic, which combined with improvements in battery technology will make electric cars last for a long time, Tesla's objective is to build in the near future the "million miles battery" (Shirouzu & Lienert, 2020). Using the average car lifespan, the cars are discontinued and subtracted from the available cumulative car count.

Production distribution

Each region will have a different delivery distribution based on demand, strategic decisions, and average selling price. This is why there is a need to put into numbers the production distribution which will be sold in each area.

Production growth

The most relevant metric for the future of Tesla is production growth, over the years analyst have failed to assess the growth of Tesla, only in the last two years they have started to see the exponential trend in Tesla's production capacity. According to their guidance, they plan to grow around 50% in the coming years, with the goal of producing 20 million cars in 2030 (Tesla, 2020). Based on this it must be decided what is the probability distribution for the future production projected growth.

Tesla can produce millions of cars per year, but if they do not achieve real autonomous driving the potential of the Robotaxi network will not be realized. Therefore, the date for the open release of the fully autonomous Level 4 driving automation ride-hailing network is relevant for the rate of adoption of the technology and effects on society and competition. In terms of economic impact, it is not as relevant, especially in the short term, because the cumulative number of cars in the future will dwarf the number of cars available in the short term because of the growth in production.

Table 7: Monte-Carlo simulation model variables properties

Variable Name	***Number/List***	***Probability Distribution***		
		Number	**By year**	**By area**
Simulations	x			
Years	x			
Regions	x			
Price/Mile		x		
Price/Mile for APAC & China		x		
Cost/Mile		x		
Platform Fee		x		
Hours/Day		x		
Days/Week		x		
Miles/Hour		x		
Occupancy Rate		x		
Network Participation		x		
Car Lifespan		x		
Production Distribution				x
Production Growth			x	
Robotaxi Deployment		x		

5.2.2 Calculations

Miles per car

Combining multiple variables defined previously it is possible to create a new metric for each simulation which is very useful for the calculation of other results, this is the miles per car per year that the Robotaxis are being use by clients, and the formula would be the following:

$$Miles\ per\ car\ per\ year\ = 52\frac{weeks}{year} * \frac{Days}{week} * \frac{Hours}{day} * \frac{Miles}{hour} * \%ocupacy$$

Car production

In order to get a correct probability distribution for the production distribution per area, what it has been used is function which divides each area percentage by the total sum of all of them for each simulation. This produces a result with almost the same average and standard deviation as the input.

```
def get_standarise_percentages(dictionary):
    for year in years:
        for i in simulation_list:
            total_sum=0
            for area in dictionary.keys():
                total_sum+=dictionary[area][year][i]
            for area in dictionary.keys():
                dictionary[area][year][i]=dictionary[area][year][i]/total_sum
    return dictionary
```

Once the growth projection and production for 2021 is available the future production can be calculated. This is as simple as simulating the growth per year based on the probability distribution provided by the user and using this to increase production each year by that amount using 2021 as the first value.

$$Production[year][i] = Production[year-1][i] * Growth\ [year][i]$$

$$ProductionPerArea[area][year][i]$$
$$= Production[year][i] * PercentageProduction\ [area][year][i]$$

Discontinued cars

Once production has been calculated, the combination of this variable with the average lifespan of the cars, which is one of the input variables, outputs the discontinued cars per year. Since the number of average lifespan years is a rational number and not a whole number, the share of production to the decimal part must be taken into account too, which would correspond to the previous year.

$$Lifespan\,Year[i] \;=\; year \;-\; Floor\;(Avg\;Lifespan[i])$$

$$Partial\;Lifespan\,Year[i] = \;Avg\;Lifespan[i]\;\%\;1$$

$$\begin{aligned}&Discontinued\;Cars\;[area][year][i]\\&\quad = Producion\;\;[area][\;Lifespan\,Year[i]\;][i] * (1 - Partial\;Lifespan\,Year[i])\\&\quad + Producion[area]\;[Lifespan\,Year[i] - 1\;][i] * Partial\;Lifespan\,Year[i]\end{aligned}$$

Cumulative cars

Once the two previous metrics are ready it is very easy to calculate the cumulative number of cars by Tesla on the road.

$$\begin{aligned}&Cumulative\;Cars\;[area][year][i]\\&\quad = \;Cumulative\;Cars\;[area][year-1][i] + ProductionPerArea[area][year][i]\\&\quad - Discontinued\;Cars\;[area][year][i]\end{aligned}$$

Robotaxi deployment date

In order to simulate the Robotaxi deployment date it is necessary to convert the input data for the probability distribution into timestamps which can be simulated with the function developed for obtaining the random values based on the input. The function *datetime.timestamp* is used to get the Unix time for the dates. Once it has been converted to Unix time and done the simulation, it is possible to convert it back to regular datetime type for later use in the model as the time axis.

Robotaxi miles

A very relevant metric, which is quite easy to compute with the variables and calculations explained, is the total amount of miles driven by the Tesla Robotaxi network. In this formula, *Percentage Robotaxi per Year* is the amount of Robotaxi time deployed per year, to account for the right percentage the year of deployment and no Robotaxi the years previous to that one.

$$\begin{aligned} Robotaxi\ Miles\ [area][year][i] \\ &= Cumulative\ Cars\ [area][year][i] * Miles\ per\ Car\ [i] \\ &* Network\ Participation\ [i] * Percentage\ Robotaxi\ per\ Year\ [area][year][i] \end{aligned}$$

Tesla's revenue

In terms of economic impact, the first output which will be discussed is the revenue for the company, the formula for it is the following:

$$\begin{aligned} Revenue\ [area][year][i] \\ &= Price\ per\ Mile[i] * Platform\ Fee[i] * Robotaxi\ Miles[area][year][i] \end{aligned}$$

Car's owner revenue

A very similar output is the car's owner revenue. According to Tesla this figure should be around 30.000$ per year and it is also a simple calculation:

$$\begin{aligned} Car's\ owner\ Revenue[i] \\ &= Miles\ per\ Car[i] * (Price\ per\ Mile[i] * (1 - Platform\ Fee[i]) \\ &- \ Cost\ per\ Mile\ [i]) \end{aligned}$$

Robotaxi miles over VMT in the US

Some of the metrics calculated allow for the estimation of interesting outputs very easily. A good example is to calculate the percentage of Vehicles Miles Travelled (VMT) in the US. To make it more realistic, in the simulation an ARIMA model has been used to predict the future

VMT based on the data from 1970 until 2019 (U.S. Department of Energy, 2021), which is equal to 3.26 trillion miles as of 01/12/2019.

$$Percentage\ Robotaxi\ over\ VMT\ [year][i] = \frac{Robotaxi\ Miles['USA'][year][i]}{VMT[year]}$$

CO_2 saved

The tons of CO_2 saved have also been calculated. This calculation is supposing that the Robotaxi miles are replacing internal combustion engine cars. The first step was to get the difference in CO_2 emission per mile driven, considering the total lifecycle and electric grid mix, between internal combustion engines (Bieker, 2021) using this data it is trivial to calculate the tons of CO_2 saved by the Robotaxi Network.

$$CO_2saved[area][year][i] = Robotaxi\ Miles[area][year][i] * (CO_2ICE\ per\ Mile - CO_2\ EV\ per\ Mile)$$

CO_2 saved over CO_2 produced

Once the CO_2 saved is calculated it is easy to find out what percentage of the total CO_2 emissions by region, using 2021 context (Ritchie & Roser, 2020), which will not be emitted to the atmosphere. This gives a good perspective on the potential impact for the environment.

$$Percentage\ CO_2\ saved\ over\ total\ [area][year][i] = \frac{CO_2\ saved\ [area][year][i]}{CO_2\ produced[area]}$$

Economic savings derived from health-related issues

As it has been previously exposed in the implications the pollution in cities have not also a health impact in people's lives but also an economic one because of the medical help required. According to Holmes-Gen & Barret (2016), each gallon of gas has an extra cost of $1.3. Considering this data, it is possible to calculate the savings on just this metric by adding the average miles per gallon consumption into the equation, which is 25.4 (United States Environmental Protection Agency, 2021).

$$Savings\ Polution\ USA\ [year][i] = Robotaxi\ Miles\ ['USA'][year][i] * \frac{1.3}{25.4} * (CO_2 ICE\ per\ Mile - CO_2\ EV\ per\ Mile)/CO_2 ICE\ per\ Mile$$

Cars displaced per year

According to the U.S. Department of Transportation Federal Highway Administration (2018), the average miles driven per year per driver are 13476, which means that the calculation the numbers of cars displaced by the Robotaxi network can be done. This metric is not perfect because the driven miles will increase because of the cheaper price and easier access to transportation, but it is still a good indicative of the potential impact of the service.

$$Cars\ displaced\ [year][i] = \frac{Robotaxi\ Miles\ ['USA'][year][i]}{13476}$$

To calculate the capability for displacement that each Robotaxi car has metric the number of Robotaxis in the network have been calculated.

$$Robotaxies\ in\ the\ network\ [year][i] = Cummulative\ Cars\ ['USA'[year][i] * Network\ Participation\ [i]$$

$$Displacement\ Coefficient[year][i] = \frac{Cars\ displaced[year][i]}{Robotaxies\ in\ the\ network[year][i]}$$

Potential time savings

Once people do not need to pay attention by driving, many hours will suddenly become available, these hours will devoted be to entertainment, work, social time, etc. In the US the average driver spends 50.6 minutes driving every day, which is equal to almost 13 days and around 3.5% of the time (Tefft, 2017). Using the Robotaxi miles and average miles per hour the time that will become available is calculated.

$$Hours\ saved[area][year][i] = \frac{Robotaxi\ Miles\ [area][year][i]}{Miles\ per\ hour\ [i]}$$

Maximum potential GDP increase

With the new time available for the drivers, this time will definitely not be used in its entirety for work, but if it was, the potential extra GDP is a very interesting metric on the magnitude of the impact this technology would have. The only other data needed is the GDP (The World Bank, 2021) and GDP per hour worked (OECD, 2021; The Conference Board, 2018) for the regions.

$$Extra\ GDP[area][year][i] = Hours\ saved\ [area][year][i] * GDP\ per\ hour[area]$$

$$Potential\ \%\ GDP\ increase\ [area][year][i] = \frac{Extra\ GDP\ [area][year][i]}{GDP\ [area]}$$

5.3 Input data

The model needs some input data, conservative values have been chosen in order to portray a realistic view of the potential. All variables have four values for describing the normal probability distribution, minimum and maximum possible value, and “bear” and “bull” which correspond to the values one standard deviation to the left and right of the average.

Table 8: General inputs for the Monte-Carlo model

	Min	*Bear*	*Bull*	*Max*
Price/Mile	0.7	0.8	1.2	1.7
Price/Mile Asia	0.5	0.66	0.8	1.1
Costs/Mile	0.1	0.15	0.25	0.3
Platform fee	0.15	0.25	0.35	0.45
Hours/day	6	8	13	16
Days/week	4.5	5.6	6.5	7
Miles/hour	10	13	17	20
% occupancy	0.35	0.45	0.65	0.69
Network Participation	0.2	0.25	0.35	0.4
Car Lifespan	8.5	9	11.5	13

Table 9: Deployment date input for the Monte-Carlo model

	Min	*Bear*	*Bull*	*Max*
USA	01/09/2022	01/07/2023	01/10/2024	01/01/2029
Canada	01/03/2023	01/10/2023	01/12/2024	01/01/2029

Europe	01/08/2023	01/08/2024	01/12/2025	01/01/2030
China	01/03/2023	01/12/2023	01/02/2025	01/01/2030
APAC excl China	01/08/2023	01/05/2024	01/08/2025	01/01/2030

Table 10: Projected production growth input for the Monte-Carlo model

	Min	*Bear*	*Bull*	*Max*
2022	0.4	0.55	0.7	0.8
2023	0.39	0.5	0.66	0.75
2024	0.37	0.43	0.6	0.65
2025	0.35	0.4	0.55	0.62
2026	0.3	0.38	0.49	0.55
2027	0.18	0.25	0.4	0.4
2028	0.11	0.18	0.31	0.35
2029	0.07	0.12	0.17	0.22
2030	0.05	0.09	0.15	0.2
2031	0.04	0.08	0.13	0.17
2032	0.035	0.075	0.1	0.15
2033	0.03	0.07	0.09	0.13
2034	0.025	0.06	0.08	0.1
2035	0.02	0.05	0.07	0.09
2036	0.015	0.04	0.06	0.08
2037	0.01	0.03	0.05	0.07
2038	0.005	0.02	0.04	0.06
2039	0.005	0.01	0.03	0.05

Table 11: Production area distribution for the Monte-Carlo model

	Min	*Bear*	*Bull*	*Max*
USA	0.27	0.3	0.35	0.38
Canada	0.005	0.008	0.012	0.016
Europe	0.22	0.25	0.35	0.38
China	0.23	0.265	0.373	0.38
APAC excl China	0.01	0.03	0.065	0.072

The last input has no probability distribution because it is based on historical data that is publicly available. Only the production for Q4 2021 was estimated conservatively. Even though the total numbers are a metric released by Tesla, the distribution by region is provided by Troy Teslike (2021), an analyst with great track record in regard to Tesla production.

Table 12: Production history for the Monte-Carlo model

	USA	Canada	Europe	China	APAC excl China	Total
2017	49367	3478	28279	14829	7228	103181
2018	189577	8862	29257	15029	2781	245506
2019	184130	18852	111119	41298	12257	367656
2020	204235	22624	98934	146813	27041	499647
2021	338029	32224	174260	263324	50163	858000

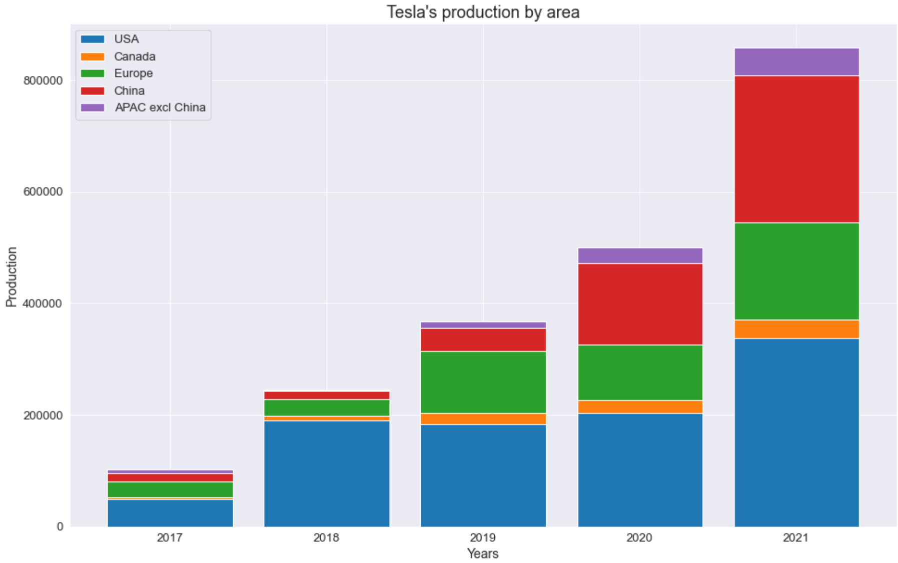


Figure 11: Historic Tesla production by area

5.4 Model output and discussion

Based on the input data and the calculations exposed previously, the following output has been obtained. The input data has a probability distribution, which means that the results have it too. This is the reason the graphs represent the average, bear, and bull scenario. The bear and bull scenarios calculated with the first and third quartile respectively.

5.4.1 Tesla’s production

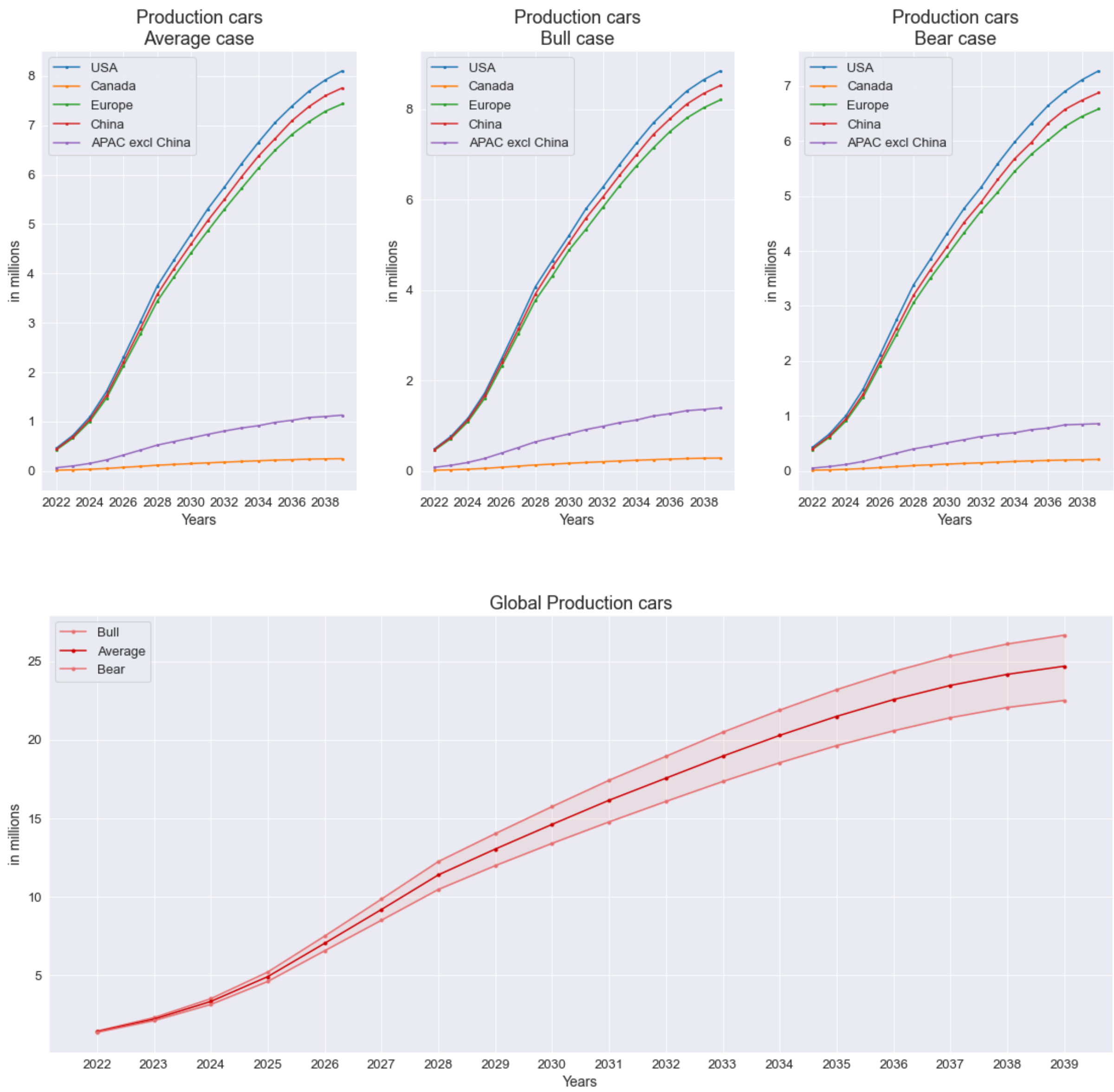


Figure 12: Projected Tesla's production

As established previously, the growth in the next few years is quite strong, around the 50% that Tesla predicts for the coming years (Tesla, 2020), but then it heavily reduces. The global production in 2030 is around 15 million, three quarters of Tesla’s goal of 20 million (Tesla, 2021c). According to this simulation Tesla would become the largest car manufacturer in the world in 2028, since the biggest manufacturer right now is Toyota with over 10 million cars produced (International Organization of Motor Vehicle Manufacturers, 2018).

5.4.2 Discontinued cars

The discontinued cars take some years to start ramping up because it is based on the average car's lifespan and the lowest are several years.

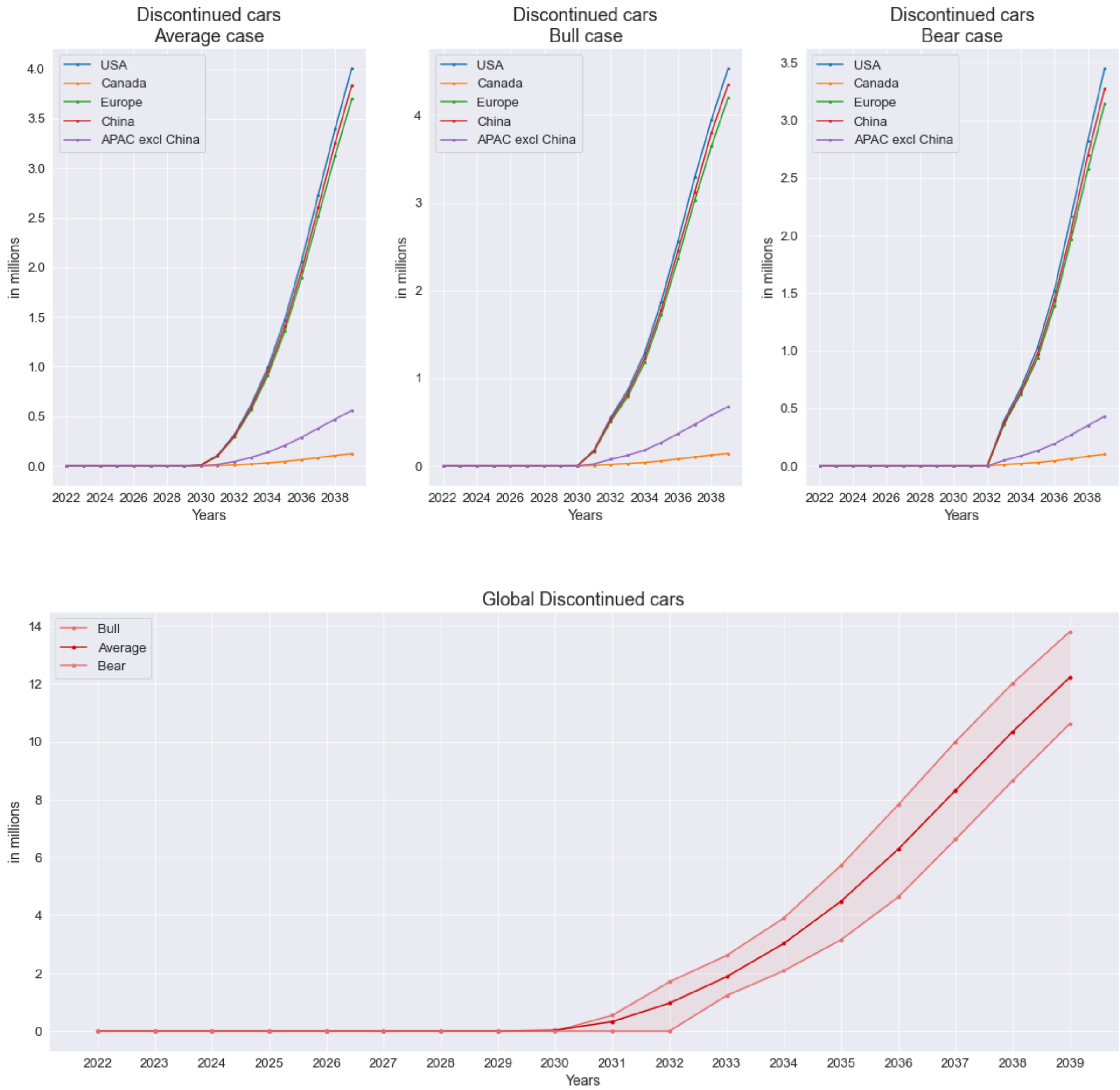


Figure 13: Projected Tesla's discontinued cars

5.4.3 Cumulative cars

Combining the two previous results the cumulative cars are obtained. This is the most relevant metric, because the available Tesla fleet is a key metric in the model.

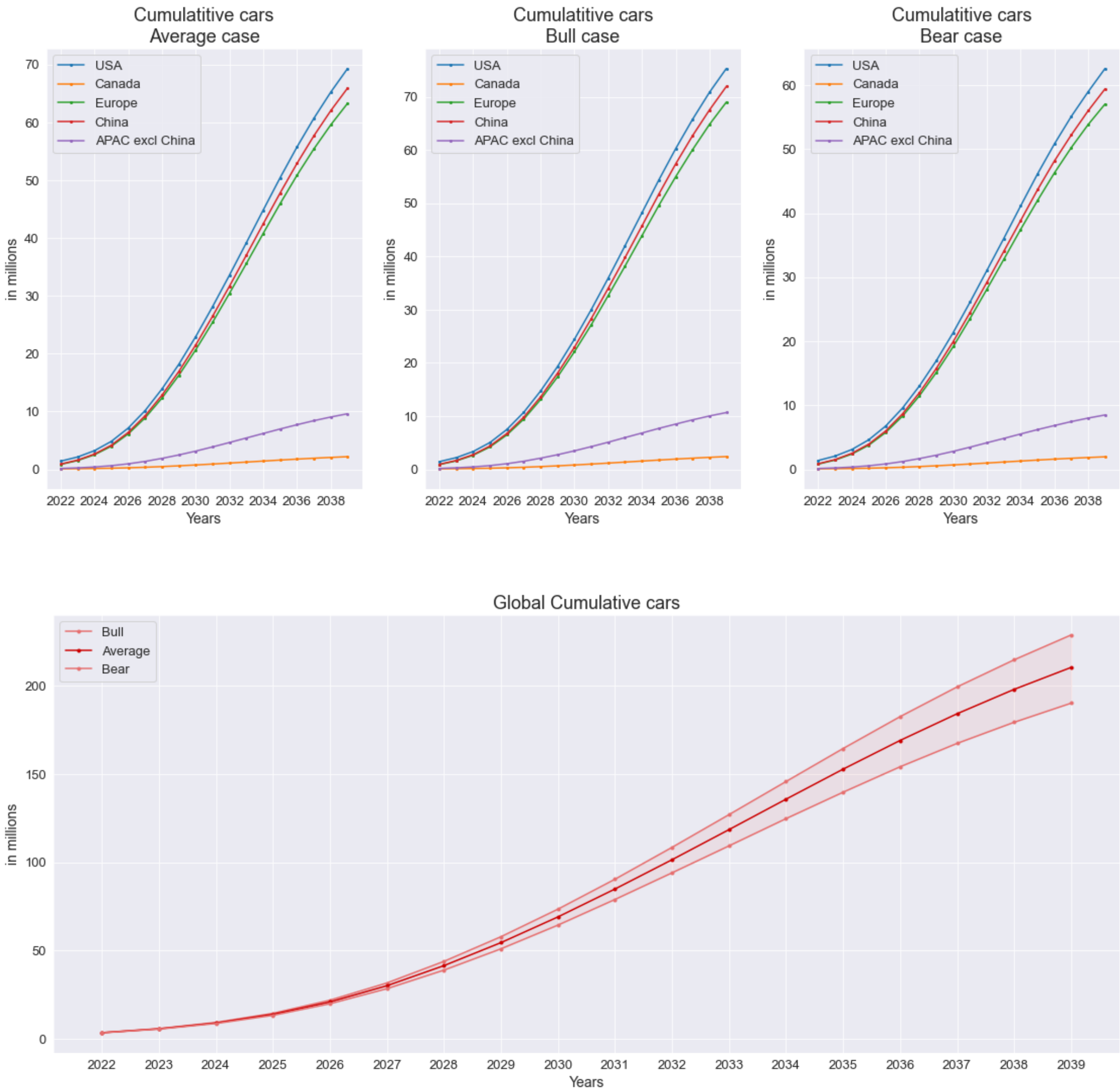


Figure 14: Projected Tesla's cumulative cars

The adoption of the Robotaxi network relies heavily on this forecast because the moment the Robotaxi deployment occurs on the different areas, millions of cars will suddenly join the network, therefore, production is the main driver for this figure. According to the production estimates by Tesla and the expected growth after their guidance, the adoption once the technology is ready will grow instantly to the millions of users. Other arguments that support this bold statement are the economical and behavioural arguments given previously in this thesis about the adoption of autonomous ride-hailing as a new transportation system.

5.4.4 Robotaxi deployment date

Based on the input the temporal Robotaxi deployment date distribution by region is the following.

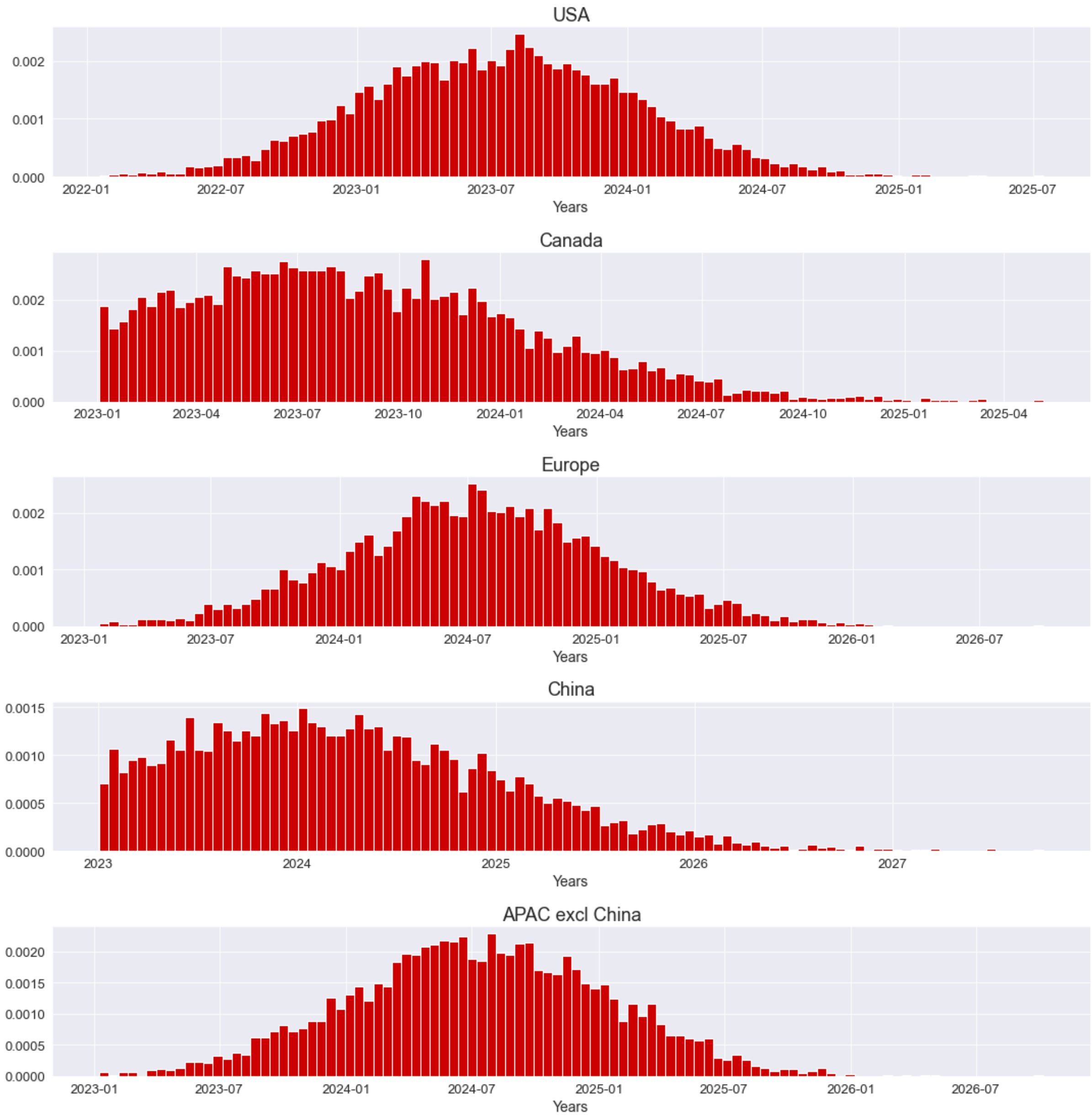


Figure 15: Tesla Robotaxi deployment date simulations distribution by area

5.4.5 Robotaxi miles per year

Making use of the cumulative cars metric and other inputs it is possible to calculate the most important output of the model, the total Robotaxi miles per year, this metric allows for the calculations of many other interesting and relevant results.

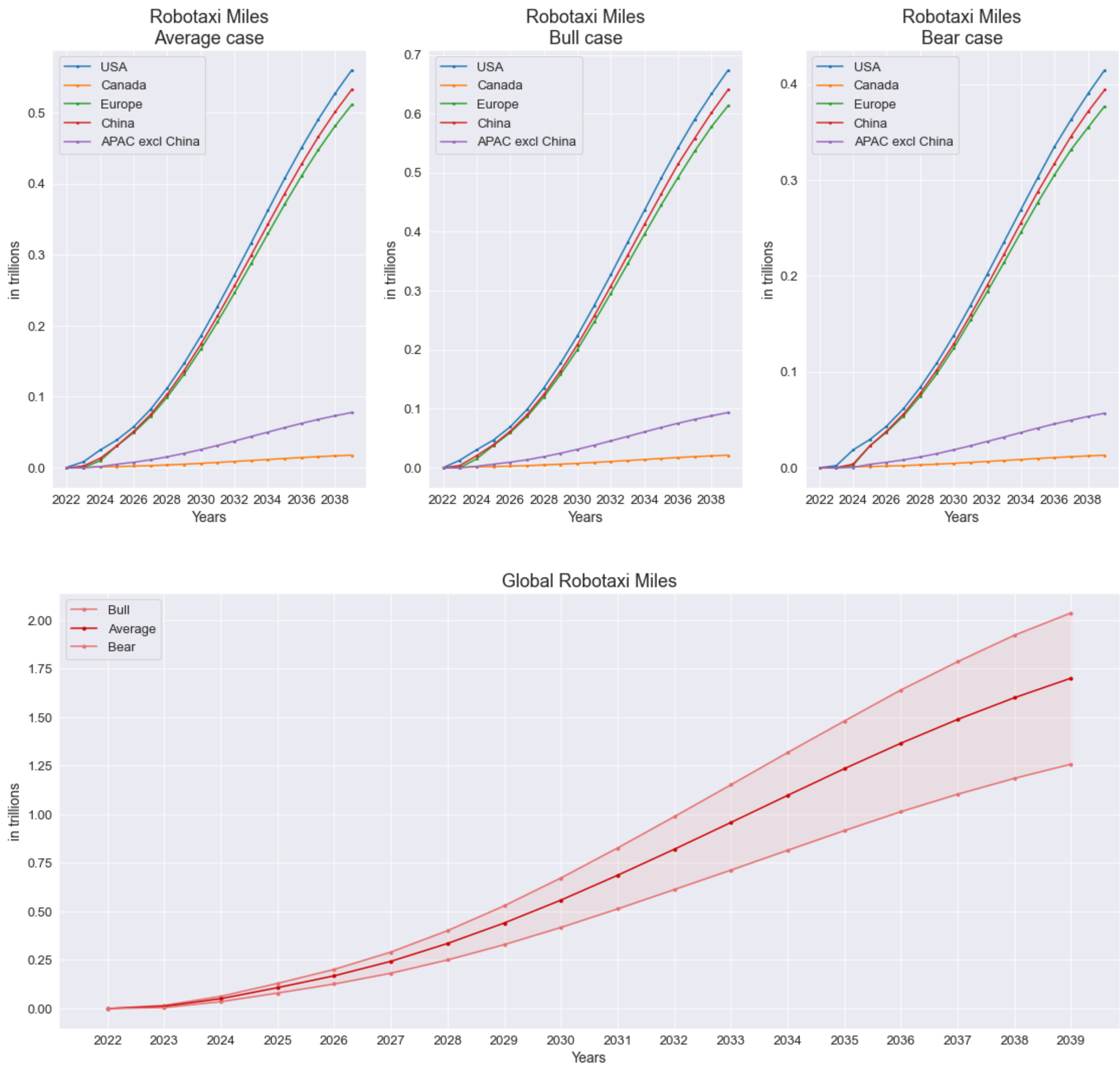


Figure 16: Projected Tesla Robotaxi miles

5.4.5 Robotaxi miles as percentage of VMT in the US

To assess the relevance of the simulated Robotaxi miles, it has been compared to the Vehicles Miles Travelled in the United States. Using the historical data (U.S. Department of Energy, 2021) and applying a simple ARIMA model the projected VMT per year can be used to have a more accurate perception of the potential impact. Most probably the VMT in the future will be higher because of the lower cost in transport that autonomous ride-hailing represents. Nevertheless, it is still a useful calculation for understanding the magnitude of the impact.

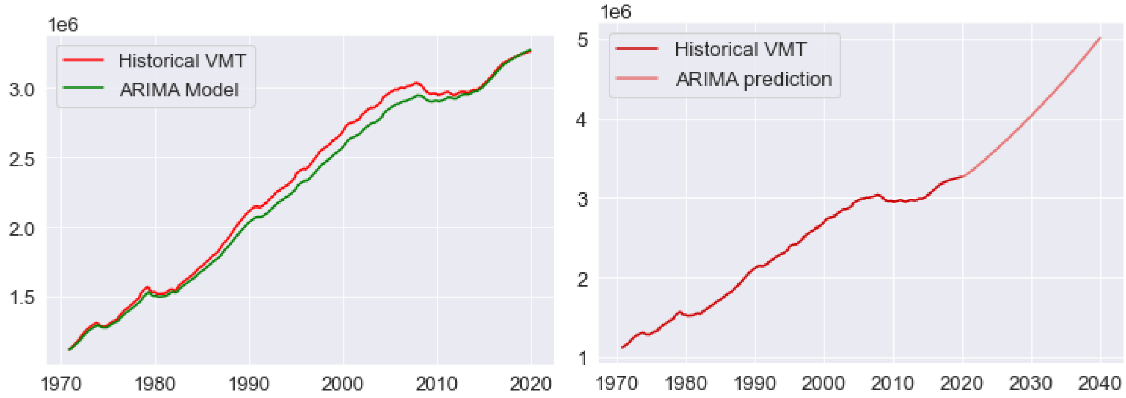


Figure 17: ARIMA model for US VMT

The result from this analysis it is that the Robotaxi network will have a significant effect on the industry because at the end of the next decade it may represent around 10% of all miles driven in the United States.

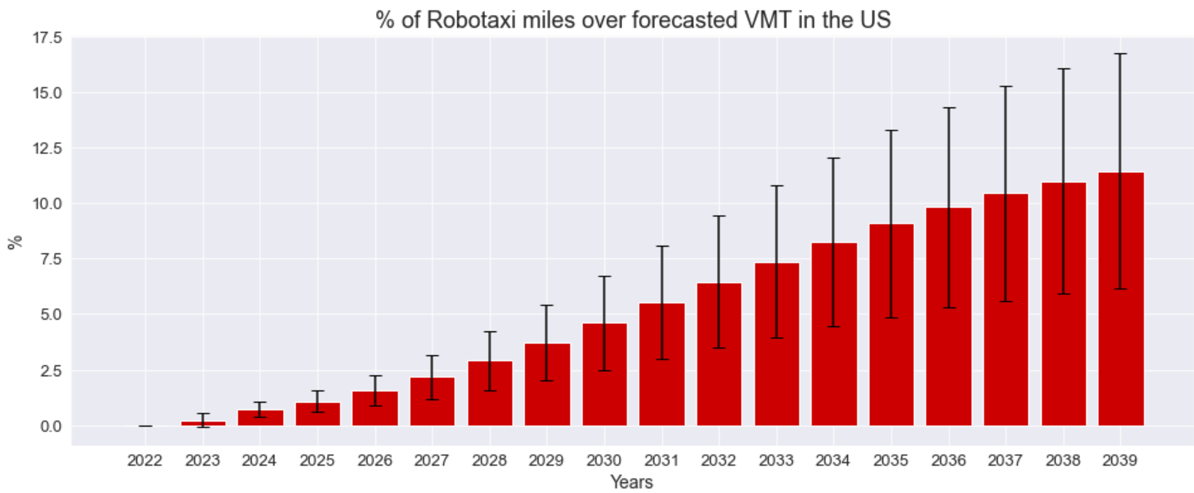


Figure 18: Projected percentage of Robotaxi miles over forecasted VMT in the US

5.4.6 Tesla's revenue

In terms of economic impact, the most important output of the model is the expected revenue for Tesla. This result helps to understand the potential economic opportunity that autonomous ride-hailing represent and explains why so many companies are investing billions of dollars into self-driving technology. The investment required is dwarfed by the potential revenue opportunity in the future if the necessary scale is achieved.

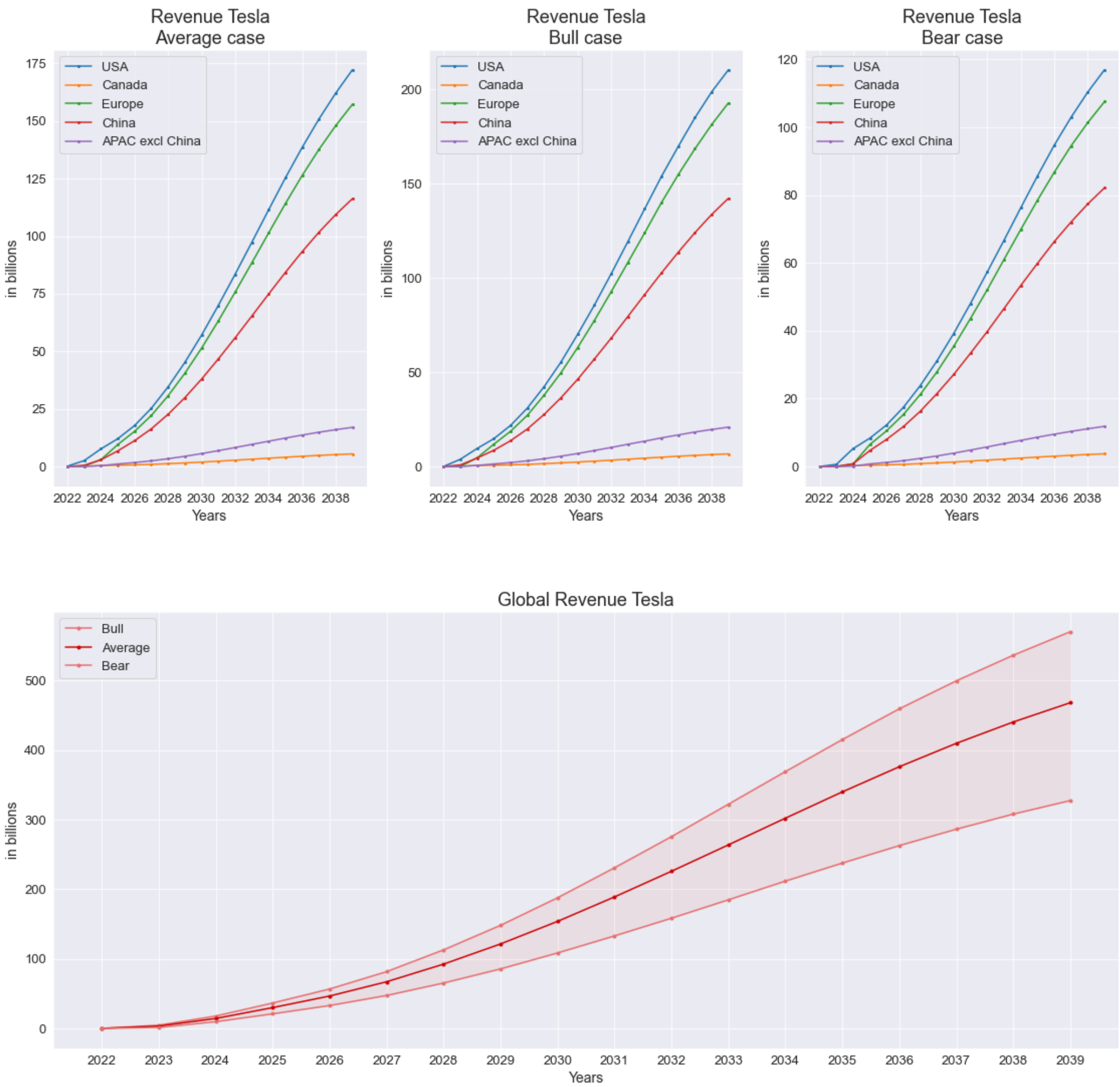


Figure 19: Projected revenue of Tesla Robotaxi Network

Another important fact about this output is that most of the revenue will become profit, as the car owner pays for the hardware and Tesla only provides the software, which requires very little operational costs in comparison with the revenue. This is also highly conservative considering that Tesla will most probably run their own fleet of Tesla Robotaxis, this would require more initial capital investment into the cars, which would easily be recovered in a short period of time because of the recurring revenue from the service.

5.4.7 Car's owner revenue

According to Tesla the total gross profit per car per year would be around $30.000 (Tesla, 2019b), most probably Tesla was given this metric not as an average for people in the network but for people with a certain time per day in the network and in densely populated areas. Therefore, the conservative result is reasonable.

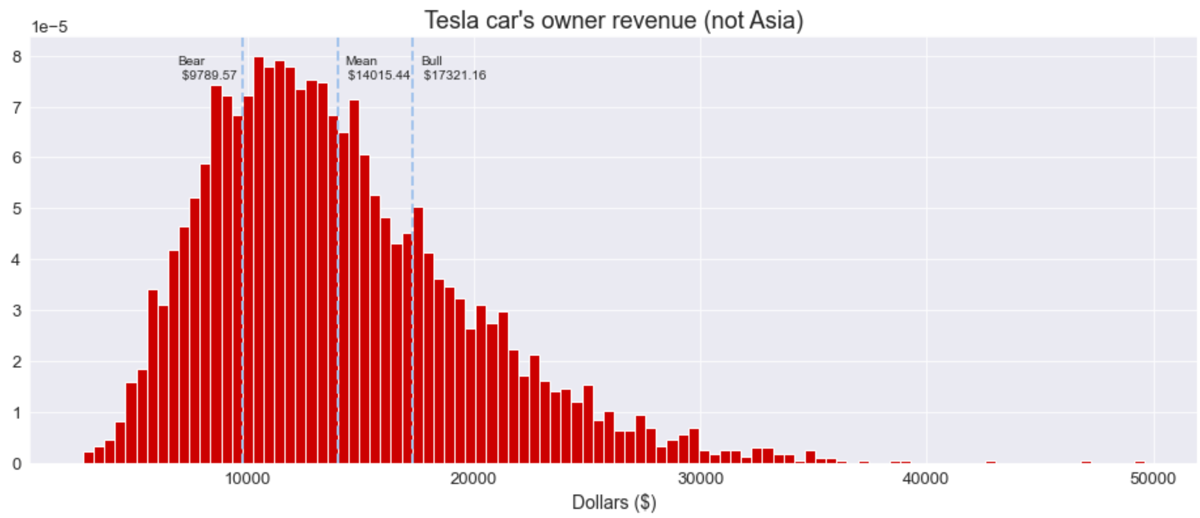


Figure 20: Projected distribution of average car's owners (not Asia) yearly revenue in the Robotaxi Network

The Robotaxi service will have a lower price in China because of the lower salaries in the region and the more competitive environment in the ride-hailing industry.

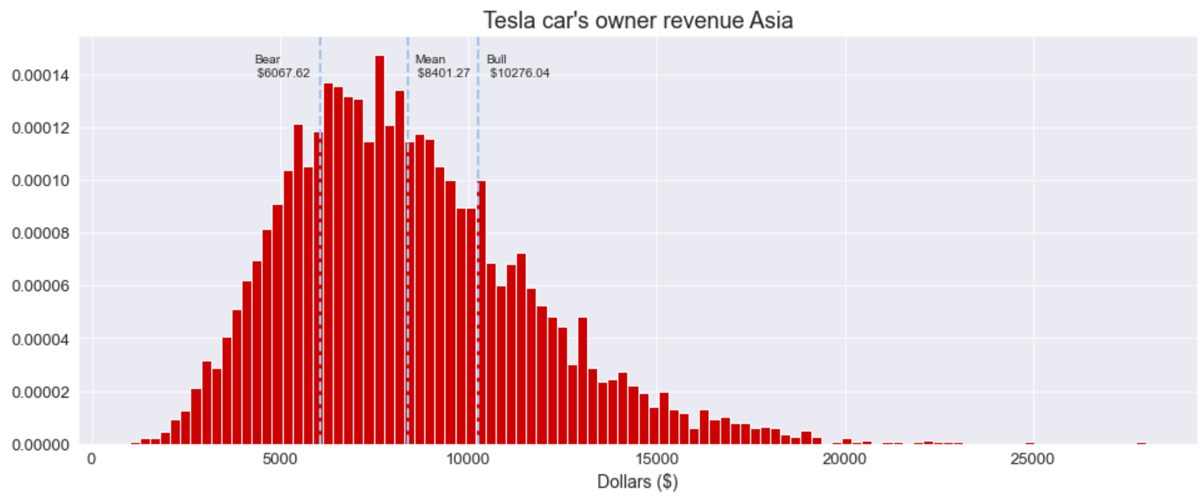


Figure 21: Projected distribution of average car's owners in Asia yearly revenue in the Robotaxi Network

Another positive data point for the car owners is that the price of the cars that the network will operate will be lower than the current ones because Tesla will release in the near future an even cheaper car than the Model 3. This has been already confirmed by Elon Musk and the cost would be around $25.000 and being conservative the release date would be 2024 (Lambert, 2021).

5.4.8 CO_2 saved

The environment is one of the biggest concerns of society right now, and the autonomous ride-hailing may play a relevant role on this issue, because of the lower cost they will displace internal combustion engine cars, and therefore pollution on those miles. Obviously not all trips will substitute ICE trips but considering the market share of electric cars most will. On the other hand, the savings will be bigger than the calculated because the data for difference in CO_2 emissions between internal combustion engine and electric cars used (Bieker, 2021) does not take into account the higher degree of utilization and lifespan that the Tesla Robotaxi cars will have or the evolution of the grid towards renewables. This result is relevant to understand the magnitude of the potential positive effects on the environment.

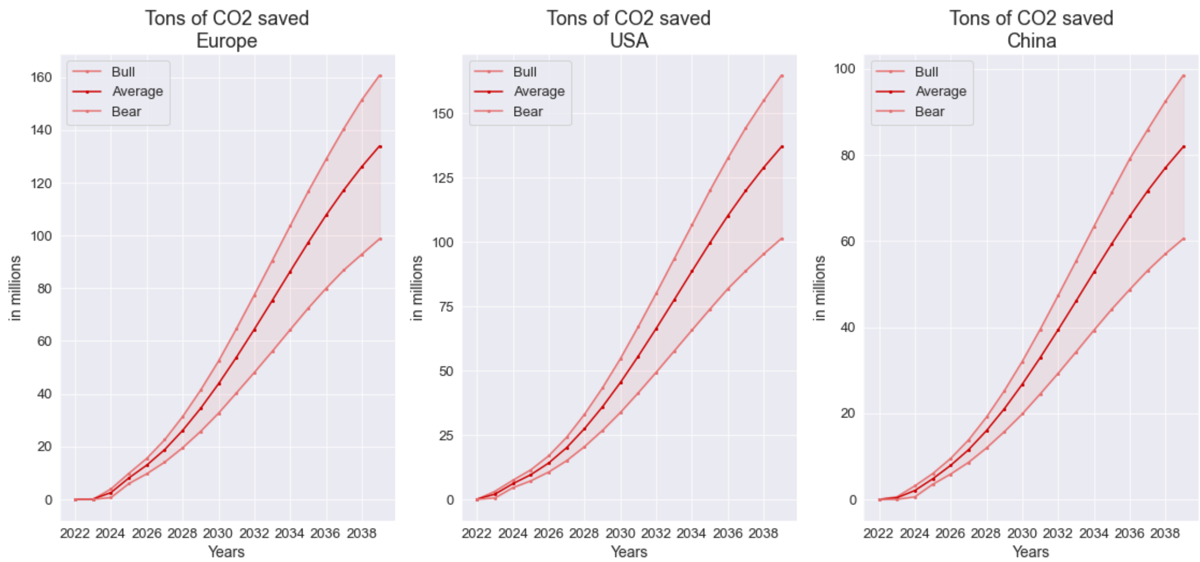
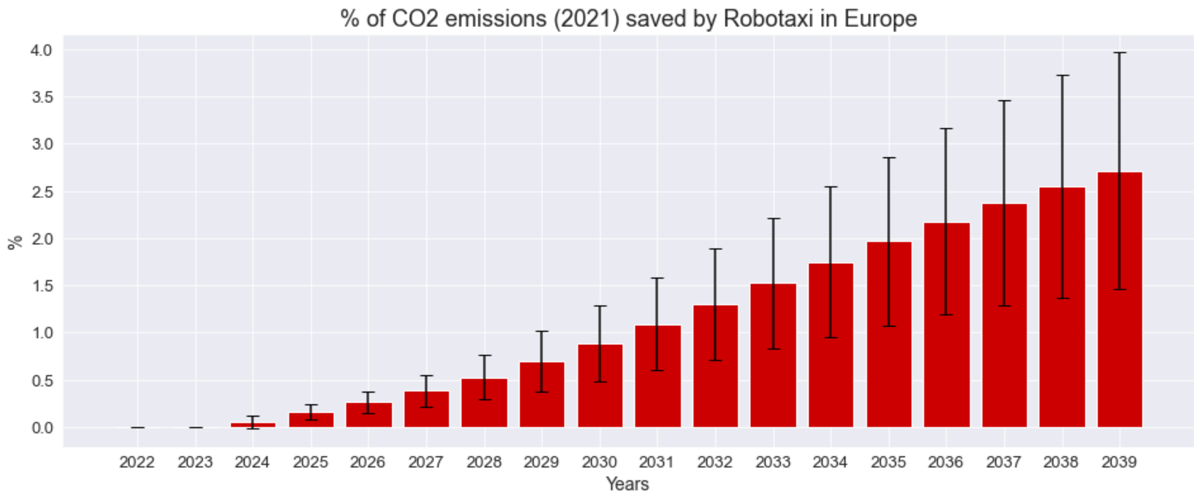
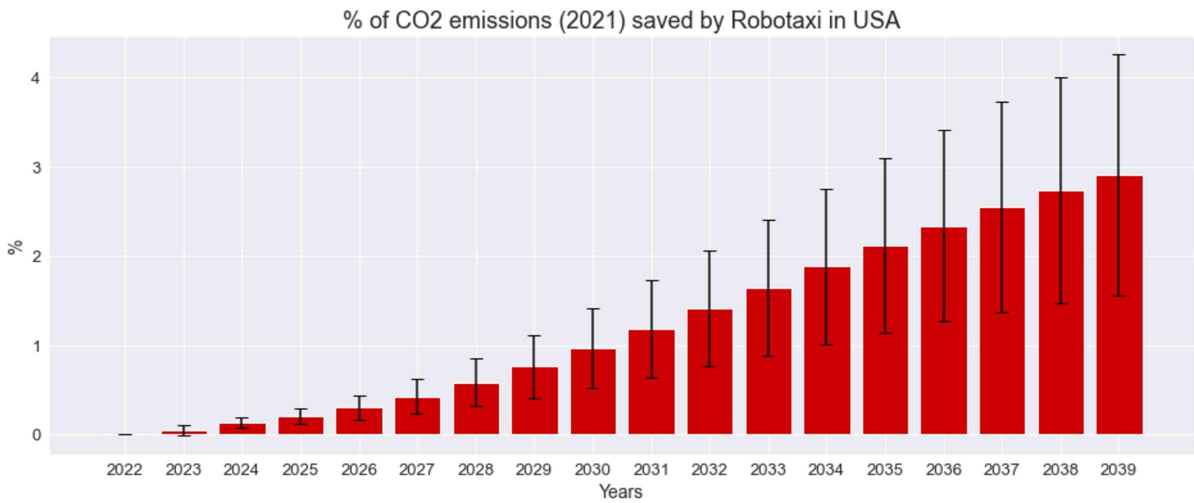


Figure 22: Projected tons of CO_2 saved by Robotaxi Network in Europe, USA, and China

This data can now easily be compared with the current CO_2 emissions (Ritchie & Roser, 2020) of the three regions in order to see the percentage that this savings may represent in the future in comparison with the present pollution.





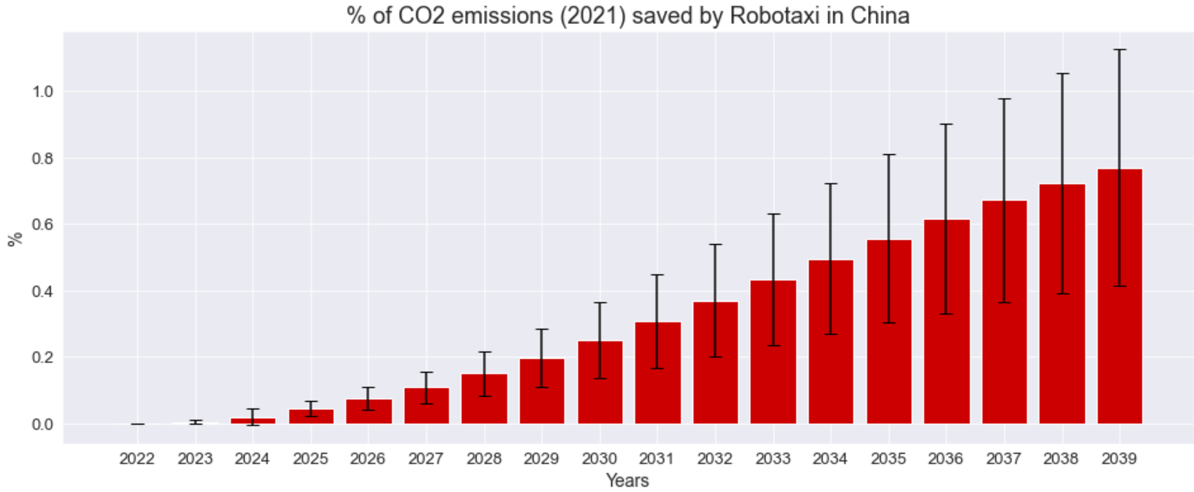


Figure 23: Projected percentage of emitted CO2 saved by Robotaxi Network in Europe, USA, and China

5.4.9 Economic savings derived from health-related issues derived from pollution

It has been previously discussed in this master thesis that the pollution has health related costs in society, to be more specific, for every gallon of gasoline used in the U.S. there is an associated $1.15 in health damage costs, like heart attacks, lung cancer and societal damage related to climate change (Holmes-Gen & Barret, 2016). Combining this data point average miles per gallon in the US (United States Environmental Protection Agency, 2021) and the Robotaxi miles and the supposition that it is substituting internal combustion engine trips, the potential savings are obtained.

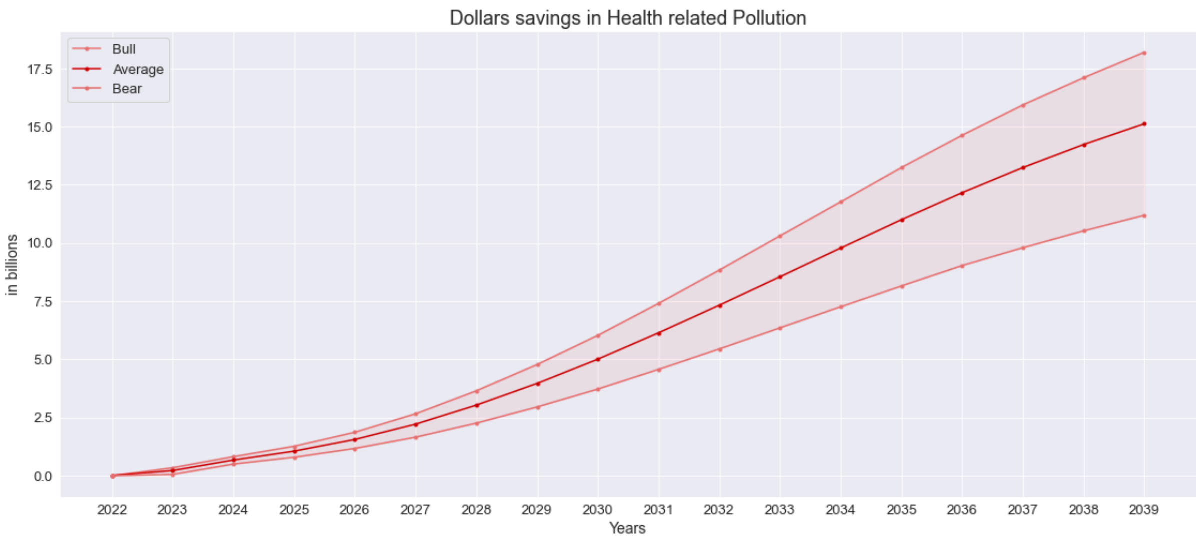


Figure 24: Projected economic savings in health-related pollution by the Robotaxi Network in the US

5.4.10 Cars displaced by Robotaxis

Making use of the total Robotaxi miles per year in combination with the average miles driven (U.S. Department of Transportation Federal Highway Administration, 2018) by cars in the United States it is possible to simulate the cars displaced. In the graph the current total registered car number has been included in order to appreciate the speed at which these cars will be displaced. Tesla cars not in the network will also displace other ICE cars but this is not analysed, as the focus is the Robotaxi network.

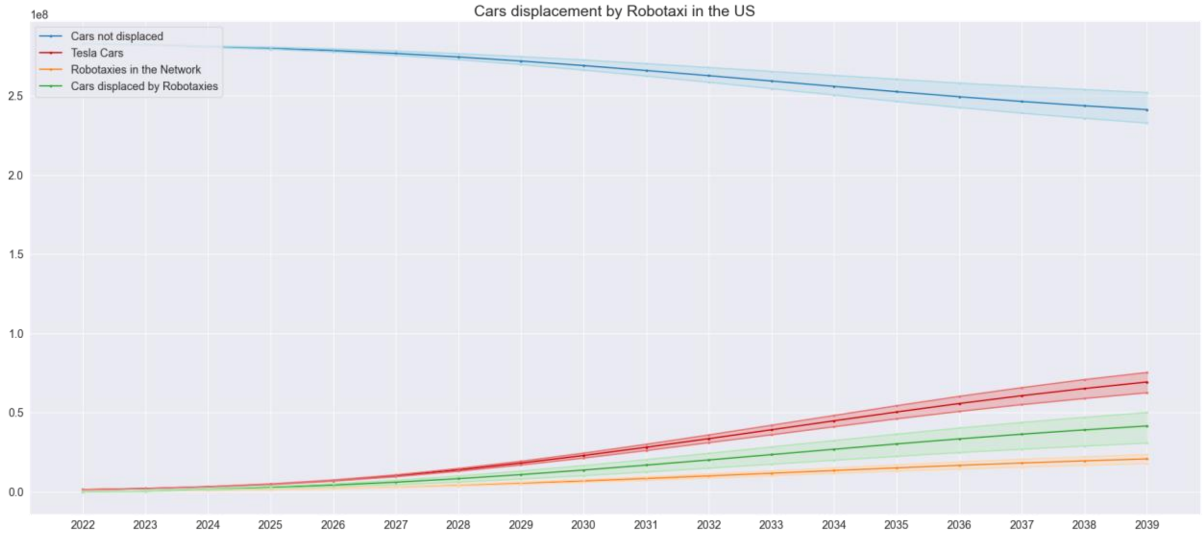


Figure 25: Projected car displacement by the Robotaxi network in the US

In the graph it can be observed that the cars displaced by each Robotaxi in the network is higher than one. According to this calculation in average each Tesla car which participates in the Robotaxi will displace approximately two cars. The potential for displacement per car could be significantly higher, the conservative inputs used should be taken into account.

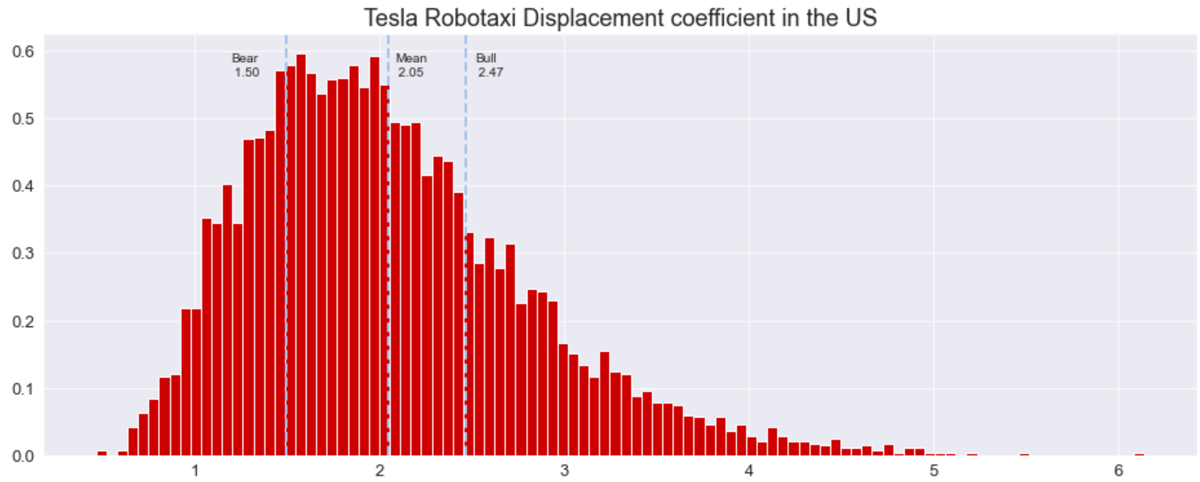
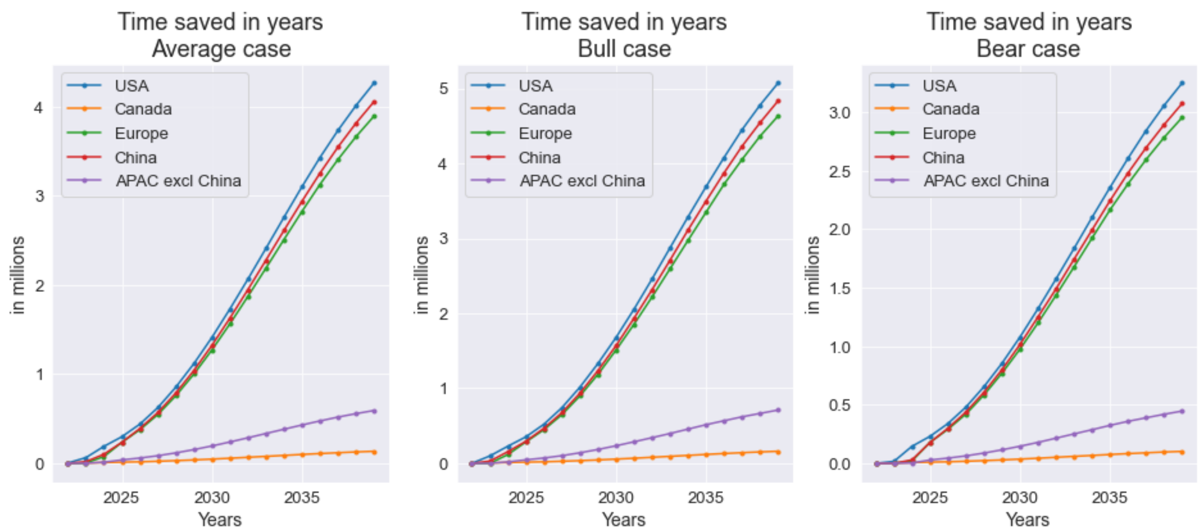


Figure 26: Projected Robotaxi displacement coefficient in the US

5.4.10 Potential time savings

Self-driving technology will suddenly make available a lot of time for its users, the simulated time saved in years for the different regions is the following.



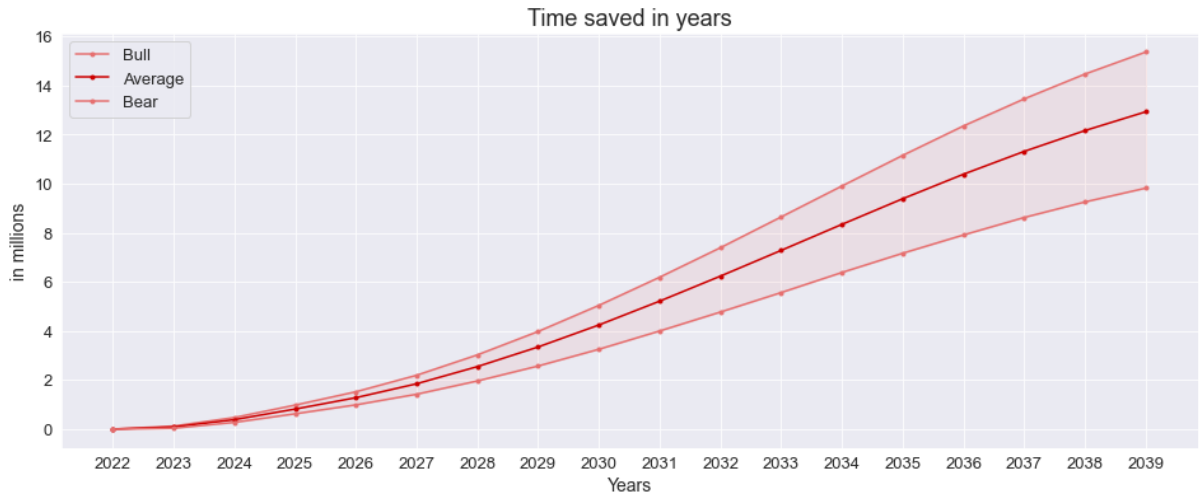
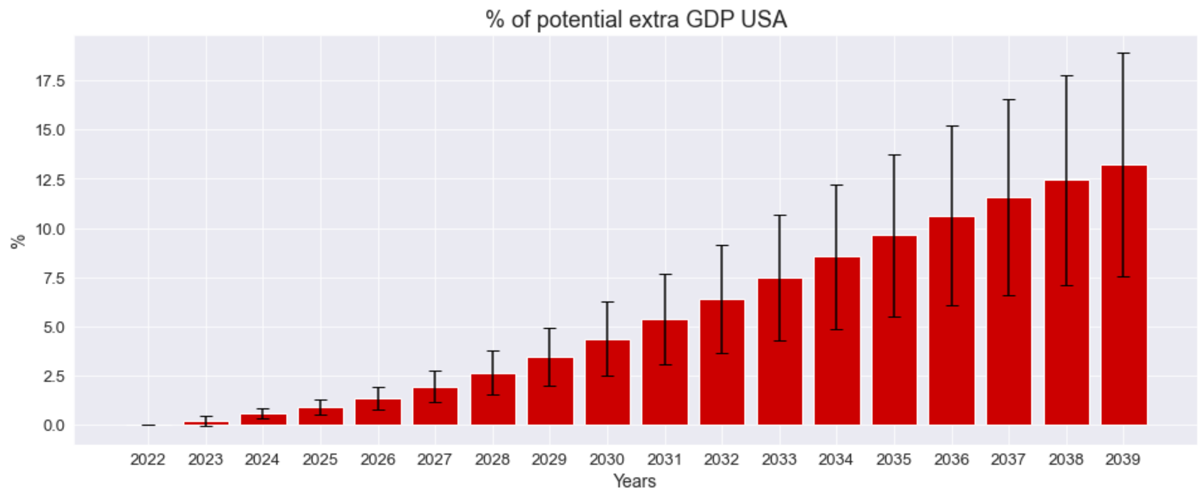


Figure 27: Projected time savings by the Robotaxi network

5.4.11 Maximum potential GDP increase

This time will mostly be used for entertainment most probably, but it nevertheless interesting to see what potential this paradigm change would have if this time was used for productivity purposes. The hypothetical potential increase in GDP (comparing with 2020 data) because of the Robotaxi network would be:



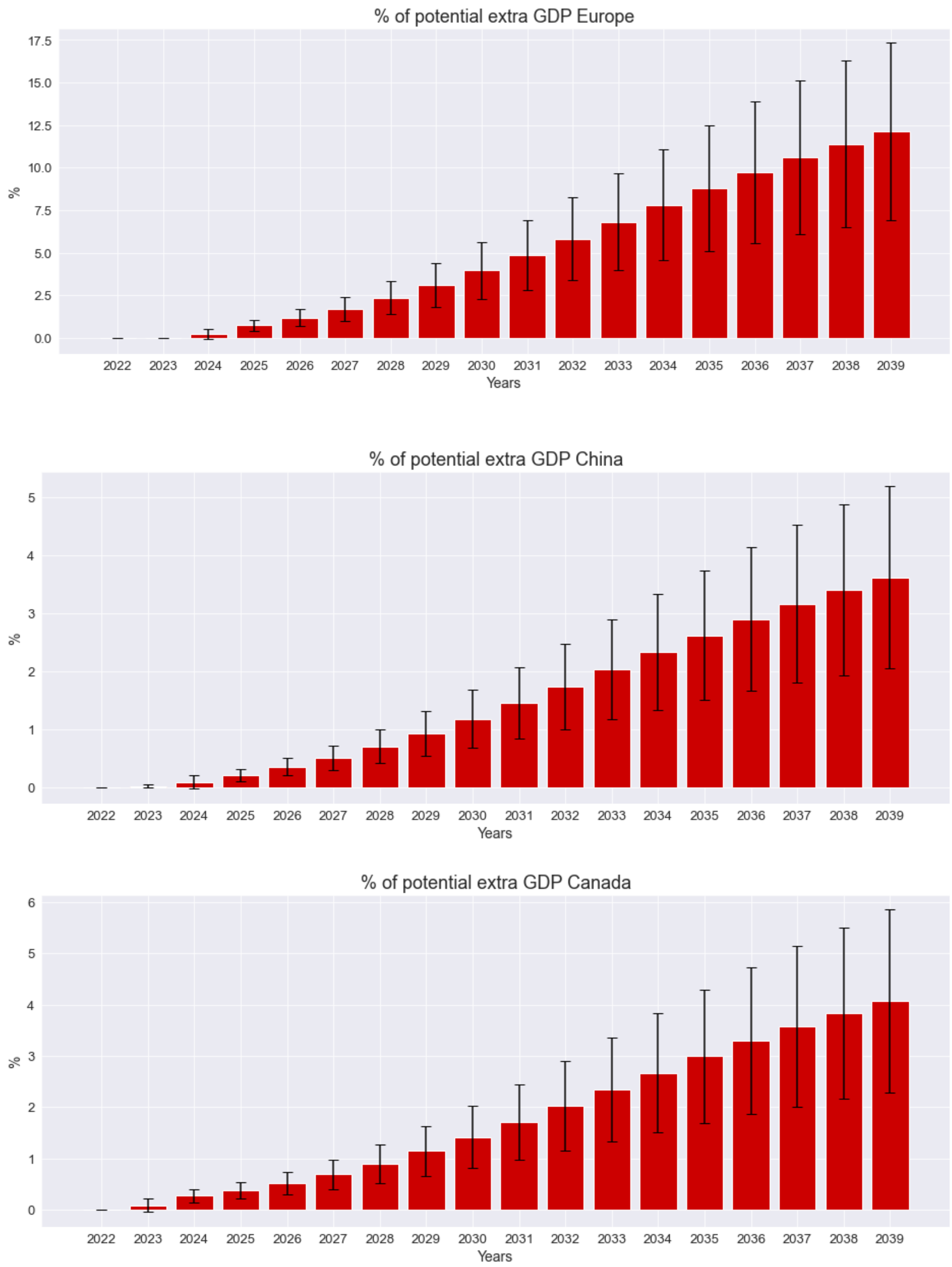


Figure 28: Projected potential extra GDP by Robotaxi network by area

6. Conclusions

Self-driving technology is possible thanks to thousands of inventors, entrepreneurs, engineers, and scientists that worked on the different technologies that empower the incoming technological revolution. At this point in time multiple technologies and cost curves are converging for this new chapter in the history of transportation and the world. The automotive industry is about to be disrupted, a bigger and faster disruption than the electric vehicle revolution taking place. Based on the conducted research, Tesla is one of the leaders in the race for solving level 4 or 5 autonomous technology. But they are not alone, billions of dollars are being invested every year and there are tens of companies trying to be a relevant player in this new industry.

The economic potential is enormous, and the companies that deploy their autonomous ride-hailing service will have a first mover advantage and an economic flywheel which will help them scale at a tremendous pace. The scale of the opportunity is reflected in the output from the Monte Carlo simulation model developed for this master thesis. Using conservative inputs, the results of the simulation indicate that the revenue per year in 2040 for the Robotaxi Network could be, considering the hypothesis in the model, of half trillion dollars, which would be mostly profit because of the business model and cost structure of the business. According to the production growth projections Tesla could also become the biggest automaker in ten years approximately, surpassing Toyota in the year 2029.

Their Robotaxi network would be able to capture a significant part of the total addressable market, representing around 10% of all vehicle miles travelled by 2040. The environment would greatly benefit from this transition to electric vehicles because, the lower costs of the service would displace millions of internal combustion cars every year helping to save over 2% of current CO_2 emissions in the US and Europe and around 0.7% in China. Without the need for driving millions of hours per year will be freed, which will have a significant impact on the productivity and gross domestic products of countries if some part of that time can now be used for other productive tasks.

The disruption also offers an opportunity to improve the city's urban planning, new plots of land will progressively become available as the demand for parking diminishes thanks to the autonomous ride-hailing services. This will be the right set of circumstances to redesign the cities focusing more on people's needs and not the car needs. The faster electrification of the car fleet thanks to the higher displacement rate will make the cities air cleaner and save billions on health-related issues.

Traffic and accident rates will greatly improve with the introduction of autonomous vehicles because a significant share of the traffic and accidents occur because of human errors, because the slow reaction time, lack of communication or distractions. Millions of lives will be saved and hundreds of millions of injuries will be avoided. People will also experience important cost savings because of the higher utilization rate of autonomous ride-hailing in comparison with owning a car, this will definitely have a positive effect on other industries that will grow because of the higher disposable income of families.

In terms of unemployment a lot of jobs will be displaced by this technology, like taxi driver or truck drivers. Retraining for these workers will be crucial, as other job opportunities will be created in other areas of the economy because of the disruption and the increase in productivity in the economy. This growth will be caused in part by the higher efficiency transportation system, which has the potential of offsetting the lost jobs. On a longer term this technology could be applied to other uses, because one key element of autonomous driving is interpreting the world around the vehicle, which is one of the first steps for developing other artificial intelligence tools that interact with the real world in a physical manner and not just software.

Regulators are already setting the groundwork for setting the rules that the industry will need to follow, but there is a lot of work to be done on this area, and the disruption may happen before most people expect. This is why further research on the topic is necessary, in order to make a smoother and more beneficial transition to the autonomous future.

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Appendix

Appendix A

California DMV disengagement Report

2019

Company	Miles	Diseng.	Miles / Diseng.
Waymo	1,454,137	110	13,219.40
CRUISE	831,040	68	12,221.20
Pony.ai	174,845	27	6,475.80
Baidu	108,300	6	18,050.00
Nuro	68,762	34	2,022.40
Zoox	67,015	42	1,595.60
Lyft	42,931	1667	25.8
AutoX	32,054	3	10,684.70
Mercedes Benz	14,238	2054	6.9
Aurora	13,429	141	95.2
DiDi	12,279.40	8	1,534.90
Apple	7,544	64	117.9
NVIDIA	7,218	655	11
Aimotive	6,056	26	232.9
WeRide	5,917	39	151.7
ThorDrive	5,089.00	27	188.5
Drive.ai	3,974	75	53
SF Motors / Seres	3,493	140	24.9
Ambarella	3,161.00	52	60.8
Gatik AI	2,553.00	24	106.4
Nullmax	2,430	70	34.7
Nissan	2,277	47	48.5
SAIC	2,230	40	55.7
Qualcomm	2,164	37	58.5
PlusAI	1,880	2	940
Toyota	1,817	2947	0.6
Intel	1,295.00	165	7.8
Phantom AI	1,125	43	26.2
Udelv	707	444	1.6
Apex.Ai	448.3	63	7.1
Valeo	100	92	1.1
Box Bot	38.5	109	0.4
Telenav	22	3	7.3
BMW	21	8	2.7
RIDECELL	8.7	6	1.4

2020

Company	Miles	Diseng.	Miles / Diseng.
Cruise	770,049	27	28,520.34
Waymo	628,839	21	29,944.69
Pony.AI	225,496	21	10,737.90
Zoox	102,521	63	1,627.32
Nuro	55,370	11	5,033.62
AutoX	40,734	2	20,367.00
Lyft	32,731	123	266.11
Mercedes	29,984	1,167	25.69
Argo.AI	21,037	2	10,518.59
Apple	18,805	130	144.66
WeRide	13,014	2	6,507.00
Aurora	12,208	37	329.93
DiDi	10,401	2	5,200.75
Deeproute.AI	10,018	3	3,339.33
QCraft	7,582	16	473.88
NVIDIA	3,033	125	24.26
Aimotive	2,987	113	26.43
Toyota	2,875	1,215	2.37
Gatik.AI	2,352	11	213.82
Qualcomm	1,727	90	19.19
SF Motors	875	61	14.34
EasyMile	424	128	3.31
Nissan	395	4	98.63
Ridecell	148	189	0.78
BMW	122	3	40.67
Udelv	66	49	1.35
Valeo	49	99	0.49
Atlas R.	47	10	4.74
Telenav	4	2	2

Appendix B

Monte-Carlo Simulation Code

Libraries

```
#Data manipulation
import numpy as np
import pandas as pd
import math
import scipy.stats as stats
from datetime import timedelta
from datetime import datetime
#Data visualization
import matplotlib.pyplot as plt
%matplotlib inline
from tabulate import tabulate
import seaborn as sns
from matplotlib.ticker import MaxNLocator
# ARIMA forecast
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.arima_model import ARIMA
from pandas.plotting import register_matplotlib_converters
register_matplotlib_converters()
```

General Settings

```
years_to_simulate=2039
years=list(range(2022, years_to_simulate+1))
simulations=5000
simulation_list = list(range(0, simulations))
```

Graphs style defaults

```
sns.set_style('darkgrid')
sns.color_palette('pastel')
plt.rc('axes', titlesize=18)
plt.rc('axes', labelsize=14)
plt.rc('xtick', labelsize=13)
plt.rc('ytick', labelsize=13)
plt.rc('legend', fontsize=13)
plt.rc('font', size=13)
```

Functions

```
# This function returns the random simulations based on the normal probability distribution given
def simulate_norm_dist (mini,bear,bull,maxi):
    mu = (bear+bull)/2
    sigma = bull-mu
    list_return = stats.truncnorm(
    (mini - mu) / sigma, (maxi - mu) / sigma, loc=mu, scale=sigma)
    x=list_return.rvs(simulations)
    return(x)

# Given a row with a distribution returns the simulations
def simulate_normal_dist_row(row):
    return simulate_norm_dist(row['Min'],row['Bear'],row['Bull'],row['Max'])

# This function returns the simulation of Robotaxi Deployment date
def get_sims_robo_deployment(table):
```

```
    areas=table.index
    robo_deployment_simulations=[]
    for area in areas:
        sim_result=simulate_norm_dist(table['Min'][area],table['Bear'][area],table['Bull'][area],table
['Max'][area])
        robo_deployment_simulations.append(sim_result)
    robo_deployment_simulations_df = pd.DataFrame(robo_deployment_simulations, index=table.index).T
    return robo_deployment_simulations_df

#This function transforms a dataframe from datetime to timestamp
def datetime_to_timestamp(table):
    table_timestamp=pd.DataFrame(index=table.index, columns=table.columns)
    for row in table.index:
        for column in table.columns:
            table_timestamp[column][row]=datetime.timestamp(table[column][row])
    return table_timestamp

#This function transforms a dataframe from timestamp to datetime
def timestamp_to_datetime(table):
    table_datetime=pd.DataFrame(index=table.index, columns=table.columns)
    for row in table.index:
        for column in table.columns:
            table_datetime[column][row]=datetime.fromtimestamp(table[column][row])
    return table_datetime

#This function creates the simulation of future production growth for a region
def get_years_regions_future_production(row):
    years_simulations=pd.DataFrame()
    for year in years:
        sim_result=simulate_norm_dist(row['Min'],row['Bear'],row['Bull'],row['Max'])
        years_simulations[year]=sim_result
    return years_simulations

#This function standarises the simulation percentages so they add up to 100%
def get_standarise_percentages(dictionary):
    for year in years:
        for i in simulation_list:
            total_sum=0
            for area in dictionary.keys():
                total_sum+=dictionary[area][year][i]
            for area in dictionary.keys():
                dictionary[area][year][i]=dictionary[area][year][i]/total_sum
    return dictionary

#Percentage of Robotaxi network availability per year per region
def get_all_percentage_years_robo (dates_by_area):
    result = {}
    years_percentage_list=[]
    for area in dates_by_area.columns:
        result_temp = pd.DataFrame(columns=years, index = simulation_list)
        for i in simulation_list:
            initial_year=dates_by_area[area][i].year
            years_to_change = [year_no_robo for year_no_robo in years if year_no_robo <= initial_year]
            for year in years_to_change:
                if year == initial_year:
                    result_temp[year][i] = get_percentage_year_left(dates_by_area[area][i])
                else:
                    result_temp[year][i]=0
        result_temp.fillna(1, inplace=True)
        result[area]=result_temp
    return result

#Get expected revenue by Tesla based on Robotaxi miles and price
def get_revenue_tesla_per_region(gen_inp, robo_miles):
    ppm = gen_inp['Price/Mile']
    ppma = gen_inp['Price/Mile Asia']
    pf = gen_inp['Platform fee']
```

```
    result = {}
    for area in robo_miles:
        if area == 'China' or area == 'APAC excl China':
            ppm_aux = ppma
        else:
            ppm_aux = ppm
        result_area = pd.DataFrame(index = simulation_list,columns=years)
        for i in simulation_list:
            for year in years:
                result_area[year][i]= ppm_aux[i]*robo_miles[area][year][i]*pf[i]
        result[area]=result_area
    return result

#Return percentage of availability of the robotaxi network based on deployment date
def get_percentage_years_robo (date):
    years_percentage_list=[]
    initial_year=date.year
    for year in years:
        if year > initial_year:
            years_percentage_list.append(1)
        elif year == initial_year:
            years_percentage_list.append(get_percentage_year_left(date))
        else:
            years_percentage_list.append(0)
    return pd.DataFrame(years_percentage_list, index = years)

#Return percentage of a year left based on a date
def get_percentage_year_left (date):
    return (365-date.timetuple().tm_yday)/365

#Returns the average for dataframe by years
def get_average_per_year(dataframe):
    result = pd.DataFrame(columns=['average'], index = years )
    for year in years:
        result.loc[year]=dataframe[year].mean()
    return result

#Returns the quantile of a series
def get_quantile_per_year(dataframe, q):
    result = pd.DataFrame(columns=['Q'], index = years )
    for year in years:
        result.loc[year]=dataframe[year].quantile(q)
    return result

#Given the dictionary with the areas you get the global dataframe
def get_global_from_areas(data):
    result = pd.DataFrame(0,columns=years, index = simulation_list)
    for area in data:
        result+=data[area]
    return result
#Plot areas avg, bear, bull
def plot_area_series(data,legend,magnitude=0):
    fig, axes = plt.subplots(figsize=(19,8), nrows=1, ncols=3)
    if magnitude==6:
        magnitude_label='in millions'
    elif magnitude==9:
        magnitude_label='in billions'
    elif magnitude==12:
        magnitude_label='in trillions'
    else:
        magnitude_label=''
        magnitude=0
    magnitude=pow(10,magnitude)
    i=0
    for graph in axes:
        graph.set_xlabel('Years')
        graph.set_ylabel(magnitude_label)
```

```
        if i==0:
            graph.set_title(legend + "\nAverage case")
            for area in data:
                graph.plot(get_average_per_year(data[area])/magnitude,label=area, marker='o', markersi
ze=2)
        elif i==1:
            graph.set_title(legend + "\nBull case")
            for area in data:
                graph.plot(get_quantile_per_year(data[area]/magnitude,0.75),label=area, marker='o', ma
rkersize=2)
        else:
            graph.set_title(legend + "\nBear case")
            for area in data:
                graph.plot(get_quantile_per_year(data[area]/magnitude,0.25),label=area, marker='o', ma
rkersize=2)
        graph.legend(loc=2)
        i+=1
        graph.xaxis.set_major_locator(MaxNLocator(integer=True))
    return

#Plot global avg, bear, bull together
def plot_global_series(data,legend,magnitude=0):
    if magnitude==6:
        magnitude_label='in millions'
    elif magnitude==9:
        magnitude_label='in billions'
    elif magnitude==12:
        magnitude_label='in trillions'
    else:
        magnitude_label=''
        magnitude=0
    magnitude=pow(10,magnitude)
    fig, axes = plt.subplots(figsize=(19,8))
    axes.set_xlabel('Years')
    axes.set_ylabel(magnitude_label)
    axes.set_title(legend)
    axes.plot(get_quantile_per_year(data,0.75)/magnitude, marker='o', markersize=3,label='Bull',color=
'#e67070')
    axes.plot(get_average_per_year(data)/magnitude, marker='o', markersize=3,label='Average',color='#c
c0000')
    axes.plot(get_quantile_per_year(data,0.25)/magnitude, marker='o', markersize=3,label='Bear',color=
'#e67070')

    sup=(pd.DataFrame(get_quantile_per_year(data,0.75)['Q'].tolist())/magnitude)[0].tolist()
    bot=(pd.DataFrame(get_quantile_per_year(data,0.25)['Q'].tolist())/magnitude)[0].tolist()
    axes.fill_between(years,sup, bot,color='#e67070', alpha=.1)
    axes.xaxis.set_major_locator(MaxNLocator(integer=True))
    axes.legend(loc=2)
    plt.xticks(years)
    return

#Plot just three areas and their avg, bear, bull together
def plot_3_areas(data,legend,magnitude=0):
    areas=list(data.keys())
    if magnitude==6:
        magnitude_label='in millions'
    elif magnitude==9:
        magnitude_label='in billions'
    elif magnitude==12:
        magnitude_label='in trillions'
    else:
        magnitude_label=''
        magnitude=0
    magnitude=pow(10,magnitude)
    fig, axes = plt.subplots(figsize=(19,8), nrows=1, ncols=3)
    i=0
    for graph in axes:
```

```
        graph.set_xlabel('Years')
        graph.set_ylabel(magnitude_label)
        graph.set_title(legend+ '\n' + areas[i])
        graph.plot(get_quantile_per_year(data[areas[i]],0.75)/magnitude, marker='o', markersize=2,labe
l='Bull',color='#e67070')
        graph.plot(get_average_per_year(data[areas[i]])/magnitude, marker='o', markersize=2,label='Ave
rage',color='#cc0000')
        graph.plot(get_quantile_per_year(data[areas[i]],0.25)/magnitude, marker='o', markersize=2,labe
l='Bear',color='#e67070')
        graph.legend(loc=2)
        sup=(pd.DataFrame(get_quantile_per_year(data[areas[i]],0.75)['Q'].tolist())/magnitude)[0].toli
st()
        bot=(pd.DataFrame(get_quantile_per_year(data[areas[i]],0.25)['Q'].tolist())/magnitude)[0].toli
st()
        graph.fill_between(years,sup, bot,color='#e67070', alpha=.1)
        graph.xaxis.set_major_locator(MaxNLocator(integer=True))
        i+=1
    return

# Plot Graph based on percentages
def plot_percentage_graph (data,title):
    percetage_avg=get_average_per_year(data)
    percetage_bear=get_quantile_per_year(data,0.25)
    percetage_bull=get_quantile_per_year(data,0.75)
    percetage_bull_bear_diff=percetage_bull['Q']*100-percetage_bear['Q']*100
    fig, axes = plt.subplots(figsize=(16,6))
    axes.set_xlabel('Years')
    axes.set_ylabel('%')
    axes.set_title(title)
    axes.bar(percetage_avg.index,percetage_avg['average']*100,color='#cc0000',yerr=percetage_bull_bear
_diff, capsize=5)
    axes.xaxis.set_major_locator(MaxNLocator(integer=True))
    plt.xticks(years)
```

General Inputs

```
general_inputs=pd.read_csv('./Data/general_inputs.csv', index_col = 0)
general_inputs_sims = pd.DataFrame()

for item in general_inputs.index:
    general_inputs_sims[item]=simulate_normal_dist_row(general_inputs.loc[item])

general_inputs_sims['Miles/car']= 52*general_inputs_sims['Days/week']*general_inputs_sims['Hours/day']
*general_inputs_sims['Miles/hour']*general_inputs_sims['% ocupacy']
```

Production History

```
#Global Historic
glob_del_hist=pd.read_csv('./Data/tesla_production_history.csv', index_col = 0)
glob_del_hist.loc['Total']= glob_del_hist.sum(axis=0)
glob_del_hist_wo_total=glob_del_hist[:-1]
glob_del_hist_graph=glob_del_hist_wo_total.drop(columns=['Total'])

# Plot production history
fig, ax = plt.subplots(figsize=(16,10))

prev_aux=glob_del_hist_graph['USA']*0
for area in glob_del_hist_graph:
    ax.bar(list(glob_del_hist_graph.index), glob_del_hist_graph[area], label=area,bottom=prev_aux)
    prev_aux+=glob_del_hist_graph[area]
ax.set_xlabel('Years')
ax.set_ylabel('Production')
```

```
ax.set_title("Tesla's production by area")
ax.legend()
plt.show()
```

Production distribution

```
#Percentage’s future
percent_region_future = pd.read_csv('./Data/production_area_distribution.csv', index_col = 0)

percent_region_future_sims={}
for area in percent_region_future.index:
    percent_region_future_sims[area]=get_years_regions_future_production(percent_region_future.loc[are
a])

percent_region_future_sims = get_standarise_percentages(percent_region_future_sims)
```

Production, Discontinued and Cumulative cars

```
#Starting point
start_by_area_2021 = glob_del_hist.loc['Total'][:-1]

#Production 2021
production_2021_pred = glob_del_hist['Total'][2021]

#Projected growth input data
proj_prod_input=pd.read_csv('./Data/projected_production_growth.csv', index_col = 0)

# Get growth percentage
proj_prod_input
growth_percentage = pd.DataFrame(columns=years, index = simulation_list)
for year in years:
    growth_percentage[year]=simulate_norm_dist(proj_prod_input['Min'][year],proj_prod_input['Bear'][ye
ar],proj_prod_input['Bull'][year],proj_prod_input['Max'][year])

#Simulations of lifespan
discontinued_sims = general_inputs_sims['Car Lifespan']

#Get discontinued cars by region
def get_discontinued_by_calculation (area,year,i,ls,ls_dec):
    result = 0
    if (year - ls) in glob_del_hist :
        result += glob_del_hist[area][year - ls]*(1-ls_dec)
    elif (year - ls) in temp_result_prod:
        result += temp_result_prod[year - ls][i]*(1-ls_dec)
    if (year - ls-1) in glob_del_hist :
        result += glob_del_hist[area][year - ls-1]*ls_dec
    elif (year - ls-1) in temp_result_prod:
        result += temp_result_prod[year - ls-1][i]*ls_dec
    return result

# Get cumulative cars per area
cum_cars_by_area = {}
prod_cars_by_area = {}
prod_disc_by_area = {}
for area in start_by_area_2021.index:
    temp_result_cum = pd.DataFrame(columns=years, index = simulation_list)
    temp_result_prod = pd.DataFrame(columns=years, index = simulation_list)
    temp_result_disc = pd.DataFrame(columns=years, index = simulation_list)
    for i in simulation_list:
        lifespan_sim = math.floor(discontinued_sims[i])
        decimal_lifespan_sim = discontinued_sims[i] % 1
        for year in years:
            if year == 2022:
                temp_result_prod[year][i] = production_2021_pred*(1+growth_percentage[year][i])*percen
t_region_future_sims[area][year][i]
```

```
                temp_result_disc[year][i] = get_discontinued_by_calculation(area,year,i,lifespan_sim,d
ecimal_lifespan_sim)
                temp_result_cum[year][i] = start_by_area_2021[area] + temp_result_prod[year][i]
            else:
                temp_result_prod[year][i] = temp_result_prod[year - 1][i]/percent_region_future_sims[a
rea][year-1][i]*(1+growth_percentage[year][i])*percent_region_future_sims[area][year][i]
                temp_result_disc[year][i] = get_discontinued_by_calculation(area,year,i,lifespan_sim,d
ecimal_lifespan_sim)
                temp_result_cum[year][i] = temp_result_cum[year - 1][i] + temp_result_prod[year][i] -
temp_result_disc[year][i]
    prod_cars_by_area[area] = temp_result_prod
    prod_disc_by_area[area] = temp_result_disc
    cum_cars_by_area[area] = temp_result_cum

#Plot results
plot_area_series(prod_cars_by_area,"Production cars",6)
plot_area_series(prod_disc_by_area,"Discontinued cars",6)
plot_area_series(cum_cars_by_area,"Cumulatitive cars",6)

cum_cars= get_global_from_areas(cum_cars_by_area)
prod_cars= get_global_from_areas(prod_cars_by_area)
prod_disc= get_global_from_areas(prod_disc_by_area)

plot_global_series(prod_cars,"Global Production cars",6)
plot_global_series(prod_disc,"Global Discontinued cars",6)
plot_global_series(cum_cars,"Global Cumulative cars",6)
```

Robotaxi Deployment date

```
robotaxi_deployment_input=pd.read_csv('./Data/robotaxi_deployment_date.csv', index_col = 0, parse_date
s=['Min','Bear','Bull','Max'])

robotaxi_deployment_input_timestamp=datetime_to_timestamp(robotaxi_deployment_input)
sims_robo_deployment = get_sims_robo_deployment(robotaxi_deployment_input_timestamp)
sims_robo_deployment_datetime=timestamp_to_datetime(sims_robo_deployment)

#Plot results
fig, axes = plt.subplots(figsize=(16,16), nrows=5, ncols=1)
fig.tight_layout(pad=5.0)
i=0
for area in sims_robo_deployment_datetime:
    axes[i].hist(sims_robo_deployment_datetime[area],bins=100,density=True, stacked=True, color='#cc00
00')
    axes[i].set_xlabel('Years')
    axes[i].set_title(area)
    i+=1
```

Robotaxi driven miles

```
#Get the percentage of Robotaxi per year to accurately calculate
percentage_years_robo = get_all_percentage_years_robo(sims_robo_deployment_datetime)
robotaxi_miles_per_region = {}
percentage_years_robo
sims_robo_deployment_datetime

for area in cum_cars_by_area:
    aux = pd.DataFrame(columns=years, index = simulation_list)
    for i in simulation_list:
        for year in cum_cars_by_area[area]:
            aux[year][i] = cum_cars_by_area[area][year][i] * general_inputs_sims['Miles/car'][i] * gen
eral_inputs_sims['Network Participation'][i]*percentage_years_robo[area][year][i]
    robotaxi_miles_per_region[area]=aux
robotaxi_miles_per_region

#Global robotaxi miles
robotaxi_miles= get_global_from_areas(robotaxi_miles_per_region)
```

```
plot_area_series(robotaxi_miles_per_region,"Robotaxi Miles",12)
plot_global_series(robotaxi_miles,"Global Robotaxi Miles",12)

#Simulation trend for VMT
vmt_history=pd.read_csv('./Data/VMT_US.csv',parse_dates=['DATE'],index_col = ['DATE'],dayfirst=True)

#ARIMA model

vmt_history_log = np.log(vmt_history)

vmt_model = ARIMA(vmt_history_log, order=(1,1,1))
vmt_model_fit = vmt_model.fit(disp=-1)

predictions_ARIMA_diff = pd.Series(vmt_model_fit.fittedvalues, copy=True)
predictions_ARIMA_diff_cumsum = predictions_ARIMA_diff.cumsum()
predictions_ARIMA_log = pd.Series(vmt_history_log['VMT'].iloc[0], index=vmt_history_log.index)
predictions_ARIMA_log = predictions_ARIMA_log.add(predictions_ARIMA_diff_cumsum, fill_value=0)
predictions_ARIMA = np.exp(predictions_ARIMA_log)
plt.plot(vmt_history, color= 'r',label='Historical VMT')
plt.plot(predictions_ARIMA, color = 'g',label='ARIMA Model')
plt.legend()
vmt_months_sim=12*(years_to_simulate-2019)

vmt_model_fit.plot_predict(1,588+vmt_months_sim)
vmt_forecast=vmt_model_fit.forecast(steps=vmt_months_sim, exog=None, alpha=0.05)

residuals = pd.DataFrame(vmt_model_fit.resid)
fig, ax = plt.subplots(1,2)
residuals.plot(title="Residuals", ax=ax[0])
residuals.plot(kind='kde', title='Density', ax=ax[1])
plt.show()

result_list=[]
for i in range(2020,years_to_simulate+1):
    for j in range(1,13):
        result_list.append('1/'+str(j)+'/'+str(i))
vmt_forecast_dates=pd.to_datetime(result_list,dayfirst=True)
vmt_predicted=pd.DataFrame(columns=['DATE','VMT'])
vmt_predicted['DATE']=vmt_forecast_dates
vmt_predicted['VMT']=np.exp(vmt_forecast[0])
vmt_predicted=vmt_predicted.set_index('DATE')

vmt_history_predicted=vmt_history.append(vmt_predicted)

plt.plot(vmt_history.index,vmt_history['VMT'],color='#cc0000',label='Historical VMT')
plt.plot(vmt_predicted.index,vmt_predicted['VMT'],color='#e67070',label='ARIMA prediction')
plt.legend()


# Percentage of Vehicle Miles Travelled USA (01/02/2020 3271512)
VMT_MA= vmt_predicted.rolling(12, min_periods=1).mean()

us_percetage_vmt=pd.DataFrame(columns=years, index = simulation_list)
for year in years:
    us_percetage_vmt[year]=robotaxi_miles_per_region['USA'][year]/VMT_MA['VMT'][str(year)+'-06-
01']/1000000

plot_percentage_graph(us_percetage_vmt,'% of Robotaxi miles over forecasted VMT in the US')
```

Tesla Revenue

```
revenue_tesla_per_region = get_revenue_tesla_per_region(general_inputs_sims, robotaxi_miles_per_region
)
revenue_tesla_global = get_global_from_areas(revenue_tesla_per_region)

plot_area_series(revenue_tesla_per_region,"Revenue Tesla",9)
plot_global_series(revenue_tesla_global,"Global Revenue Tesla",9)
```

Car owner's revenue

```
car_owner_revenue = (general_inputs_sims['Price/Mile'] * (1-
general_inputs_sims['Platform fee']) - general_inputs_sims['Costs/Mile']) * general_inputs_sims['Miles
/car']

car_owner_revenue_avg=car_owner_revenue.mean()
car_owner_revenue_bear=car_owner_revenue.quantile(0.25)
car_owner_revenue_bull=car_owner_revenue.quantile(0.75)


fig, axes = plt.subplots(figsize=(16,6))
axes.hist(car_owner_revenue, bins=100, density=True, stacked=True, color='#cc0000')
#Average
axes.axvline(car_owner_revenue_avg, color='#a4c4ec', linestyle='dashed', linewidth=2)
min_ylim, max_ylim = plt.ylim()
plt.text(car_owner_revenue_avg*1.02, max_ylim*0.9, 'Mean\n ${:.2f}'.format(car_owner_revenue_avg))
#Bear
axes.axvline(car_owner_revenue_bear, color='#a4c4ec', linestyle='dashed', linewidth=2)
min_ylim, max_ylim = plt.ylim()
plt.text(car_owner_revenue_bear*0.71, max_ylim*0.9, 'Bear\n ${:.2f}'.format(car_owner_revenue_bear))
#Bull
axes.axvline(car_owner_revenue_bull, color='#a4c4ec', linestyle='dashed', linewidth=2)
min_ylim, max_ylim = plt.ylim()
plt.text(car_owner_revenue_bull*1.02, max_ylim*0.9, 'Bull\n ${:.2f}'.format(car_owner_revenue_bull))

axes.set_title("Tesla car's owner revenue (not Asia)")
axes.set_xlabel('Dollars ($)')
```

CO_2 saved

```
g_co2_mile_2021=pd.DataFrame([[395.721596,133.897421],[410.141318,165.730245],[419.137551,265.413012]]
, index=['Europe','USA','China'], columns=['ICE','EV'])

tons_co2_saved = {}
for area in g_co2_mile_2021.index:
    temp_result = pd.DataFrame(columns=years, index = simulation_list)
    for year in years:
        for i in simulation_list:
            temp_result[year][i]=robotaxi_miles_per_region[area][year][i] * (g_co2_mile_2021['ICE'][ar
ea]-g_co2_mile_2021['EV'][area]) / 1000000
    tons_co2_saved[area]=temp_result
plot_3_areas(tons_co2_saved,"Tons of CO2 saved",6)

# Percentage of CO2 saved compared to CO2 produced by region
tons_co2_produced = pd.DataFrame([4712770573,4946034489,10667887453],index=['USA','Europe','China'], c
olumns=['CO2 Tons/year']).T
percentage_tons_co2_saved_per_region = {}
for area in g_co2_mile_2021.index:
    temp_result=pd.DataFrame(columns=years, index = simulation_list)
    for year in years:
        for i in simulation_list:
            temp_result[year][i]=tons_co2_saved[area][year][i]/tons_co2_produced[area][0]
    percentage_tons_co2_saved_per_region[area]=temp_result

for area in percentage_tons_co2_saved_per_region:
    plot_percentage_graph(percentage_tons_co2_saved_per_region[area],'% of CO2 emissions (2021) saved
by Robotaxi in '+area)
```

Savings in pollution

```
#Pollution in
cities is a known issue,  very difficult to quantify, but accordingly to the American Lung Association


ALA_cost_gallon = 1.15
usa_mpg = 25.4

savings_pollution_ALA = robotaxi_miles_per_region['USA'] * ALA_cost_gallon / usa_mpg * (g_co2_mile_202
1['ICE']['USA'] - g_co2_mile_2021['EV']['USA']) / g_co2_mile_2021['ICE']['USA']
```

```
plot_global_series(savings_pollution_ALA,"Dollar savings in Health related Pollution",9)
```

Displaced cars

```
cars_usa=282.8E6
avg_miles_car=13476

cars_displaced = robotaxi_miles_per_region['USA']/avg_miles_car

s_negative = pd.DataFrame(cars_usa,index = simulation_list,columns=years)
for i in simulation_list:
    hours_day=general_inputs_sims['Hours/day'][i]
    for year in years:
        s_negative[year][i]-=cars_displaced[year][i]

s_tesla_cars = cum_cars_by_area['USA']
s_robo_cars = pd.DataFrame(index = simulation_list,columns=years)
for i in simulation_list:
    s_robo_cars.loc[i] = cum_cars_by_area['USA'].loc[i] * general_inputs_sims['Network Participation']
[i]

fig_1 = plt.figure(figsize=(19,8),dpi=100)
axes_1 = fig_1.add_axes([0,0,1,1])
displaced_curves=[s_negative,s_tesla_cars,s_robo_cars,cars_displaced]
displaced_color=['#ADD8E6','#e67070','#fed8b1','#B3E6B5']
displaced_color_main=['#1f77b4','#cc0000','#ff7f0e','#2ca02c']
displaced_legend=['Cars not displaced','Tesla Cars','Robotaxies in the Network','Cars displaced by Rob
otaxies']

i=0
for curve in displaced_curves:
    axes_1.plot(get_average_per_year(displaced_curves[i]),label=displaced_legend[i], marker='o',color=
displaced_color_main[i] ,markersize=2)
    axes_1.plot(get_quantile_per_year(displaced_curves[i],0.25),color=displaced_color[i], marker='o',
markersize=2)
    axes_1.plot(get_quantile_per_year(displaced_curves[i],0.75),color=displaced_color[i], marker='o',
markersize=2)
    sup=(pd.DataFrame(get_quantile_per_year(displaced_curves[i],0.75)['Q'].tolist()))[0].tolist()
    bot=(pd.DataFrame(get_quantile_per_year(displaced_curves[i],0.25)['Q'].tolist()))[0].tolist()
    axes_1.fill_between(years,sup, bot,color=displaced_color[i], alpha=.35)
    i+=1

axes_1.legend(loc=2)
axes_1.set_title('Cars displacement by Robotaxi in the US')
plt.xticks(years)

#Displacement capability, all years have the same
displacement_coefficient_all = cars_displaced/s_robo_cars
displacement_coefficient=displacement_coefficient_all[2030]
displacement_coefficient_avg=displacement_coefficient.mean()
displacement_coefficient_bear=displacement_coefficient.quantile(0.25)
displacement_coefficient_bull=displacement_coefficient.quantile(0.75)

fig, axes = plt.subplots(figsize=(16,6))
axes.hist(displacement_coefficient, bins=100, density=True, stacked=True, color='#cc0000')
#Average
axes.axvline(displacement_coefficient_avg, color='#a4c4ec', linestyle='dashed', linewidth=2)
min_ylim, max_ylim = plt.ylim()
plt.text(displacement_coefficient_avg*1.02, max_ylim*0.9, 'Mean\n {:.2f}'.format(displacement_coeffici
ent_avg))
#Bear
axes.axvline(displacement_coefficient_bear, color='#a4c4ec', linestyle='dashed', linewidth=2)
min_ylim, max_ylim = plt.ylim()
plt.text(displacement_coefficient_bear*0.8, max_ylim*0.9, 'Bear\n {:.2f}'.format(displacement_coeffici
ent_bear))
#Bull
axes.axvline(displacement_coefficient_bull, color='#a4c4ec', linestyle='dashed', linewidth=2)
min_ylim, max_ylim = plt.ylim()
plt.text(displacement_coefficient_bull*1.02, max_ylim*0.9, 'Bull\n {:.2f}'.format(displacement_coeffic
ient_bull))

axes.set_title("Tesla Robotaxi Displacement coefficient in the US")
```

Time freed

```
hours_saved_per_region =  {}
hours_in_year = 8760

for area in robotaxi_miles_per_region.keys():
    temp_hours_saved_per_region = pd.DataFrame(index = simulation_list,columns=years)
    for i in simulation_list:
        for year in years:
            temp_hours_saved_per_region[year][i] = robotaxi_miles_per_region[area][year][i] / general_
inputs_sims['Miles/hour'][i]
    hours_saved_per_region[area]=temp_hours_saved_per_region

years_saved_per_region =  {}
for area in hours_saved_per_region:
    years_saved_per_region[area]=hours_saved_per_region[area]/hours_in_year

years_saved_global=get_global_from_areas(years_saved_per_region)

plot_area_series(years_saved_per_region,"Time saved in years",6)
plot_global_series(years_saved_global,"Time saved in years",6)

#Maximum potential extra GDP percentage
gdp_per_hour_work = pd.DataFrame([74.19,54.25,15,56.61],index=['USA','Europe','China','Canada'], colum
ns=['Productivity']).T
gdp_per_area = pd.DataFrame([20936600*1000000,15276468.99*1000000,14722730.70*1000000,1644037.29*10000
00],index=['USA','Europe','China','Canada'], columns=['GDP']).T

extra_gdp={}
percentage_extra_gdp={}
for area in gdp_per_hour_work:
    extra_gdp[area]=hours_saved_per_region[area]*gdp_per_hour_work[area]['Productivity']
    percentage_extra_gdp[area] = extra_gdp[area]/gdp_per_area[area]['GDP']
    plot_percentage_graph(percentage_extra_gdp[area],'% of potential extra GDP '+area)
```

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