THREE ESSAYS ON TRANSITION TO ALTERNATIVE FUEL VEHICLES THROUGH DISTRIBUTIVE JUSTICE

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Wissam EL HACHEM

JURY

Pietro DE GIOVANNI	Supervisor	Associate Professor, ESSEC Business School (France)
Wout DULLAERT	Referee	Professor, Vrije Universiteit (Amsterdam, Netherlands)
Alberto GRANDO	Referee	Professor, Bocconi University (Milan, Italy)
Laurent ALFANDARI	Chair	Professor, ESSEC Business School (Cergy, France)

DECLARATION

I hereby declare that this thesis has been composed by myself and has not been presented or accepted in any previous application for a degree. The work, of which this is a record, has been carried out by myself unless otherwise stated and where the work is mine, it reflects personal views and values. All quotations have been distinguished by quotation marks and all sources of information have been acknowledged by means of references.

Wissam EL Hachem
July 5th 2019

To Neemtallah, Jihane, Rebecca and Marwan

‘Love the Lord your God with all your heart and with all your soul and with all your mind and with all your strength’. The second is this: ‘Love your neighbor as yourself.’ There is no commandment greater than these.

(Mark, 12:30-31)

‘All true good carries with it conditions which are contradictory and as a consequence is impossible. He who keeps his attention really fixed on this impossibility and acts, will do what is good.’

(Simone Weil, Gravity and Grace, 1947)

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GENERAL INTRODUCTION

The transition from internal combustion engines (ICE) to alternative fuel vehicles (AFV) is an urgent and challenging issue in today's world. According to the International Energy Agency (IEA, 2014), passenger light-duty vehicles account for more than 40% of total transportation energy demand. Trillions of dollars will be invested in the near future (until 2035) to increase energy efficiency, with $2.1 trillion directed toward electric vehicles. If the ICE design remains unchallenged, the carbon dioxide (CO_2) emissions will most likely double by 2050 (Sterman, 2015).

Responding to this circumstance, most major car manufacturers offer a good assortment of AFV, such as the Nissan Leaf and Ford Focus Electric. This creates competition between the established ICE and the new entrant AFV. The transition to a more sustainable transportation system is a complex and dynamic process (Zhang et al., 2011; Struben & Sterman, 2008). Despite the many AFV alternatives on the market, the history of the AFV transition across nations has exhibited "sizzle and fizzle" behavior, as illustrated in Sterman (2015). Many dominant feedback loops (e.g., transportation networks and infrastructure, research and development (R&D) investments) strengthen the ICE dominance and render the AFV transition slow and unsustainable. Given the fact that the transition to AFV is embedded within a complex and dynamic system, it is essential to analyze it by considering four key ideas:

1- Purpose: Reason behind and Purpose of AFV transition;
2- Perspectives: Stakeholders and their Objectives in the transition;
3- Relationships: Connections between the different Stakeholders;
4- Patterns: Behavior of the AFV transition system.

Purpose is the most straightforward to discern. The Energy Return on Investment (EROI) of fossil fuels has been historically high, but is quickly decreasing (Taylor&Tainter, 2016). The EROI of oil and gas in the United States in 1940 is estimated to have been greater than 100:1. Today it is about 15:1. Electrical generation from wind is about 18:1.

The higher the EROI of a fuel, the more energy is available for activities outside of energy production. A minimum EROI of 3:1 is required to maintain a functioning industrial society

(Hall et al., 2009). The decrease in EROI due to diminishing marginal returns is one of the reasons behind the recent surge of interest in renewable energy.

The surge in interest led to a disruptive innovation in 2008 that is the Tesla Roadster sports car. It was the first to use lithium-ion battery pack and the first capable of a range over 320 kilometers per charge. Now, most major car manufacturers have an assortment of commercially available AFV's.

More so, the high levels of ICE emissions (IEA, 2014) and the rise in consumer environmental awareness (CEA) (Zhang et al., 2015; Liu et al., 2012), led governments and societies to push for the transition towards AFV to preserve the environment.

As for the remaining three issues, they are less straightforward to discern due to the different perspectives embedded within the AFV transition system and the tradeoffs between them. We offer our answers to these questions in this thesis. Each essay complements the other two and tackles these questions from different angles via essay specific research questions.

One of our main contributions throughout the thesis is our focus on the second issue, more specifically on the social perspective/dimension of the AFV transition. We argue that neglecting the social perspective exacerbates some of the already existing inequalities in our societies by leaving people behind in our quest to save the environment (Harrison and Shepherd, 2013). This inevitably slows downs the AFV transition and makes it unsustainable (Zhang et al., 2011; Struben & Sterman, 2008).

One striking example of the importance of considering the social dimension is the recent 'yellow vests' movement in France which was initially sparked by what is perceived as 'unfair green' policies. This movement led the government to cancel some of the taxes, hence slowing down the AFV transition. If policies were designed with the social dimension explicitly in mind, these setbacks would have been averted and the transition would have been catalyzed.

We consider and quantify the social dimension's objective via the Distributive Justice (DJ) concept (Walzer, 1983). Martens et al. (2012) define DJ in transportation as the indiscriminate and equitable access to transportation, the latter being a vital means for people to realize their full capabilities in the society. The main premise of DJ is that transportation policies should influence travelers to choose environmentally friendly alternatives rather than force them to do so. The DJ principle can help both individuals and governments to fully realize the AFV's benefits.

Essay 1 considers the governmental and consumers perspectives and asks the following questions:

1.1. *Can policy makers overcome the trade-offs between environmental and social agendas when catalyzing the AFV transition by adopting Distributive Justice criteria along with environmental criteria?*

1.2. *Which combination of instruments (fuel tax, AFV subsidies, and ZEV regulations) should policy makers use to maximize the Sustainable Transition index?*

1.3. *Which instrument (fuel tax, AFV subsidies, or ZEV regulations) provides the highest contribution to the Sustainable Transition index?*

Essay 2 complements the first one by considering the manufacturer's research and development (R&D) investment strategy, market segmentation and the triple bottom line. It asks the following:

2.1. *How are innovation investments and cannibalization related to each other in a segmented market with both dominating and non-dominating preference structures?*

2.2. *How can firms design a R&D innovation strategy to overcome tradeoffs and balance the dynamics between the three sustainability pillars to positively impact the triple bottom line in an AFV transition context?*

2.3. *How do quality and prices of ICE and AFV alternatives change with different policy objectives? More specifically, does including the DJ index via the ST index increase the quality and decrease the prices of vehicle alternatives?*

Essay 3 complements the first two by considering the interactions between the government and the manufacturer, the triple bottom line and the impact of DJ on them. It asks the following:

3.1. *How can we incorporate DJ into the social dimension of sustainable development in a government-manufacturer interaction model?*

3.2. *How do the optimal product pricing, greening and government intervention strategies (ICE Tax, AFV Subsidy) change with and without DJ?*

3.3. How do the three sustainability pillars interact with each other with and without DJ?

3.4. How do the government utility and manufacturer profit change with and without DJ?

By considering these questions within the confines of our models, we contribute to the on-going efforts to catalyze AFV transition. Figure 1.1 visualizes the three essays of the thesis and summarizes their main contributions:

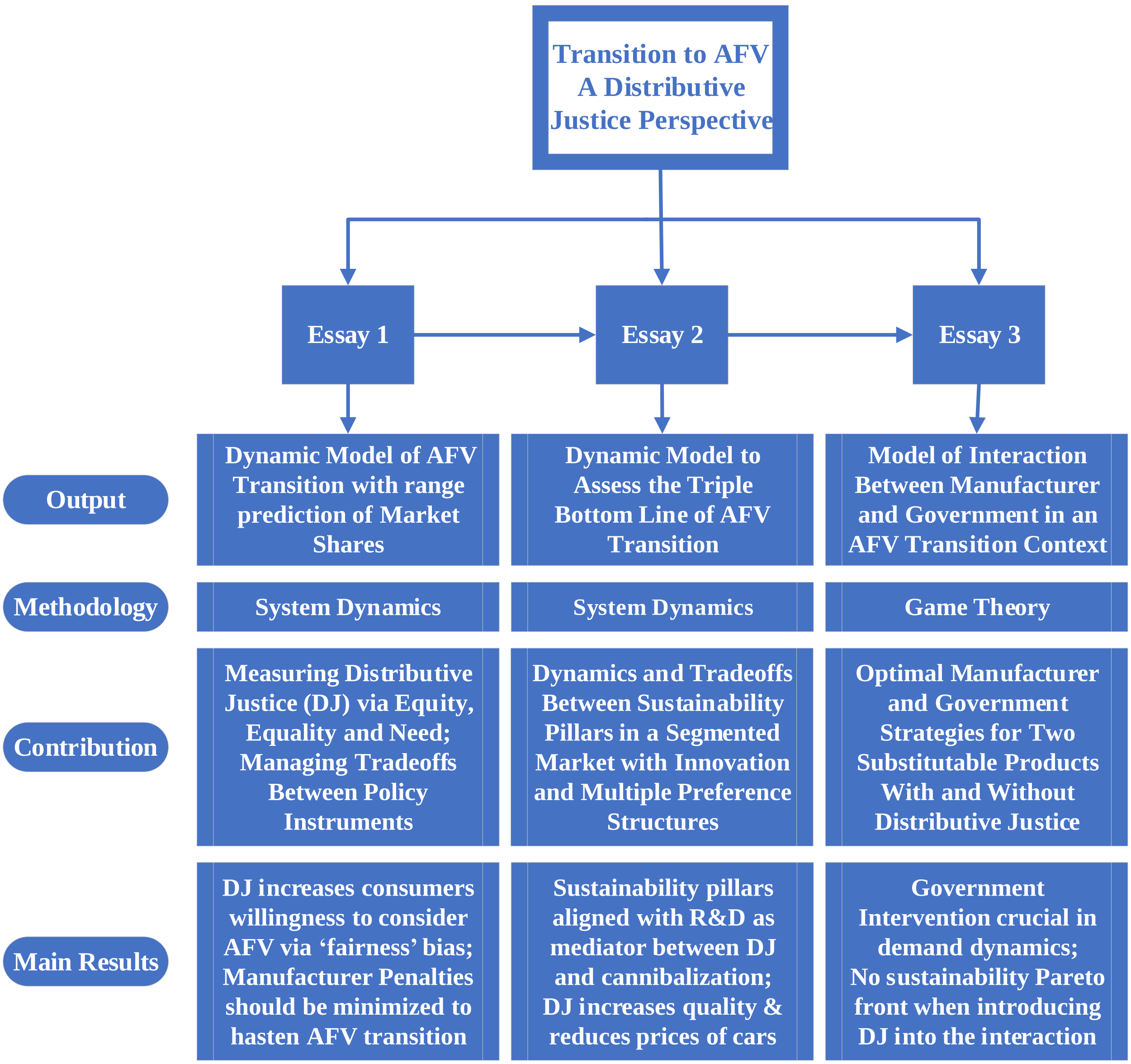


Figure 1.1: Thesis Schema

In our first essay, we focus on the current transportation policies and argue for the necessity to explicitly incorporate the social dimension into their design. Most of the transportation policy instruments (i.e. regulations and taxes) are based on coercive mechanisms, aiming to decrease the transportation emissions while fully disregarding DJ principles (Boussauw & Vanoutrive, 2017; Hulle et al., 2017; Heindl & Kanschik, 2016; Colquitt & Rodell, 2015; Harrison & Shepherd, 2013; Martens et al., 2012; Stenman & Konow, 2010).

This approach results in low willingness to consider AFV among potential consumers and generates several types of paradoxes, leading to an unsustainable transition. Boussauw and Vanoutrive (2017) propose concrete examples of these paradoxes linked to such instruments: 1- Taxing fuel consumption affects more residents of poorer regions, who have longer commutes on average; 2- banning old "dirty" vehicles limits the travel choice freedom of lower income groups that rely on these vehicles; and 3- providing fixed financial incentives penalizes groups with lower incomes because their access to sustainable vehicles is still limited by the high purchase price. These policies aim to incentivize AFV adoption, while being de facto not socially sustainable.

Hence, the first essay focuses on explicitly reconsidering these policies by incorporating a social dimension, specifically through the Distributive Justice (DJ) concept, to prevent the disproportional suffering of the economically worse off

The development of the DJ index allows us to address our second focus which is investigating whether the existing trade-offs (Boussauw and Vanoutrive, 2017) between the social and environmental objectives of AFV transition can be surmounted or not.

To the best of our knowledge, current research has not quantified the social impact of the AFV transition using the DJ concept. Therefore, we contribute to the literature by developing a DJ index and operationalizing its three components (Equity, Equality, and Need) given our AFV transition context.

DJ implies a lower limit of consumption with maximum policy equity; in contrast, an environmental-oriented policy implies an upper limit of consumption with maximum policy efficiency (Heindl & Kanschik, 2016). We explicitly analyze these trade-offs and demonstrate the potential benefits obtainable when policies maximize both pillars. For this purpose, we define an indicator of sustainability that embeds both DJ and environmental objectives, namely, the Sustainable Transition (ST) index that harnesses the potential synergy between the two objectives, thus minimizing the unintended consequences (i.e., worsening of the social objective) and the “policy resistance” behavior typical of complex systems. Because the AFV transition is a complex process filled with many trade-offs, we investigate it by employing systems thinking, particularly system dynamics simulation methodology.

We use these two indexes to test whether the AFV transition process can be accelerated when policy makers adopt DJ principles in the elaboration of their policies. In particular, we suggest to policy makers how to modify their current policies (e.g., fuel tax, AFV subsidies, zero emission vehicle (ZEV) regulations) to accelerate AFV adoption when also incorporating DJ principles.

In the second essay, we build a theoretical model to investigate and design innovation strategies for firms that want to be proactive when it comes to changing consumer preferences, mainly the increase in consumer environmental awareness (Zhang et al., 2015; Liu et al., 2012). We consider consumer heterogeneity (i.e. market segmentation) and its ensuing cannibalization problem when designing innovation strategies.

Typically, firms are weary of increasing cannibalization within their product line fearing lower profits (Li et al., 2018; Sinitsyn, 2016; Kim et al., 2013), thus they tend to stifle innovation that would exacerbate it. However, the disruptive and radical technological innovation, which is the emergence of the electric car, cannot be ignored. By stifling the emergence of AFV, an automotive manufacturer risks its own disappearance from the marketplace by not accommodating evolving consumer preferences.

Given this context, firms adopt product proliferation strategy (Li, 2018). Product proliferation has inter-brand competition effect and intra-brand cannibalization effect. Intra-brand cannibalization occurs since products offered by the same firm are often considered by consumers as close substitutes so that one product’s customers are at the expense of other products offered by the same firm (Li et al., 2018; Sinitsyn, 2016; Kim et al., 2013).

In this essay, we focus on the intra-brand cannibalization effect by considering a multi-product monopolist that offers an assortment of products. The monopolist has to satisfy the demand of a market segmented into High vs Low consumers. High segment consumers value all vehicle attributes more than the Low segment consumers. Since more than one characteristic is needed to define product quality (Walter and Peterson, 2017; Garella and Lambertini 2014), we focus on both performance and level of emissions of vehicles as indicators of their quality. So, within each of the segments, we have two types of consumers: Emissions-oriented consumers who value vehicle's lower emissions more than high performance, and Performance-oriented consumers who value high performance more than lower emissions. To accommodate for these preferences, the monopolist offers two products within each segment. One product is designed for the emissions-oriented consumers (i.e. AFV), and the other is designed for the performance-oriented consumers (i.e. ICE).

A segmented transportation market with R&D investments is a complex system filled with many trade-offs, feedbacks and long delays. Therefore we investigate it by employing systems thinking, particularly system dynamics methodology.

We consider simultaneously cannibalization with both dominating and non-dominating preference structures as well as product and process innovation strategies. This allows us to model endogenously both the price and the quality versus having one of them fixed or exogenous decision variables as in previous product line design literature (Desai, 2001; Heese and Swaminathan, 2006; Kim et al., 2013; Sinitsyn, 2016). More so, R&D and innovation investments are influenced by market segmentation and consumer heterogeneity; therefore, we consider them in a heterogeneous market rather than in a homogeneous market (Li, 2018; Lambertini et al., 2017; Pan and Li, 2016; Li and Ni, 2016; Lambertini and Orsini, 2015; Chenafaz, 2012).

We find that cannibalization and innovation are both needed to accommodate for evolving customer values while maximizing the sustainability of the transition to alternative fuel vehicles (AFV). Despite the many tradeoffs between the three sustainability pillars, with one of them being cannibalization decreasing profits ceteris paribus while enabling a quicker transition to AFV, we find the sustainability pillars can interact in harmony. This happens when firms have a healthy R&D budget for innovation while still allowing for within-segment cannibalization.

More so, maximizing for profits and/or minimizing emissions would produce lower quality and higher prices than when we consider simultaneously with them the DJ index. This confirms the benefits of explicitly including the social pillar quantified by the DJ index in our decision making when designing R&D and innovation strategies.

In the third essay we adopt the 'Public policy and planning' theory of sustainable development and stress the integration of the social, economic and environmental aspects of sustainability along with the institutional (Sala et al., 2015; Patterson, 2010).

One concept that governments and organizations have utilized to operationalize and transition towards sustainability is the triple bottom line approach (Liu et al., 2019; Sinayi & Rasti-Barzoki, 2018; Besiou and Van Wassenhove, 2015; De Giovanni, 2012; Seuring and Müller, 2008; Elkington, 2002). It defines sustainability as dependent on the balance between the economy, environment and society. This balance is dependent on the interaction between the government and the companies (Liu et al., 2019).

Government efforts to influence business behaviors toward socially and environmentally desirable outcomes take a variety of forms, with two of the most recognized being taxes and subsidies (Liu et al., 2019, Sinayi & Rasti-Barzoki, 2018; Zhang et al., 2015) which we utilize in our model.

Rising environmental awareness among consumers (Jamali & Rasti-Barzoki, 2018; Basiri & Heydari, 2017; Zhang et al., 2015; Conrad, 2005), known as Consumer Environmental Awareness (CEA), led to the entry of green products (i.e. AFV) into the car market. This led to the issue of competition between these green (e.g. AFV) and non-green products (e.g. ICE) which has been the subject of research lately (Jamali & Rasti-Barzoki, 2018; Sinayi & Rasti-Barzoki, 2018; Basiri & Heydari, 2017; Ma et al., 2018; Zhu & He, 2017; Zhang et al., 2015). We focus on the pricing and the degree of greenness of a product in competition with an established non-green product while considering government intervention.

This study is the first to consider competition between two substitutable products offered by a manufacturer while including government intervention in the form of subsidies and taxes into the model. More so, it is the first to focus on sustainable development by quantifying its social dimension via consumer surplus and the concept of DJ. We investigate and compare the alignment issues and tradeoffs between environmental, economic and social sustainability dimensions with and without DJ.

We do so by building a game theory model with two players, Government (leader) and one Manufacturer (follower). The decision variables for the manufacturer are the prices of the two products (ICE and AFV) and degree of greenness of the AFV; the decision variables for the government are the subsidies for the AFV and taxes on the ICE. We also incorporate the concept of Distributive Justice (DJ) by modifying the social pillar of sustainability in such a way to maximize access to vehicles.

The government's tax and subsidy override the manufacturer's prices when determining the dynamics highlighting the decisiveness of government intervention in such a setting. The dynamics of the environmental and economic pillars show several tradeoffs that are partially alleviated when DJ is considered. We also show that when introducing DJ into the model, there is no Pareto frontier where all three pillars improve simultaneously and that the government's utility remains more or less the same. The manufacturer's profits and consumer surplus exhibit a harmonious relationship whereby they increase together. More so, we notice that demand for AFV is always cannibalizing the demand for ICE.

The three essays complement each other in their purpose as well as in their results. All three highlight the inevitable tradeoffs between the sustainability pillars (i.e. economic, environmental and social). DJ is found to be a suitable means to quantify the social dimension and to minimize these tradeoffs. It does so by regulating the transportation policies and the interaction between the government and the manufacturer by minimizing consumer dissatisfaction (i.e. social dimension), thus catalyzing the AFV transition and reducing ICE emissions (i.e. environmental dimension) while respecting the manufacturers profits (i.e. economic dimension).

ESSAY ONE

Accelerating the Transition to Alternative Fuel Vehicles through a Distributive Justice Perspective

Abstract

In this paper, we investigate the ongoing endeavor to transition from conventional transportation to more sustainable systems. In addition to the traditional environmental objective, we propose a novel measure to quantify the social performance by using the concept of Distributive Justice (DJ) and investigating the transition to alternative fuel vehicles (AFV). In our context, DJ is defined as fair access to transportation, the latter being a vital means for people to realize their full capabilities in the society. Our findings show that policy makers should adjust their targets to consider DJ criteria along with environmental objectives, thus aiming at a sustainable transition. By doing so, they can control and hasten the transition to AFV. Finally, we evaluate the contribution of each policy instrument to guide the policy-making process and catalyze this transition.

Keywords: Distributive Justice, Alternative Fuel Vehicles, Sustainable Transition, System Dynamics.

1.1 Introduction

The transition from internal combustion engines (ICE) to alternative fuel vehicles (AFV) is becoming an urgent and challenging issue in today's world. According to the International Energy Agency (IEA, 2014), passenger light-duty vehicles account for more than 40% of total transportation energy demand. Also, trillions of dollars will be invested in the near future (until 2035) to increase energy efficiency, with $2.1 trillion directed toward electric vehicles. If the ICE design remains unchallenged, the carbon dioxide (CO_2) emissions will most likely double by 2050 (Sterman, 2015).

Responding to this circumstance, most major car manufacturers offer a good assortment of AFV, such as the Nissan Leaf and Ford Focus Electric. However, the transition to a more sustainable transportation system is a complex and dynamic process (Zhang et al., 2011; Struben & Sterman, 2008). To date, the history of the AFV transition across nations has exhibited "sizzle and fizzle" behavior, as illustrated in Sterman (2015). Many dominant feedback loops (e.g., transportation networks and infrastructure, research and development (R&D) investments strengthen the ICE dominance and render the AFV transition slow and unsustainable. A key factor in this slow transition is that demand for AFV is strongly influenced by the word-of-mouth (WOM) effect and consumers' willingness to consider such alternatives (Zhang et al., 2011; Struben & Sterman, 2008). Since the latter are both currently under-investigated and given little attention by policy makers, we aim to investigate the adoption of AFV by focusing on the social dimension of the transition.

Current sustainable transportation objectives established by policy makers solely focus on the environmental and economic impacts of people's current reliance on ICE (Boussauw & Vanoutrive, 2017; Harrison & Shepherd, 2013; Martens et al., 2012). This approach results in low willingness to consider AFV among potential consumers, as well as in several paradoxes, both leading to an unsustainable transition. Boussauw and Vanoutrive (2017) propose concrete examples of these paradoxes linked to such instruments: 1-Taxing fuel consumption affects more residents of poorer regions, who have longer commutes on average; 2- banning old "dirty" vehicles limits the travel choice freedom of lower income groups that rely on these vehicles; and 3- providing fixed financial incentives penalizes groups with lower incomes because their access to sustainable vehicles is still limited by the high purchase price. These policies aim to incentivize AFV adoption, while being de facto not socially sustainable. Hence, the first contribution of this paper is to explicitly reconsider these policies by incorporating a social dimension, specifically through the Distributive Justice (DJ) concept.

Martens et al. (2012) define DJ in transportation as the indiscriminate and equitable access to transportation, the latter being a vital means for people to realize their full capabilities in the society. The main premise of DJ is that transportation policies should influence travelers to choose environmentally friendly alternatives rather than force them to do so. The DJ principle can help both individuals and governments to fully realize the AFV's benefits.

The development of the DJ index allows us to address the existing trade-offs between the social and environmental objectives of AFV transition previously mentioned in Boussauw and Vanoutrive (2017). DJ implies a lower limit of consumption with maximum policy equity; in contrast, an environmental-oriented policy implies an upper limit of consumption with maximum policy efficiency (Heindl & Kanschik, 2016). Therefore, our second contribution is explicitly analyzing these trade-offs and demonstrating the potential benefits obtainable when policies maximize both pillars. For this purpose, we define an indicator of sustainability that embeds both DJ and environmental objectives, namely, the Sustainable Transition (ST) index that harnesses the potential synergy between the two objectives, thus minimizing the unintended consequences (i.e., worsening of the social objective) and the "policy resistance" behavior typical of complex systems. Because the AFV transition is a complex process filled with many trade-offs, we investigate it by employing systems thinking, particularly system dynamics simulation methodology.

To the best of our knowledge, current research has not quantified the social impact of the AFV transition using the DJ concept. Therefore, we seek to contribute to the literature by developing a DJ index and operationalizing its three components (Equity, Equality, and Need) given our AFV transition context. Using the DJ index, we develop a further index linked to the entire transition process, namely, the ST index. The latter aims at evaluating the system capacity to accelerate the AFV transition through both DJ and environmental principles. We will then use these two indexes to test whether the AFV transition process can be accelerated when policy makers adopt DJ principles in the elaboration of their policies. In particular, we suggest to policy makers how to modify their current policies (e.g., fuel tax, AFV subsidies, zero emission vehicle (ZEV) regulations) to accelerate AFV adoption when also incorporating DJ principles.

The remainder of the paper is structured as follows. Section 1.2 introduces the literature on DJ within the framework of AFV transition, highlights the current policy instruments, and introduces our research questions. Section 1.3 reports the indexes to measure both the DJ and the sustainable transition to AFV. Section 1.4 introduces the methodology and the model. Section 1.5 presents the main findings and proposes new prescriptions to policy makers to accelerate the AFV transition process. Section 1.6 concludes.

1.2 Literature Review and Research Questions

1.2.1 Distributive Justice within the AFV transition context

Most of the research on AFV transition focuses on its environmental and economic aspects. Struben and Sterman (2008) develop a systems dynamic model to investigate the transition to AFV and find that subsidies for AFV must remain in place for a long time before the AFV becomes self-sustained. Zhang et al. (2011) design an agent-based model (ABM) to explain the AFV transition. They show that technology push and market pull (such as AFV quota and WOM) both play a positive role in the successful diffusion of AFV. Using an ABM, Eppstein et al. (2011) study the diffusion of plug-in hybrid electric vehicles (PHEVs) and find that the purchase price is the most influential factor in customer adoption. Furthermore, they demonstrate the importance of familiarity with the PHEV technology to its diffusion, even in the presence of financial incentives. Liao et al. (2017) and Al-Alawi and Bradley (2013) compile more than 50 peer-reviewed papers with different methodological approaches sharing the theme of transition to AFV. All these papers focus on the future penetration rate of different AFV alternatives, with no emphasis on the social implications.

While the literature investigates the AFV transition under different perspectives, few papers highlight the social aspects of such a transition (Boussaw & Vanoutrive, 2017; Harrison et al., 2013; Lucas et al., 2012). In particular, the concept of DJ has been disregarded by policy makers in their attempt to accelerate the diffusion of AFV. According to Walzer (1983), goods that have a distinct social meaning should be governed by a "Distributive Justice" sphere to prevent the compounding of inequalities. Martens et al. (2012) define DJ in transportation as the indiscriminate and equitable access to transportation, the latter being a vital means for people to realize their full capabilities in society. DJ's main premise is that transportation policies should influence travelers to choose environmentally friendly alternatives rather than force them to do so.

In general, DJ consists of three main components (Hulle et al., 2017; Colquitt & Rodell, 2015; Stenman & Konow, 2010) which are explained in more detail in section 3.1: *Equity* (i.e., allocating benefits between different groups proportionally to their respective invested efforts), *Equality* (i.e., allocating benefits between different groups regardless of invested efforts), and *Need* (i.e., providing access to transportation to the maximum number of people). Using these three components, DJ aims to make goods equally accessible and usable for the largest number of individuals. In fact, the concept of DJ adheres to the principle of Pareto optimality, that is, do not leave anyone worse off (Martens et al., 2012; Lucas, 2012).

Although a few qualitative and theoretical studies evoke the use of DJ principles, there are no indicators to explain and measure how a certain policy or a given legislation performs in terms of DJ. Therefore, the first objective of this study is to develop a DJ index for considering all the aforementioned components (Equity, Equality, and Need), which is called the DJ index. Policy makers can use this index to evaluate and select the best AFV transition policies that uphold the Equity, Equality, and Need principles.

The development of the DJ index allows us to address the existing trade-offs between the social and environmental objectives of AFV transition (see Boussauw and Vanoutrive, 2017). According to Harrison and Shepherd (2013), the current trend of car ownership is not going to change in the near to mid-term future (20-30 years) due to technological and cultural lock-in. Today, people pursue faster and more convenient travel modes, which undermine current efforts toward sustainable mobility (Cohen, 2010). This is known as "car dependence" (Sustainable Development Commission, 2010), implying that car ownership is necessary for full participation in society. Hence, environmental coercive policies (limiting users' choice set) that may push people into social exclusion are often seen as inequitable. Therefore, we seek to make policy makers aware of the existing trade-offs between environmental and social outcomes and demonstrate the potential benefits when policies simultaneously maximize both pillars. For this purpose, we define an indicator of sustainability that embeds both DJ and environmental objectives, that is, the ST index.

1.2.2 Research questions

AFV transition entails deep changes to a large socio-technical system (Shafiei et al., 2012; Struben & Sterman, 2008). In such a system, we can assess the importance of the policy instruments in promoting a sustainable transition only within policy portfolios (Edmondson et al., 2018; Bjerkan et al., 2016; Rogge & Reichardt, 2016). Although policy makers' traditional instruments (e.g., fuel tax, AFV subsidies, ZEV regulations) aimed at optimizing environmental performance work moderately well (Zhang et al., 2011; Eppstein et al., 2011; Liao et al., 2017) , we firmly think that better results can be obtained by also considering DJ targets.

AFV are still in the early adoption phase, so many barriers hinder their widespread diffusion, including battery/vehicle costs, battery range, and lack of charging infrastructure (Bjerkan et al., 2016; Egbue & Long, 2012; Burer, 2009; Diamond, 2009). To pursue our objectives, we focus on the following policy instruments:

- *Fuel tax*: The fuel tax is the most common policy instrument used to collect funds for maintenance of transportation infrastructure and is employed as a deterrent to excessive fuel consumption (Clerides & Zachariadis, 2008). Thus, it has a considerable impact on the AFV transition.
- *AFV subsidies*: Along with the fuel tax, policy makers have introduced subsidies (Wee et al., 2018; Glerum et al., 2014; Qian & Soopramanien, 2011) to mitigate the most critical upfront barrier that consumers face, that is, the purchase price (Brand et al., 2013; Bakker et al., 2013). In the same line, Larson et al. (2014) demonstrate that a direct cut in the AFV purchase price finds significant appreciation among consumers. Therefore, we aim to investigate whether subsidies speed up the adoption of AFV when also considering DJ targets.
- *ZEV regulations*: ZEV regulations are mainly targeted toward manufacturers to incentivize them to introduce low-emission vehicles in their fleets (CARB, 2017; Bjerkan et al., 2016). The government has set a minimum low-emission vehicles quota for cars sold in the previous three years. The sale of low-emission vehicles generates AFV credits, categorized between those earned by full electric vehicles and those earned by hybrids. If the amount of AFV

credits generated is below the minimum quota, an AFV penalty must be paid (CARB, 2017). A certain percentage of this penalty can be reallocated by manufacturers to consumers when purchasing both ICE and AFV. This instrument catalyzes AFV penetration since it actively promotes the manufacturing and adoption of AFV.

Note that greenhouse gases (GHGs) regulation is also part of our model because it is an integral part of current environmental policies (Lee et al., 2010) to drive down emissions. However, ceteris paribus, it does not have a noticeable impact on the outcomes from a DJ perspective. This result is compatible with data from the United States Department of Transportation (2017), which show that manufacturers have mostly been able to keep up with the GHG regulations; therefore, GHG penalties are minimal and have no impact in terms of evaluating policies from a DJ perspective.

Most of the policy instruments are based on coercive mechanisms, aiming to decrease the transportation emissions (Harrison & Shepherd, 2013) while fully disregarding DJ principles. Instead, such policies should be complemented by DJ principles to prevent the disproportional suffering of the economically worse off. According to Boussauw and Vanoutrive (2017), the current policies intensify the tension between the social and environmental objectives. Taxing fuel consumption to affect residents of poorer regions having longer commutes or banning old “dirty” vehicles to limit the travel choice of lower income groups are well-fitting examples. Therefore, we formulate our first research question:

Research question 1. *Can policy makers overcome the trade-offs between environmental and social agendas when catalyzing the AFV transition by adopting DJ criteria along with environmental criteria?*

To answer research question 1, we observe the trade-offs between the environmental (i.e., AFV sales) and social (i.e., DJ index) performance indicators. Then, based on the observed trade-offs, we propose a DJ index to measure the perceived fairness of the AFV transition.

Finally, we seek to suggest to policy makers the best policies (i.e., combination of environmental policy instruments along with their individual strengths) to be undertaken to speed up the adoption of AFV while simultaneously considering the DJ outcome. This implies that decision makers maximize their targets according to the ST index. In particular, we aim to answer the following research questions:

Research question 2. Which combination of instruments (fuel tax, AFV subsidies, and ZEV regulations) should policy makers use to maximize the ST index?

Research question 3. Which instrument (fuel tax, AFV subsidies, or ZEV regulations) provides the highest contribution to the ST index?

1.3 Distributive Justice and Sustainable Transition Indexes

For clarity's sake, Figure 1.2 is a high-level flow chart of the main elements and steps in our methodology, which we will explore in more detail throughout the paper. It illustrates in red our theoretical contributions through the DJ and ST indexes, whose impact we will discuss later in relation to policy makers' decisions.

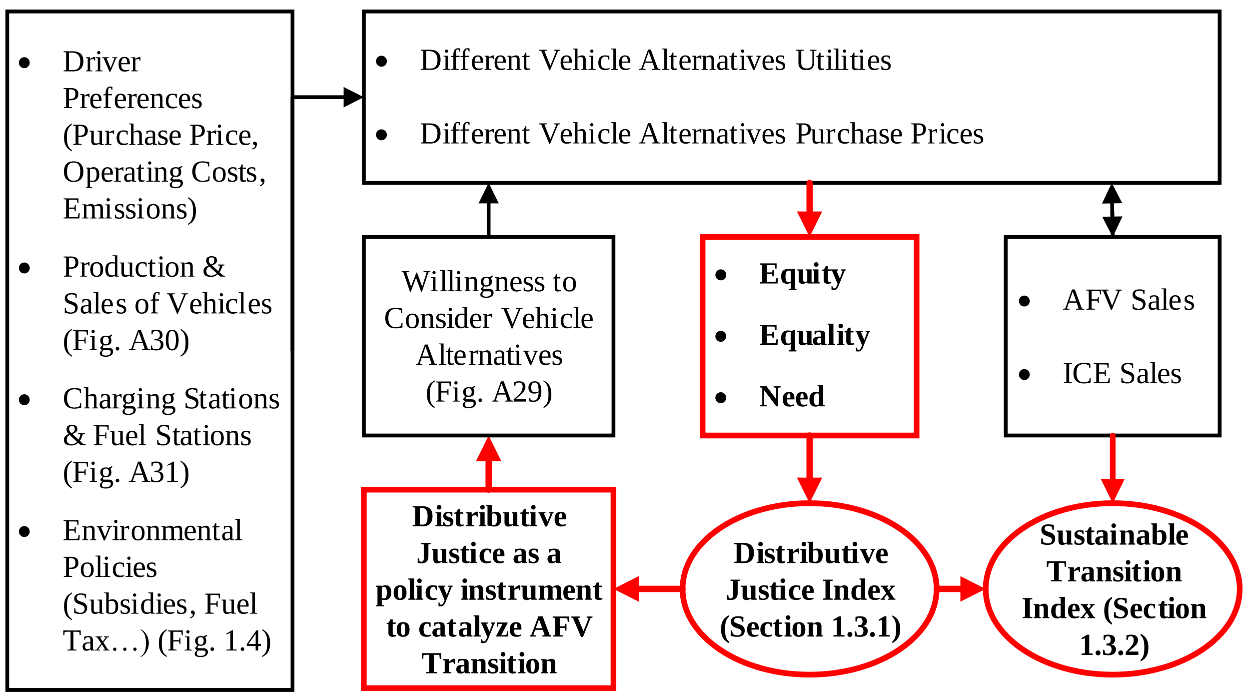


Figure 1.2: Complex AFV market system investigated through a Distributive Justice lens

1.3.1 A Distributive Justice index

DJ refers to the perceived fairness of the distribution of social and economic benefits (as well as burdens) among a group of individuals (Stenman & Konow, 2010). Traditionally, DJ has three components (Hulle et al., 2017; Colquitt & Rodell, 2015): *Equity*, *Equality*, and *Need*.

To meet the DJ objective, we consider both access to transportation (i.e., Equality of opportunity) as well as the benefit/utility derived from this access to the different vehicle alternatives (i.e., Equality of outcome). Following Hulle et al. (2017), Colquitt and Rodell (2015), Martens et al. (2012), Lucas (2012), and Stenman and Konow (2010), we define:

- *Equity* as allocating benefits between different groups proportionally to their respective invested efforts (the purchase price of a vehicle acts as a proxy indicator of the amount of efforts invested to access and extract utility/benefit from the vehicle).
- *Equality* as allocating benefits equally between different groups regardless of invested efforts.
- *Need* as providing access to transportation (either ICE or AFV) to the maximum number of people.

Each of these components contributes to the final common objective of DJ, that is, fairness in both providing access to transportation and allocating its benefits to consumers. *Equality* refers to "Equality of outcome," *Need* links to "Equality of opportunity," and *Equity* is a bridge between the two. Then, we propose operational measures to quantify DJ and its components by tracking the evolution of the purchase price (i.e., input) and utility (i.e., output) of the different alternatives: The former represents the efforts to access the different types of cars and the latter represents the derived benefit associated with each type of car, which depends, for example, on emissions and running costs.

Following the earlier definition, *Equity* considers the utility of alternatives j, u_j, and their respective purchasing prices, p_j, where j are the different alternatives. We compute the ratios $r_j = \frac{u_j}{p_j}$, which inform us on the benefits derived from the vehicles proportional to the amount of efforts invested to access them. Then, to maximize *Equity*, we seek to minimize the variance in the ratios, $\sigma^2(r_j)$, such that individuals derive the same level of benefit proportionally to their invested effort. So, *Equity* is computed as follows:

$$\text{EQUIT}Y = \frac{1}{\sigma^{2}(r_j)}$$

Equality only considers the utility, u_j, of different alternatives by computing the variance in the utilities, $\sigma^2(u_j)$. Then, we maximize *Equality* by minimizing $\sigma^2(u_j)$, such that different groups derive equal benefits from their different vehicle alternatives. Accordingly, we define *Equality* as follows:

$$\text{EQUALIT}Y = \frac{1}{\sigma^{2}(u_j)}$$

In the transportation context, the *Need* component is defined as providing access to transportation to the maximum number of people. Purchase price is used as a proxy to access level. The higher the purchase price, the lower the access level. Therefore, *Need* is measured as follows:

$$\text{NEED} = \text{Lowest Access Level} = \frac{1}{Minimum\ (p_j)}$$

Finally, we combine all three components into one measure, as follows:

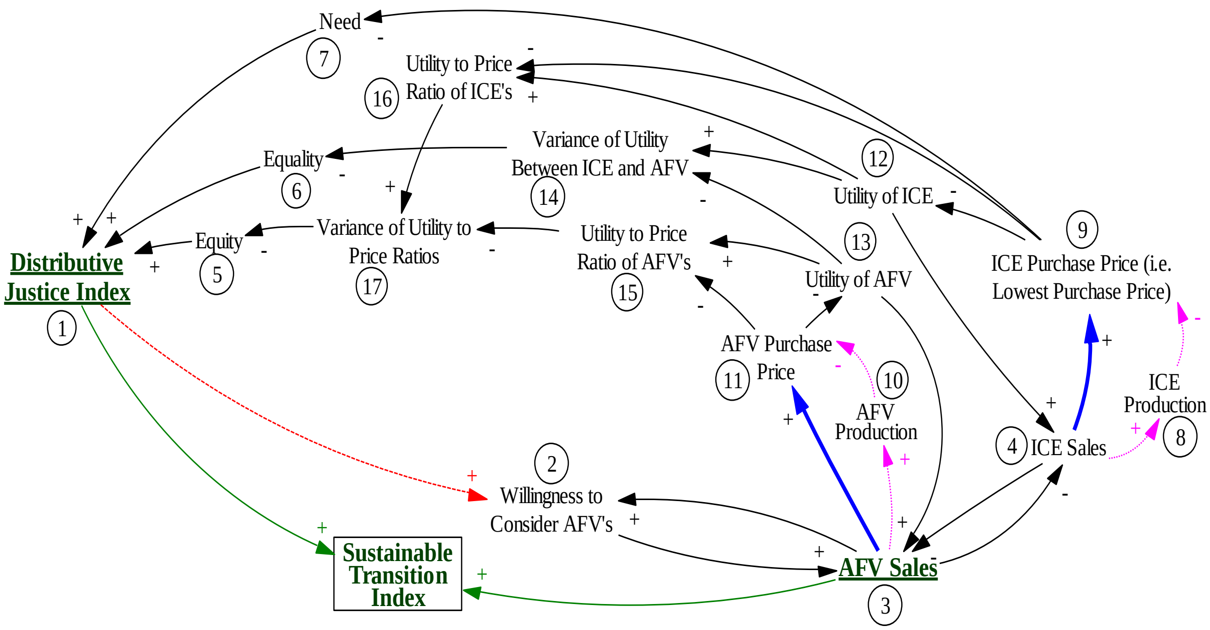
$$Distributive\ Justice\ Index = \sum_{i=1}^{3} Weight_{\boldsymbol{i}}\left(\frac{Component_{i,t} - Component_{i,t_0}}{Component_{i,t_0}}\right)$$

where *i*=*Equity*, *Equality*, *Need* and $\sum_{i=1}^{3} Weight_i = 1$. "$Component_{i,t}$" refers to the level of a component *i* at time *t*, whereas "$Component_{i,t_0}$" refers to its initial level at t_0. Thus, the ratio shows the relative improvement realized during the analyzed period. In our model, the normalized components vary within the range [-0.5, 0.5], with values higher (lower) than 0 indicating an improvement (worsening) in performance. We split weights equally (i.e., 1/3) between the three components in accordance with the literature (e.g., De Giovanni & Zaccour, 2014). Nonetheless, we ran sensitivity analyses to check the impact of these weights by varying them between 0.2→0.4 while respecting the logical constraint that their sum should always be equal to 1. We notice no qualitative change, meaning that if DJ is increasing (decreasing) with equal weights, it keeps increasing (decreasing) with different weights given to its three components.

If the DJ measure is equal to 0, it is at the same level of the year 2000. If it is increasing above (decreasing below) 0, then it is improving (worsening) relative to its initial level. This indicator allows us to fulfill the first theoretical objective of this research, that is, providing a measure for DJ that policy makers can use to evaluate whether their actions are aligned with DJ principles (and then, social outcomes).

1.3.2 Sustainable transition index

Figure 1.3 explains the links between environmental (i.e., AFV sales) and DJ targets in a system dynamics model.



Balancing Loops		Reinforcing Loops	
B1	1→2→3→4→9→12→16→17→5→1	**R1**	1→2→3→4→8→9→12→16→17→5→1
B2	1→2→3→4→9→16→17→5→1	**R2**	1→2→3→4→8→9→16→17→5→1
B3	1→2→3→11→15→17→5→1	**R3**	1→2→3→10→11→15→17→5→1
B4	1→2→3→11→13→15→17→5→1	**R4**	1→2→3→10→11→13→15→17→5→1
B5	1→2→3→4→9→12→14→6→1	**R5**	1→2→3→4→8→9→12→14→6→1
B6	1→2→3→11→13→14→6→1	**R6**	1→2→3→10→11→13→14→6→1
B7	1→2→3→4→8→9→7→1	**R7**	1→2→3→4→9→7→1

Figure 1.3: Transition to AFV through a Distributive Justice perspective

Note that the + (-) sign at the end of each arrow between its origin A and destination B indicates - ceteris paribus - the sign of the derivative $\frac{dB}{dA}$. To measure *Equity*, *Equality*, and *Need*, we keep track of the utilities and purchase prices of the different vehicle alternatives, which in turn are intertwined in feedback loops with AFV sales and ICE sales. Then, these three components give us the DJ index.

Figure 1.3 shows 14 loops that connect the DJ index with AFV sales, which are split between balancing and reinforcing loops. When the multiplication of the signs of the arrows along the loop is negative (positive), we identify a balancing (reinforcing) loop. So, if we increase an element in a balancing (reinforcing) loop, we will obtain its relative decrease (further increase).

If we consider the loops passing through the *Equality* and *Equity* components, six of these loops (B1 to B6) pass through the thick blue arrows (i.e., links 3→11 and 4→9). These loops are balancing and they directly connect the *sales* with the *purchase prices*. The six loops, R1 to R6, passing through the dotted pink arrows (i.e., links 3→10→11 and 4→8→9), that is, the ones that pass through the vehicle production elements, are reinforcing. As for the remaining two loops passing through the *Need* component, it is the other way around (one balancing loop B7 through the wide dotted pink arrow and one reinforcing loop R7 through the thick blue arrow).

We can derive two main intuitions from this. First, the *Equality* and *Equity* components move in harmony with respect to each other, while the *Need* component reflects trade-offs with the other two components. Second, since there are eight balancing loops, we surely have trade-offs between AFV sales and the DJ index. The eight reinforcing loops allow us to overcome these trade-offs, since an increase in AFV sales leads to an increase in the DJ index, which in turn leads to a further increase in AFV sales. However, since three of the reinforcing loops pass through AFV production (R3, R4, and R6), which is limited compared to ICE production, we can suspect that the balancing loops are initially stronger than the reinforcing loops. If the red dotted link (1→2) is activated, the reinforcing loops will grow stronger and eventually overcome the balancing loops, allowing AFV sales and the DJ index to move in harmony. The trade-offs between the DJ components are discussed in Appendix A.2.

The red dotted link in Figure 1.3 (link between DJ and AFV sales), seen as a DJ-oriented policy instrument, captures the impact of the perceived fairness of the AFV transition on AFV sales. The DJ index indicates the perceived fairness of such a transition. According to Luo (2007), individuals judge policies and make decisions by considering various justice criteria. Hammar and Jagers (2007) examine the perceived fairness of an increase in the CO_2 tax on gasoline and diesel and report that people show preferences for fairness in policy design by supporting higher CO_2 taxes. Stenman and Konow (2010) confirm that individuals do consider fairness criteria in environmental policies and tend to have a "fairness bias" manifested by judging policies in a self-serving manner. So, people pay attention to policy fairness. Accordingly, we introduce the concept of "fairness bias" into the model, which influences the willingness to consider AFV.

To meet the environmental goals, policy makers should lower people's utility from ICE and increase the utility obtainable from AFV, hence increasing AFV sales and reducing the overall emissions. Since there exist several trade-offs and synergies between environmental and DJ objectives, we create a composite indicator that considers both and that we call the *Sustainable Transition* (ST) index. This index allows policy makers to evaluate a given policy (i.e., particular combination of instruments) considering both the DJ index (social performance indicator) and AFV sales (environmental performance indicator) with the target of sustainably catalyzing AFV adoption. The red dotted link between the DJ index and willingness to consider (WTC) AFV in Figure 1.2 (i.e., link 1→2) is active only when policy makers simultaneously target both DJ and environmental objectives, maximizing the ST index. Such an indicator should consider both the current as well as the transitional dynamics of the DJ index and AFV sales. Specifically, we define the indicator as follows:

$$Sustainable\ Transition\ Index = \sum_{i=1}^{2}(Weight_i * \int_{t=2000}^{t=2035} Impact\ of\ Component_{i,t})\ ,$$

$$\text{Where } \sum_{i=1}^{2} Weight_i = 1$$

The two components are the DJ index and AFV sales. The weights are set by default to 0.5 (i.e., equal importance). Same as with the *DJ index*, we run sensitivity analyses to check the impact of these weights. We notice no qualitative change when we vary its weights. We integrate the impact of each component over the simulation period, thus taking into consideration a negative impact that might occur at any period *t*. By doing so, we target a smooth improvement of the indicators without relapses. The impact of each component is defined as the difference between its value at period *t* and the previous period *(t-1)*:

$$Impact\ of\,Component_{i,t} = Component_{i,t} - Component_{i,(t-1)}$$

The higher the AFV sales and the DJ index, the better the sustainability of the AFV transition. Note that both the DJ index and the AFV sales impact start at a value of 0. For example, if AFV sales are currently 12% (of total vehicle sales), and this figure was at 11% during the last period, then AFV sales have a positive impact of (0.12-0.11) = 0.01. If, on the other hand, we have a current DJ index at 0.2, and it was at 0.22 during the last period, then the DJ index has a negative impact of (0.2-0.22) = -0.02. So, the larger the increase (decrease), the better (worse) the impact on the ST index.

If the ST index is equal to 0, the AFV transition is at the same sustainability level relative to its initial level at year 2000. If it is higher (lower) than 0, then the AFV transition is more (less) sustainable relative to its initial level at year 2000.

Policy makers can use these indicators when developing policies and instruments to target, among others, social objectives through a DJ perspective. Policy makers can also use these indicators to evaluate the existing trade-offs between environmental and social outcomes and to search for solutions to mitigate them.

1.4 Methodology and Model

In this section, we present the model through which we will test the improvements in the AFV transition through a DJ perspective. The two main parts of the model (sections 1.4.2 and 1.4.3) along with the policies (section 1.4.4) determine the components of DJ: The cross-nested logit (CNL) model determines the utilities of the different vehicle alternatives, while the supply-demand dynamics define their purchase prices, with the utilities and purchase prices contributing to the three DJ components. See Appendix A.1 for an overview of the model dynamics.

1.4.1 A system dynamic model of AFV transition

When dealing with energy transition and sustainability topics, we can identify three main modeling approaches (Ventosa et al., 2005): equilibrium models, optimization models, and simulation models. Optimization models focus on the profit maximization problem for one of the firms competing in the market. Equilibrium models (i.e., game theory) represent the overall market behavior taking into consideration competition among all participants. Simulation models are an alternative to equilibrium models when the problem under consideration is too complex to be addressed within a formal equilibrium framework. Within the simulation category are agent-based models (Zhang et al., 2011; Eppstein et al., 2011; Mueller & Haan, 2009) and system dynamics (SD) models (Kwon, 2012; Struben & Sterman, 2008). Both of these approaches are suitable for modeling transportation systems and are widely utilized.

AFV transition entails deep changes to a large socio-technical system that is non-linear (e.g., learning), plagued with long delays (e.g., infrastructure installation, production capacity buildup, consumer awareness), and intertwined in a web of feedback loops (e.g., supply/demand/prices of vehicles) (Shafiei et al., 2012; Struben & Sterman, 2008). Hence, a systems-based approach to investigate the dynamics of sustainability transitions embedded in a socio-technical context (such as the AFV transition) is warranted (Bolton & Hannon, 2016). The technological developments are path-dependent (Struben & Sterman, 2008) and the transitional dynamics are crucial to realistically investigate the feasibility and effectiveness of suggested policies.

For the reasons mentioned above, we adopt the system dynamics simulation methodology to capture the most important feedback loops at play in such a transition. One clear strength of an SD model is that our designed policies ensure realistic transitional dynamics. Also, SD can be particularly useful in capturing the trade-offs between the social and environmental pillars and defining policies that benefit from their synergies.

In SD, we measure the most relevant aspects of the problem under investigation (in our case AFV transition) as stocks and flows. A stock Y accumulates changes over time (in our case the timeline is 2000 through 2035), while a flow X is the instantaneous change that increases (or decreases) the stock at each point in time *t*, resulting in the following dynamics:

$$Y(t) = Y(t_0) + \int_{t_0}^{t} X \, dt$$

In our model, we have many stocks, such as the vehicle inventory, and many flows, such as the vehicle sales. For a more detailed introduction of SD, refer to Appendix A.4, as well as to Barlas (2009) and Sterman (2002). The SD model captures the dynamics behind the transition from traditional to alternative fuel vehicles and its main output is the mix of different types of vehicles between 2000 and 2035. The model is built and tested by using Vensim DSS 6.4 software.

1.4.2 User preferences and adoption of vehicles

There are five types of vehicles in the model depending on their size and fuel-type used: ICE SM (internal combustion engine small to medium-sized vehicle), ICE ML (internal combustion engine medium-sized to large vehicle), H SM (hybrid small to medium-sized vehicle), H ML (hybrid medium-sized to large vehicle), and EV (full battery-powered electric vehicle, no size in this category). These five types are further split between new and used vehicles. For simplicity sake, we bundle the types of vehicles into two main categories: ICE and AFV. We highlight below the most important components of the model.

Figure 1.2 summarizes the most important elements and dynamics that policy makers consider when investigating the AFV transition process through a DJ lens. In the Appendix A.1, we report the main stocks and flows of the SD model in greater detail.

Indeed, the main components of our SD model are AFV sales and ICE sales. These flows are clearly in a trade-off, since increasing the stock of AFV implies a relative decrease in the ICE vehicle stock, and vice versa. Individuals have private motivations for purchasing AFV or ICE (e.g., green/emissions awareness, sensitivity to purchasing price and operating costs, influence from other drivers). Building on these motivations, the purchasing phase leads to the maximization of individuals' utility, which is estimated using a CNL choice model (Bierlaire, 2006), which takes the following form:

$$\sigma_{i,j} = \frac{\sum_{m} \alpha_{j,m} x_{i,j}^{1/\mu_m} \left(\sum_{n=1}^{n_m} \alpha_{n,m} x_{i,n}^{1/\mu_m}\right)^{\mu_m - 1}}{\sum_{m} \left(\sum_{n=1}^{n_m} \alpha_{n,m} x_{i,n}^{1/\mu_m}\right)^{\mu_m}}$$

where $\sigma_{i,j}$ is the share of drivers switching from vehicle type *i* to type *j*. $x_{i,j} = (W_{i,j} * a_{i,j})$ is the perceived utility of vehicle *j* by current drivers of vehicle *i*; $a_{i,j} = e^{\sum_k \text{indicator}_{k,i,j} * \beta_{k,i,j}}$ is the perceived affinity of vehicle *j* by current drivers of vehicle *i* with the *k* index referring to attribute indicators (e.g., price indicator, emissions indicator). These indicators are formulated such that if they are positive, then the target alternative *j* is better than the reference alternative *i*; $W_{i,j}$ is the willingness to consider vehicle j by current drivers of vehicle i; $\alpha_{j,m}$ is the degree to which vehicle j belongs to nest m and μ_m is the degree of independence between alternatives within nest m. Within each nest m, there are $n = 1 \rightarrow n_m$ alternatives. If $\alpha_{j,m} = 1$ and $\mu_m = 1\ \forall\ j, m$ → CNL model collapses into the standard multinomial logit model. Figure A.28 in online Appendix A.1 depicts the choice model.

The vehicle attributes we use in our choice model are purchase price, driving/battery range, emissions, maintenance costs, refueling costs, and availability of fueling/charging stations. We use the CNL formulation since it captures the degree of dependence between relatively similar alternatives (i.e., alternatives that belong to the same nest) while allowing for one alternative to belong to more than one nest simultaneously. For example, an ICE vehicle and a hybrid vehicle belong to the same ICE nest, while the hybrid belongs simultaneously to the ICE and AFV nests. Drivers decide to adopt AFV according to utility maximization principles (CNL model) coupled with bounded rationality; the latter is implemented via a gap between actual and perceived performance and a WTC factor (Struben & Sterman, 2008). The perceived affinity of an alternative is multiplied by its willingness to consider with the purpose of determining its final perceived utility. This WTC factor captures the familiarity of drivers with different alternatives and consequently whether they will consider switching to them. The WTC vehicle j by current drivers of vehicle i at time $t+1$ (i.e., next period) is then:

$$\mathrm{W}_{\mathrm{i,j,t+1}} = (\rho_{\mathrm{i,j,t}} * PF_{i,j,t})\left(1 - \mathrm{W}_{\mathrm{i,j,t}}\right) - (\theta_{\mathrm{i,j,t}} * NF_{i,j,t}) * \mathrm{W}_{\mathrm{i,j,t}}$$

where $\rho_{\mathrm{i,j,t}}$ is the impact of social exposure on the willingness to consider (comprised of marketing effectiveness of a certain alternative and WOM between the drivers of different alternatives), $\theta_{\mathrm{i,j,t}}$ is the decay rate of the WTC and $PF_{i,j,t}$ ($NF_{i,j,t}$) are the positive (negative) fairness effect of DJ on consumers WTC AFV. See Appendix A.1.1 for more details about the user preferences and vehicle adoption dynamics.

1.4.3 Production and sales of vehicles

The vehicle stock increases with sales and decreases with aging (in the case of new vehicles) or discards (in the case of used vehicles), as shown below:

$$\frac{dV_j}{dt}(unit\ of\ Vehicle/year) = Sales_j - Discards_j$$

The desired sales of vehicle j are determined from the user preferences (section 1.4.2) plus possible transfer of other alternatives supply shortages/gaps:

$$Desired\ sales_j = (\sum_i \sigma_{i,j}(Discards_i + g * V_i)) + Gap\ Transfer_j$$

The first half in the equation above is inspired by Struben and Sterman (2008). The "$\sigma_{i,j}$" is the share of drivers switching from vehicle i to j (it is possible for a driver to decide to keep his or her own type of vehicle). g is the exogenous fractional growth rate meant to replicate the historical demand and its projected forecast through 2035. The gap transfer accounts for the possibility of drivers switching to vehicle j (i.e., their next best available alternative) due to supply shortage of their preferred alternative. This gap transfer is regulated by an algorithm that allocates the different excess of demands (i.e., demand for different types of vehicles that exceed their capacity constraints) to different supplies (i.e., available inventory of different types of vehicles) taking into consideration the preferences of the drivers, the priority of demand sources, as well as the capacity constraints. So, if the preferred alternative of a driver is not available (i.e., shortage of supply), then this driver will be allocated to the next best available alternative (see Appendix A.1.1.2 for more details). This formulation ensures mass balance in the model, that is, the sum of all outgoing flows is equal to the sum of all incoming flows at all times.

The sales of a particular type of vehicle j are constrained by the available supply of that vehicle:

$$Sales_j = Min\left(Desired\ sales_j, Supply_j\right)$$

The supply is determined by the production and sales of vehicles:

$$Supply_j = (P_j - V_j)/Sales\ Period - (P_j\ \ Outflow - V_j\ Outflow)$$

P_j is the stock of produced vehicles of type j, V_j is the stock of vehicles of type j that are currently being used. This formulation ensures $P_j \geq V_j$. $Supply_j$ is the current inventory of vehicles j that are available to be sold to potential buyers. The stock of new vehicles is determined by the production of new vehicles. Also, in the case of used vehicles, the stock is determined by the aging of the new fleet.

The desired production of vehicles is determined from sales and a reordering point (ROP):

$$Desired\ Production_j = Sales_j + Max((ROP_j - Supply_j) * Demand\ Visibility, 0)$$

The desired production is determined by the new sales plus the existing gap between the ROP and the current supply (i.e., inventory) of vehicles. The gap is only partly observed by the manufacturer since the ROP is determined based on a desired customer service level and desired sales. The production of vehicles is constrained by the production capacity:

$$Production_j = MIN(Production\ Capacity_j, Desired\ Production_j)$$

The change in production capacity (if needed) is determined by the ROP and constrained by a maximum increase of capacity in a year. See Appendix A.1.1.3 for more details about the dynamics of production and sales of vehicles.

The purchase price of the alternatives is determined based on production and sales:

$$Price_j = \frac{Reference\ Purchase\ Price_j}{Learning\ Multiplier} * \left(\frac{Production_j}{Sales_j}\right)^{Supply\ Price\ Elasticity_j}$$

The purchase price is based on three components: nominal reference price, a learning by doing effect, and the current dynamics of supply and demand.

It is worth noting that the model also considers fuel and charging stations as complementary goods to the AFV technological diffusion. The development of the infrastructure is driven by a desired profitability, which in turn triggers infrastructure investments. See appendix A.1.2 for more details.

1.4.4 AFV transition and policy instruments

Figure 1.4 presents the relationships between AFV and ICE sales with the classical instruments developed by policy makers to accelerate the AFV transition. When policy makers introduce *AFV subsidies*, this intuitively leads to higher AFV sales and, consequently, to lower ICE sales. Higher AFV sales generate larger ZEV credits for the manufacturers, which minimizes the existing credit gaps and credit penalties. Therefore, policy makers can modify the *ZEV sales threshold* to incentivize manufacturers to invest more in AFV development and further increase AFV sales. This policy can have a considerable negative impact on the sale of ICE. Policy makers can use the *fuel tax* instrument to increase these costs even more and further decrease ICE sales, thus favoring the AFV transition. Finally, both AFV and ICE vehicles generate some emissions, whose stock can be regulated though emissions credits. Policy makers directly act on the credit amounts by modifying the *emissions threshold*, thus influencing both the credit gaps and the investments needed to cut these emissions.

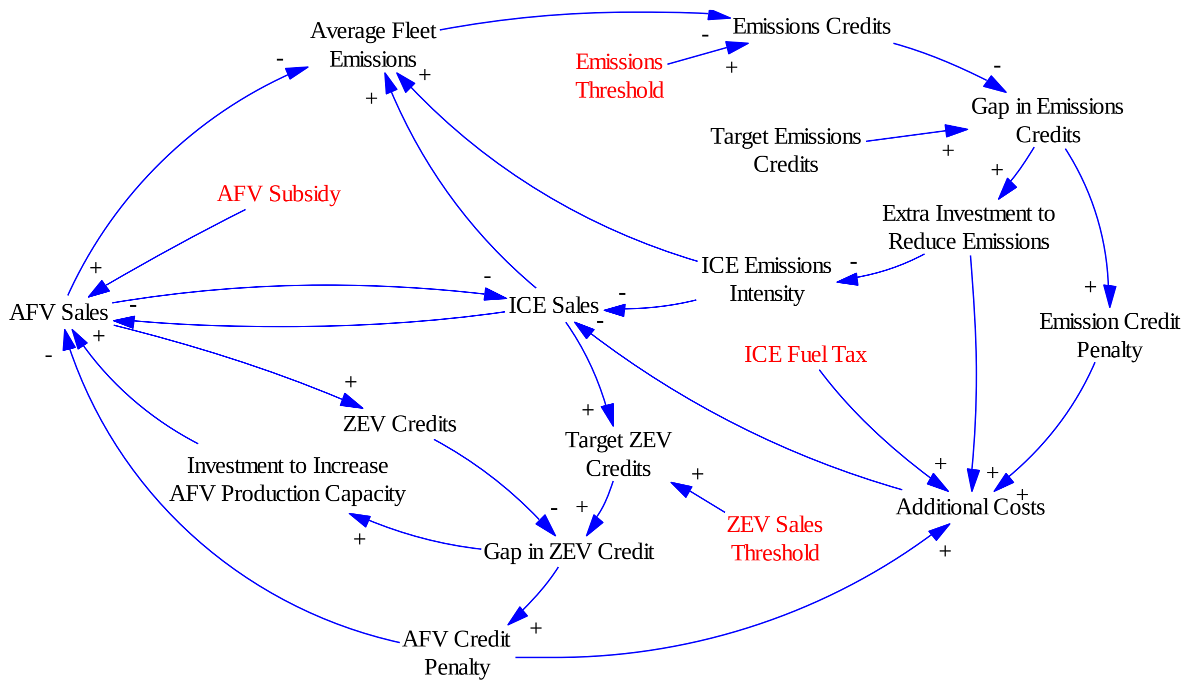


Figure 1.4: Dynamics of policy instruments

Our baseline scenario is a combination of these instruments at their status-quo levels determined from the literature (CARB, 2017; Walther, 2010). To fill the research gap that we identify in section 1.2.2 and properly answer research questions 2 and 3, several scenarios are simulated by varying the parameters of these instruments. This allows us identify the combination of instruments leading to the best balance between environmental performance and social outcomes (see sections 1.5.2 and 1.5.3).

1.4.5 Model behavior and results

As with any model, including SD models, we need to check whether the model can follow the historical behavior observed in real life. If so, we can establish confidence in the model and its ability to provide a good base to judge the policies' outcome.

We collect historical data (2000-2017) for several key variables in the model, such as sales, vehicle miles traveled (VMT), GHG standards, and ZEV standards (US Department of Energy, 2018a; US Department of Energy, 2018b; US Department of Energy, 2017; US Energy

Information Administration, 2017; US Department of Transportation, 2017; US Environmental Protection Agency, 2012). In the case of vehicle sales and VMT, these are secondary data (from reliable governmental sources) since these variables cannot be measured firsthand by definition. In the case of GHG and ZEV standards, these are set by the government and we collect them from public sources. The data are used to calibrate and validate the model behavior.

We achieve a good fit between the model behavior and historical data, as seen in Figure 1.5. Hence, it is deemed to be representative of reality with its behavior taken as prescriptive of policy outcomes. See Appendix A.3 for more details concerning calibration.

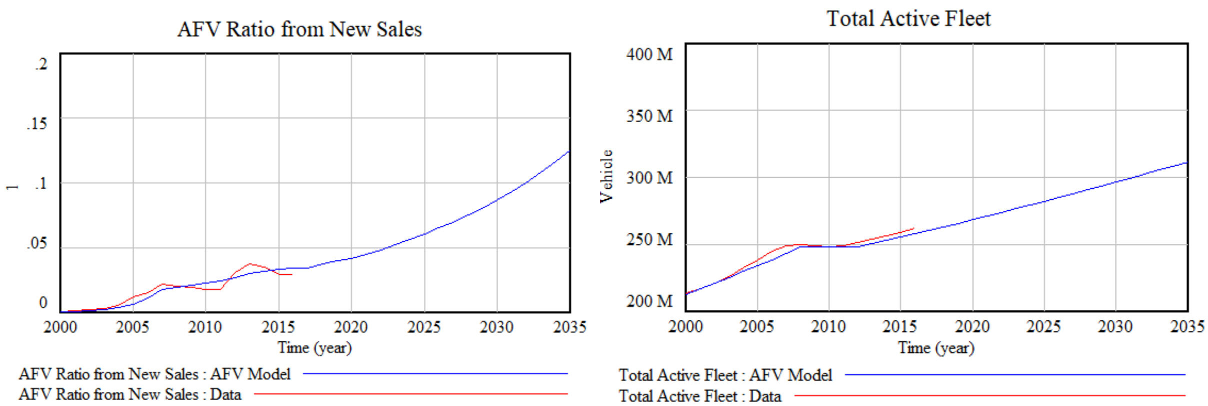


Figure 1.5: Model vs. data, AFV ratio from new sales and total active fleet of vehicles

In addition, sensitivity analysis tests the importance of the weights assigned to the different components of the DJ index and ST index. Figure 1.6 shows that the ST index is marginally sensitive to these weights both quantitatively (i.e., value of index does not vary much) and qualitatively (i.e., if index is increasing or decreasing, it does not change directions when we vary the weights).

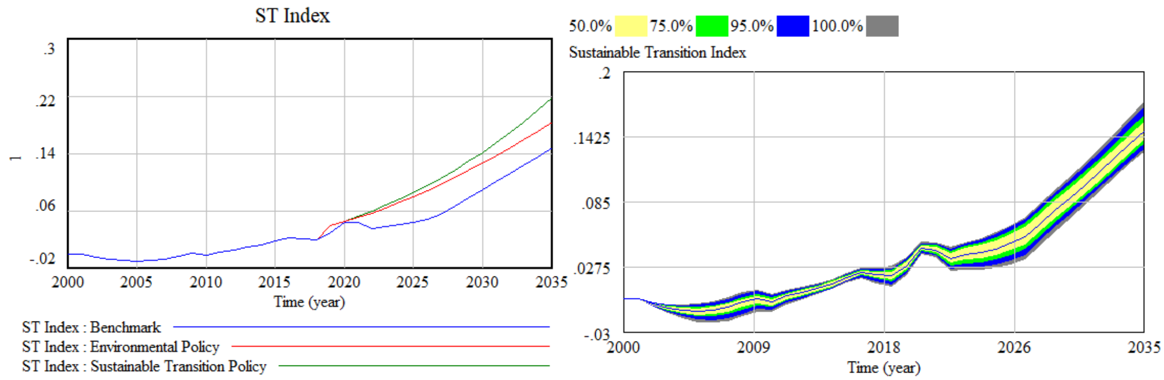


Figure 1.6: Sustainable transition index behavior under different scenarios (left) and its sensitivity to its two components (AFV sales and DJ index) weights (right)

To test the model assumptions, we run robustness and multivariate sensitivity analysis. Over 3,000 iterations, we simultaneously vary the most important parameters in the model (spanning across sales, production, and policies) within large ranges. Some of the results are shown in Figure A.35 in Appendix A.3 and demonstrate the robustness of our findings.

1.4.6 Scenario Building

We will use the conceptual model in Figure 1.2 to investigate the effectiveness of DJ in accelerating the sustainable transition of AFV. To do so, we consider two scenarios:

Scenario 1**:** Policy makers only consider environmental targets when looking at the AFV transition. We perform the optimization problem by only maximizing the AFV sales with the link between the DJ index and AFV sales being not active.

Scenario 2: Policy makers consider both environmental and social targets when investigating the AFV transition. In this case, we perform the optimization problem by maximizing both AFV sales and DJ, leading to maximization of the ST index. The latter is achieved by activating the link between the DJ index and WTC AFV.

1.5 Results

1.5.1 Impact of adopting DJ on policy performance

In this section, we display the results of our research by comparing the outcomes in Scenario 1 and Scenario 2 in Table 1.1 with the aim of answering research question 1: *Can policy makers* *overcome the trade-off between environmental and social agendas, hence catalyzing the AFV transition, by adopting DJ criteria along with environmental criteria?*

We target AFV sales (i.e., environmental objective) in Scenario 1 and combine it with the DJ index (i.e., social objective) under the ST index in Scenario 2 in an attempt to overcome the trade-offs. Furthermore, we report a *benchmark* outcome where policy makers set policies (i.e., combination and strength of policy instruments) without having any specific objective in mind. Therefore, Table 1.1 displays the outcomes of the performance indicators when optimizing with respect to specific objectives. For example, policy makers can achieve a DJ index=0.33 when optimizing according to the ST index. Accordingly, we derive the following intuitions:

1. The decision maker gets higher AFV sales, which implies a faster transition from ICE vehicles to AFV, by adopting an environmental policy compared to the benchmark scenario (Δ=+6.3%). Nevertheless, it experiences a decrease in DJ (Δ=-6.7%) from 0.201 to 0.188. This result informs of the trade-offs entailed by such a policy and warns decision makers about the need to adopt a more comprehensive policy that also includes social aspects. Since ST incorporates both DJ and AFV sales targets, the overall performance generated by environmental policy does not improve the social welfare, as it can be perceived as unjust.
2. Decision makers considering DJ principles (Scenario 2) when designing their policies experience an even faster transition process from ICE vehicles to AFV (Δ=16.1% compared to 6.3%), and they manage to increase the DJ index as well from 0.201 to 0.334 (Δ=65.8%). Hence, including DJ principles in the decision-making process allows policy makers to improve DJ as well as AFV sales, leading to a better overall ST index. ST policy is both environmentally and socially sustainable and mitigates all inconvenient trade-offs emerging when using an environmental policy.
3. Under the ST policy, individuals perceive the policies to consider the existing heterogeneity among consumers' utility and accessibility to transportation, as well as the differences in purchasing price and benefits of alternative vehicles. Such a policy, as intended by incorporating the DJ index, is seen as fairer.
4. If policy makers explicitly convey to consumers (through marketing and awareness campaigns) that they are increasing the fairness of the AFV transition by explicitly adopting

DJ principles, the willingness to consider AFV increases as well. In turn, this results in increasing AFV market penetration as seen under the ST policy.

5. Decision makers aiming to accelerate the adoption of AFV should embed DJ policy criteria into their decision-making process. This finding provides a positive result for research question 1: policy makers should use both DJ and environmental criteria when evaluating and implementing policies to accelerate the AFV transition; the potential improvements to both objectives can be significantly high.

		Range of Instruments	Benchmark	Env Policy (Scenario 1)		ST Policy (Scenario 2)	
				Value	**% Change**	**Value**	**% Change**
Performance Indicators	DJ Index	N/A	0.2011	0.1876	-6.7%	0.3335	+65.8%
	AFV Sales		0.1219	0.1296	+6.3%	0.1416	+16.1%
	ST Index		0.1482	N/A		0.2181	+47.1%
Policy Instruments	Fuel Tax	0→0.2	0.1	0.2			
	Hybrid Subsidy	0→5000	2000	5000			
	EV Subsidy	0→7500	3000	7500			
	Penalty for ZEV Gap per Credit	1000→7500	4250	7500		1000	
	Manufacturer % Transferring ZEV Penalty	0→1	0.5	1		0	

Table 1.1: Performance indicators and policy instruments under different scenarios

1.5.2 Combination of policy instruments under different policy objectives

In this section, we answer research question 2: *Which combination of instruments (fuel tax, AFV subsidies, and ZEV regulations) should policy makers use to maximize the ST index (i.e., both AFV sales and the DJ index)?*

Table 1.1 (bottom rows labeled policy instruments) reports the best values to be used under each policy, which shows that the best combination depends on the policy makers' targets. The column "Range" informs of the minimum and maximum values that a certain policy instrument can take. Accordingly, we have the following recommendations:

1. When policy makers formulate a policy, the fuel tax should be fixed at the maximum level, independent of the criteria adopted. This policy has negative implications for consumers, who pay more when consuming fuel and show a lower willingness to prefer ICE over AFV.

Imposing a policy through penalties threatens the number of ICE vehicles and reduces, consequently, the emissions. At the same time, consumers can intuitively appreciate the mechanism behind it and better realize the benefits in comparison to alternative solutions. Also, they perceive the purchase price difference between ICE and AFV as justified by the high savings eventually linked to the fuel tax.

2. Decision makers should use "penalty for ZEV gap per credit" very parsimoniously and depending on the fixed target. When policy makers consider only environmental criteria, the penalty should be set at the highest level. When DJ criteria are a part of the decision-making process, the penalty should be fixed at the minimum. The latter case also applies when ST is considered, highlighting the idea that DJ is more important than sole environmental criteria to speed up the adoption of AFV.
3. The hybrid subsidy amount and EV subsidy supply a clear and pure incentive for consumers to shift their preferences from ICE to AFV and thus accelerate the adoption process. Policy makers can fix this incentive at the maximum level to simultaneously maximize both objectives. These subsidies make AFV more accessible and affordable, directly acting on the purchase price and increasing the appreciation of related benefits.
4. When manufacturers do not fulfill their obligations and are subject to penalties, the latter should be evaluated by the policy makers according to the targets. When optimizing the environmental policy, the penalties should be fully transferred to consumers, allocating more penalty quotas to ICE vehicles. This will encourage consumers to purchase more green cars and accelerate the adoption of AFV. In contrast, when the optimization problem also includes DJ criteria, manufacturers should not transfer the penalties to consumers at all. Rather, manufacturers should be fully responsible for these penalties and make this information clear to society. Therefore, consumers would appreciate these efforts, feel more responsible in their purchasing decisions, and thus accelerate the adoption of AFV.

This argument allows us to answer our second research question. When policy makers aim only at reducing emissions, the best policies to be implemented include a maximum fuel tax, maximum ZEV penalty per credit gap, maximum hybrid and ZEV subsidies, and full transfer of the ZEV penalty. In contrast, when policy makers seek to optimize both the environmental performance and the DJ index, the best policies to be implemented include a maximum fuel tax, maximum hybrid and ZEV subsidies, and minimum ZEV gap per credit. Consequently, there is no transfer of the ZEV penalty. The latter combination naturally leads to ST index maximization and a faster and more efficient transition to AFV.

We notice that the optimal policy under the ST objective still relies on some coercive mechanisms (fuel tax) as well as potentially paradoxical instruments (AFV subsidies) (Boussauw & Vanoutrive, 2017). This is justified because the current trend of car ownership is not going to change in the near future; hence, coercive policies are needed to bring down the transportation emissions and prevent the deterioration in quality of life to society as a whole due to pollution (Harrison & Shepherd, 2013). However, where possible, such policies should be constrained by DJ principles to prevent the disproportional suffering of the worse off. Such constraints include maximizing access to transportation (i.e., preventing a large increase in ICE purchase prices) and ensuring that different people derive the same utility/benefit from different vehicles, which in our case is realized by minimizing the ZEV-related penalties.

5.3 Analysis of the instruments' marginal contributions to AFV adoption

Here we answer research question 3: *Which instrument (fuel tax, AFV subsidies, or ZEV regulations) provides the highest contribution to the ST index?*

While in Table 1.1 we display the optimal combination of sustainable policies by acting on each of them simultaneously, we refine this analysis in Table 1.2. Here, we aim to discover the marginal impact of each policy instrument on the DJ, environment, and ST targets to suggest which policy instruments are to be given more weight in the policy-making process. Table 1.2 reports the marginal changes in the performance scores when taking the minimum and the maximum of each policy instrument. We compute the benchmarks as the scores obtained by taking the mean of minimum and maximum values of each policy instrument. For example, we take fuel tax=0.1 when computing the benchmark. This allows us to compare the changes in the outcomes to the benchmark. The information that we provide below allows policy makers to select policies to be implemented when some constraints exist. Accordingly, we can formulate the following recommendations, which directly answer our research question 3:

1. We notice that under the environmental policy (status quo) all policy instruments play a positive role in increasing AFV sales, which is their intended goal.

2. ZEV penalty instruments have a conflicting impact under environmental vs. ST policies. They are beneficial under environmental policy (i.e., they increase AFV sales) and harmful under ST policy (i.e., decrease both AFV sales and the DJ index).
3. When policy makers only target the optimization of environmental targets, they should be aware of the considerable impact of the EV subsidy amount, which provides the higher marginal contributions to AFV sales and environmental performance. More generally, environmentally conscious decision makers should use the following classification of sustainable policies to perform environmental targets: (1) EV subsidy, (2) fuel tax, (3) hybrid subsidy, (4) manufacturer percentage transferring ZEV penalty to consumers, and (5) penalty for ZEV gap per credit.
4. When policy makers target the optimization of both DJ and environmental criteria (i.e., ST policy), they should focus their effort on the manufacturer percentage transferring ZEV penalty to consumers, which supplies the highest contribution to the ST index. The following classification applies when looking for the optimization of ST: (1) manufacturer percentage transferring ZEV penalty to consumers, (2) penalty for ZEV gap per credit, (3) hybrid subsidy, (4) EV subsidy, and (5) fuel tax.

		Env Policy (Scenario 1)	**Sustainable Transition Policy (Scenario 2)**		
	Instrument Value	AFV Sales	AFV Sales	DJ Index	ST Index
Fuel Tax	0	0.1221	0.1303	0.2442	0.1699
	0.2	**0.1236 (2)**	0.1322	0.2511	**0.1728 (5)**
Penalty for ZEV Gap per Credit	1000	0.1227	0.1351	0.2891	**0.1941 (2)**
	7500	**0.1231 (5)**	0.1286	0.2178	0.1549
Hybrid Subsidy Amount	0	0.1224	0.1299	0.2316	0.1634
	5000	**0.1234 (3)**	0.1328	0.2681	**0.1811 (3)**
EV Subsidy Amount	0	0.1189	0.1269	0.2375	0.1656
	7500	**0.1272 (1)**	0.1362	0.2587	**0.1797 (4)**
Manufacturer Percentage Transferring ZEV Penalty to Consumers	0	0.1226	0.1364	0.3005	**0.2011 (1)**
	1	**0.1232 (4)**	0.1278	0.2118	0.1513

Table 1.2: Marginal contribution of policy instruments under different objectives

1.6 Conclusions

This paper introduces the concept of DJ in the context of AFV adoption and checks its impact on policy makers' sustainable policies and instruments. After operationalizing the DJ concept according to Equity, Equality, and Need, we embed this new concept in a stylized system dynamics model of AFV adoption. We investigate whether considering DJ targets along with environmental targets accelerates the adoption of AFV during the period 2018-2035, as the same path during 2000-2017 evolved quite smoothly.

Although the traditional instruments used by policy makers (fuel tax, AFV subsidies, and ZEV regulations) aiming to optimize environmental performance work moderately well, better results can be obtained in the future by also considering DJ targets. In particular, policy makers should look at the sustainable transition index, which includes both environmental and DJ components. By doing so, they can enjoy an increase in the speed of AFV adoption as well as a significant increase in DJ performance. Furthermore, our findings show that DJ provides a large contribution to the adoption of AFV, suggesting that policy makers should abandon the view of simple environmental preservation to also embrace DJ principles.

We look at a combination of policy instruments to optimize sustainable transition targets and accelerate the AFV adoption. We discover that policy makers can speed up the adoption of AFV when a fuel tax as well as hybrid and EV subsidies are set at the maximum level while both the ZEV penalty per credit gap and manufacturer percentage transferring ZEV penalty should be fixed at the minimum level. Our findings suggest that when policy makers adopt instruments that maximize DJ, people are more willing to adopt AFV. This entails an additional operative instrument (complementing the environmental instruments), linked to increasing the perceived fairness of the AFV transition through development of the "willingness to consider" concept, which in turn leads to an increase in AFV adoption.

Finally, we investigate the marginal contribution of each instrument on AFV adoption to provide suggestions to policy makers when some constraints exist (e.g., budget constraints). We discover that when policy makers focus on maximizing environmental targets, they should devote more efforts to the EV subsidy, while investing more on manufacturer percentage transferring ZEV penalty to consumers when maximizing the DJ and sustainable transition targets. We also show that policy makers should prioritize differently the instruments according to the targets they have in mind.

Our results are not free of limitations, which we mention here to inspire future research on this subject. The different vehicle alternatives are summarized under a limited number of types based on fuel type and vehicle size. This simplifies the choice drivers make in real life, but without losing any insights. We focus on the main policy instruments that span the spectrum presented in the literature (Bjerkan et al., 2016); however, there are more instruments to be investigated, including, for example, parking permit fees and road tax/tolling. Other methodologies can be applied to investigate whether considering DJ principles in other contexts leads to improvements as well. One such endeavor would be to look at R&D investments while considering DJ targets. This is an ongoing project of the authors.

ESSAY TWO

Innovation as driver of sustainability in a segmented market

Case of the Automobile Market

Abstract

We build a model to investigate and design R&D innovation strategies for a multi-product monopolist that is proactive when it comes to changing consumer preferences, mainly the increase in consumer environmental awareness. Along with product and process innovation, we consider consumer heterogeneity and its ensuing cannibalization problem. We do so first via market segmentation into High vs Low segments, second via focusing on two attributes to define product quality, performance and the emission levels of vehicles. The monopolist offers an assortment of Alternative Fuel Vehicles (AFV) and Internal Combustion Engine (ICE) vehicles to accommodate for these preferences. Accordingly, R&D investments are split between those targeting to increase the performance, to lower emissions and to decrease costs with the entire budget dependent on profits. We particularly focus on the social dimension of the AFV transition by relying on the concept of Distributive Justice (DJ) to quantify it. We find that cannibalization and innovation are both needed to accommodate for changing customer values and maximize the sustainability of the transition to AFV and that it is possible for the three sustainability pillars to interact in harmony. More so, maximizing for profits and/or minimizing emissions would result in lower quality and higher prices than when we consider simultaneously with them the DJ index. This confirms the benefits of explicitly including the social pillar quantified by the DJ index when designing innovation strategies.

Keywords: R&D investment, Market segmentation, Distributive Justice, Sustainability, Preferences, Cannibalization

2.1 Introduction

The transition from internal combustion engines (ICE) to alternative fuel vehicles (AFV) is becoming an urgent and challenging issue in today's world. The transition to a more sustainable transportation system is a complex and dynamic process (Zhang et al., 2011; Struben & Sterman, 2008) where innovation is the key word. Innovation is commonly acknowledged as a key aspect of modern market place competition (Veldman et al., 2014; Gomellini, 2013; Cellini and Lambertini, 2009; Aghion et al., 2005; Bonanno and Haworth, 1998).

Typically, firms are weary of increasing cannibalization within their product line fearing lower profits (Li et al., 2018; Sinitsyn, 2016; Kim et al., 2013), thus they tend to stifle innovation that would exacerbate it. However, the disruptive and radical technological innovation which is the emergence of the electric car cannot be ignored. If an automotive manufacturer stifles the emergence of AFV, it does so at its own risk of disappearance by not accommodating evolving consumer preferences. We build a theoretical model to investigate and design innovation strategies for firms seeking to be proactive when it comes to changing consumer preferences, mainly the increase in consumer environmental awareness (Zhang et al., 2015; Liu et al., 2012). We consider consumer heterogeneity (i.e. market segmentation) and its ensuing cannibalization problem when designing innovation strategies.

Given the competitive landscape of today's markets, including the automobile manufacturing sector, multiproduct firms have come to dominate the marketplace (Li et al., 2018). Most major car manufacturers offer an assortment of Internal Combustion Engine (ICE) and Alternative Fuel Vehicles (AFV).

This product proliferation has inter-brand competition effect and intra-brand cannibalization effect. Inter-brand competition is when introducing a greater variety of products, a firm can attract new consumers with heterogeneous tastes (Li et al., 2018; Desai, 2001). Intra-brand cannibalization occurs since products offered by the same firm are often considered by consumers as close substitutes so that one product's customers are at the expense of other products offered by the same firm (Li et al., 2018; Sinitsyn, 2016; Kim et al., 2013). In this paper we focus on the intra-brand cannibalization effect by considering a multi-product monopolist that offers an assortment of products.

The monopolist has to satisfy the demand of a market segmented into High vs Low consumers. High segment consumers value all the attributes of the vehicle more so than the Low segment consumers. Since more than one characteristic is needed to define product quality (Walter and Peterson, 2017; Garella and Lambertini 2014), we focus on both performance and level of emissions of vehicles as indicators of their quality. So, within each of the segments, we have two types of consumers: Emissions oriented consumers who value lower emissions more than high performance of the vehicle, and Performance oriented consumers who value high performance more than lower emissions. To accommodate for these preferences, the monopolist offers two products within each segment, one product destined to the emissions oriented consumers (i.e. AFV), another destined to the performance oriented consumers (i.e. ICE).

Accordingly, R&D investments are split between those targeting to increase the performance of the vehicle, to lower emissions and to decrease costs (i.e. process innovation) with the entire budget for R&D dependent on profits. A segmented transportation market with R&D investments is a complex system filled with many trade-offs, feedbacks and long delays. Therefore we investigate it by employing systems thinking, particularly system dynamics methodology.

In section 2.1, we discuss the gaps in the product line design and innovation literature that this study aims to fill. Mainly, we simultaneously consider cannibalization with both dominating and non-dominating preference structures as well as product and process innovation strategies (i.e. the different factors illustrated in middle section of Figure 2.7). This allows us to model endogenously both price and quality versus having one of them as an exogenous decision variable as in previous product line design literature (Desai, 2001; Heese and Swaminathan, 2006; Kim et al., 2013; Sinitsyn, 2016). More so, R&D and innovation investments are influenced by market segmentation and consumer heterogeneity. So, we investigate them in a heterogeneous market rather than in a homogeneous market (Li, 2018; Lambertini et al., 2017; Pan and Li, 2016; Li and Ni, 2016; Lambertini and Orsini, 2015; Chenafaz, 2012).

We contribute to the sustainability assessment of the AFV transition and its ensuing policy implications. Within the context of transition to AFV, the literature mostly neglects (or places little importance on) the social dimension. However, individuals judge policies and make decisions by considering various justice criteria (Luo, 2007; Colquitt et al., 2001). The tradeoffs between the sustainability pillars are not trivial to discern and require systematic thinking (Boussauw and Vanoutrive, 2017; Harrison and Shepherd, 2013; Cohen, 2010).

To our knowledge, (El Hachem & De Giovanni, 2019) is the only paper to have explicitly and quantitatively tackled this issue within the AFV transition context, and they did so by quantifying the social dimension using the concept of Distributive Justice (DJ) (Hulle et al., 2017; Heindl & Kanschik, 2016; Colquitt & Rodell, 2015; Stenman & Konow, 2010). However they did not investigate innovation and market segmentation within the context of AFV transition. We do so in our paper for a more complete investigation of the dynamics at play in such a transition.

Our work lies at the intersection of sustainable operations management and marketing, with particular focus on price and quality optimization for product lines. Sustainable operations management research has argued and found that profit and environmental benefits are not necessarily antithetical (Jalili et al., 2017). We focus on the social dimension as well via DJ, and investigate whether it is possible for the three sustainability pillars to interact in harmony with each other. For this purpose, we define an indicator of sustainability that embeds the DJ with the environmental and economic objectives, namely, the Sustainable transition (ST) index which harnesses the potential synergy between the three objectives, thus minimizing the unintended consequences (i.e., worsening of the social objective).

We find that cannibalization and innovation are both needed to accommodate for evolving customer values while maximizing the sustainability of the transition to alternative fuel vehicles (AFV). Despite the many tradeoffs between the three sustainability pillars, we find that the three sustainability pillars can interact in harmony. This is possible when firms have a healthy R&D budget for innovation while allowing for within-segment cannibalization. More so, maximizing for profits and/or minimizing emissions would produce lower quality and higher prices than when we consider simultaneously with them the DJ index. This confirms the benefits of explicitly including the social pillar quantified by the DJ index in our decision making process when designing R&D and innovation strategies.

The remainder of the paper is structured as follows. Section 2.2 introduces the literature, highlights our contributions and develops the research questions. Section 2.3 describes the methodology and presents the main model dynamics. Section 2.4 presents the main findings and Section 2.5 briefly concludes.

2.2 Literature Review and Research Questions

2.2.1 Product Line Design Literature

Model setup allows us to model simultaneously several concepts from the product line design literature such as dominating and non-dominating consumer preferences, commonality and cannibalization.

Heightened market competition and evolving consumer preferences naturally led manufacturers to adopt product proliferation (Li et al., 2018, Kim et al., 2013). Product proliferation has two competing effects on firm's profitability. First, it has an inter-brand competition effect: when introducing a greater variety of product offerings, a firm can attract new consumers with heterogeneous tastes and induce consumers to switch from competitors (Li et al., 2018, Kim et al., 2013). Second, it has an intra-brand cannibalization effect: products offered by the same firm are often considered by consumers as close substitutes so that one product's customers are at the expense of other products offered by the same firm (De Giovanni and Ramani, 2018; Li et al., 2018; Desai, 2001).

One important decision marketing and manufacturing managers must make when designing their product lines is whether to use product-specific components for individual products or common components for the entire product line. Marketing and operations scholars have cautioned against using the commonality strategy by showing that commonality dilutes product differentiation and intensifies product cannibalization within the product line (Desai et al. 2001; Heese and Swaminathan 2006).

Durable goods manufacturers, such as car manufacturers, often design product lines by segmenting their markets (i.e. consumers heterogeneity) on quality attributes that exhibit a “more is better” property for all consumers (Desai, 2001; Kim et al., 2013; Jalili et al., 2017). Consumers in one segment (i.e., the high segment) value all product attributes more so than consumers in the other segment (i.e., the low segment).

Such a dominating consumer preference framework partly captures our situation where we split the consumers into those well-off (i.e. High) and less well-off (i.e. Low). High segment values higher performance and lower emissions more than the low segment does.

If lower-quality products are sufficiently attractive, higher-valuation consumers may find it beneficial to buy lower-quality products rather than the higher quality products targeted to them. That is, lower-quality products can potentially cannibalize higher-quality products. This is intra-brand cannibalization (De Giovanni and Ramani, 2018).

A few papers such as (Kim et al., 2013; Jalili et al., 2017) consider the case where preference structure is non-dominating, meaning each consumer segment values at least one attribute higher than the other segment. In such a case, the flow of consumers between segments goes both ways. In such a setting, a commonality strategy (common components/attributes between products) can relieve cannibalization under some circumstances.

This echoes some of the results from (Desai, 2001), since more competition between products in the high segment will push their quality up and render the low segment products less attractive, thus easing the cannibalization problem.

Given our ICE and AFV market, we consider a segmented market with two consumer segments (High and Low), and two vehicles alternatives within each segment (AFV and ICE). Segmenting the market into two segments reflects that consumers are heterogeneous with one segment (i.e. High) valuing all vehicle attributes more than the other segment (i.e. Low). Therefore we have a dominating preference structure between the two segments similar to Desai (2001).

Considering two vehicle alternatives within each segment reflects the fact that consumers have different taste preferences (Garela and Lambertini, 2014), with some valuing more lower emissions, while others valuing more higher vehicle performance.

From our discussion, we see that previous papers studied cannibalization in a segmented market with dominating preference structure (Desai, 2001) and non-dominating preference structure (Kim et al., 2013; Jalili et al., 2017). However none to our knowledge considered simultaneously these two structures by having a monopolist selling products to a segmented market with multiple products within each segment, a gap which we fill in this paper.

By considering simultaneously these two structures, we have both potential for cannibalization between segments which is prevented via cannibalization constraints, as well as realized cannibalization within each segment.

More so, to our knowledge, there are no papers that address product line design and its ensuing cannibalization problem in a segmented market simultaneously with innovation. However, innovation has a direct impact on how a market is segmented (Chen and Schwartz, 2013; Bandyopadhyay and Acharyya, 2004) and influences the cannibalization within it. Hence the need to consider both product line design/cannibalization and innovation simultaneously.

2.2.2 Innovation Literature

The literature on process and product innovation considers a single product (Lambertini et al., 2017; Pan and Li, 2016; Li and Ni, 2016; Lambertini and Orsini, 2015; Chenafaz, 2012) or multi-product monopoly (Li, 2018). From this literature we will take the concepts of learning by doing, knowledge accumulation, spillovers and the distinction between process and product innovation.

Lambertini et al. (2017) focus on the possibility of having superior product quality levels at lower marginal production cost over time. They investigate the optimal R&D portfolio of a single product monopolist investing in cost-reducing activities accompanied by efforts improving the quality of its product. They find that one should not expect the firm to supply an increasing quality level at a decreasing production cost. We implement this finding in our model.

Pan and Li (2016) present a dynamic optimal control model of process–product innovation with learning by doing, and extend the model of Chenavaz (2012) to an even more general model in which the firm’s cost functions of product and process innovation depend on both the innovation investments and the knowledge accumulations of product and process innovation.

Li (2018) develops a dynamic control model of a multiproduct monopolist’s product and process innovation with knowledge accumulation resulting from learning by doing. They investigate the optimal investment behavior in such a setting under the monopolist optimum and social planner optimum.

All of these papers deal with innovation in a somewhat extensive manner by considering knowledge accumulation, learning by doing and/or spillovers. However, they do not consider consumer taste preferences and assume consumers are homogenous. Yet, as we have seen, consumers are heterogeneous in their taste preferences and are split up in a segmented market.

A few papers have investigated product and process innovation while considering consumer heterogeneity; however, they did so with no knowledge accumulation, no spillover, no learning by doing, and no explicit consideration of market segmentation and its ensuing cannibalization problem (Chen and Schwartz, 2013; Bandyopadhyay and Acharyya, 2004). This is a research gap which we fill in this paper.

In our paper, the innovation strategy of a firm considers explicitly the impact of market segmentation and consumer heterogeneity on decisions of splitting R&D investments between product/process innovation and degrees of permissible spillover. Therefore, innovation investments have to be also split between different market segments taking into consideration consumer preferences within each segment. The importance of considering market segmentation simultaneously with innovation investments can be shown with these points for reflection:

1- Investing more into process innovation for low segment products, thus lowering their costs would appeal more to the low segment than if we invested more into the high segment products; thus the decision of how to split process innovation investments between segments can have a large impact on market share and profits;
2- Allowing for spillover from high segment products to low segment ones (this increases commonality between products), would render low products more attractive and increases the threat of cannibalization; thus the decision and amount of permissible spillover between segments can as well have a large impact on profits;
3- Investing more to lower emissions of vehicles rather than increasing their overall performance, would appeal more to the emissions oriented consumers versus the performance oriented ones, thus increasing cannibalization within each segment; thus the decision of splitting R&D investments between emissions or performance oriented efforts, can have a large impact on profits.

From this thread of innovation literature, we deduce that the incentive to innovate is higher under the social optimum than under the profit-seeking monopolist. There are a few papers that consider the social planner scenario (Li, 2018; Lambertini et al., 2017; Lambertini and Orsini, 2015; Walter and Peterson, 2017). However none of them considers explicitly the social dimension and none considers the concept of DJ to quantify it. This brings us to our second main contribution, which is Distributive Justice and its policy implications.

2.2.3 Distributive Justice

The history of the AFV transition across nations has exhibited "sizzle and fizzle" behavior, as illustrated in Sterman (2015). A key factor in this slow transition is the neglect of the social dimension of this transition (Boussauw & Vanoutrive, 2017; Harrison & Shepherd, 2013; Martens et al., 2012).

While the literature investigates the AFV transition under different perspectives, few papers highlight the social aspects of such a transition (Boussaw & Vanoutrive, 2017; Harrison et al., 2013; Lucas et al., 2012). In particular, the concept of DJ has been disregarded by policy makers in their attempt to accelerate the diffusion of AFV. According to Walzer (1983), goods that have a distinct social meaning should be governed by a "Distributive Justice" sphere to prevent the compounding of inequalities. Martens et al. (2012) define DJ in transportation as the indiscriminate and equitable access to transportation, the latter being a vital means for people to realize their full capabilities in society. DJ's main premise is that transportation policies should influence travelers to choose environmentally friendly alternatives rather than force them to do so.

In general, DJ consists of three main components (Hulle et al., 2017; Colquitt & Rodell, 2015; Stenman & Konow, 2010) which are explained in more detail in section 2.3.7: *Equity* (i.e., allocating benefits between different groups proportionally to their respective invested efforts), *Equality* (i.e., allocating benefits between different groups regardless of invested efforts), and *Need* (i.e., providing access to transportation to the maximum number of people). Using these three components, DJ aims to make goods equally accessible and usable for the largest number of individuals.

There are a few qualitative and theoretical studies which evoke the use of DJ principles. El Hachem and De Giovanni (2019) quantify DJ via a composite 'DJ index' of Equity, Equality and Need in order to explain and measure DJ performance.

The application of the DJ index allows us to address the existing trade-offs between the social and environmental objectives of AFV transition (see Boussauw and Vanoutrive, 2017). According to Harrison and Shepherd (2013), the current trend of car ownership is not going to change in the near to mid-term future (20-30 years) due to technological and cultural lock-in. Today, people pursue faster and more convenient travel modes, which undermine current efforts toward sustainable mobility (Cohen, 2010). This is known as “car dependence” (Sustainable Development Commission, 2010), implying that car ownership is necessary for full participation in society. Hence, environmental coercive policies (limiting users’ choice set) that may push people into social exclusion are often seen as inequitable.

Therefore, we seek to make firms aware of the existing trade-offs between environmental/economic and social outcomes and demonstrate the potential benefits when we simultaneously maximize all pillars. For this purpose, we define an indicator of sustainability that embeds DJ with environmental and economic objectives, that is, the ST index. This indicator can be utilized by firms when designing their R&D investment strategy in a segmented market with heterogeneous consumer preferences.

2.2.4 Cannibalization Vs Distributive Justice and Innovation as Mediator

From (Desai, 2001), we know that more competition in low segment (via having closer substitutable products within that segment) increases cannibalization by decreasing vertical differentiation, whereas more competition in high segment decreases it by increasing vertical differentiation.

From (Kim et al., 2013), we know that a non-dominating preference structure (as is the case within each segment in our model) can decrease cannibalization within each segment by having a bi-directional flow of consumers between products.

Based on the results from these two studies, more competition within high segment decreases cannibalization within its segment as well as between segments. Whereas, more competition in the low segment can have conflicting outcomes in terms of reducing cannibalization.

When there is cannibalization (i.e. competition between two products), the quality of the product destined to the low segment will drop and the price of the product destined to the high segment will drop as well. This minimizes cannibalization by enlarging the gap between low and high segment compared to the no cannibalization case. More cannibalization given a certain product line will have a negative impact on the profits (Li et al., 2018, Kim et al., 2013).

From a Distributive Justice perspective, we are interested in decreasing the difference in quality and prices between the different vehicle alternatives (i.e. we are interested in reducing differentiation), which necessarily increases cannibalization. DJ results in a smaller gap between low and high segment relative to the no DJ case therefore improving the social performance.

DJ implies a smaller gap between the high and low products, versus cannibalization which implies a larger gap. Cannibalization and Distributive Justice are by definition conflicting with each other. Lower (higher) DJ leads to less (more) cannibalization.

We are interested in maximizing profits (which is partly accomplished by minimizing cannibalization), maximizing distributive justice while minimizing emissions. Innovation in such a context connects all three sustainability pillars together. More innovation and the way it is split between its different types (process, emission or performance innovation), changes both cannibalization and distributive justice, while necessarily decreasing emissions.

2.2.5 Research Questions

We contribute to the literature in two different ways:

1- We consider a unique set of relationships/dynamics in our model that have not been simultaneously considered before in the literature. We do so by combining ideas and insights from different streams of literature, more specifically from both product line design and innovation streams, into a single model. This allows us to connect these streams together, capture nuances and offer new insights. This is represented in the middle section of Figure 2.7.

2- We focus explicitly on the social dimension of the transition to AFV, and we do so by quantifying this dimension using a newly defined Distributive Justice index (El Hachem & De Giovanni, 2019). This index impacts how policy makers design policies. We measure this index via the price and quality dynamics of different vehicle alternatives which our model generates endogenously. This is represented in the section to the right in Figure 2.7.

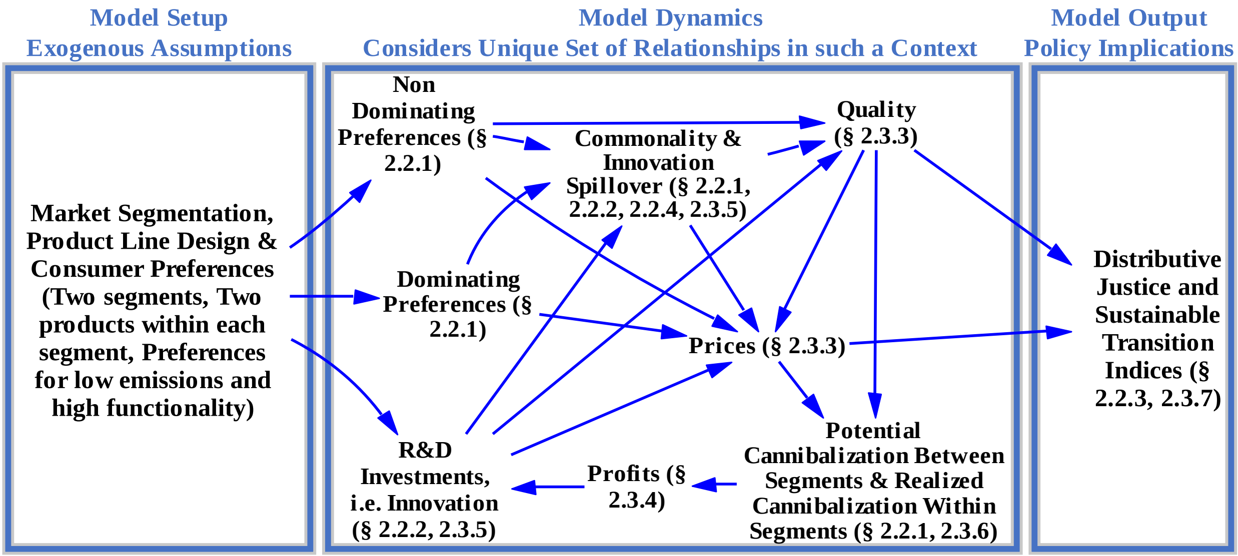


Figure 2.7: Model Setup, Dynamics and Output

According to Figure 2.7 and the research gaps presented earlier, we formulate our research questions.

Given our discussion in section 2.2, we know that more (less) innovation in high segment can relieve (increase) cannibalization, and vice versa for innovation in low segment (Desai, 2001). We also know that more commonality (i.e. innovation spillover in our context), given a non-dominating preference structure within each segment, can relieve cannibalization by allowing bi-directional flow of consumers between products (Kim et al., 2013). In our model we have both preference structures, so we ask the following question:

Research Question 1: How are innovation investments and cannibalization related to each other in a segmented market with both dominating and non-dominating preference structures?

There are tradeoffs between the three sustainability pillars (Boussauw and Vanoutrive, 2017; Harrison and Shepherd, 2013; Cohen, 2010, Jalili et al., 2017). The dynamics between the economic, environmental and social pillars can follow different regimes (Marasco et al., 2016). It can be either mutually beneficial (i.e. pure competition) when all three pillars are increasing, or predator-prey when one pillar grows at the detriment of at least one other pillar, or mutualism when all three pillars are decreasing over time. We ask the following research question:

Research Question 2: How can firms design a R&D innovation strategy to overcome tradeoffs and balance the dynamics between the three sustainability pillars to positively impact the triple bottom line in an AFV transition context?

We have been considering profits, emissions and DJ as our performance indicators. These indicators are determined by the simultaneous fluctuations of the relative quality and prices of different vehicle alternatives. However, this might obscure the dynamics of the absolute values of the quality and prices of the different vehicle alternatives. Therefore, we study the absolute values of quality and prices of vehicle alternatives and how they are impacted by different objectives, since they might convey additional information:

Research Question 3: How do quality and prices of ICE and AFV alternatives change with different policy objectives? More specifically, does including the DJ index via the ST index increase the quality and decrease the prices of vehicle alternatives?

2.3 Methodology and Model

In this section, we present the model through which we will answer our research questions.

2.3.1 A system dynamics model of R&D investments in an AFV transition context

Investigating R&D investment in a segmented car market entails a large socio-technical system that is non-linear (e.g., learning) and intertwined in a web of feedback loops (e.g., demand/quality/prices of vehicles) (Kwon, 2012; Shafiei et al., 2012; Struben & Sterman, 2008). Hence, a systems-based approach to investigate the dynamics of sustainability transitions embedded in a socio-technical context is warranted (Bolton & Hannon, 2016).

For the reasons mentioned above, we adopt the system dynamics simulation methodology to capture the most important feedback loops at play in such a transition. SD can be particularly useful in capturing the trade-offs between the social, environmental and economic pillars and defining policies that benefit from their synergies.

For a more detailed introduction of SD, refer to Appendix A.4, as well as to Barlas (2009) and Sterman (2002). The SD model captures the dynamics behind the different types of innovation investments and its impact on vehicles quality and prices in a segmented market. The model is built and tested by using Vensim DSS 6.4 software.

For clarity sake, Table 2.3 lists the abbreviations, symbols and indices used in our model.

	Notation	Explanation
Abbreviations and Symbols	DJ	Distributive Justice
	ST	Sustainable Transition
	WTP	Willingness to Pay
	V	Vehicle
	ICE	Internal Combustion Engine
	AFV	Alternative Fuel Vehicle
	U	Utility
	P	Price
	E	Emissions
	Per	Performance
	α	Sensitivity to Price
	γ	Sensitivity to Emissions
	β	Sensitivity to performance
	Q	Quality (i.e. combination of emissions and performance)
	Δ	Fractional Improvement when experience doubles
Indices	i	Segment: Low or High
	j	Type of vehicle: ICE or AFV
	k	Type of innovation: Process, Emissions or Performance
	l	Type of consumers: Emissions or performance oriented
	m	DJ components: Equity, Equality
	n	Sustainability Pillars: Social, Environmental, Economic

Table 2.3: Abbreviations, Symbols and Indices in Model

2.3.2 Market Share Dynamics

We model market share dynamics within each segment following a Lotka-Volterra (LV) formulation (Marasco et al., 2016) since an increase in the market share of one type of vehicle (e.g. AFV) will necessarily come at the expense of the market share of the other type of vehicle (e.g. ICE). These two types of vehicles are competing for a common pool of consumers. Most papers that use LV assume competition dynamics to be fixed and constant from the beginning (Cerqueti et al., 2015; Miranda and Lima, 2013; Chiang, 2012). We follow (Marasco et al., 2016), by recognizing that the competition dynamics can evolve over time, and we do so by allowing for the market growth rates to change signs. Market share dynamics are as follows:

$$Market\ Share_{i,j}(t) = \ Market\ Share_{i,j}(t-1) + Market\ Share\ Change_{i,j}(t)$$

Where i = Low, High segments; and j = ice, afv

The evolution of the market share of the i*th* product, i.e. $Market\,Share\,Change_{i,j}(t)$ is determined by two factors: the intrinsic $Market\,Growth\,Rate_{i,j}(t)$, and the competition measured by the ratio of the market growth rates of the ith and jth product. At any time t, the competitive roles are determined by the sign of $Market\,Growth\,Rate_{i,j}(t)$. The signs of the $Market\,Growth\,Rate_{i,j}(t)$ determine the competitive roles and they can change over time. Therefore we are able to capture different possible competitive scenarios such as pure competition (when they are all positive), predator-prey (when some are positive and others are negative) and mutualism (when all are negative).

$$Market\,Share\,Change_{i,j}(t) =$$

$$Market\,Share_{i,j}(t)*$$

$$[Market\,Growth\,Rate_{i,j}(t)\text{-}\sum_j Market\,Growth\,Rate_{i,j}(t) * Market\,Share_{i,j}(t)]$$

The $Market\,Growth\,Rate_{i,j}$ is determined from the change in the utility of a given vehicle. If the utility increases (decreases) over time, then its market growth rate increases (decreases):

$$Market\,Growth\,Rate_{i,j}(t) = \frac{d(U_{i,j})}{dt}$$

The utility of a vehicle increases with its performance ‘Per’ and decreases with its level of emissions E and price P:

$$U_{i,j}(t) = \beta_{i,j}Per_{i,j}(t) - \gamma_{i,j}E_{i,j}(t) - \alpha_{i,j}P_{i,j}(t)$$

The performance (i.e. Per), emissions (i.e. E) and price (i.e. P) dynamics are explained below.

2.3.3 Quality and Vehicle Prices

Previous Papers in the product line design and cannibalization literature discuss optimal prices and qualities of products (Sinitsyn, 2016; Kim et al., 2013; Desai, 2001). At the same time, in the innovation literature, it is commonly stated that a firm’s ability to improve quality and reduce costs, hence its pricing and quality decisions are dependent on current and past R&D investments (i.e. innovation) (Li, 2018; Lambertini et al., 2017; Pan and Li, 2016; Chenavaz, 2012). In this paper, instead of looking at (and determining) prices and qualities, we investigate instead the R&D investments (section 2.3.5) which would in turn determine the firm's pricing and quality decisions endogenously.

Prices are endogenous determined from the quality levels which are in turn determined from innovation investments. Quality is determined endogenously in the model based on the investments to lower emissions (i.e. emissions innovation) and improve the overall performance of the vehicle (i.e. performance innovation). We have as well two types of consumers, those that value lower emissions more than higher performance, and those the other way round. Accordingly, each one of these types of consumers would place different weights to the performance and emissions when assessing the quality of a vehicle. Therefore, the quality is determined as follows:

$$Q_{i,j,l}(t) =$$

$$\text{Performance } Coefficient_{i,j,l} * Per_{i,j}(t) +$$

$$Emissions\ Coefficient_{i,j,l} * E_{i,j}(t)$$

Where l = Emissions, Performance oriented consumers

The performance increases with R&D investments and decreases over time due to obsolescence:

$$Per_{i,j}(t) =$$

$$Per_{i,j}(t-1) + Impact\ of \text{ performance } Investment_{i,j}(t) - \text{performance } Obsolescence_{i,j}(t)$$

The more we invest into performance innovation, the more we build up a knowledge stock which renders the efforts more fruitful through learning:

$$Impact\ of \text{ performance } Investment_{i,j}(t) = Per_{i,j}(t-1) * \text{Performance } Inovation\ Learning\ Multiplier_{i,j}(t)$$

$$\text{Performance } Innovation\ Learning\ Multiplier_{i,j}(t) =$$

$$\left(\frac{Cumulative \text{ performance } Innovation\ Investment_{i,j}}{Initial \text{ performance } Innovation\ Investment_{i,j}}\right)^{\wedge} Learning\ Coefficient_{i,j}$$

$$Learning\ Coefficient_{i,j} = \frac{\ln(1+\Delta_{i,j})}{\ln(2)}$$

Where $\Delta_{i,j}$ = Fractional Improvement when experience doubles

The emissions are decreased over time due to investments dedicated to lowering them, and the dynamics follow the same logic as that of performance above:

$$E_{i,j}(t) = E_{i,j}(t-1) + Impact\ of\ Emission\ Investment_{i,j}(t)$$

The product line design literature commonly assumes that firms cannot discriminate between self-selecting consumers (Kim et al., 2013; Desai, 2001). It is most profitable if a company offers different products with each one having an efficient quality level to extract the maximum willingness to pay (WTP) from different consumer segments. However, the reality is that we have a second degree price discrimination setting. Hence the need for self-selection and participation constraints to prevent cannibalization. Prices are determined from the Willingness to Pay (WTP) which is in turn determined from the quality of different vehicles. To satisfy the cannibalization constraints, the prices are determined as follows:

$$P_{Low,j}(t) = \begin{cases} Min\ WTP_{Low,j,l}(t), & j\ has\ Lowest\ Quality\ in\ Low\ Segment \\ Max\ WTP_{Low,j,l}(t), & j\ has\ Highest\ Quality\ in\ Low\ Segment \end{cases}$$

The price of the product with lowest quality in the low segment is the minimum WTP of the consumers in the low segment. This way we ensure access to vehicles (i.e. V) for all individuals, i.e. we enforce participation constraint. The price of the product with highest quality is the maximum WTP of the consumers in the low segment, this way we extract the maximum we can from the low segment in an effort to minimize cannibalization as commonly acknowledged in the literature (Desai, 2001; Kim et al., 2013).

$$P_{High,j}(t) = \begin{cases} Min\ [WTP_{High,j}(V_{High,j,l}) + Max\ WTP_{Low}(t) - WTP_{High,j}(V_{Low,j,l})], & j\ Lowest\ Quality \\ Max\ [WTP_{High,j}(V_{High,j,l}) + Max\ WTP_{Low}(t) - WTP_{High,j}(V_{Low,j,l})], & j\ Highest\ Quality \end{cases}$$

The prices of the products in high segment are determined in a way to prevent the consumers in the high segment from switching to products destined to the low segment, i.e. to prevent cannibalization. The product with lowest quality in high segment is priced at the minimum WTP of high segment consumers, while the one with the highest quality is priced at the maximum WTP to maximize profits.

2.3.4 Costs and Profits

We extend the models of (Li, 2018; pan and li, 2016; Chenavaz, 2012) since the firm's cost functions of product and process innovation depend on the innovation investments, the knowledge accumulations of product and process innovation and learning by doing; prices are endogenous determined based on quality levels which are determined from innovation investments; finally, the firm is in a segmented market and it offers two products within each segment, hence potential for cannibalization between segments and actual cannibalization within each segment.

More so, (Lambertini et al., 2017) found that one should not expect the firm to supply an increasing quality level at a decreasing production cost. Hence, we incorporate into the model a 'quality increase effect' which impacts the production costs.

The profits of the firm are the sum of the profits from each one of the vehicle alternatives on offer:

$$Profits\ (t) = \sum_{j=1}^{2} \sum_{i=1}^{2} (Profit_{i,j})$$

The profitability of these vehicles increases with its price and decreases with its production and innovation costs:

$$Profit_{i,j}(t) = \\ [P_{i,j}(t) - Production\ Cost_{i,j}(t) - Innovation\ Costs_{i,j}(t)] * Production_{i,j}(t)$$

The vehicles are produced to meet demand of the market. So, based on the vehicle market share and the number of years a consumer owns a car before replacing it, the production is determined as follows:

$$Production_{i,j}(t) = \frac{Number\ of\ Consumers_i(t) * Market\ \ Share_{i,j}(t)}{Number\ of\ Years\ Before\ Changing\ Cars}$$

The production cost is impacted by three factors. First, the 'learning by doing' effect reflects the fact that the firm builds up a knowledge stock as it produces more vehicles, which renders its operation smoother and less costly. Second, the 'technology learning' effect which is a result of the investment into process innovation to lower the production costs. Third, the 'quality increase' effect to reflect the fact that a higher quality product is more expensive to produce.

$$Production\ Cost_{i,j}(t) =$$
$$Initial\ Production\ Cost_{i,j}(t) * \ Effect\ of\ Technology\ Learning_{i,j}(t)$$
$$* Effect\ of\ Learning\ by\ Doing_{i,j}(t) * Effect\ of\ Quality\ Increase_{i,j}(t)$$

$$Effect\ of\ Learning\ by\ Doing_{i,j}(t) =$$
$$\left(\frac{Cumulative\ Production_{i,j}}{Initial\ Production_{i,j}}\right)^\wedge Production\ Learning\ Coefficient_{i,j}$$

$$Production\ Learning\ Coefficient_{i,j} = \frac{\ln(1 + \Delta_{i,j})}{\ln(2)}$$

Where $\Delta_{i,j}$ = Fractional Performance Improvement when experience doubles

$$Effect\ of\ Technology\ Learning_{i,j}(t) =$$
$$\left(\frac{Cumulative\ Process\ Innovation_{i,j}}{Initial\ Process\ Innovation_{i,j}}\right)^\wedge Process\ Innovation\ Learning\ Coefficient_{i,j}$$

$$Effect\ of\ Quality\ Increase_{i,j}(t) =$$
$$Maximum\ Increase\ in\ Production\ Costs_{i,j} * Relative\ Increase\ in\ Quality_{i,j}(t) + 1$$

When it comes to innovation costs, there are two opposite effects. One that tends to lower the costs due to learning, similar to the learning by doing effect on production costs. The other tends to increase the costs due to a decreasing marginal return on innovation investments since the higher the performance, the higher the cost to improve it further (Lambertini et al., 2017; Taylor and Tainter, 2016). This is incorporated into the model as follows:

$$Innovation\ Costs_{i,j}(t) =$$
$$Functionality\ Innovation\ Costs_{i,j}(t) + Emissions\ Innovation\ Costs_{i,j}(t)$$

$$Functionality\ Innovation\ Costs_{i,j}(t) = Initial \text{ Performance } Innovation\ Costs_{i,j} * Effect\ of\ Scarcity\ on \text{ Performance } Innovation\ Costs_{i,j}(t) * Effect\ of\ Learning\ by\ Doing_{i,j}(t)$$

The effect of learning by doing is same as the one in production costs above. While the effect of scarcity is measured as follows:

$$Effect\ of\ Scarcity\ on \text{ Performance } Innovation\ Costs_{i,j}(t) = \left(\frac{\text{Cumulative Performance Investment}}{\text{Initial Performance Investment}}\right)^{\text{Performance Innovation Scarcity Coefficient}}$$

As we invest more into performance innovation, the more expensive it becomes to improve the performance of the product due to innovation scarcity. The emissions innovation costs follow similar dynamics.

$$Emissions\ Innovation\ Costs_{i,j}(t) = Initial\ Emissions\ Innovation\ Costs_{i,j} * Effect\ of\ Scarcity\ on\ Emissions\ Innovation\ Costs_{i,j}(t) * Effect\ of\ Learning\ by\ Doing_{i,j}(t)$$

2.3.5 R&D Investments

The R&D investments are dependent on profits which are in turn dependent on costs (hence on process innovation) with the latter increasing (or decreasing) with higher (lower) quality (hence dependent on product innovation as well).

$$R\&D\ Investment\ (t) = Profits\ (t) * R\&D\ Investment\ Share$$

The R&D investments are split between those destined to process, emissions and performance innovation. Process innovation lowers the production cost of vehicles. Emissions innovation lowers the emissions of vehicles. Performance innovation improves the reliability and performance of the vehicle.

$$Investment_k(t) = R\&D\ Investment\ (t) * Share_k$$

$\sum_{k=1}^{3} Share_k = 1$ Where k = Process, Emissions, Performance

The investments destined to each one of these activities are further split between the different vehicle alternatives:

$$\sum_{j=1}^{2}\sum_{i=1}^{2} Investment\ Share_{i,j} = 1 \quad \forall k$$

It is possible that innovation in one vehicle spills over to another vehicle, or that some of the investments are originally destined to several vehicles. Therefore, the effective R&D investment is in fact larger than its original share:

$$Effective\ Investment_{i,j,k} = \\ Investment_{i,j,k} + Investment_{\bar{\imath},j,k} * Spillover_{j,k} + Investment_{i,\bar{\jmath},k} * Spillover_{i,k}$$

2.3.6 Cannibalization

Most papers consider cannibalization between segments and infer its strength indirectly from cross-product price elasticity (Li et al., 2018), or from the change of firm performance when it changes the length of its product line (Draganska and Jain, 2005). In our paper, given our model setup, we have both potential cannibalization between segments which is prevented via cannibalization constraints, and realized cannibalization within each segment.

Prices and quality determine the utility of the different vehicle alternatives. These utilities in a LV fashion determine the market shares of each product. The utilities of the different products determine the potential for cannibalization, while the change in market shares reflect the cannibalization within each segment. We measure the two types of cannibalization as follows:

1- Cannibalization Potential between segments: Since we consider a multiproduct firm that offers two products within each of the two segments, we have in place cannibalization constraints which determine prices in such a way to prevent the consumers in the high segment from switching to the products targeted to the low segment consumers as explained in section 3.3. So, we define cannibalization potential as the potential/likelihood for the high consumers to switch from the products in the high segment to the products in the low segment if the cannibalization constraints are not in place. The larger the difference in the valuation of the high segment consumers between the products destined to them and those destined to the low segment, the lower the cannibalization potential. We measure it as follows:

$$Cannibalization\ Potential = \int_{t_0}^{t_f} \sum_{l} \sum_{j} \frac{U_{Low\ Product\ j\ to\ High\ Segment,j,l}}{U_{High\ Product\ j\ to\ High\ Segment,j,l}}$$

Where j = ICE, AFV; and l = Emissions, Performance oriented consumers

Please find in Appendix B some conditions to check that we have indeed prevented cannibalization between the two segments.

2- Actual Cannibalization within each segment: This tracks the actual switching of consumers between the two different products within each segment due to the non-dominating preference structure in place. It is measured as follows:

$$Actual\ Cannibalization_i = \int_{t_0}^{t_f} ABS\left(Market\ Share\ Change_{i,j}\right) \quad \forall i$$

Where i = Low, High Segments and j = ICE or AFV (the market share change of ICE is equal to that of AFV in absolute terms).

2.3.7 Distributive Justice and Sustainable Transition Indices

DJ refers to the perceived fairness of the distribution of social and economic benefits (as well as burdens) among a group of individuals (Stenman & Konow, 2010). Traditionally, DJ has three components (Hulle et al., 2017; Colquitt & Rodell, 2015): Equity, Equality, and Need.

To meet the DJ objective, we consider both access to transportation (i.e., Equality of opportunity) as well as the benefit/utility derived from this access to the different vehicle alternatives (i.e., Equality of outcome). Following Hulle et al. (2017), Colquitt and Rodell (2015), Martens et al. (2012), Lucas (2012), and Stenman and Konow (2010), we define:

- Equity as allocating benefits between different groups proportionally to their respective invested efforts (the purchase price of a vehicle acts as a proxy indicator of the amount of efforts invested to access and extract utility/benefit from the vehicle).
- Equality as allocating benefits equally between different groups regardless of invested efforts.
- Need as providing access to transportation (either ICE or AFV) to the maximum number of people.

Each of these components contributes to the final common objective of DJ, that is, fairness in both providing access to transportation and allocating its benefits to consumers. *Equality* refers to "Equality of outcome," *Need* links to "Equality of opportunity," and *Equity* is a bridge between the two. Then, we propose operational measures to quantify DJ and its components by tracking the evolution of the purchase price (i.e., input), quality and utility (i.e., outputs) of the different alternatives: The former represents the efforts to access the different types of cars and the latter represents the derived benefit associated with each type of car.

Following the earlier definition, *Equity* considers the quality of alternatives *j*, Q_j, and their respective purchasing prices, P_j, where *j* are the different alternatives. We compute the ratios $r_j = \frac{Q_j}{P_j}$, which inform us on the benefits derived from the vehicles proportional to the amount of efforts invested to access them. Then, to maximize *Equity*, we seek to minimize the variance in the ratios, $\sigma^2(r_j)$, such that individuals derive the same level of benefit proportionally to their invested effort. So, *Equity* is computed as follows:

$$\mathrm{EQUIT}Y = \frac{1}{\sigma^{2}(r_j)}$$

Equality considers the utility, U_j, of different alternatives by computing the variance in the utilities, $\sigma^2(U_j)$. Then, we maximize *Equality* by minimizing $\sigma^2(U_j)$, such that different groups derive equal benefits from their different vehicle alternatives. Accordingly, we define *Equality* as follows:

$$\mathrm{EQUALIT}Y = \frac{1}{\sigma^{2}(U_j)}$$

In the transportation context, the *Need* component is defined as providing access to transportation to the maximum number of people. Purchase price is used as a proxy to access level. The higher the purchase price, the lower the access level. Since in our model, we have a segmented market with participation constraints, the Need component is automatically satisfied by guaranteeing that purchase prices are lower than the willingness to pay for vehicles.

Finally, we combine the Equity and Equality components into one measure, as follows:

$$DJ\ Index\ (t) = \sum_{m=1}^{2} Weight_{\boldsymbol{i}}\left(\frac{Component_{m,t} - Component_{m,t_0}}{Component_{m,t_0}}\right)$$

where *m*=*Equity*, *Equality* and $\sum_{m=1}^{2} Weight_i = 1$. "$Component_{m,t}$" refers to the level of a component *m* at time *t*, whereas "$Component_{m,t_0}$" refers to its initial level at t_0. Thus, the ratio shows the relative improvement realized during the analyzed period. In our model, the normalized components vary within the range [-0.5, 0.5], with values higher (lower) than 0 indicating an improvement (worsening) in performance. We split weights equally (i.e., 1/2) between the two components in accordance with the literature (e.g., De Giovanni & Zaccour, 2014). Nonetheless, we ran sensitivity analyses to check the impact of these weights by varying them between 0.2→0.7 while respecting the logical constraint that their sum should always be equal to 1. We notice no qualitative change, meaning that if DJ is increasing (decreasing) with equal weights, it keeps increasing (decreasing) with different weights given to its two components.

If the DJ measure is equal to 0, it is at the same level of the year t_0. If it is increasing higher (decreasing lower) than 0, then it is improving (worsening) relative to its initial level. This indicator provides a measure for DJ that firms can use to evaluate whether their actions are aligned with DJ principles (and then, social outcomes).

Since there exist several trade-offs and synergies between environmental, economic and DJ objectives, we create a composite indicator that considers all three and that we call the *Sustainable Transition* (ST) index. This index allows a firm to evaluate a given policy (i.e., repartition of R&D investments) considering the DJ index (social performance indicator), Emissions (environmental performance indicator) and profits (economic performance indicator). Specifically, we define the indicator as follows:

$$ST\ Index = \sum_{n=1}^{3} (Weight_n * Performance\ of\ Pillar_n)$$

Where n = Social, Environmental, Economic and $\sum_{n=1}^{3} Weight_n = 1$

The weights are set by default to 1/3 (i.e., equal importance). The higher the DJ and the profits, and the lower the emissions, the better the sustainability performance of the R&D

investment policy. Note that the performance of the pillars follows the same normalization formulation as the components of DJ index.

If the ST index is equal to 0, then we are at the same sustainability level relative to the initial level at t_0. If it is higher (lower) than 0, then the R&D investment policy is more (less) sustainable relative to its initial level at year t_0.

Firms can use these indicators to evaluate the existing trade-offs between environmental, social and economic outcomes and to search for solutions to mitigate them.

Figure 2.8 is a high-level overview of the dynamics presented in section 2.3. It represented the dynamics within each consumer segment and a given type of vehicle in the model, and specifically in this case the dynamics within the ICE low segment:

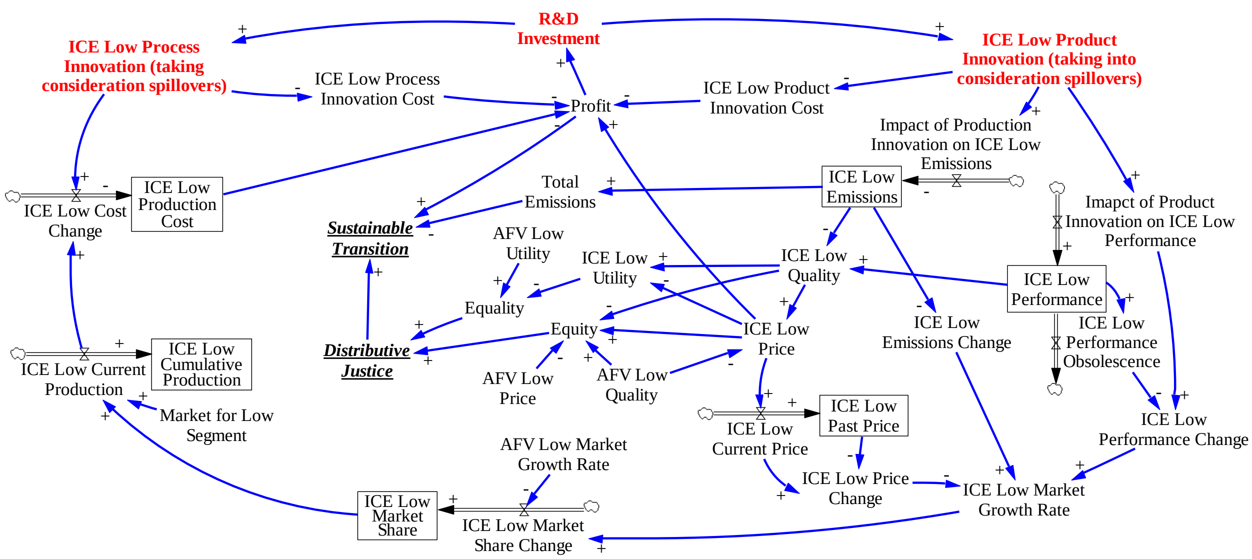


Figure 2.8: Transition to AFV through a Distributive Justice perspective

Note that the + (-) sign at the end of each arrow between its origin A and destination B indicates - ceteris paribus - the sign of the derivative $\frac{dB}{dA}$. To measure *Equity* and *Equality*, we keep track of the utilities, quality and purchase prices of the different vehicle alternatives, which in turn are intertwined in feedback loops. Then, these two components give us the DJ index. The DJ index along with the profits and Emissions give us the Sustainable Transition index. Highlighted in red, the R&D investments are the decision variables in our model which we determine to maximize an objective function given specific scenarios presented in section 2.4.

2.4 Results

2.4.1 Scenario Building

We use the model explained in section 2.3 and conceptually represented in Figures 2.7 and 2.8 to investigate the effectiveness of different types of innovation investments in improving the sustainability performance of the multiproduct monopolist. We consider the following scenarios:

- ST Scenario: We target maximizing the ST index which combines all three pillars
- Eco+Env Scenario: We target maximizing only the economic and environmental pillars
- Economic Scenario: We target maximizing only the economic pillar
- Environmental Scenario: We target maximizing only the environmental pillar
- ST2 Scenario: Similar to ST scenario, we target maximizing the ST index, however with an additional constraint to regulate the dynamics between its three pillars

In each of these different scenarios, we utilize the decision variables listed in Table 2.4 to maximize their respective objectives. These decision variables capture the 15 different possible combinations of innovation investments. For example, we can have the firm investing in all three types of innovation (process, performance and emissions) with spillover activated as well. We can have the firm investing only in process innovation with no possible spillover.

Each column in Table 2.4 shows the best possible performance under each of the scenarios. For each of these scenarios, we are maximizing only their relevant performance indicators. For example, under the ST scenario, we maximize only the ST index, which results in the ST index being at its maximum possible value while the other indicators (i.e. emissions, profits, DJ index) not necessarily at their maximum possible values.

Note: SEI refers to Spillover of Emissions Innovation, SFI refers to Spillover of Functionality/Performance Innovation and SPI refers to Spillover of Process Innovation.

An interesting observation is that the highest environmental performance (i.e. lower level of emissions) does not necessarily entail the highest AFV market share. This makes sense since the AFV market share is small compared to that of ICE. Therefore improvements of ICE vehicles in terms of reducing their emissions can overshadow the benefits of increasing the AFV market share.

		Scenarios				
		ST	Eco+Env	Eco	Env	ST2
Indicators	Sustainability Performance	0.265	0.2275	0.014	0.2261	0.246
	Environmental Performance	0.759	0.863	0.001	0.903	0.517
	Social Performance	0.016	-0.2245	-0.09	-0.2291	0.137
	Economic Performance	0.019	0.043	0.134	0.0036	0.083
Other Indicators	AFV Market Share	0.07	0.054	0.047	0.055	0.062
	R&D Investments (Million $)	70.34	80.28	102.8	76.77	84.85
	Low Segment Investment Share	0.481	0.3922	0.5722	0.3684	0.5022
	Spillover within Low Segment	0.115	0.046	0.5	0.045	0.2673
	Spillover within High Segment	0.076	0.5	0.5	0.5	0.3055
	Cannibalization Potential Between Segments	145.6	144.5	144.2	144.3	145.2
	Cannibalization within High Segment	0.027	0.013	0.0005	0.014	0.02
	Cannibalization within Low Segment	0.018	0.00247	0.004	0.00263	0.009
Decision Variables	Emissions Share	0.77	0.907	0	1	0.389
	Performance Share	0.077	0	0	0	0.11
	Process Share	0.153	0.093	1	0	0.501
	AFV Low Emissions Share	0.1	0.1	0	0.1	0.1
	AFV Low Performance Share	0.278	0	0	0	0.102
	AFV Low Process Share	0.33	0.33	0.314	0	0.328
	ICE High Emissions Share	0.33	0.33	0	0.33	0.33
	ICE High Performance Share	0.1	0	0	0	0.224
	ICE High Process Share	0.33	0.33	0.33	0	0.33
	ICE Low Emissions Share	0.33	0.33	0	0.33	0.33
	ICE Low Performance Share	0.1	0	0	0	0.1
	ICE Low Process Share	0.33	0.33	0.33	0	0.33
	SEI Between AFV High and AFV Low	0	0	0	0	0
	SEI between ICE High and ICE Low	0.5	0.5	0	0.5	0.5
	SEI in High Segment	0	0.5	0	0.5	0
	SEI in Low Segment	0	0	0	0.5	0
	SFI Between AFV High and AFV Low	0.5	0	0	0	0.185
	SFI between ICE High and ICE Low	0	0	0	0	0.049
	SFI in High Segment	0	0	0	0	0.5
	SFI in Low Segment	0.5	0	0	0	0.16
	SPI Between AFV High and AFV Low	0.5	0.5	0.5	0	0.5
	SPI between ICE High and ICE Low	0.5	0.5	0.5	0	0.5
	SPI in High Segment	0.5	0.5	0.5	0	0.5
	SPI in Low Segment	0.5	0.5	0.5	0	0.5

Table 2.4: Indicators and Decision Variables under different scenarios

2.4.2 Research Question 1

How are innovation investments and cannibalization related to each other in a segmented market with both dominating and non-dominating preference structures?

In our model, we simultaneously have both preference structures, dominating (Desai, 2001) and non-dominating (Kim et al., 2013). We also have innovation investments while allowing for spillovers. We know that more (less) innovation in high segment can relieve (increase) cannibalization, and vice versa for innovation in low segment (Desai, 2001). We also know that given a non-dominating preference structure within each segment, more commonality (i.e. innovation spillover in our context) within a segment can relieve cannibalization by allowing bi-directional flow of consumers between products (Kim et al., 2013).

Given this web of relationships shown in Figure 2.7, we notice that the relationship between innovation and cannibalization is dependent on two factors:

- The investment share that targets low segment vs high segment.
- The spillover within each segment.

Our results in general confirm the previous findings (Desai, 2001; Kim et al., 2013), that is cannibalization lowers profits, increases prices of low product while decreasing prices of high product. However they add an extra layer of precision by distinguishing between potential for cannibalization and actual cannibalization. This distinction is made possible by having both preference structures in the model.

We notice that potential for cannibalization between segments is dependent on the split of investment between the consumer segments: By investing more (less) into low segment, we would relatively increase (decrease) the overall quality of the products in the low segment. This in turn makes them more (less) attractive to high segment consumers; therefore, increasing (decreasing) the potential for cannibalization between segments. These results are similar to (Desai, 2001).

The actual cannibalization within a given segment is dependent on both the amount of investment that targets this segment and the spillover within it: By increasing (decreasing) spillover within a segment, we decrease (increase) actual cannibalization, echoing the results of (Kim et al., 2013). By investing more (less) into a segment, we increase (decrease) the cannibalization within it. The interplay of these two opposite effects determine the actual cannibalization within each segment.

We confirm previous results in literature while highlighting the need to consider the distinction between potential and actual cannibalization which have different relationships with innovation investments. To reduce both potential and actual cannibalization, firms should invest less in the low segment while allowing for more spillovers within each segment.

This is problematic from a DJ (i.e. social) point of view while being beneficial from an economic point of view. We analyze these tradeoffs and others in our second research question.

2.4.3 Research Question 2

How can firms design a R&D innovation strategy to overcome tradeoffs and balance the dynamics between the three sustainability pillars to positively impact the triple bottom line in an AFV transition context?

There are tradeoffs between the sustainability pillars (Boussauw and Vanoutrive, 2017; Cohen, 2010; Harrison and Shepherd, 2013). These dynamics between the economic, environmental and social pillars can follow different regimes (Marasco et al., 2016). It can be either mutually beneficial (i.e. pure competition) when all three pillars are growing, or predator-prey when one pillar grows at the detriment of at least one other pillar, or mutualism when all three pillars are decreasing over time.

If we look at cannibalization from an economic lens, it has a negative impact. Ceteris paribus, the higher the product cannibalization, the lower the profits are, as in accordance with (Li et al., 2018; Kim et al., 2013; Desai, 2001).

At the same time, we are interested in increasing DJ index and decreasing cannibalization (i.e. increasing profits). The two are fundamentally opposite to each other as discussed in section 2.2.4 and our results confirm this reasoning. The higher the cannibalization (i.e. the worse economic performance), the higher the DJ index (i.e. the better social performance).

Therefore, tradeoffs between the sustainability pillars are immediately clear. To answer our second research question, we look at the first four scenarios in Table 2.4 in order to assess the impact of R&D investment on the different pillars.

We notice that the social performance is always negative when we do not explicitly consider it in our innovation investment strategy. We know that people assess policies based on fairness principles, and this applies to the transportation and AFV transition context (Hammar and Jagers, 2007). Therefore we need to explicitly include the social dimension into our policies objective to avert unintended social repercussions which could undermine the performance of the other two environmental and economic pillars.

The environmental performance is maximized under the environmental scenario. However this comes at a heavy cost, since the social performance is almost 23% lower than its initial value, and the economic performance is almost zero.

The economic performance is maximized under the economic scenario with 13.4% improvement over its initial value, however this comes at a heavy cost since it entails heavy losses on the social performance which drops 9% compared to its initial value, and the environmental performance is almost zero.

We also consider simultaneously the economic and environmental pillars. We get under this scenario relatively high environmental and economic scores, however at the cost of a drop of 22.45% in the social performance.

The ST index which considers all three pillars is maximized under the ST scenario by achieving its best performance with 26.5% improvement over its initial value. This is mainly due to the environmental pillar which experiences significant improvement. The social (i.e. DJ index) and economic (i.e. profits) pillars experience improvement as well, if modest compared to the environmental one.

When we consider the social pillar (i.e. DJ) under the ST scenario, we have the highest levels of potential and actual cannibalization, since we are trying to minimize the product differentiation between the different vehicle alternatives. This results in low profits and therefore low economic performance.

At a closer examination, we notice that the environmental pillar is always improving (i.e. positive derivative sign), while the other two pillars alternate between improving and worsening. In other words, we can say that the environmental pillar at more than one occasion acts as a predator to the other two pillars. This explains the uneven dynamics between the three pillars whereby the environmental pillar improves significantly while the other two improve modestly or even deteriorate over time.

Therefore, we propose ST 2 scenario where we impose an additional constraint to regulate the dynamics between the three sustainability pillars. We enforce that the dynamics must be under a pure competition regime whenever possible, where the three pillars are simultaneously improving over time, albeit at a potential slower pace. The fifth column in Table 2.4 reports the results of this scenario.

We still manage to get a relatively high ST index (second highest behind the ST scenario), with a smaller yet a still significant improvement of the environmental performance, and most importantly a significant increase in the economic and social pillars.

This entails a higher overall R&D investment than under the ST scenario. The investment is split evenly between the two consumer segments with moderate spillover within the two segments.

This scenario is preferable over the original one since it is more balanced. We can be certain that on the long run, the pillars and their respective performance scores would continue to improve and would not drop below zero.

So far, we have been looking at the relative improvement or worsening of the quality and prices of vehicles. The dynamics of their absolute values might convey additional information, which brings us to research question 3.

2.4.4 Research Question 3

How do quality and prices of ICE and AFV alternatives change with different policy objectives? More specifically, does including the DJ index via the ST index increase the quality and decrease the prices of vehicle alternatives?

In research question 2, we considered profits, emissions and DJ as performance indicators. These indicators are influenced by the simultaneous fluctuations of the relative quality and prices of vehicle alternatives. It is interesting to see how the absolute values of quality and prices, and consequently utilities change under different objectives. Table 2.5 displays the average prices, quality and utilities under different scenarios:

		ST	Eco+Env	Eco	Env	ST 2
		Scenarios				
All	**Average Utility**	1.72	1.612	1.667	1.61	1.705
	Average Price	20730	21270	20850	21270	21250
	Average Quality	0.779	0.681	0.705	0.681	0.768
ICE	**Average ICE Utility**	1.642	1.626	1.677	1.624	1.657
	Average ICE Price	19450	19670	20030	19650	19840
	Average ICE Quality	0.6424	0.6263	0.6771	0.6242	0.6568
AFV	**Average AFV Utility**	1.797	1.597	1.657	1.595	1.753
	Average AFV Price	22010	22870	21680	22890	22670
	Average AFV Quality	0.9165	0.7364	0.7364	0.7364	0.8795
Low Segment	**Average Utility Low Segment**	1.699	1.621	1.643	1.619	1.676
	Average Price Low Segment	18500	18620	18760	18610	18610
	Average Quality Low Segment	0.7739	0.6897	0.7052	0.6887	0.7454
High Segment	**Average Utility High Segment**	1.741	1.602	1.691	1.6	1.734
	Average Price High Segment	22960	23920	22940	23930	23890
	Average Quality High Segment	0.7851	0.673	0.7083	0.6719	0.7909

Table 2.5: Average Utility, Price and Quality under Different Scenarios

These results agree with those found in Table 2.4, since under the economic scenario, we have the lowest average price in High segment while having the highest average price in Low segment. This reduces cannibalization and maximizes profits.

Under the ST and ST2 scenarios, the average quality is higher and the average prices are lower for all alternatives compared to the other scenarios. So, we can conclude that in terms of prices and quality of vehicles, the ST scenario is the best followed by the ST 2 scenario. Maximizing for profits and/or minimizing emissions would produce lower quality and higher prices than when we consider simultaneously with them the DJ index. This further confirms the benefits of explicitly including the social pillar quantified by the DJ index in our decision making when designing R&D and innovation strategies.

2.5 Conclusion

We considered a multi-product monopolist that offers two products/vehicle alternatives within each of the Low and High segments to accommodate for both dominating and non-dominating preference structures of consumers in the vehicle market. We looked at process and product innovation strategies with spillovers and knowledge accumulation effects. We focused as well as on the intra-brand cannibalization effect (Li et al., 2018), which emerges from product proliferation as the firm is offering multiple products to satisfy consumer demand in a competitive market.

We are interested in measuring the sustainability of the R&D investment strategy of the car manufacturer firm, with sustainability composed of its three traditional pillars: economic, environmental and social.

We introduce the concept of DJ within this context to quantify the social dimension and we operationalized its components, Equity and Equality. Then, we embed this new concept in a stylized system dynamics model which measures as well profits and emissions. Then, using the DJ index, along with the profits and emissions, we defined the sustainable transition (ST) index. The DJ and ST index help policy makers to capture the tradeoffs between the three sustainability pillars in a holistic and rigorous manner. We investigate whether considering DJ targets along with economic and environmental targets can lead to a higher sustainability performance of the R&D strategy.

We find that it is possible for the three sustainability pillars to interact in harmony when we have a healthy R&D budget for innovation. Innovation thus functions as a mediator between the cannibalization problem and the DJ index. By investing into R&D and splitting it evenly between high and low segments while allowing for spillover, all pillars improve nicely whilst withstanding relatively high levels of cannibalization.

More so, maximizing for profits and/or minimizing emissions would result in lower quality and higher prices of the different vehicle alternatives than when we consider simultaneously with them the DJ index. This confirms the benefits of explicitly including the social pillar quantified by the DJ index in our decision making when designing R&D and innovation strategies.

Our results are not free of limitations, which we mention here to inspire future research on this subject. We consider in this paper a multiproduct monopolist to be able to keep track of its pricing and quality decisions in such a complex context. It would be beneficial to generalize the model and include competitors; thus, we would consider the inter-brand competition and intra-brand cannibalization simultaneously. This would however make the pricing and quality decisions less tractable. We focus in this paper on the car manufacturer, without considering the impact of government intervention on its decisions. It would be beneficial to include government intervention, such as AFV subsidy and ICE tax, and see how they would impact the manufacturer's R&D strategy. This is an ongoing project of the authors.

ESSAY THREE

Optimal Manufacturer Strategies and Government Intervention for AFV Transition under a Distributive Justice Perspective

Abstract

We build a model with two players, Government and Manufacturer, to focus on government intervention (taxes and subsidies) in the context of transition to Alternative Fuel Vehicles (AFV) under two scenarios. In one there is no Distributive Justice (DJ), and in the other DJ enters by modifying the social pillar in the government's utility to maximize consumer's access to vehicles. The government's tax and subsidy override the manufacturer's prices when determining the dynamics highlighting the decisiveness of government intervention in such a setting. The dynamics of the environmental and economic pillars show tradeoffs which are partially alleviated when we consider DJ. We show that when introducing DJ into the model, there is no Pareto front where all three pillars improve simultaneously and the government's utility remains more or less the same. The manufacturer's profits and consumer surplus exhibit a harmonious relationship whereby they increase together. Finally, the demand for AFV is always cannibalizing the demand for ICE.

Keywords: AFV transition, Distributive justice, Innovation investments, Price, Government intervention

3.1 Introduction

Rising environmental awareness among consumers (Jamali & Rasti-Barzoki, 2018; Basiri & Heydari, 2017; Zhang et al., 2015; Conrad, 2005), known as Consumer Environmental Awareness (CEA), led to the entry of green products (i.e. AFV) into the car market. This led to the issue of competition between these green (e.g. AFV) and non-green products (e.g. ICE) which has been the subject of research lately (Jamali & Rasti-Barzoki, 2018; Sinayi & Rasti-Barzoki, 2018; Basiri & Heydari, 2017; Ma et al., 2018; Zhu & He, 2017; Zhang et al., 2015; De Giovanni and Ramani, 2018; Ramani and De Giovanni, 2018). We focus on the pricing and the degree of greenness of a product in competition with an established non-green product while considering government intervention.

One concept that governments and organizations have utilized to operationalize and transition towards sustainability is the triple bottom line approach (Liu et al., 2019; Sinayi & Rasti-Barzoki, 2018; Besiou and Van Wassenhove, 2015; Seuring and Müller, 2008; Elkington, 2002). It defines sustainability as dependent on the balance between the economy, environment and society. This balance is dependent on the interaction between the government and the companies (Liu et al., 2019).

Therefore, we adopt the 'Public policy and planning' theory of sustainable development which stresses the integration of the social, economic and environmental aspects of sustainability along with the institutional (Sala et al., 2015; Patterson, 2010). Given the 'public policy and planning' theory of sustainable development, governments are integral to operationalizing and transitioning toward sustainability, since they are the leaders when it comes to policy making to meet social demands and legislative requirements (Gouda et al., 2016; Tang and Zhou, 2012).

Government efforts to influence business behaviors toward socially and environmentally desirable outcomes take a variety of forms, with two of the most recognized being taxes and subsidies (Liu et al., 2019, Sinayi & Rasti-Barzoki, 2018; Zhang et al., 2015), which we utilize in our model.

Most research on sustainable development and government interventions focuses on the economic and environmental dimensions of sustainability (Sinayi & Rasti-Barzoki, 2018; Choi, 2013; Govindan et al., 2016; Jafari et al., 2017; Li et al., 2016; Wang et al., 2014; Zhu and He, 2017).

This applies within the context of transition to AFV, where the literature mostly neglects (or places little importance on) the social dimension despite having clear transportation studies which clearly report that individuals judge policies and make decisions by considering various justice criteria (Luo, 2007; Colquitt et al., 2001).

It is not trivial to discern whether the tradeoffs between the social, environmental and economic pillars of sustainability are surmountable or not (Boussauw and Vanoutrive, 2017; Harrison and Shepherd, 2013; Cohen, 2010). To our knowledge, (El Hachem& De Giovanni, 2019) is the only paper to have explicitly and quantitatively tackled this issue within the AFV transition context, and they did so by quantifying the social dimension using the concept of Distributive Justice (DJ) (Hulle et al., 2017; Heindl & Kanschik, 2016; Colquitt & Rodell, 2015; Stenman & Konow, 2010). However they did not investigate the interaction between the government and the manufacturer, which we do in our paper.

This study is the first to consider competition between two substitutable products offered by a manufacturer while including government intervention in the form of subsidies and taxes into the model. More so, it is the first to focus on sustainable development by quantifying its social dimension via consumer surplus and the concept of DJ. We investigate and compare the alignment issues and tradeoffs between environmental, economic and social sustainability dimensions with and without DJ.

We do so by building a game theory model with two players, Government (leader) and one Manufacturer (follower). The decision variables for the manufacturer are the prices of the two products (ICE and AFV) and degree of greenness of the AFV; the decision variables for the government are the subsidies for the AFV and taxes on the ICE. We also incorporate the concept of Distributive Justice by modifying the government's social pillar of sustainability in such a way to maximize access to vehicles.

The government's tax and subsidy override the manufacturer's prices when determining the dynamics highlighting the relevance of government intervention in such a setting. The dynamics of the environmental and economic pillars show tradeoffs which decrease when we consider DJ versus when we do not. We also show that when introducing DJ into the model, there is no Pareto frontier where all three pillars improve simultaneously and that the government's utility remains more or less the same. The manufacturer's profits and consumer surplus exhibit a harmonious relationship whereby they increase together. More so, we notice that demand for AFV is always cannibalizing the demand for ICE.

The remainder of the paper is structured as follows. Section 3.2 introduces the literature, highlights our contributions and introduces our research questions. Section 3.3 presents the main model. Section 3.4 presents the equilibria before proceeding to analyze the main findings in section 3.5. Section 3.6 concludes.

3.2 Literature review

3.2.1 Environmental Policies and its Dynamics with the Economic and Social Pillars

Taxes are the single most important way of raising revenue for governments (Sinayi & Rasti-Barzoki, 2018). Governments impose taxes or pay subsidies on products in order to protect the environment, support producers of green products (Ritzenhofen et al., 2016), raise revenue for public projects (Mankiw, 2007) and improve social welfare (El Hachem and De Giovanni, 2019).

Governmental environmental policies (e.g. environmental standards, subsidy and tax policy) are designed to encourage consumers to purchase green products and manufacturers to improve the environmental quality of their products. However, these policies entail tradeoffs between the environmental dimension and the economic and social ones, leading to mixed results in terms of success in reducing emissions.

There has been plenty of research that investigate the impact of environmental policies on the remaining two sustainability dimensions. (El Hachem and De Giovanni, 2019) show that stricter environmental standards might not necessarily benefit the environment. (Gonzalez and Fumero, 2002) demonstrate how environmental policies influence the social welfare. Bansal and Gangopadhyay (2003) investigated the impact of subsidy and tax policies influence on total pollution and aggregate welfare considering CEA. (Lombardini-Riipinen, 2005) studied how governments set the socially optimal emission and commodity tax policies while considering CEA with willingness to pay a higher price for green variants of a product. More so, sustainable operations management research has argued and found that profit and environmental benefits are not necessarily antithetical (Jalili et al., 2017).

The traditional and its green alternative products are considered to be substitutable (Brécard, 2013; Conrad, 2005; Liu et al., 2012; Reinhardt, 1998; Rodriguez-Ibeas, 2007). Given the impact of CEA, researchers introduced environmental quality (e.g. green level) as one variable that could potentially enhance the green product demand function (Liu, Anderson, & Cruz, 2012). The green product presents a tradeoff between its greater environmental benefits and its higher price/costs. This is known as environmental product differentiation (Reinhardt, 1998). AFV are an example of such an environmental product that contribute to reducing emissions, but come with a higher price tag than ICE vehicles (Yakita, 2009). This environmental product differentiation introduces a cannibalization effect into our model which we discuss next.

3.2.2 Cannibalization effect

Heightened market competition and evolving consumer preferences led manufacturers to adopt product proliferation (Li et al., 2018, Kim et al., 2013). One of product proliferation's effects is intra-brand cannibalization: products offered by the same firm are often considered by consumers as close substitutes so that one product's customers are at the expense of other products offered by the same firm (Li et al., 2018; Desai, 2001, De Giovanni and Ramani, 2018).

Durable goods manufacturers, such as car manufacturers, design product lines by taking into consideration consumer's heterogeneity in terms of preferences for different product attributes. Cars are designed with their price and emissions levels in mind among other possible attributes. Considering two vehicle alternatives, ICE and AFV, reflects the fact that consumers have different taste preferences (Garela and Lambertini, 2014), with some valuing more lower emissions (i.e. CEA), and while others valuing more lower prices.

A few papers such as (Kim et al., 2013; Jalili et al., 2017) consider the case where consumer preference structure is non-dominating, meaning each consumer segment values at least one attribute higher than the other segment. In such a case, the flow of consumers between segments goes both ways depending on the balance between the several attributes of each product.

Customers presented with a set of alternative and substitutable products would choose the one that best meets their preferences. Therefore, pricing strategies of substitutable products along with their ‘quality’ levels have become a popular research area in the supply chain management and sustainable development literature (Ma et al., 2018; Zhang et al., 2015; Jamali & Rasti-Barzoki, 2018; Basiri & Heydari, 2017; De Giovanni and Zaccour, 2019).

If a lower-quality car in terms of emissions (i.e. ICE) is sufficiently cheaper than the higher-quality product with lower emissions (i.e. AFV), then even environmentally conscious consumers would find it beneficial to buy ICE rather than AFV targeted to them. That is ICE can potentially cannibalize AFV. This cannibalization goes both ways, as an AFV with low enough emissions can be favored by price sensitive consumers over the cheaper ICE alternative with much higher emissions. This is intra-brand cannibalization.

We incorporate into our demand functions this cannibalization effect by considering the price differential as well as the green level differential between the two products. Similar demand functions are utilized in previous studies (Basiri and Heydari, 2017; Zhang et al., 2015) that investigate pricing and quality decisions of substitutable products.

3.2.3 Distributive Justice

While the literature investigates the AFV transition under different perspectives, few papers highlight the social aspects of such a transition (Boussaw & Vanoutrive, 2017; Harrison et al., 2013; Lucas et al., 2012). In particular, the concept of DJ has been disregarded by policy makers in their attempt to accelerate the diffusion of AFV. According to Walzer (1983), goods that have a distinct social meaning should be governed by a “Distributive Justice” sphere to prevent the compounding of inequalities. Martens et al. (2012) define DJ in transportation as the indiscriminate and equitable access to transportation, the latter being a vital means for people to realize their full capabilities in society. DJ’s main premise is that transportation policies should influence travelers to choose environmentally friendly alternatives rather than force them to do so.

In general, DJ consists of three main components (Hulle et al., 2017; Colquitt & Rodell, 2015; Stenman & Konow, 2010): *Equity* (i.e., allocating benefits between different groups proportionally to their respective invested efforts), *Equality* (i.e., allocating benefits between different groups regardless of invested efforts), and *Need* (i.e., providing access to transportation to the maximum number of people). Using these three components, DJ aims to make goods equally accessible and usable for the largest number of individuals.

There are a few qualitative and theoretical studies which evoke the use of DJ principles. As far as the authors know, there is only one paper (El Hachem& De Giovanni, 2019) which quantifies DJ via a composite index of Equity, Equality and Need in order to explain and measure how a certain firm performs in terms of DJ. However, they do not consider the interaction between the government and the manufacturer and they do not focus on the green level of the products. We focus on both in this paper.

We incorporate into our model the first component of DJ, i.e. Need, by modifying the consumer surplus formulation. This modification can under some conditions maximize the access to vehicles by decreasing the price of the lowest alternative, i.e. the price of ICE and increase the consumer surplus.

We seek to investigate the conditions under which DJ principles would increase the overall consumer surplus, maximize access to vehicles by decreasing the lowest alternative price while being convenient for both players.

We ask the following research questions:

RQ 1: How can we incorporate DJ into the social dimension of sustainable development? (Answered in section 3.3)

RQ 2: How do the optimal product pricing, greening and government intervention strategies change with and without DJ?

RQ 3: How do the three sustainability pillars interact with each other with and without DJ?

RQ 4: How do the government utility and manufacturer profit change with and without DJ?

3.3 A game theory model

We characterize a single period game theory model that is composed of two players: a car manufacturer, player M, and a government, player G. M manages two types of goods, namely, Internal Combustion Engines (ICE) cars and Alternative Fuel Vehicles (AFV). In the rest of the paper, we will use the subscripts I for ICE cars and A for AFV, with j=I,A.

For each car type, M sets the selling price, p_j, and the optimal green technology efforts, E_j. Because the ICE market is mature and the consumers' willingness to purchase ICE cars, we assume that the investments in green efforts for ICE cars, EI, is exogenous and that the marginal production cost for each car is constant and given by c_j. M decides the optimal strategies by considering the G's strategies, which are exemplified by the subsidies, denoted as 's', granted to consumers purchasing AFV, and the tax, denoted as 't', applied to consumers purchasing ICE vehicles. It does not matter whether a tax or subsidy on a product is imposed on the seller or buyer of a product since they will both share the burden or gain of the tax or subsidy (Sinayi & Rasti-Barzoki, 2018; Mankiw, 2007).

Therefore, the consumers purchasing AFV pay the amount $p_A - s$, while consumers purchasing ICE pay the amount $p_I + t$. The presence of both vehicles types is highly challenging for M due to the existence of a cannibalization effect that we model as follows:

$$\gamma\left(p_j, E_A, s, t\right) = \theta(p_I + t - p_A + s) + \theta_G(E_A - E_I)$$

Accordingly, the consumers evaluate the price difference when making their purchasing, which is subject to the scaling parameter θ>0. Furthermore, consumers evaluate the green efforts differences $E_A - E_I$, which is subject to the scaling parameter θ_G>0. The cannibalization effect influences the demand functions of both car types, which we model as follows:

$$D_A\left(p_j, E_A, s, t\right) = \alpha_A - \beta(p_A - s) + \delta E_A + \gamma$$

$$D_I\left(p_j, E_A, s, t\right) = \alpha_I - \beta(p_I + t) + \delta E_I - \gamma$$

The demand function for AFV includes α_A consumers, representing the market potential. β represents the consumers' sensitivity to AFV purchasing price, $p_A - s$, while δ is the consumers' sensitivity to the *M*'s green efforts. In sum, the sales for AFV decrease in the price through β and increases in the green efforts through δ. Finally, the AFV sales are influenced by the cannibalization effect, γ.

The demand function for ICE cars is composed of αI consumers, representing the market potential. β is the consumers' sensitivity to ICE purchasing price, $p_I + t$, while δ is the consumers' sensitivity to the M's green efforts for ICE. In sum, the sales for ICE decrease in the price through β and increases in the green efforts through δ. Finally, the ICE sales are influenced by the cannibalization effect given by γ.

These demand functions are similar to ones in (Sinayi & Rasti-Barzoki, 2018; Li et al., 2016; Ghosh and Shah, 2012). Note that the two players' strategies influence both the cannibalization effect and the sales, resulting in a very complex network of relationships among the five strategies.

M's investments in green efforts for AFV and ICE are modeled through a traditional quadratic cost function (Sinayi & Rasti-Barzoki, 2018; Li et al., 2016; Swami and Shah, 2013; Ghosh and Shah, 2012) as follows:

$$C_{E_j}(E_j) = \frac{hE_j^2}{2}$$

Where h is a scaling parameter that informs on the green investment efficiency: the larger h is, the higher the negative impact that green efforts E_A has on the M's objective function.

We assume that the game is played à la Stackelberg with G being the leader. Therefore, we solve the game by solving for the M's objective function first. In particular, M maximizes a profit function by selling both ICE and AFV cars and deciding the optimal p_j and E_A. The M's profit function is described as follows:

$$\pi_M = \max_{p_A, p_I, E_A} \{D_A(p_A, p_I, E_A, s, t)(p_A - c_A) + D_I(p_A, p_I, E_A, s, t)(p_I - c_I) - C_{E_j}(E_j)\}$$

The G's objective function is more complex as it is composed of three main components linked to the triple bottom line, that is, economic, environmental and social performance. The economic component, Φ_{Ec} takes into consideration the monetary flows that G generates when optimally setting both s and t. Specifically, G increases its economic outcomes by imposing some fees t to ICE consumers while decreases its monetary outcomes when granting the subsidy s to AFV consumers. Providing subsidies to purchase AFV would generate some additional economic activity, and imposing taxes on ICE would decrease economic activity. However, this increase and decrease in economic activity is far lower than the actual amounts of subsidies and taxes (Alagic, 2017; Ecola and Wachs, 2012). Accordingly, the G's economic component is given as follows:

$$\Phi_{Ec} = tD_I(p_j, E_A, s, t) - sD_A(p_j, E_A, s, t)$$

Interestingly, we can see that Φ_{Ec} entails a trade-off between product types, as both have contrasting effects on G's economic outcomes.

These economic outcomes should be confronted with the G's benefits linked to emissions. Clearly, AFV and ICE have different emission capacity and their sales have a direct effect on the amount of pollution created. Accordingly we define the environmental component of G's objective function, Φ_{En}, as dependent on both sales types. Specifically, Φ_{En} takes the following form:

$$\Phi_{En} = \left[D_A\left(p_j, E_A, s, t\right) - D_I\left(p_j, E_A, s, t\right)\right]e$$

Where e is the marginal impact on the environment generated by the sales of AFV and ICE. The emissions of AFV are lower than the emissions of ICE given the same distance travelled. Therefore, when $D_A\left(p_j, E_A, s, t\right) > D_I\left(p_j, E_A, s, t\right)$ G gets some environmental benefits given by saved emissions. Rather, when $D_A\left(p_j, E_A, s, t\right) < D_I\left(p_j, E_A, s, t\right)$, the G's environmental component gets damaged by the emissions generated by ICE.

Finally, we compute the social performance according to the consumers' surplus (Sinayi & Rasti-Barzoki, 2018; Xie, 2016; Panda, 2014; Swami and Shah, 2013) created when selling both ICE and AFV.

The consumer's surplus takes into consideration the price that consumers pay, $(p_I + t)$ in case of ICE and $(p_A - s)$ in case of AFV, in addition to the maximum prices that consumers would be willing to pay, given by:

$$p_{Amax} = \frac{\alpha_A + s\beta + E_A\delta + (p_I + s + t)\theta + (E_A - E_I)\delta\theta}{\beta + \theta}$$

$$p_{Imax} = \frac{\alpha_I - t\beta + E_I\delta + (p_A - s - t)\theta + (E_I - E_A)\delta\theta}{\beta + \theta}$$

These maximum prices are determined by finding the price at which the demand for each type of vehicle would be zero. Accordingly, we compute the G's social component as:

$$\Phi_{Soc} = \int_{p_A}^{p_{A\max}} D_A\left(p_j, E_A, t, s\right) dp_A + \int_{p_I}^{p_{I\max}} D_I\left(p_j, E_A, t, s\right) dp_I$$

Therefore, the higher the consumers' surplus created through both AFV and ICE, the higher the G's social performance.

We should highlight the difficulties that G encounters when setting the optimal s and t. The maximization of AFV sales, ceteris paribus, leads to higher environmental performance while leading to the deterioration in the economic performance, while its impact on the social performance changes under different conditions. Further, the maximization of ICE sales leads to higher economic component while deteriorating the environmental component, with its impact on the social performance changing under different conditions. Overall, the G's maximization problem is given as follows:

$$U_G = \max_{s,t}\left\{ w_{Ec}\Phi_{Ec} + w_{Env}\Phi_{Env} w_{Soc}\Phi_{Soc} \right\}$$

Where w_{Ec}, w_{Env}, w_{soc} are all positive scaling parameters that we introduce in the maximization problem because the outcomes $\Phi_{En}, \Phi_{Ec}, \Phi_{soc}$ are measured through heterogeneous scales.

While the first objective of this paper is to investigate the players' strategies and outcomes according to all trade-offs that we earlier described, the second objective consists of evaluating the conditions where introducing distributive justice (DJ) principles into the G's objective function would be beneficial.

DJ consists of three main components (Hulle et al., 2017; Colquitt & Rodell, 2015; Stenman & Konow, 2010): Equity (i.e., allocating benefits between different groups proportionally to their respective invested efforts), Equality (i.e., allocating benefits between different groups regardless of invested efforts), and Need (i.e., providing access to transportation to the maximum number of people). We incorporate into our model the first component, i.e. Need, by modifying the consumer surplus (i.e. social dimension) formulation. We are interested in finding the conditions under which this modification can maximize the access to vehicles by decreasing the price of the lowest alternative, while increasing the consumer surplus.

Therefore, we aim at measuring the social performance when G undertakes DJ principles. To do so, the social performance, Φ_{soc} is now computed as follows answering our first research question:

$$\Phi_{soc}^{DJ} = \int_{p_A}^{p_{Imax}} D_A(p_j, E_A, s, t)\, dp_A + \int_{p_I}^{p_{Imax}} D_I(p_j, E_A, s, t)\, dp_I$$

That is, the consumers who are willing to contribute to the environment by purchasing AFV should not pay a price that is higher than the maximum ICE price. Therefore, the consumers' surplus linked to AFV is computed within the same region where ICE consumer's surplus is computed. The objective is to influence G's strategies s and t to maximize the overall consumer surplus by minimizing p_A (ceteris paribus increasing D_A), minimizing p_I (ceteris paribus increasing D_I and overall access to vehicles) and maximizing p_{Imax} (ceteris paribus increasing the utility derived from ICE). However, the dynamics between the G's decision variables (i.e. s and t) and M's decision variables (p_j and E_A) render the outcome of this modification more difficult to discern with DJ beneficial only under certain conditions, mainly when high weights are given to the environmental and economic dimensions in the G's utility as it will illustrated and explained in section 3.5.

When G uses DJ principles to compute the social component, the players' objective functions become:

$$\Pi_M^{DJ} = \max_{p_A^{DJ}, p_I^{DJ}, E_I^{DJ}} \left\{ D_A^{DJ}\left(p_j^{DJ}, E_A^{DJ}, s^{DJ}, t^{DJ}\right)\left(p_A^{DJ} - c_A\right) + D_I^{DJ}\left(p_j^{DJ}, E_A^{DJ}, s^{DJ}, t^{DJ}\right)\left(p_I^{DJ} - c_I\right) - C_{E_A^{DJ}}\left(E_A^{DJ}\right) \right\}$$
$$U_G^{DJ} = \max_{s^{DJ}, t^{DJ}} \left\{ w_{Ec}\Phi_{Ec}^{DJ} + w_{Env}\Phi_{Env}^{DJ} w_{Soc}\Phi_{Soc}^{DJ} \right\}$$

Where the DJ principles embedded in Φ_{soc}^{DJ} influence the G's optimal strategies s^{DJ} and t^{DJ} and in turn the U_G^{DJ}. This will have an impact on M's optimization problem, that is P_A^{DJ}, P_I^{DJ}, E_A^{DJ} as well as on π_M^{DJ}. We seek to establish the equilibria for both games and compare the solutions to investigate the conditions under which DJ principles support the AFV transition, measured by AFV sales, increase the overall consumer surplus while being convenient for both players.

3.4 Equilibria

We solve the two stage game under two scenarios: No DJ, with DJ. The only difference between the two scenarios is the modification to the formulation of the consumer surplus in the social dimension of the G's utility.

3.4.1 Scenario 1: No DJ

Under this scenario, we first have to establish that the manufacturer profit π_M is concave in its decision variables (p_j *and* E_A) and that government's utility is concave in its decision variables (s and t), so that we can determine the decision variables unique optimal values that maximize the objective functions.

Theorem 1: The government utility is jointly concave in s and t for given parameter ranges and there are unique optimal values for s^* and t^* that maximize the objective function. The optimal equations are too large to include here, however we will investigate them visually via graphs in the next section.

Proof: We compute the Hessian matrix of the G's utility as follows:

$$\mathrm{H}\ [U_G(\mathrm{s},\mathrm{t})] = \begin{bmatrix} \partial^2 U_G/\partial s^2 & \partial^2 U_G/\partial s\,\partial t \\ \partial^2 U_G/\partial t\,\partial s & \partial^2 U_G/\partial t^2 \end{bmatrix} =$$

$$\begin{bmatrix} \mathrm{wEc}(-2\beta-2\theta)+\mathrm{wS}(\frac{(-\beta-\theta)^2}{\beta+\theta}+\frac{\theta^2}{\beta+\theta}) & -2\mathrm{wEc}\theta+\mathrm{wS}(\theta-\frac{(-\beta-\theta)\theta}{\beta+\theta}) \\ -2\mathrm{wEc}\theta+\mathrm{wS}(\theta-\frac{(-\beta-\theta)\theta}{\beta+\theta}) & \mathrm{wEc}(-2\beta-2\theta)+\mathrm{wS}(\beta+\theta+\frac{\theta^2}{\beta+\theta}) \end{bmatrix}$$

In order for $U_G(\mathrm{s},\mathrm{t})$ to be concave in s and t, the hessian must be negative definite. Therefore, we have two conditions:

$$H_{1,1} = \mathrm{wEc}(-2\beta-2\theta)+\mathrm{wS}(\frac{(-\beta-\theta)^2}{\beta+\theta}+\frac{\theta^2}{\beta+\theta}) < 0$$

$$Det\ H_{2\times 2} =$$

$$Det\begin{bmatrix} \mathrm{wEc}(-2\beta-2\theta)+\mathrm{wS}(\frac{(-\beta-\theta)^2}{\beta+\theta}+\frac{\theta^2}{\beta+\theta}) & -2\mathrm{wEc}\theta+\mathrm{wS}(\theta-\frac{(-\beta-\theta)\theta}{\beta+\theta}) \\ -2\mathrm{wEc}\theta+\mathrm{wS}(\theta-\frac{(-\beta-\theta)\theta}{\beta+\theta}) & \mathrm{wEc}(-2\beta-2\theta)+\mathrm{wS}(\beta+\theta+\frac{\theta^2}{\beta+\theta}) \end{bmatrix} > 0$$

Then we determine the parameter values for which these conditions are satisfied. The blue areas in Figure 3.9 display the region where the two constraints above are satisfied:

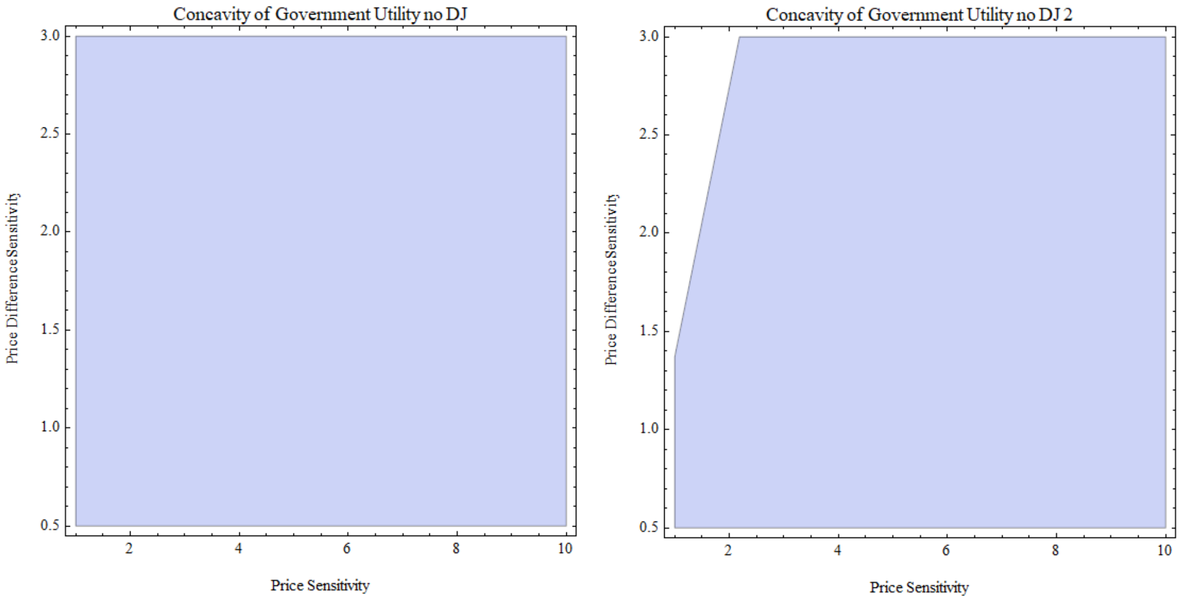


Figure 3.9: Negativity of First quadrant and positivity of the determinant of government's utility hessian matrix with no DJ

Theorem 2: The manufacturer's profit function is jointly concave in p_A, p_I and E_A for given parameter ranges and there are unique optimal values for ${p_A}^*$, ${p_I}^*$ and ${E_A}^*$ that maximize the objective function. The optimal equations are too large to include here, however we will investigate them visually via graphs in the next section.

Proof: We compute the Hessian matrix of the π_M as follows:

$$H\,[\pi_M(p_A,\ \ p_I, E_A)] =$$

$$\begin{bmatrix} \partial^2\pi_M/\partial {p_A}^2 & \partial^2\pi_M/\partial p_A\,\partial p_I & \partial^2\pi_M/\partial p_A\,\partial E_A \\ \partial^2\pi_M/\partial p_I\,\partial p_A & \partial^2\pi_M/\partial {p_I}^2 & \partial^2\pi_M/\partial p_I\,\partial E_A \\ \partial^2\pi_M/\partial E_A\,\partial p_A & \partial^2\pi_M/\partial E_A\,\partial p_I & \partial^2\pi_M/\partial {E_A}^2 \end{bmatrix}$$

$$= \begin{bmatrix} -h & \delta + \theta G & -\theta G \\ \delta + \theta G & -2\beta - 2\theta & 2\theta \\ -\theta G & 2\theta & -2\beta - 2\theta \end{bmatrix}$$

In order for $\pi_M(p_A,\ p_I, E_A)$ to be concave in p_A, p_I and E_A, the hessian must be negative definite. Therefore, we have three conditions:

$$First\ order\ leading\ principal\ minor = H_{1,1} = -h < 0$$

$$Second\ order\ leading\ principal\ minor = H_{1,1} * H_{2,2} - H_{1,2} * H_{2,1} = -h\,(-2\beta - 2\theta) - (\delta + \theta G)^2 > 0$$

$$Third\ order\ leading\ principal\ minor = Det\begin{bmatrix} -h & \delta + \theta G & -\theta G \\ \delta + \theta G & -2\beta - 2\theta & 2\theta \\ -\theta G & 2\theta & -2\beta - 2\theta \end{bmatrix} < 0$$

The first condition is always met. So, we have to determine the parameter values for which the second and third conditions are satisfied as illustrated in the blue areas in Figure 3.10:

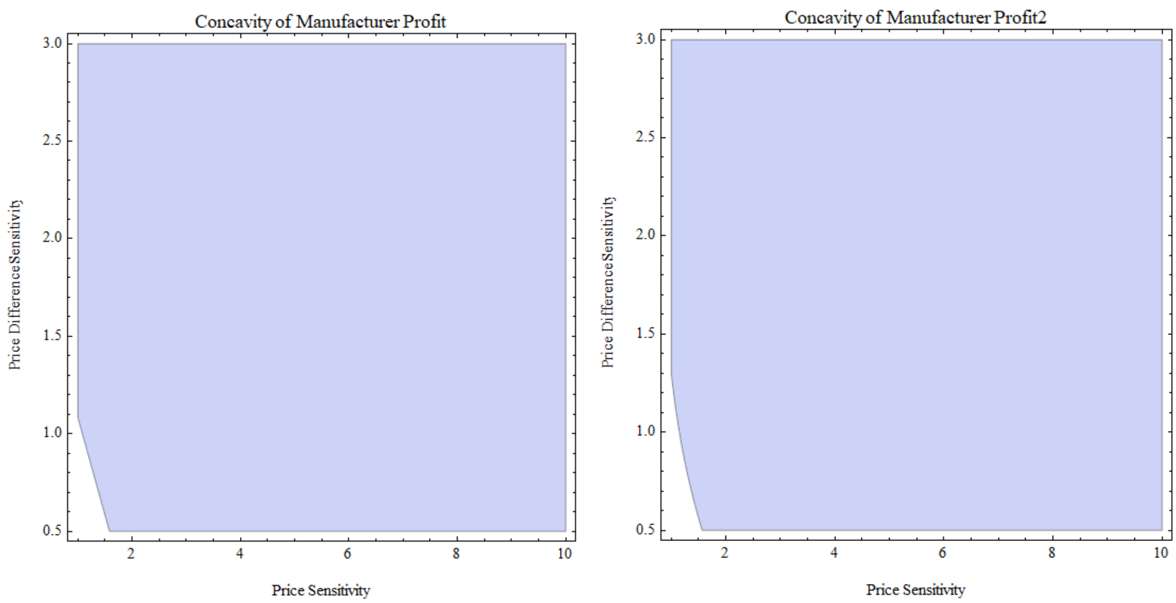


Figure 3.10: Concavity conditions for the manufacturer profit function

3.4.2 Scenario 2: With DJ

Under this scenario, we establish that the manufacturer profit π_M^{DJ} is concave in its decision variables (p_j^{DJ} *and* E_A^{DJ}) and that government's utility is concave in its decision variables (s^{DJ} and t^{DJ}), so that we can determine the decision variables unique optimal values that maximize the objective functions.

Theorem 3: The government utility is jointly concave in s^{DJ} and t^{DJ} for given parameter ranges and there are unique optimal values for s^{DJ^*} and t^{DJ^*} that maximize the objective function. The optimal equations are too large to include here, however we will investigate them visually via graphs in the next section.

Proof: We compute the Hessian matrix of the G's utility as follows:

$$\mathrm{H}\left[U_G^{DJ}(s^{DJ}, t^{DJ})\right] = \begin{bmatrix} \partial^2 U_G/\partial s^2 & \partial^2 U_G/\partial s\,\partial t \\ \partial^2 U_G/\partial t\,\partial s & \partial^2 U_G/\partial t^2 \end{bmatrix} =$$

$$\begin{bmatrix} \mathrm{wEc}(-2\beta-2\theta)+\mathrm{wS}(-\beta-3\theta+\frac{(-\beta-\theta)^2}{\beta+\theta}) & -2\mathrm{wEc}\theta+\mathrm{wS}(\frac{1}{2}(-2\beta-3\theta)+\frac{(-\beta-3\theta)\theta}{2(\beta+\theta)}-\frac{(-\beta-\theta)\theta}{\beta+\theta}) \\ -2\mathrm{wEc}\theta+\mathrm{wS}(\frac{1}{2}(-2\beta-3\theta)+\frac{(-\beta-3\theta)\theta}{2(\beta+\theta)}-\frac{(-\beta-\theta)\theta}{\beta+\theta}) & \mathrm{wEc}(-2\beta-2\theta)+\mathrm{wS}(\frac{(-2\beta-3\theta)\theta}{\beta+\theta}+\frac{\theta^2}{\beta+\theta}) \end{bmatrix}$$

In order for $U_G^{DJ}(s^{DJ}, t^{DJ})$ to be concave in s^{DJ} and t^{DJ}, the hessian must be negative definite. Therefore, we have two conditions:

$$H_{1,1} = \mathrm{wEc}(-2\beta-2\theta)+\mathrm{wS}(-\beta-3\theta+\frac{(-\beta-\theta)^2}{\beta+\theta}) < 0$$

$$Det\ H_{2\times 2} =$$

$$Det\begin{bmatrix} \mathrm{wEc}(-2\beta-2\theta)+\mathrm{wS}(-\beta-3\theta+\frac{(-\beta-\theta)^2}{\beta+\theta}) & -2\mathrm{wEc}\theta+\mathrm{wS}(\frac{1}{2}(-2\beta-3\theta)+\frac{(-\beta-3\theta)\theta}{2(\beta+\theta)}-\frac{(-\beta-\theta)\theta}{\beta+\theta}) \\ -2\mathrm{wEc}\theta+\mathrm{wS}(\frac{1}{2}(-2\beta-3\theta)+\frac{(-\beta-3\theta)\theta}{2(\beta+\theta)}-\frac{(-\beta-\theta)\theta}{\beta+\theta}) & \mathrm{wEc}(-2\beta-2\theta)+\mathrm{wS}(\frac{(-2\beta-3\theta)\theta}{\beta+\theta}+\frac{\theta^2}{\beta+\theta}) \end{bmatrix} > 0$$

Then we determine the parameter values for which these conditions are satisfied, displayed by the blue areas, with close results to the first scenario as seen in Figure 3.11:

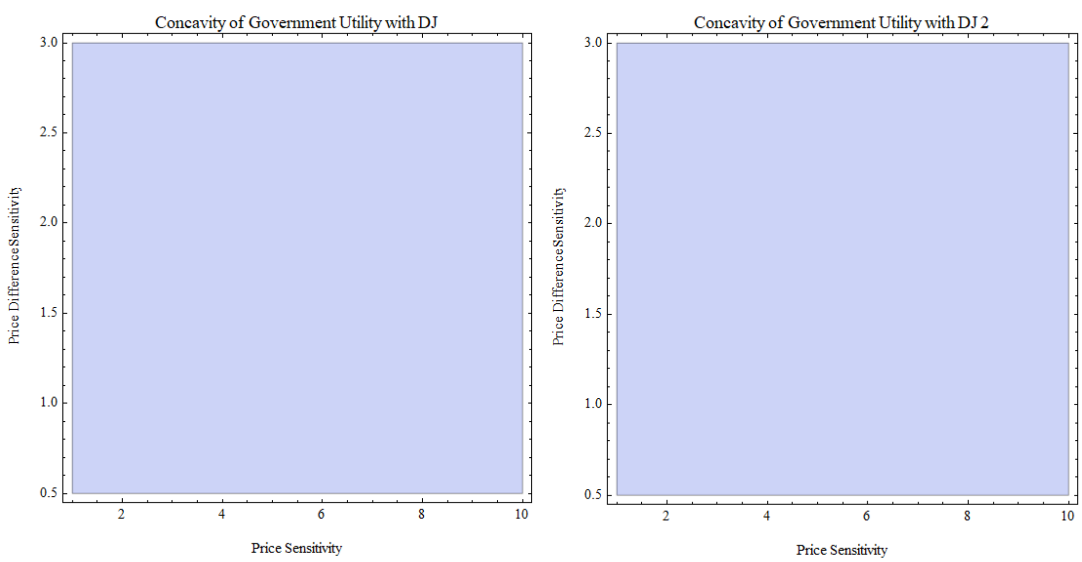


Figure 3.11: Negativity of first quadrant and positivity of determinant of government utility hessian with DJ

Theorem 4: Similar to Theorem 2.

3.5 Analysis and Results

Within the parameter ranges that satisfy concavity conditions for both objective functions, we analyze the results, while making sure that positivity constraints are also satisfied.

Our first research question was answered in section 3.3. We modified the AFV consumer surplus formulation by setting the maximum price equal to that of the maximum price of ICE. The objective is to influence G's strategies s and t to maximize the overall consumer surplus. However, the dynamics between the G's decision variables (i.e. s and t) and M's decision variables (p_j and E_A) render the outcome of this modification more difficult to discern with DJ beneficial only under certain conditions which will be explored in the following subsections when answering the remaining research questions.

First, let us introduce how we analyzed the model before answering our research questions. Table 3.6 displays the overall results and below is explanation on how to read this table.

We notice that when we vary the weight of the social pillar w_{soc}, the results do not vary qualitatively in a significant manner (except for Φ_{soc} and π_M), so we focus on the variation of weights of the remaining two pillars. Hence, we look at the 4 possible combinations (i.e. quadrants) of weights assigned to the environmental and economic pillars: (Low w_{Env}, Low w_{Ec}), (Low w_{Env}, High w_{Ec}), (High w_{Env}, Low w_{Ec}), (High w_{Env}, High w_{Ec}). Since we vary the weights for each pillar between 1 and 2, we categorize 'Low' weight for a given pillar as being between 1 and 1.5, and 'High' weight between 1.5 and 2.

We assess the results in terms of when the given component being analyzed (i.e. specific row in Table 3.6) is higher or lower with DJ compared to when there is no DJ within a given quadrant. If it is higher with DJ, we indicate in Table 3.6 'Higher', and if it is lower with DJ, we indicate 'Lower'.

It is also possible that a component is split between being higher and lower with DJ compared to when there is no DJ within a given quadrant. There are two possible ways for this split to happen which we define below.

Split I: It is when within a given quadrant, higher w_{Ec} and lower w_{Env} lead to higher values with DJ, while lower w_{Ec} and higher w_{Env} lead to lower values with DJ. For example, if within the first quadrant (L,L) of ICE tax, an economic weight of $w_{Ec} = 1.4$ and an environmental weight $w_{Env} = 1.1$ give a higher value for the ICE tax with DJ while when $w_{Ec} = 1.1$ and an environmental weight $w_{Env} = 1.4$ give a lower value for the ICE tax with DJ, then we say that the ICE tax in the first quadrant displays a 'Split I' behavior.

Split II: It is the reverse of Split I. It is when within a given quadrant Lower w_{Ec} and Higher w_{Env} lead to higher values with DJ, while Higher w_{Ec} and Lower w_{Env} lead to lower values with DJ. For example, if within the first quadrant (L,L) of ICE price, an economic weight of $w_{Ec} = 1.1$ and an environmental weight $w_{Env} = 1.4$ give a higher value for the ICE price with DJ while when $w_{Ec} = 1.4$ and an environmental weight $w_{Env} = 1.1$ give a lower value for the ICE price with DJ, then we say that the ICE price in the first quadrant displays a 'Split II' behavior.

Next, we will answer our research questions by looking more closely at some of the dynamics displayed in Table 3.6.

		Weight Combination (Env,Eco)			
		L,L	**L,H**	**H,L**	**H,H**
Decision Variables	ICE Tax (i.e. t)	Split I	Higher	Lower	Split I
	AFV Subsidy (i.e. s)	Split I	Higher	Lower	Split I
	AFV Green Level (i.e. E_A)	Split I	Higher	Lower	Split I
	ICE Price (i.e. p_I)	Split II	Lower	Higher	Split II
	AFV Price (i.e. p_A)	Split I	Higher	Lower	Split I
Sustainability Pillars	Environmental (i.e. Φ_{En})	Split I	Higher	Lower	Split I
	Economic (i.e. Φ_{Eco})	Split II	Lower	Higher	Split II
	Social (i.e. Φ_{soc}) with Low w_{soc}	Split II	Lower	Higher	Split II
Objectives	Utility (i.e. U_G)	Equal	Equal	Equal	Equal
	Manufacturer Profit (i.e. π_M) with Low w_{soc}	Split II	Lower	Higher	Split II
Interesting model components	Cannibalization	Split I	Higher	Lower	Split I
	ICE Demand (i.e. D_I)	Split II	Lower	Higher	Split II
	AFV Demand (i.e. D_A)	Split I	Higher	Lower	Split I
	Final price of ICE (i.e. p_I + t)	Split I	Higher	Lower	Split I
	Final Price of AFV (i.e. p_A – s)	Split II	Lower	Higher	Split II
	ICE max Price (i.e. p_{Imax})	Split II	Lower	Higher	Split II
	Max Price Difference (i.e. $p_{Amax} - p_{Imax}$)	Split I	Higher	Lower	Split I

Table 3.6: Overview of model components dynamics of when they are higher or lower with DJ given different weight combinations

3.5.1 Research Question 2

RQ2: How do the optimal product pricing, greening and government intervention strategies change with and without DJ?

The modification we did to the consumer surplus formulation results in interesting changes in the optimal strategies of the two players. We will compare each strategy below and determine under which conditions they increase or decrease with DJ compared to when there is no DJ.

3.5.1.1 Tax

Player G decides on the optimal tax t to impose on ICE consumers to disincentivize them from purchasing an ICE vehicle. Figure 3.12 displays the graphs that show how the ICE tax changes with and without DJ:

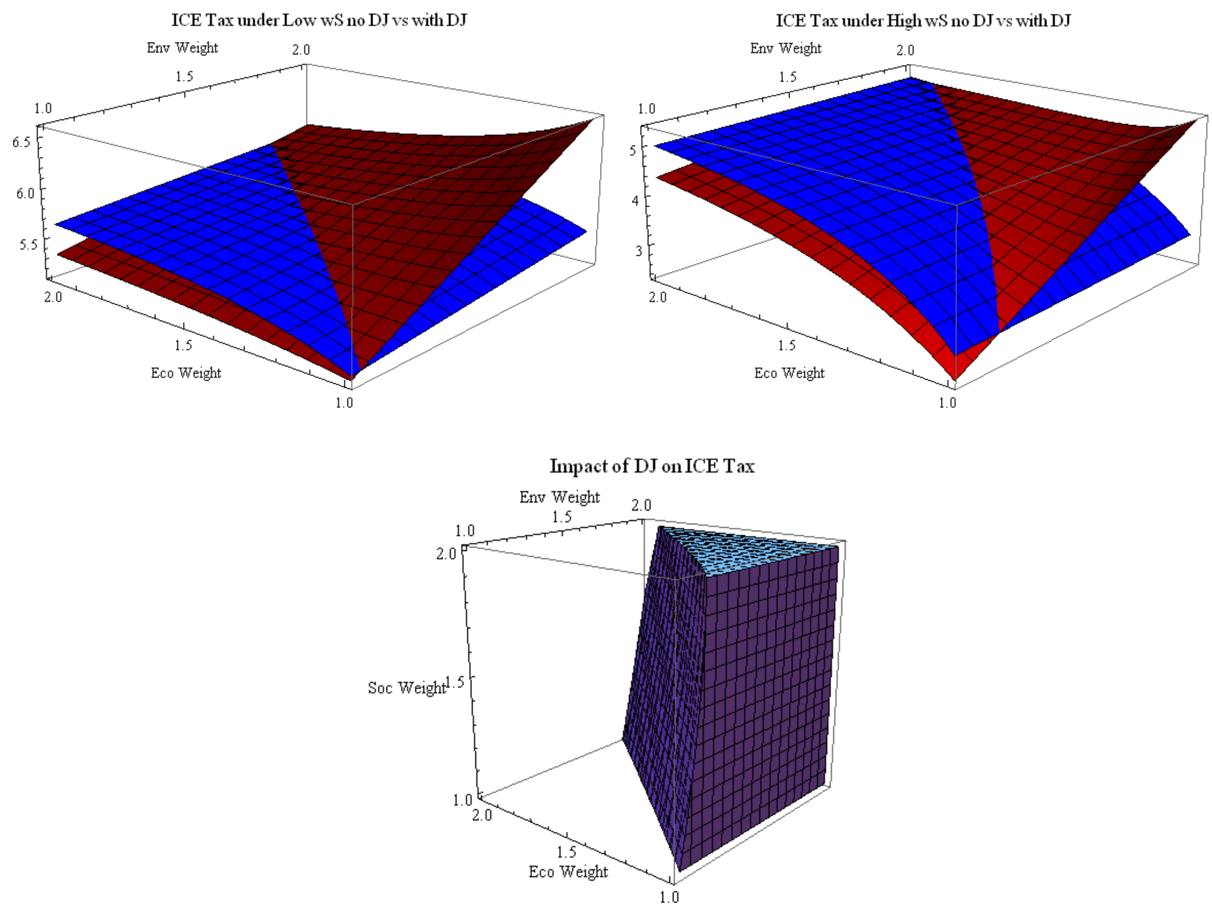


Figure 3.12: ICE Tax under Low and High wS with and without DJ

The graph on upper left corner shows the ICE tax when we have low weight for the social dimension, i.e. w_{soc} = 1. Red surface is tax with no DJ while Blue surface is tax with DJ. We notice that just about a little over 50% of red surface is higher than the blue one, and that is mostly when we have high environmental weight w_{En} and low economic weight w_{Ec}. So, when G values little the economic dimension and highly the environmental dimension, the ICE tax with no DJ is higher than with DJ. The same logic applied to the upper right corner graph where we have high weight for the social dimension, i.e. w_{soc}=2. This is captured nicely in the bottom graph where all three weights are varied between 1 and 2, with the filled surface representing the area where ICE tax with no DJ is greater than with DJ.

Please note that we are comparing the impact of including or not including DJ on the optimal value of Tax. Tax would always increase in importance as the economic and environmental dimensions grow in importance, however it would do so more (or less) when we consider DJ depending on the weights of the different sustainability pillars.

The most interesting insight here is that the ICE tax can increase or decrease with DJ depending on the weight the player G assigns to different sustainability pillars. The tax would increase with DJ when we have high economic weight and low environmental weight. We can interpret this as tax playing a larger (smaller) role as the economic (environmental) dimension gains importance when we consider DJ versus when we do not consider it.

3.5.1.2 Subsidy

Player G decides on the optimal subsidy s to give to AFV consumers to incentivize them to purchase and AFV. Figure 3.13 displays the graphs that show how the ICE tax changes with and without DJ where the filled area is when s > s^{DJ}:

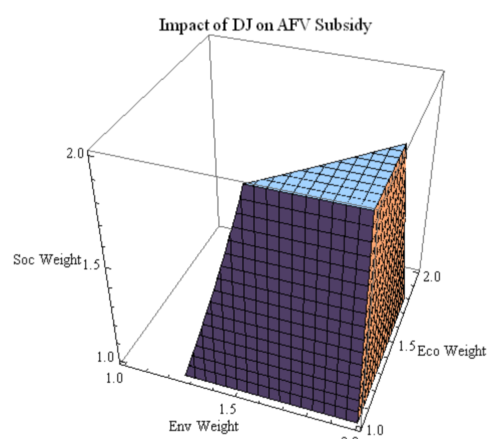


Figure 3.13: AFV Subsidy under Low and High wS with and without DJ

The dynamics of Subsidy are similar to the tax, with the subsidy increasing or decreasing with DJ depending on the weight the player G assigns to different sustainability pillars. The subsidy would increase with DJ when we have high economic weight and low environmental weight. We can interpret this as subsidy playing a larger (smaller) role as the economic (environmental) dimension gains importance when we consider DJ.

3.5.1.3 AFV Green Level (i.e. E_A)

The AFV green level (i.e. E_A) represents the efforts invested by the manufacturer to enhance the environmental quality of its AFV. It follows similar dynamics as the ICE tax and AFV Subsidy, mainly increasing with DJ when we have high economic weight and low environmental weight. We can interpret this as AFV green level playing a larger (smaller) role as the economic (environmental) dimension gains importance when we consider DJ versus when we do not consider it. This is illustrated in Figure 3.14 where the filled area is where the $E_A > E_A^{DJ}$:

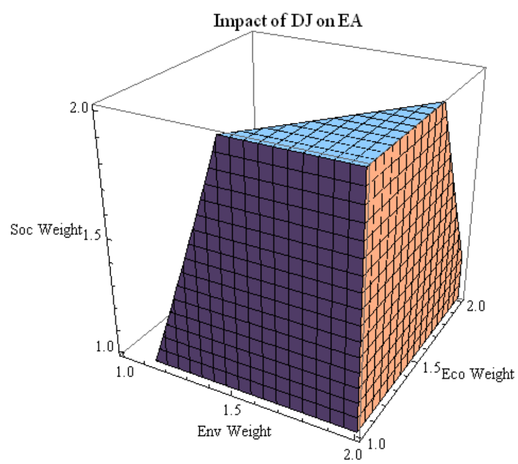


Figure 3.14: Impact of DJ on E_A

3.5.1.4 AFV Price (i.e. P_A)

The price of AFV follows the same dynamics as the previous decision variables by playing a larger (smaller) role as the economic (environmental) dimension gains importance when we consider DJ versus when we do not consider it. This is illustrated in Figure 3.15 where the filled area is $P_A > P_A^{DJ}$:

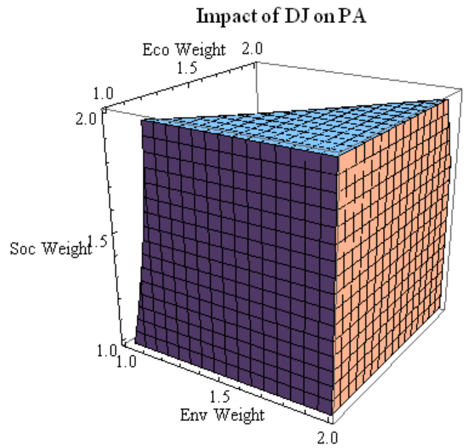


Figure 3.15: Impact of DJ on pA

3.5.1.5 ICE Price (i.e. P_I)

The price of ICE follows the opposite dynamics as the previous decision variables by playing a smaller (larger) role as the economic (environmental) dimension gains importance when we consider DJ versus when we do not consider it. This is illustrated in Figure 3.16 where the area filled is $p_I > p_I^{DJ}$:

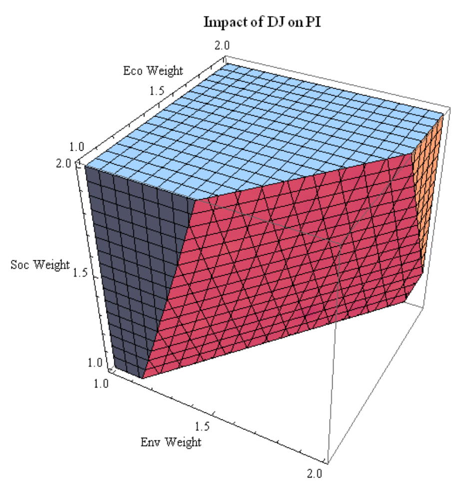


Figure 3.16: ICE Price under Low and High wS with and without DJ

3.5.1.6 Prices paid by Consumers

It is interesting to look at the dynamics of the prices paid by the consumers. For the ICE, it is the manufacturer price plus the tax. For AFV, it is the manufacturer price minus the subsidy.

The price paid by consumers for ICE follows the same dynamics as the tax. Meaning, the increase (decrease) in tax with DJ is greater than the decrease (increase) in ICE manufacturer price. The price paid by consumers for an ICE is larger (smaller) as the economic (environmental) dimension gains importance when we consider DJ versus when we do not consider it. In Figure 3.17, the area filled displays when $(p_I + t)$ > $(p_I^{DJ} + t)$:

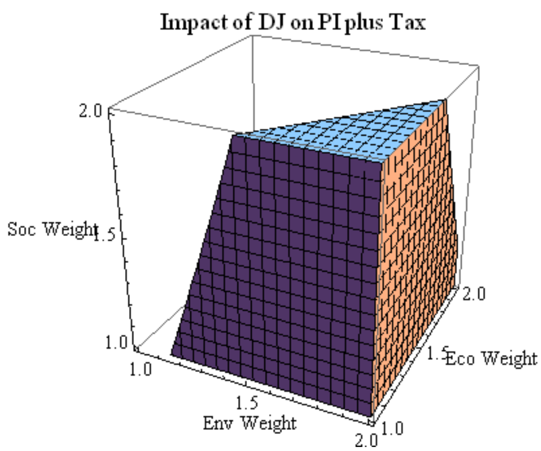


Figure 3.17: P_I + Tax with vs without DJ

As for the AFV price paid by consumers, it follows the opposite dynamics of the ICE price paid by consumers. Meaning the increase (decrease) in AFV subsidy is greater than the increase (decrease) in the AFV manufacturer price. The price paid by consumers for an AFV is smaller (larger) as the economic (environmental) dimension gains importance when we consider DJ versus when we do not consider it. In Figure 3.18, the area filled displays when $(p_A - s)$ > $(p_A^{DJ} - s)$:

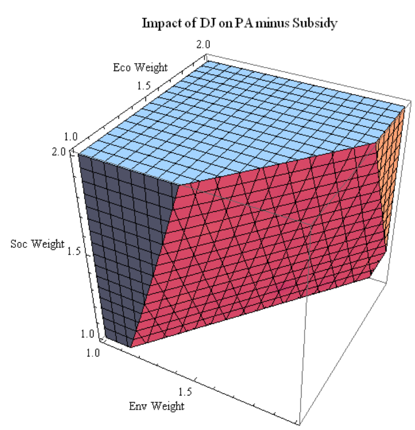


Figure 3.18: Impact of DJ on pA minus Subsidy

One interesting insight is that the government's tax and subsidy override the manufacturer's prices when determining the dynamics of the final prices paid by consumers. Hence, the importance of government intervention in such a setting such as AFV transition.

So far, we have been looking at the dynamics of the individual decision variables of the two players. It is interesting to analyze the dynamics of the objective functions of the two players which are determined by the cumulative impact of these decision variables, and which more easily provide policy oriented insights.

3.5.2 Research Question 3

RQ 3: How do the three sustainability pillars interact with each other with and without DJ?

As already mentioned, there are 3 pillars which we consider: Environmental, Economic and Social. Below we will analyze the dynamics of each one with and without DJ.

3.5.2.1 Environmental (i.e. Φ_{En})

The environmental dimension measures the gap between the demands for AFV and for ICE, with higher demand for AFV (ICE) improving (worsening) its performance. Its dynamics are shown in Figure 3.19 with the red surface depicting the scenario with no DJ, while the blue surface the scenario with DJ:

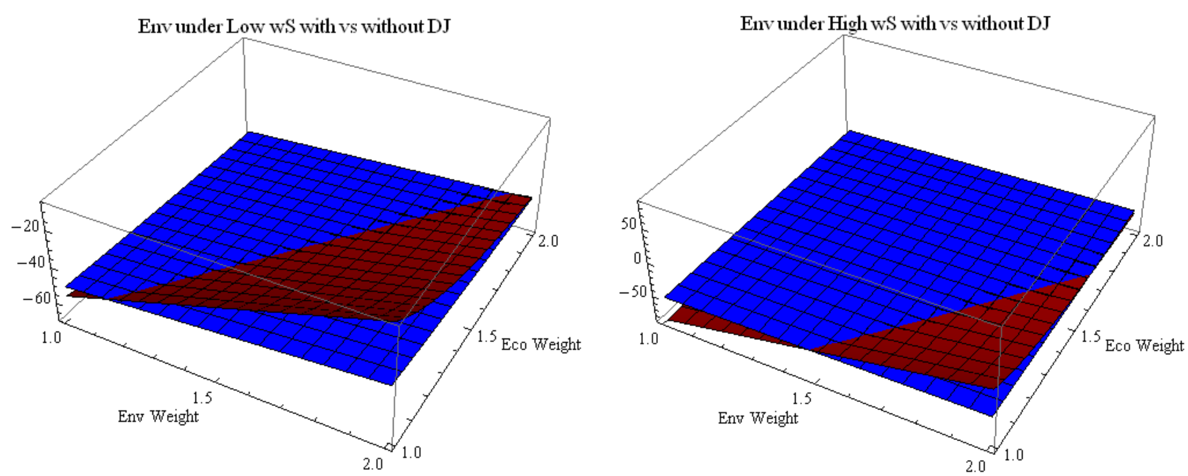


Figure 3.19: Environmental Dimension dynamics with vs without DJ

First, we notice that it is mostly negative, meaning the demand for AFV is mostly lower than that of ICE, except when we have high environmental weight and low economic one. This makes perfect sense since the higher the environmental weight, the more beneficial the AFV are; and the lower the economic dimension, the lower the disadvantage the AFV subsidy presents to the G's utility.

The environmental performance is higher (lower) as the economic (environmental) dimension gains importance when we consider DJ versus when we do not consider it. This behavior follows the dynamics of the AFV demand shown in Figure 3.20:

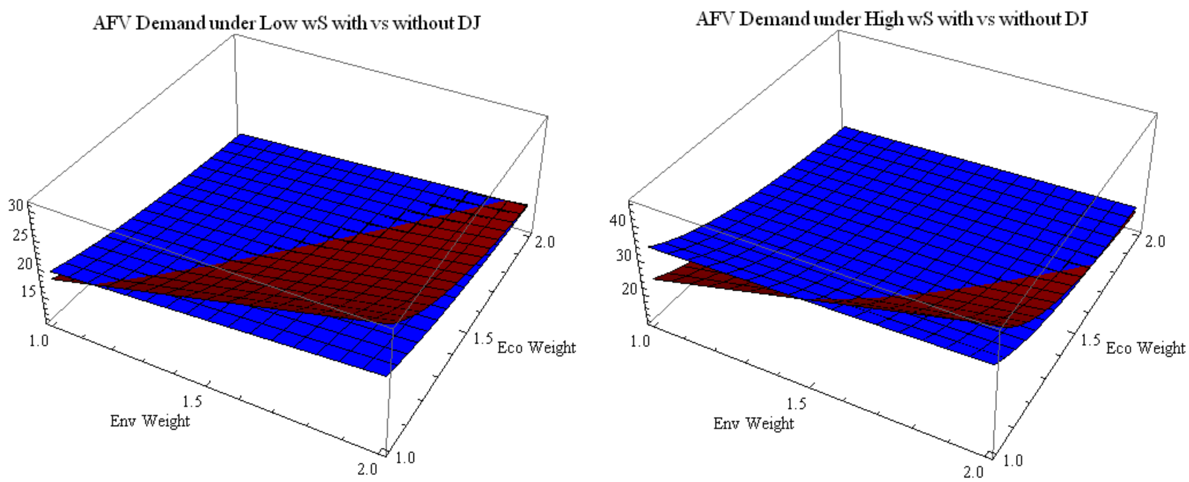


Figure 3.20: Dynamics of AFV demand with vs without DJ

The dynamics of the ICE demand are the opposite of AFV demand and since the ICE demand enters into the environmental performance in the negative form (i.e. being subtracted from the AFV demand), then it reinforces the dynamics seen in the graphs above. When AFV demand is greater with DJ, the ICE demand would be lower with DJ compared to without DJ, resulting in higher environmental performance with DJ compared to with no DJ.

So, it seems that the environmental performance and the weight of the economic (environmental) dimension are more (less) aligned when we consider DJ versus when we do not.

One interesting insight is that from the point of view of comparing the performance of a pillar with and without DJ, the performance of a pillar is not necessarily aligned with the weight it is given. Naturally, when we increase the weight of a pillar, its performance would improve under both the DJ and without DJ scenarios. However, it could improve more (or less) so depending on the weights given to the three pillars. Hence, the inclusion of DJ is beneficial only under some circumstances which themselves depend on the weights given to the three pillars.

3.5.2.2 Economic (i.e. Φ_{Eco})

The economic pillar increases with the ICE taxes collected and the ICE demand, while it decreases with the distributed AFV subsidies and the AFV demand. Figure 3.21 displays its dynamics:

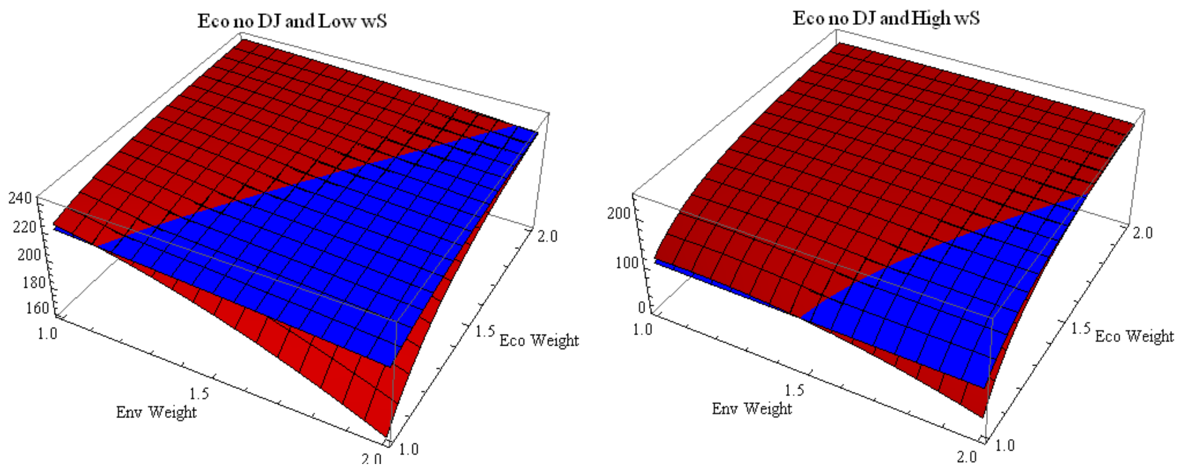


Figure 3.21: Dynamics of Economic Pillar with vs without DJ

The dynamics are opposite to the environmental dynamics in Figure 3.19. The economic performance is lower (higher) as the economic (environmental) dimension gains importance when we consider DJ versus when we do not consider it.

The dynamics of the environmental and economic pillars clearly show tradeoffs between the two. We cannot expect to improve simultaneously both pillars when we introduce DJ into the model.

3.5.2.3 Social (i.e. Φ_{Soc})

We have yet to analyze the social performance to see whether indeed the social performance is improving when we consider DJ, and if yes, under what conditions. The social performance is measured via consumer surplus for both the ICE and AFV consumers. When, we consider DJ, or more specifically, its Need component, we modify the AFV consumer surplus formulation by setting the maximum price equal to that of the maximum ICE price, in hopes of influencing the G's strategies to lower the price of both ICE and AFV while increasing overall consumer surplus.

The consumer surplus depends on the demands, the manufacturer prices and the maximum prices. The demands are themselves dependent on the prices paid by consumers (themselves dependent on G's and M's strategies) and the green level of the AFV. Meaning, the consumer surplus is dependent simultaneously on all strategies by both players, making for dynamics which are quite complex since they depend on several dynamic components.

Given the consumer surplus formulation, the following conditions help to push the consumer surplus with DJ to be greater than with no DJ:

- $P_I^{DJ} < P_I^{No\ DJ}$ (Figure 3.16)
- $P_A^{DJ} < P_A^{No\ DJ}$ (opposite dynamics of Figure 3.16)
- $P_{Imax}^{DJ} > P_{Imax}^{No\ DJ}$ (Figure 3.23)
- $D_I^{DJ} > D_I^{No\ DJ}$ (opposite dynamics of Figure 3.20)
- $D_A^{DJ} > D_A^{No\ DJ}$ (Figure 3.20)
- $(P_{Amax}^{DJ} - P_{Imax}^{DJ}) < (P_{Amax}^{No\ DJ} - P_{Imax}^{No\ DJ})$ (Figure 3.24)

These 6 conditions are not always satisfied and there are tradeoffs between them which leads to the dynamics of the consumer surplus shown in Figure 3.22. The dynamics alternate between not favoring DJ for low environmental weight and high economic weight, to favoring DJ when environmental weight is high and economic weight is low:

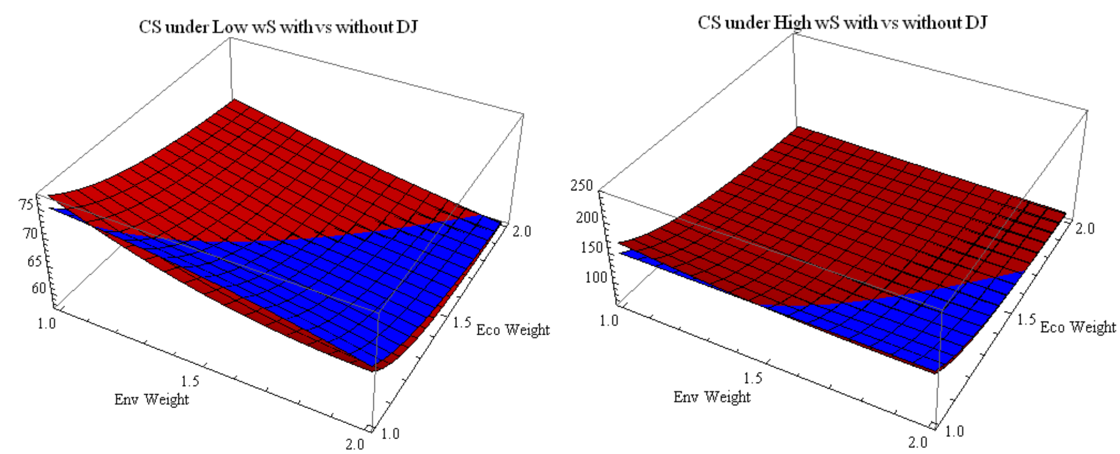


Figure 3.22: Consumer Surplus dynamics with vs without DJ

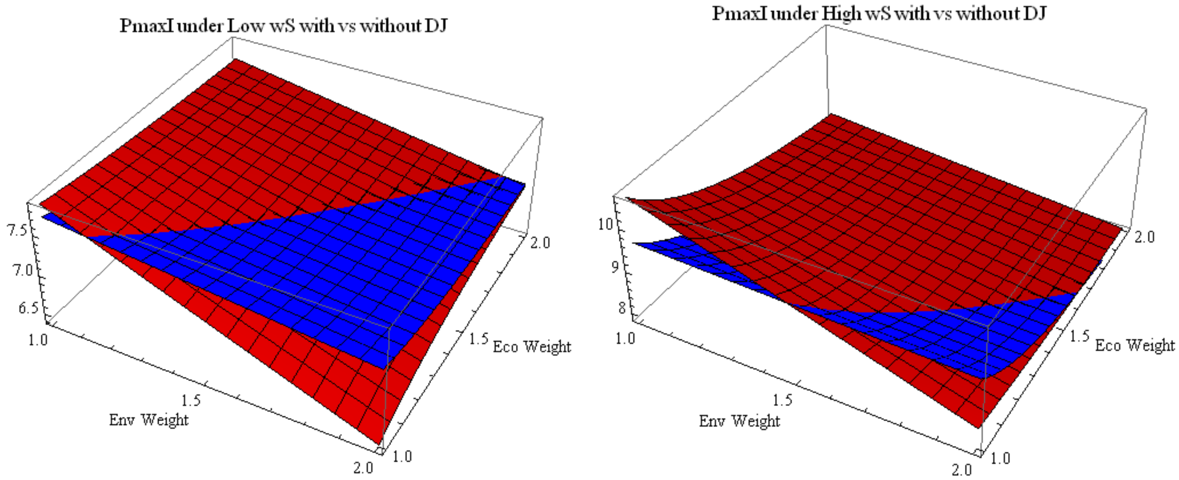


Figure 3.23: Dynamics of ICE pmax with vs without DJ

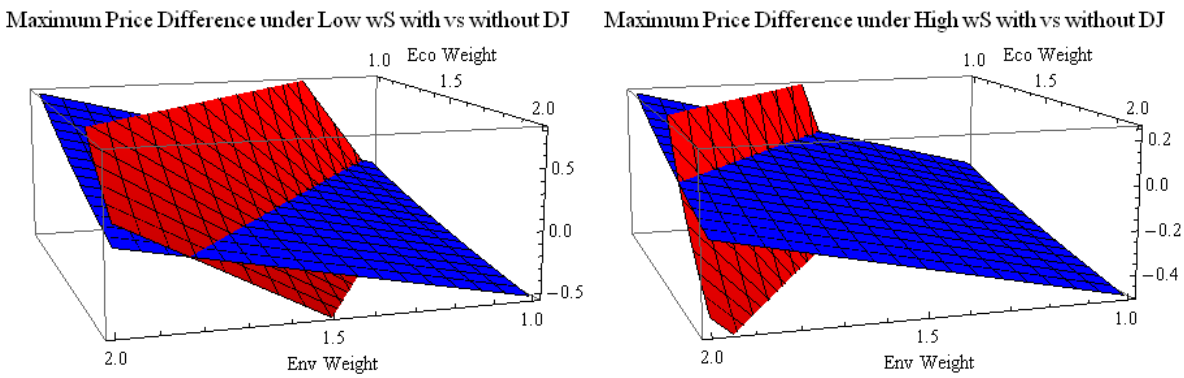


Figure 3.24: Difference in Maximum Prices with vs without DJ

From Figure 3.22, we can deduce that there are regions where the consumer surplus increases with DJ. In particular, the region in the upper right corner, where player G places high weights to both the economic and environmental dimensions, is split according to Split II (i.e. Lower w_{Ec} and Higher w_{Env} lead to higher CS with DJ). In this region, there is a part where consumer surplus always increases with DJ under both High and Low w_{Soc}.

In this region, DJ would increase the overall consumer surplus, maximize access to vehicles by decreasing the lowest alternative price (i.e. minimize final price of ICE) while being convenient for both players.

In the regions where CS increases with DJ, the economic dimension would be also increasing with DJ, however the environmental dimension would be decreasing with DJ compared to when there is no DJ. Hence, there is always a tradeoff between on one hand the social and economic pillars and on the other hand the environmental one.

We can deduce that when introducing DJ into the model by modifying the consumer surplus, there is no Pareto frontier where all three pillars improve simultaneously.

3.5.3 Research Question 4

RQ 4: How do the government utility, manufacturer profit and cannibalization change with and without DJ?

3.5.3.1 Government Utility (i.e. U_G)

The government utility is dependent on all three sustainability pillars: Environmental, Economic, Social. From the previous section, we know that with our current model, we cannot overcome the tradeoffs between the three pillars, hence it is interesting to see how the governments utility changes with DJ, shown in Figure 3.25:

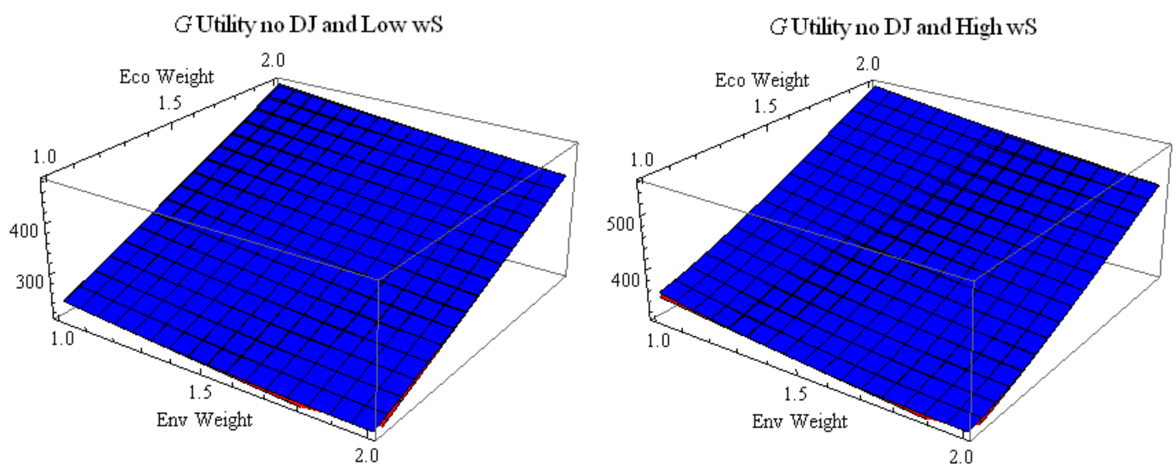


Figure 3.25: Government Utility with vs without DJ

The government utility remains more or less the same with and without DJ, with either a slight increase or decrease with DJ compared to without DJ depending on the parameter values and pillar weights. This shows that the government's utility is resilient to changes. It increasing or decreasing each of its pillars performances as needed.

One important insight is that the government can introduce modifications into one of its pillars, such as modifying the social pillar to include the concept of DJ, while not fearing a sharp decrease in its overall utility, nor anticipating a sharp increase either.

3.5.3.2 Manufacturer Profit (i.e. π_M)

The manufacturer profit is dependent on profit from each type of vehicle with the unit profit increasing with the price and decreasing with the production cost, the latter being a parameter in the model. Similar to the government's utility, the profits are dependent on decision variables from both players with tradeoffs amongst them. Figure 3.26 showcases the profits dynamics:

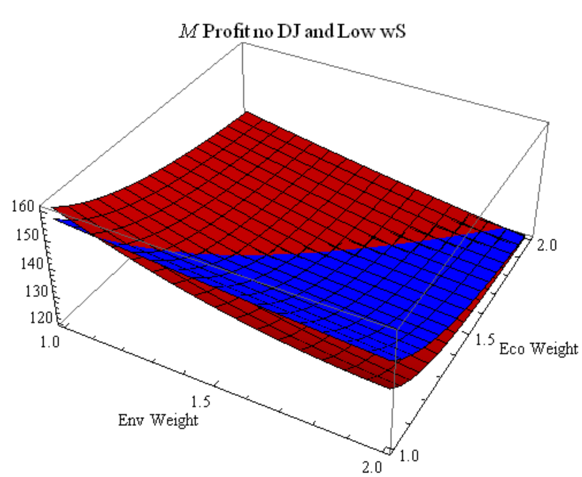


Figure 3.26: Manufacturer Profit with vs without DJ

We notice that the profits can increase or decrease with DJ depending on the weights assigned to the pillars. With low social weight (i.e. w_{soc}=1), the dynamics follow roughly the same pattern as the economics pillar with profits decreasing (increasing) as the economic (environmental) dimesnions gain importance when we consider DJ versus when we do not. When the social weight is high (i.e. w_{soc}=2), the dynamics are roughly the same as those of consumer surplus, with the profits increasing with DJ when both the economic and environmental dimensions are given equally high weights.

One additional insight is that the profits are higher with higher social weight, meaning the social dimension, i.e. consumer surplus, contributes significantly into the profits of the manufacturer, with higher consumer surplus leading to higher manufacturer profits, a nice harmonious relationship.

3.5.3.3 Cannibalization

It is interesting to investigate the dynamics of the cannibalization component in the demand functions shown in Figure 3.27:

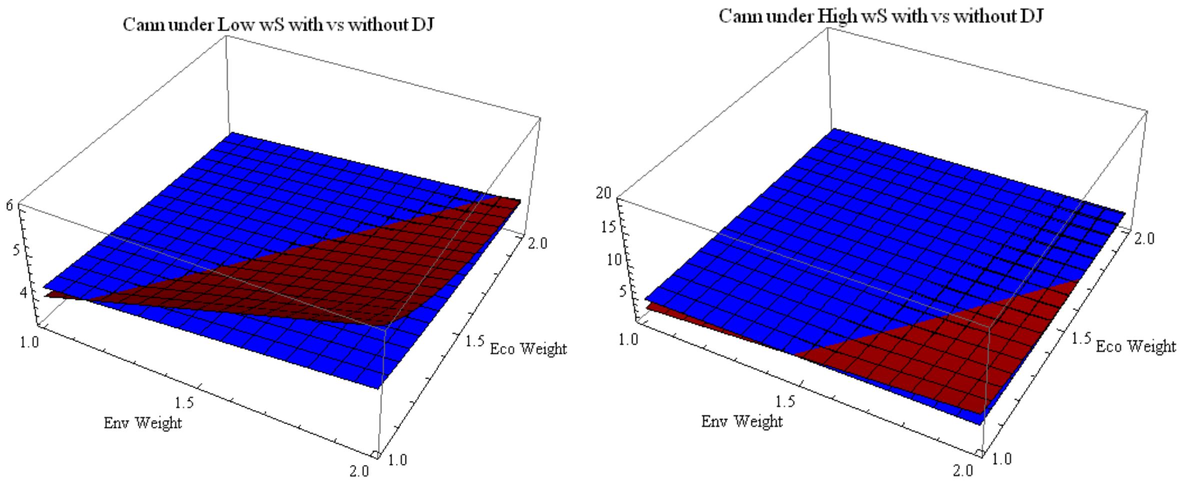


Figure 3.27: Cannibalization dynamics with vs without DJ

We notice that cannibalization can increase or decrease with DJ depending on weights assigned to the pillars. Also, we notice that cannibalization is always positive, meaning the demand for AFV is always cannibalizing the demand for ICE, with consumers switching from ICE to AFV.

The dynamics follow roughly the same as those of the final prices by consumers. The dynamics of the final prices paid by ICE and AFV users are harmonious in the sense that when one increases with DJ, the other decreases, leading to a unified effect on the cannibalization component. The cannibalization is larger (smaller) as the economic (environmental) dimension gains importance when we consider DJ versus when we do not consider it.

3.6 Main Findings and Conclusions

We have focused on government intervention in the context of transition to AFV under two scenarios, where in one we assume status quo where DJ is not included, and in the other we include DJ by modifying the formulation of the social pillar in the government's utility in hopes of maximizing the access to vehicles.

Most research on sustainable development and government interventions focuses on the economic and environmental dimensions of sustainability. This applies within the context of transition to AFV, where the literature mostly neglects (or places little importance on) the social dimension despite having clear transportation studies which clearly report that individuals judge policies and make decisions by considering various justice criteria.

It is not trivial to discern whether the tradeoffs between the social, environmental and economic pillars of sustainability are surmountable or not. To do so, we have built a game theory model with two players, Government (leader) and one Manufacturer (follower). The decision variables for the manufacturer were the prices of the two products (ICE and AFV) and degree of greenness of the AFV; the decision variables for the government were the subsidies for the AFV and taxes on the ICE.

When we analyze the final prices paid by the consumers, i.e. (ICE price + Tax) or (AFV price – Subsidy), one interesting insight is that the government's tax and subsidy override the manufacturer's prices when determining the dynamics. Hence, government intervention in a setting such as AFV transition is decisive in shaping the demand for the different vehicle alternatives.

The environmental performance is higher (lower) as the economic (environmental) dimension gains importance when we consider DJ versus when we do not consider it. The dynamics of the economic performance are opposite to those of the environmental pillar.

The dynamics of the environmental and economic pillars clearly show tradeoffs, so we cannot expect to improve simultaneously both pillars when we introduce DJ into the model.

However, it seems that the environmental and economic performance are more aligned when we consider DJ versus when we do not. We can deduce that including DJ would help in decreasing the tradeoffs between the two pillars.

In some regions, the CS increases with DJ, hence it would be beneficial to include the DJ from a societal point of view which is its main objective. In those regions, the economic dimension would be also increasing with DJ, however the environmental dimension would be decreasing with DJ compared to when there is no DJ. Hence, there is always a tradeoff between on one hand the social and economic pillars and on the other hand the environmental one.

We can deduce that when introducing DJ into the model by modifying the consumer surplus, there is no Pareto front where all three pillars improve simultaneously. More so, the government utility remains more or less the same with and without DJ. This shows that the government's utility is resilient to changes by increasing or decreasing each of its pillars performances as needed.

As for the manufacturer profit, the dynamics follow roughly the same pattern as the government's economic pillar with profits decreasing (increasing) as the economic (environmental) dimension gains importance when we consider DJ versus when we do not.

One additional insight is that the profits increase with higher social weight, meaning the social dimension, i.e. consumer surplus, contributes significantly into the profits of the manufacturer, with higher consumer surplus leading to higher manufacturer profits, a nice harmonious relationship.

We notice that cannibalization is always positive, meaning the demand for AFV is always cannibalizing the demand for ICE, with consumers switching from ICE to AFV. The cannibalization dynamics follow roughly the same as those of the final prices by consumers. The dynamics of the final prices paid by ICE and AFV users are harmonious in the sense that when one increases with DJ, the other decreases, leading to a unified effect on the cannibalization component. The cannibalization is larger (smaller) as the economic (environmental) dimension gains importance when we consider DJ versus when we do not consider it.

The model is not without limitations. It would be interesting to investigate what happens when the green level of ICE vehicle is also dynamic, since it could potentially increase in an effort to reduce the cannibalization effect. Also, it would be beneficial to include a feedback from the DJ into the demand functions to investigate whether increasing the consumer surplus via DJ can potentially eliminate the tradeoffs between the three sustainability pillars resulting in a Pareto front. This is an ongoing project of the authors.

GENERAL CONCLUSION

In this thesis, we have investigated the transition from internal combustion engines (ICE) to alternative fuel vehicles (AFV) while considering the social dimension via the concept of DJ. This enabled us to highlight the many tradeoffs at play between the different policy instruments as well as between the three sustainability pillars, and therefore to minimize them. Each of the essays looked at AFV transition from a different angle with each one complementing the other two.

First essay introduced the concept of DJ in the context of AFV adoption and checked its impact on policy makers' sustainable policies and instruments. After operationalizing the DJ concept according to Equity, Equality, and Need, we embed this new concept in a stylized system dynamics model of AFV adoption. We investigate whether considering DJ targets along with environmental targets accelerates the adoption of AFV during the period 2018-2035. Our findings show that policy makers should adjust their targets to consider DJ criteria along with environmental objectives, thus aiming at a sustainable transition. By doing so, they can control and hasten the transition to AFV. We discover that policy makers can speed up the adoption of AFV when a fuel tax as well as hybrid and EV subsidies are set at the maximum level while both the ZEV penalty per credit gap and manufacturer percentage transferring ZEV penalty should be fixed at the minimum level. Our findings suggest that when policy makers adopt instruments that maximize DJ, people are more willing to adopt AFV. This entails an additional operative instrument (complementing the environmental instruments), linked to increasing the perceived fairness of the AFV transition through development of the "willingness to consider" concept, which in turn leads to an increase in AFV adoption. Finally, we evaluated the contribution of each policy instrument to guide the policy-making process and catalyze this transition.

Second essay considered a multi-product monopolist that offers two products/vehicle alternatives within each of the Low and High segments to accommodate for both dominating and non-dominating preference structures of consumers in the vehicle market. We are interested in measuring the sustainability of the R&D investment strategy of the car manufacturer firm, with sustainability composed of its three traditional pillars: Economic, Environmental and Social. We find that it is possible for the three sustainability pillars to interact in harmony when we have a healthy R&D budget for innovation coupled with a decent amount of cannibalization. Innovation thus functions as a mediator between the cannibalization problem and the DJ index. By investing a moderate amount into R&D and splitting it almost evenly between high and low segments with moderate spillover as well, we can have high scores on all pillars whilst withstanding relatively high levels of cannibalization. More so, maximizing for profits and/or minimizing emissions would result in lower quality and higher prices of the different vehicle alternatives than when we consider simultaneously with them the DJ index. This confirms the benefits of explicitly including the social pillar quantified by the DJ index in our decision making when designing R&D and innovation strategies.

Third essay focused on government intervention in the context of transition to AFV under two scenarios, where in one we assume status quo where DJ is not included, and in the other we include DJ by modifying the formulation of the social pillar in the government's utility in hopes of maximizing the access to vehicles. We built a game theory model with two players, Government (leader) and one Manufacturer (follower). The decision variables for the manufacturer were the prices of the two products (ICE and AFV) and degree of greenness of the AFV; the decision variables for the government were the subsidies for the AFV and taxes on the ICE. When we analyze the final prices paid by the consumers, i.e. (ICE price + Tax) or (AFV price – Subsidy), one interesting insight is that the government's tax and subsidy override the manufacturer's prices when determining the dynamics. Hence, government intervention in a setting such as AFV transition is decisive in shaping the demand for the different vehicle alternatives. We deduce as well that when introducing DJ into the model by modifying the consumer surplus, there is no Pareto front where all three pillars improve simultaneously. More so, the government utility remains more or less the same with and without DJ. This shows that the government's utility is resilient to changes by increasing or decreasing each of its pillars performances as needed. We notice that cannibalization is always positive, meaning the demand for AFV is always cannibalizing the demand for ICE, with consumers switching from ICE to AFV.

Each of the essays has some limitations that were partially dealt with in the other two essays. However, there remains plenty of work to be done on this subject in the future.

REFERENCES

Alagic, A. 2017. An analysis of the causal relationship between transportation and GDP: A time-series approach for the United States. Major themes in economics, volume 19, article 4.

Al-Alawi, B., Bradley, T. 2013. Review of hybrid, plug-in hybrid and electric vehicle market modeling studies. Renewable and Sustainable Energy Reviews, 21: 190-203.

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt. 2005. Competition and Innovation: An Inverted-U Relationship. The Quarterly Journal of Economics 120 (2): 701–728.

Boussauw, K., Vanoutrive, T. 2017. Transport policy in Belgium: Translating sustainability discourses into unsustainable outcomes. Transport Policy, 53: 11-19.

Basiri, Z., Heydari, J. 2017. A mathematical model for green supply chain coordination with substitutable products. Journal of Cleaner Production, 145: 232-249.

Bjerkan, K., Norbech, T., Nordtomme, M., 2016. Incentives for promoting Battery Electric Vehicle (BEV) adoption in Norway. Transportation Research D, 43: 169-180.

Bolton, R., Hannon, M. 2016. Governing sustainability transitions through business model innovation: Towards a systems understanding. Research Policy, 45: 1731-1742.

Besiou, M., Van Wassenhove, L.N., 2015. Addressing the challenge of modeling for decision-making in socially responsible operations. Production Operations Management, 24 (9): 1390-1401.

Bakker, S., Trip, J., 2013. Policy options to support the adoption of electric vehicles in the urban environment. Transportation Research D: Transportation Environment, 25: 18-23.

Brécard, D. 2013. Environmental quality competition and taxation in the presence of green network effect among consumers. Environment Resource Economics, 54(1): 1–19.

Brand, C., Anable, J., Tran, M., 2013. Accelerating the transformation to a low carbon passenger transport system: the role of car purchase taxes, feebates, road taxes and scrappage incentives in the UK. Transportation Research A: Policy Practice, 49: 132-148.

Barlas, Y. 2009. System Dynamics: Systemic Feedback Modeling for Policy Analysis. In Encyclopedia of Life Support Systems, Volume 1, edited by Barlas, Y. Eolss Publishers Company Limited: 1–68.

Burer, M. and Wustenhagen, R. 2009. Which renewable energy policy is a venture capitalist's best friend? Empirical evidence from a survey of international clean tech investors. Energy Policy 37: 4997-5006.

Bierlaire, M. 2006. A Theoretical Analysis of the Cross-Nested Logit Model. Annals of Operations Research, 144: 287-300.

Bandyopadhyay, S., and R. Acharyya. 2004. Process and Product Innovation: Complementary in a Vertically Differentiated Monopoly with Discrete Consumer Types. The Japanese Economic Review, 55 (2): 175–200.

Bansal, S., & Gangopadhyay, S. 2003. Tax/subsidy policies in the presence of environmentally aware consumers. Journal of Environmental Economics and Management, 45(2): 333–355.

Bonanno, G., and B. Haworth. 1998. Intensity of Competition and the Choice Between Product and Process Innovation. International Journal of Industrial Organization 16 (4): 495–510.

CARB (California Air Resource Board), 2017. The California Low-Emission Vehicle Regulations, With Amendments Effective October 16, 2017. Available: https://www.arb.ca.gov/msprog/levprog/cleandoc/cleancomplete_lev-ghg_regs_10-17.pdf

Colquitt, J., Rodell, J. 2015. Measuring Justice and Fairness. In The Oxford Handbook of Justice in the Workplace, 1st ed, edited by M. Ambrose and Cropanzano, R. New York: Oxford University Press.

Cerqueti, R., Tramontana, F., Ventura, M. 2015. On the coexistence of innovators and imitators. Technol. Forecast. Soc. Chang, 90: 487–496.

Chen, Y., and M. Schwartz. 2013. Product Innovation Incentives: Monopoly Vs. Competition. Journal of Economics & Management Strategy, 22 (3): 513–528.

Choi, T.-M., 2013. Optimal apparel supplier selection with forecast updates under carbon emission taxation scheme. Comput. Oper. Res. 40 (11): 2646-2655.

Chenavaz, R. 2012. Dynamic pricing, product and process innovation. European Journal of Operational Research, 222: 553-557.

Chiang, S.Y., 2012. An application of Lotka–Volterra model to Taiwan's transition from 200 mm to 300 mm silicon wafers. Technol. Forecast. Soc. Chang, 79: 383–392.

Cohen, M. 2010. Destination Unknown: Pursuing sustainable mobility in the face of rival societal aspirations. Research Policy, 39: 459-470.

Cellini, R., and L. Lambertini. 2009. Dynamics R&D with Spillovers: Competition vs. Cooperation. Journal of Economic Dynamics & Control 33 (3): 568–582.

Clerides, S., Zachariadis, T. 2008. The effect of standards and fuel prices on automobile fuel economy: an international analysis. Energy Economics, 30: 2657-2672.

Conrad, K. 2005. Price competition and product differentiation when consumers care for the environment. Environment and Resource Economics, 31: 1–19.

De Giovanni, P. Zaccour, G. 2019. A selective survey of game-theoretic models of closed-loop supply chains. 4OR, 17 (1): 1-44.

De Giovanni, P., Ramani, V. 2018. Product cannibalization and the effect of a service strategy. Journal of the Operational Research Society, 69 (3): 340-357.

De Giovanni, P., Zaccour, G. 2014. A two-period game of a closed loop supply chain. European Journal of Operational Research, 232 (1): 22-40.

De Giovanni, P. 2012. Do internal and external environmental management contribute to the triple bottom line? International Journal of Operations & Production Management, 32(3), 265-290.

Diamond, D., 2009. The impact of government incentives for hybrid-electric vehicles: evidence from US states. Energy Policy, 37: 972-983.

Draganska, M., and Jain, D. 2005. Product Line Length as a Competitive Tool. Journal of Economics and Management Strategy, 14 (1): 1-28.

Desai, P. 2001. Quality Segmentation in Spatial Market: When does cannibalization affect product line design? Marketing Science, 20(3): 265-283.

EL Hachem, W., De Giovanni, P. 2019. Accelerating the Transition to Alternative Fuel Vehicles through Distributive Justice Perspective. Transportation Research part D.

Edmondson, D., Kern, F., Rogge, K. 2018. The co-evolution of policy mixes and socio-technical systems: Towards a conceptual framework of policy mix feedback in sustainability transitions. Research Policy, https://doi.org/10.1016/j.respol.2018.03.010.

Egbue, O., Long, S., 2012. Barriers to widespread adoption of electric vehicles: an analysis of consumer attitudes and perceptions. Energy Policy, 48: 717-729.

Ecola, L., Wachs, M. 2012. Exploring the relationship between travel demand and economic growth. Rand Corporation, Federal Highway Administration, Washington, DC, USA.

Eppstein MJ, Grover DK, Marshall JS, Rizzo DM. 2011. An agent-based model to study market penetration of plug-in hybrid electric vehicles. Energy Policy, 39: 3789–802.

Elkington, J., 2002. Cannibals with Forks: the Triple Bottom Line of 21st Century Business. Capstone, Oxford.

Gouda, S.K., Jonnalagedda, S., Saranga, H., 2016. Design for the environment: impact of regulatory policies on product development. Eur. J. Oper. Res. 248 (2): 558-570.

Govindan, K., Jha, P.C., Garg, K., 2016. Product recovery optimization in closed-loop supply chain to improve sustainability in manufacturing. Int. J. Prod. Res. 54 (5): 1463-1486.

Ghosh, D., Shah, J., 2015. Supply chain analysis under green sensitive consumer demand and cost sharing contract. Int. J. Prod. Econ. 164: 319-329.

Glerum, A., Stankovikj, L., Bierlaire, M. 2014. Forecasting the demand for electric vehicles: Accounting for attitudes and perceptions. Transportation Science, 48(4): 483-499.

Garella, P., and L. Lambertini. 2014. Bidimensional Vertical Differentiation. International Journal of Industrial Organization, 32: 1–10.

Gomellini, M. 2013. Innovation and Competition: A Survey. Bank of Italy, Working paper, Retrieved from the Banca d'Italia Website: http://www.bancaditalia.it/pubblicazioni/altri-atti-convegni/2014-innovazione-italia/Gomellini.pdf.

Gonzalez, M. J., & Fumero, P. N. 2002. Environmental policy in a green market. Environmental and Resource Economics, 22: 419–447.

Hulle, S., Liebig, S., May, M. 2017. Measuring Attitudes Toward Distributive Justice: The Basic Social Justice Orientations Scale. Social Indicators Research, 136(2): 663-692.

Heindl, P. and Kanschik P., 2016. Ecological sufficiency, individual liberties and distributive justice: Implications for policy making. Ecological Economics, 126: 42-50.

Harrison, G., Shepherd, S. 2013. An interdisciplinary study to explore impacts from policies for the introduction of low carbon vehicles. Journal of Transportation Planning and Technology, 37(1): 98-117.

Hess, S., Fowler, M., Adler, T. 2012. A joint model for vehicle type and fuel type choice: Evidence from a cross-nested logit study. Transportation, 39(3): 593-625.

Hammar, H., Jagers, S. 2007. What is a fair CO2 tax increase? On fair emission reduction in the transport sector. Ecological Economics, 61: 377-387.

Heese, H., Swaminathan, J. 2006. Product line design with component commonality and cost-reduction effort. Manufacturing & Service Operations Management, 8(2): 206-219.

International Energy Agency (IEA). 2014a. World Energy Investment Outlook. Paris, France.

Jamali, M., Rasti-Barzoki, M. 2018. A game theoretic approach for green and non-green product pricing in chain-to-chain competitive sustainable and regular dual-channel supply chains. Journal of Cleaner Production, 170: 1029-1043.

Jafari, H., Hejazi, S.R., Rasti-Barzoki, M., 2017. Sustainable development by waste recycling under a three-echelon supply chain: a game-theoretic approach. J. Clean. Prod. 142 (4): 2252-2261.

Jalili, M., Aydinliyim, T., Murthy, N. 2017. Key Factors for Green Product Line Design: Opposing Consumer Perceptions, Cost Implications, Price and Quality Optimization. Baruch

College Zicklin School of Business Research Paper No. 2019-02-04. Available at SSRN: https://ssrn.com/abstract=2871583

Jason M. Walter & Jeffrey M. Peterson. 2017. Strategic R&D and the innovation of products: understanding the role of time preferences and product differentiation, Economics of Innovation and New Technology, 26(7): 575-595.

Johansson-Stenman, O., Konow, J. 2010. Fair Air: Distributive Justice and Environmental Economics, Environmental and Resource Economics, 46: 147-166.

Kwon, T. 2012. Strategic Niche Management of Alternative Fuel Vehicles: A System Dynamics Model of the Policy Effect. Technological Forecasting and Social Change, 79(9): 1672–1680.

Liu, Y., Quan, B., Xu, Q., Lin Forrest, J. 2019. Corporate social responsibility and decision analysis in a supply chain through government subsidy. Journal of Cleaner Production, 208: 436-447.

Li, B., Li., X., Liu, H. 2018. Consumer Preferences, Cannibalization and Competition: Evidence from the Personal Computer Industry. MIS Quarterly, 42(2): 661-678.

Li, S. 2018. Dynamic control of a multiproduct monopolist firm's product and process innovation. Journal of the Operational Research Society, 69(5): 714-733.

Lambertini, L., Orsini, R., Palestini, A. 2017. On the instability of the R&D portfolio in a dynamic monopoly. Or, one cannot get two eggs in one basket. International Journal of Production Economics, 193: 703-712.

Liao, F., Molin, E. & Van Wee, B. 2017. Consumer preferences for electric vehicles: a literature review. Transport Reviews, 37(3): 252-275.

Li, S., Ni, J. 2016. A Dynamic analysis of investment in process and product innovation with learning-by-doing. Economic Letters, 145: 104-108.

Li, B., Zhu, M., Jiang, Y., Li, Z., 2016. Pricing policies of a competitive dual-channel green supply chain. Journal Cleaner Prod, 112: 2029-2042.

Lambertini, L., Orsini, R. 2015. Quality improvement and process innovation in monopoly: A dynamic analysis. Operations Research Letters, 43: 370-373.

Larson, P.D., Viafara, J., Parsons, R.V., Elias, A., 2014. Consumer attitudes about electric cars: pricing analysis and policy implications. Transportation Research A: Policy Practice, 69: 299-314.

Lucas, K., 2012. Transport and social exclusion: where are we now? Transp. Policy 20, 105–113.

Liu, Z., Anderson, T. D., & Cruz, J. M. 2012. Consumer environmental awareness and competition in two-stage supply chains. European Journal of Operational Research, 218: 602–613.

Lee, J.,Veloso, F.M.,Hounshell, D.A.,Rubin, E.S. 2010. Forcing technological change: a case of automobile emissions control technology development in the US. Technovation, 30: 249-264.

Luo Y. 2007. The independent and interactive roles of procedural, distributive, and interactional justice in strategic alliances. Academy of Management Journal 50 (3), 644-664.

Lombardini-Riipinen, C. 2005. Optimal tax policy under environmental quality competition. Environmental & Resource Economics, 32: 317–336.

Ma., P., Zhang, C., Hong, X., Xu, H. 2018. Pricing decisions for substitutable products with green manufacturing in a competitive supply chain. Journal of Cleaner Production, 183: 618-640.

Marasco, A., Picucci, A., Romano, A. 2016. Market Share dynamics using Lotka-Volterra models. Technological Forecasting & Social Change, 105: 49-62.

Miranda, L.C.M., Lima, C.A.S., 2013. Technology substitution and innovation adoption: the cases of imaging and mobile communication markets. Technol. Forecast. Soc. Chang, 80: 1179–1193.

Martens, K., Golub, A., Robinson, G. 2012. A Justice-Theoretic approach to the distribution of transportation benefits: Implications for transportation planning practice in the United States. Transportation Research A, 46: 684-695.

Mueller, G., & Haan, P. 2009. How much do incentives affect car purchase? Agent-based micro simulation of consumer choice of new cars. Energy Policy, 37(3): 1072–1082.

Mankiw, N.G., 2007. Principles Of economics. Thomson Learning, Mason, Ohio.

Pan, X., Li, S. 2016. Dynamic optimal control of process-product innovation with learning by doing. European Journal of Operational Research, 248: 136-145.

Panda, S., 2014. Coordination of a socially responsible supply chain using revenue sharing contract. Transport. Res. E Logist. Transport. Rev. 67: 92-104.

Qian, L., Soopramanien, D. 2011. Heterogeneous consumer preferences for alternative fuel cars in China. Transportation Research Part D: Transport and Environment, 16(8): 607-613.

Ramani, V., De Giovanni, P. 2017. A two-period model of product cannibalization in an atypical Closed-loop Supply Chain with endogenous returns: The case of DellReconnect. European Journal of Operational Research, 262 (3): 1009-1027.

Rogge, K., Reichardt, K. 2016. Policy mixes for sustainability transitions: An extended concept and framework for analysis. Research Policy, 45: 1620-1635.

Ritzenhofen, I., Birge, J.R., Spinler, S., 2016. The structural impact of renewable portfolio standards and feed-in tariffs on electricity markets. Eur. J. Oper. Res. 255 (1): 224-242.

Reinhardt, F. L. 1998. Environmental product differentiation: Implications for corporate strategy. California Management Review, 40(4): 43–73.

Sinayi, M., Rasti-Barzoki, M.2018. A game theoretic approach for pricing, greening, and social welfare policies in a supply chain with government intervention. Journal of Cleaner Production, 196: 1443-1458.

Sinitsyn, M. 2016. Managing Price Promotions Within a Product Line. Marketing Science 35(2):304-318.

Sterman, J. 2015. Stumbling towards Sustainability: Why organizational learning and radical innovation are necessary to build a more sustainable world—but not sufficient. Organizational & Strategic Change and the Challenge of Sustainability. R. Henderson, M. Tushman and R. Gulati, eds., Oxford University Press: 51-80.

Sala, S., Ciuffo, B., Nijkamp, P. 2015. A systemic framework for sustainability assessment. Ecological Economics, 119: 314-325.

Sgouridis, S. and Csala, D. 2014. A Framework for Defining Sustainable Energy Transitions Principles, Dynamics and Implications. Sustainability 6: 2601-2622.

Swami, S., Shah, J., 2013. Channel coordination in green supply chain management. J. Oper. Res. Soc. 64 (3): 336-351.

Shafiei, E., Thorkelsson, H., Asgeirsson, EI., Davidsdottir, B., Raberto, M., Stefansson, H. 2012. An agent-based modeling approach to predict the evolution of market share of electric vehicles: a case study from Iceland. Technological Forecasting and Social Change, 79: 1638–53.

Sustainable Development Commission. 2011. Fairness in a car dependent society. Sustainable Development Commission.

Seuring, S., Müller, M., 2008. From a literature review to a conceptual framework for sustainable supply chain management. Journal Cleaner Production, 16 (15): 1699-1710.

Struben, J., Sterman, J. 2008. Transition challenges for alternative fuel vehicles and transportation systems. Environmental and Planning B: Planning and Design, 35: 1070-1097.

Sterman, J. 2002. System Dynamics: Systems Thinking and Modeling for a Complex World, Working Paper from Sloan School of Management, Massachusetts Institute of Technology.

Taylor, T., Tainter, J. 2016. The Nexus of Population, Energy, Innovation and Complexity. American Journal of Economics and Sociology, 75(4).

Tang, C.S., Zhou, S., 2012. Research advances in environmentally and socially sustainable operations. Eur. J. Oper. Res. 223 (3): 585-594.

US Department of Energy, 2018a. Alternative Fuels Data Center, Energy Efficiency & Renewable Energy: https://www.afdc.energy.gov/data/

US Department of Energy, 2018b. Impacts of Electrification of Light-Duty Vehicles in the US 2010-2017, Argonne National Laboratory, Energy Systems Division.

US Department of Energy, 2017. Transportation Energy Data Book, Oak Ridge National Laboratory: https://www.cta.ornl.gov/data/index.shtml

US Energy Information Administration (EIA), 2017. Analysis of the Effect of Zero-Emission Vehicle Policies, Washington DC.

US Department of Transportation, 2017. Passenger Travel Facts and Figures, Bureau of Transportation Statistics: https://cms.bts.dot.gov/product/passenger-travel-facts-and-figures

US Environmental Protection Agency (EPA), 2012. EPA and NHTSA Set Standards to Reduce GHG 2017-2025, Office of Transportation and Air Quality.

Veldman, J., Klingenberg, W., Gaalman, G, Teunter, R. 2014. Getting what you pay for- Strategic Process Improvement Compensation and Profitability Impact. Production and Operations Management, 23(8): 1387-1400.

Ventosa, M., Baillo, A., Ramos, A. and Rivier, M. 2005. Electricity market modeling trends. Energy Policy 33(7): 897-913.

Wee, S., Coffman, M., La Croix, S. 2018. Do electric vehicle incentives matter? Evidence from the 50 U.S. states. Research Policy, https://doi.org/10.1016/j.respol.2018.05.003.

Wang, K., Zhao, Y., Cheng, Y., Choi, T.-M., 2014. Cooperation or competition? Channel choice for a remanufacturing fashion supply chain with government subsidy. Sustainability, 6 (10): 7292-7310.

Wirges, J., Linder, S., Kessler, A. 2012. Modelling the Development of a Regional Charging Infrastructure for Electric Vehicles in Time and Space. EJTIR, 12(4): 391-416.

Walzer, M., 1983. Spheres of Justice: A Defense of Pluralism and Equality. 1st ed. New York: Basic Books.

Xie, G., 2016. Cooperative strategies for sustainability in a decentralized supply chain with competing suppliers. Journal Cleaner Production, 113: 807-821.

Zhu, W., He, Y. 2017. Green product design in supply chains under competition. European journal of Operational Research, 258: 165-180.

Zhang, L., Wang, J., You, J. 2015. Consumer environmental awareness and channel coordination with two substitutable products. European Journal of Operational Research, 241: 63-73.

Zhang, T., Gensler, S., Garcia, R. 2011. A study of the diffusion of alternative fuel vehicles: an agent-based modeling approach. Journal of Product Innovation Management, 28: 152–68.

APPENDIX A – ESSAY ONE

Appendix A.1: Model Explanation

In order to answer the research questions, we first need to build a system based model of the AFV transition to capture and investigate the dynamics of this sustainability transition. The SD model's main output is the mix of different types of vehicles between 2000 and 2035. The model is built using Vensim DSS 6.4 software. We highlight below its' most important components.

A.1.1 Vehicle Sector

There are 5 types of vehicles in the model depending on the fuel they use and their size: ICE SM (Internal Combustion Engine Small to Medium sized vehicle), ICE ML (Internal Combustion Engine Medium to Large sized vehicle), H SM (Hybrid Small to Medium sized vehicle), H ML (Hybrid Medium to Large sized vehicle) and finally EV (Full Battery Powered Electric Vehicle, no size in this category). These five types are further split between New and Used Vehicles. They all have the same dynamics:

➔ Vehicle Stock dynamics (unit of Vehicle):

$$\frac{dV_j}{dt}(unit\ of\ Vehicle/year) = sales_j - discards_j$$

The different types of vehicles are indexed by j.

A.1.1.1 Demand

➔ Vehicle Sales (unit of Vehicle/year):

$$sales_j = Min\left(Desired\ sales_j, Supply_j\right)$$

The sales of a particular type of vehicle j is constrained by the available supply of that vehicle. This allows us to add the concept of purchase price demand elasticity into the model.

➔ Desired Sales (unit of Vehicle/year):

$$Desired\ sales_j = (\sum_i \sigma_{i,j}(d_i + g * V_i)) + Gap\ Transfer_j$$

The first part is inspired by (Struben and Sterman, 2008). The "$\sigma_{i,j}$" is the share of drivers switching from vehicle type i to type j (it is possible for a driver to decide to keep its own type of vehicle). “g” is the exogenous fractional growth rate. The gap transfer accounts for the possibility of drivers switching to platform j (i.e. their next best available alternative) due to supply shortage of their preferred alternative. This gap transfer is regulated by an algorithm that allocates the different demands (i.e. demand for different types of vehicles) to different supplies (i.e. available inventory of different types of vehicles) taking into consideration the preferences of the drivers. So, if the preferred alternative of a driver is not available (i.e. shortage of supply), then this driver will be allocated to the next best available alternative. Please see section A.1.1.2 for more details.

➔ Share of drivers switching from platform i to j (Unitless):

A major component of the SD model is the driver’s choice between vehicle alternatives. Most models opt for the Multinomial Logit (MNL) or for the nested MNL choice models (Liao et al., 2017; Al-Alawi&Bradley, 2013). In our paper, we opt for the generalized version of both, which is the Cross Nested Logit (CNL) choice model (Bierlaire, 2006). The CNL model account for the fact that some vehicle alternatives could share some features (such as size, fuel type), hence the need for alternatives nests to account for the correlation between similar alternatives. The CNL accounts as well for the fact that alternatives might share some attributes and at the same time differ on others, hence the same alternative can belong to more than one nest simultaneously, effectively solving the nesting order problem of nested MNL (Hess et al., 2012). We consider as well the process of familiarization with different vehicle alternatives which impact the choice set of drivers when adopting/replacing their current vehicles. So following Struben&Sterman (2008), our driver’s pass through a two stage category selection between vehicle alternatives. First, boundedly rational consumers pay attention only to the alternatives that have entered in their consideration sets following word-of-mouth (WOM) and marketing campaigns. Second, they choose between these alternatives based on attribute-level comparison and in our case following the CNL model.

$$\sigma_{i,j} = \frac{\sum_m \alpha_{j,m} x_{i,j}^{1/\mu_m} \left(\sum_{n=1}^{n_m} \alpha_{n,\mathrm{m}} \mathrm{x}_{\mathrm{i,n}}^{1/\mu_\mathrm{m}}\right)^{\mu_m - 1}}{\sum_m \left(\sum_{n=1}^{n_m} \alpha_{n,\mathrm{m}} \mathrm{x}_{\mathrm{i,n}}^{1/\mu_\mathrm{m}}\right)^{\mu_\mathrm{m}}}$$

$x_{i,j}$ is the perceived utility of platform j by current drivers of platform i, $\alpha_{j,m}$ portrays the degree that platform j belongs to nest m and μ_m is the degree of independence between alternatives within nest m. Within each nest m, there are n=1→n_m alternatives. If $\alpha_{j,m} = 1$ and $\mu_m = 1 \ \forall \ j, m$ → CNL model collapses into the standard MNL. We have four nests and five different alternatives in our model. Figure A.28 is a sketch of the CNL choice model.

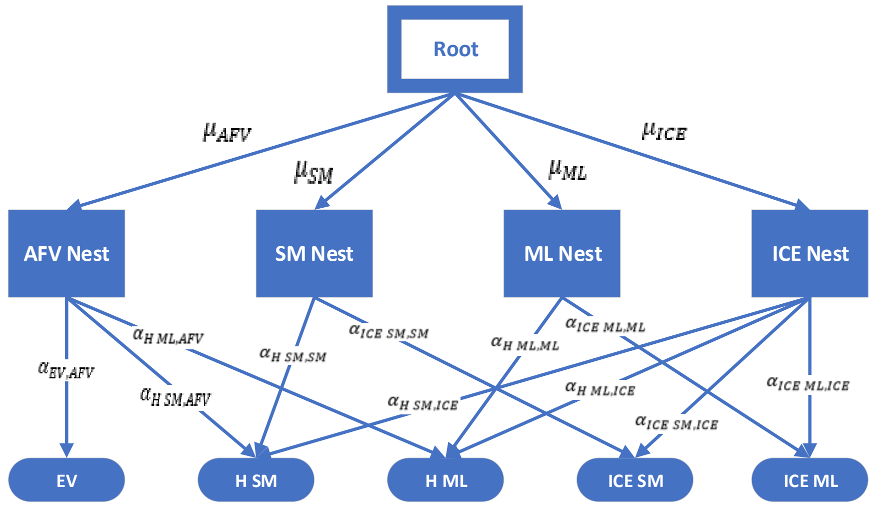


Figure A.28: CNL Choice Model

➔ Perceived utility of platform j by drivers of platform i (Unitless):

$$x_{\mathrm{i,j}} = W_{i,j} * a_{i,j}$$

$W_{i,j}$ is the willingness to consider platform j by current drivers of platform i. $a_{i,j}$ is the perceived affinity of platform j as judged by current drivers of platform i. The nice idea here is the multiplication of the perceived affinity by the "willingness to consider" (Struben&Sterman, 2008).

➔ Perceived affinity of Platform j by current drivers of platform i (Unitless):

$$a_{i,j} = e^{\sum_k indicator_{k,i,j} * \beta_{k,i,j}}$$

K is the index of the different indicators (price, emissions…). β_k are the weights given to each of the indicators when determining the utility of the platform j by current drivers of platform i. The most common attributes to investigate consumer preferences in the adoption of AFV's are:

charging infrastructure availability, maintenance cost, operating cost, driving range, emissions and purchase price (Liao et al., 2017; Al-alawi&Bradley, 2013). All of these indicators are formulated such that if they are positive, then the target alternative j is better than the reference alternative i. So, for example when considering the purchase price utility, the lower (higher) the price of target (reference) the better, so we compute:

$$Purchase\ Price\ Indicator_{i,j} = (Price_i - Price_j)/Price_i$$

Where:

$$Price_i = \frac{Reference\ Purchase\ Price_i}{Learning\ Multiplier} * \left(\frac{Production_i}{Sales_i}\right)^{Supply\ Price\ Elasticity_i}$$

➔ Willingness to Consider vehicle j by current drivers of vehicle i at time t+1 (Unitless):

$$\mathrm{W}_{\mathrm{i,j,t+1}} = (\rho_{\mathrm{i,j,t}} * PF_{i,j,t})\left(1 - \mathrm{W}_{\mathrm{i,j,t}}\right) - (\theta_{\mathrm{i,j,t}} * NF_{i,j,t}) * \mathrm{W}_{\mathrm{i,j,t}}$$

$\rho_{i,j}$ is the impact of social exposure on the willingness to consider (i.e. Marketing and WOM). $\theta_{i,j}$ is the decay rate of the willingness to consider. The adoption decision by the drivers is based on utility maximization (CNL model) coupled with bounded rationality implemented via a gap between actual and perceived performance and a 'willingness to consider' factor (Struben&Sterman, 2008). This willingness to consider captures the familiarity of the drivers with other alternatives and consequently whether they will consider switching to them (it could be that hybrids have a much better utility than ICE, however drivers are not familiar with them, so they would not even consider them in their decision). The $PF_{i,j,t}$ (and $NF_{i,j,t}$) stand respectively for Positive (Negative) Fairness effect of Distributive Justice on Willingness to consider AFV vehicles (Hybrid or full EV) by current drivers of ICE vehicles.

The willingness to consider is crucial in determining the share of drivers that switch from one type of vehicle to another. The traditional ICE vehicles are assumed to have perfect willingness to consider (i.e. 1) since they are well developed and are the current dominant design in the market. However, the hybrids and EV have to build up this willingness in other drivers.

The willingness to consider captures the social impact on the decision to switch between alternatives so it naturally has the “impact of social exposure” component. There can only be gain in Willingness to consider by capturing some of those drivers that are not currently willing, so we multiply the social exposure by (1-Willingness to consider).

➔ Impact of social exposure (from Struben and Sterman, 2008) (1/Year):

$$\rho_{i,j} = \alpha_j + c_{i,j} * W_{j,j} * \frac{V_j}{N} + \sum_{m \neq j} c_{i,m} * W_{m,j} * \frac{V_m}{N}$$

α_j is the marketing effectiveness of vehicle j, $c_{i,j}$ is the strength of the WOM between drivers i and j, N is the total number of vehicles.

The impact of social exposure has 3 components. First is the marketing effectiveness of the target vehicle j (how well is that type of vehicle being marketed). Second is the Word of Mouth from the drivers who are currently driving that vehicle j (These drivers have full knowledge of the hybrid option, so their willingness to consider j is 1). The third are the Word of Mouth from Drivers that are not currently driving j. Each of the word of mouth components is weighed by its current popularity measured through the current adoption rates (for example: popularity of Hybrids is measured through Hybrids/Total number of vehicles).

➔ Positive (negative) Fairness effect of Distributive Justice on Willingness to consider AFV by ICE drivers:

$PF_{i,j,t}$ = IF THEN ELSE (Distributive Justice > 0, Distributive Justice, 0) + 1

$NF_{i,j,t}$ = IF THEN ELSE (Distributive Justice < 0, (- Distributive Justice), 0) + 1

They are only active for the ‘willingness to consider’ AFV vehicles (Hybrid or full EV) by current ICE drivers.

Figure A.29 is a diagram of the Willingness to Consider:

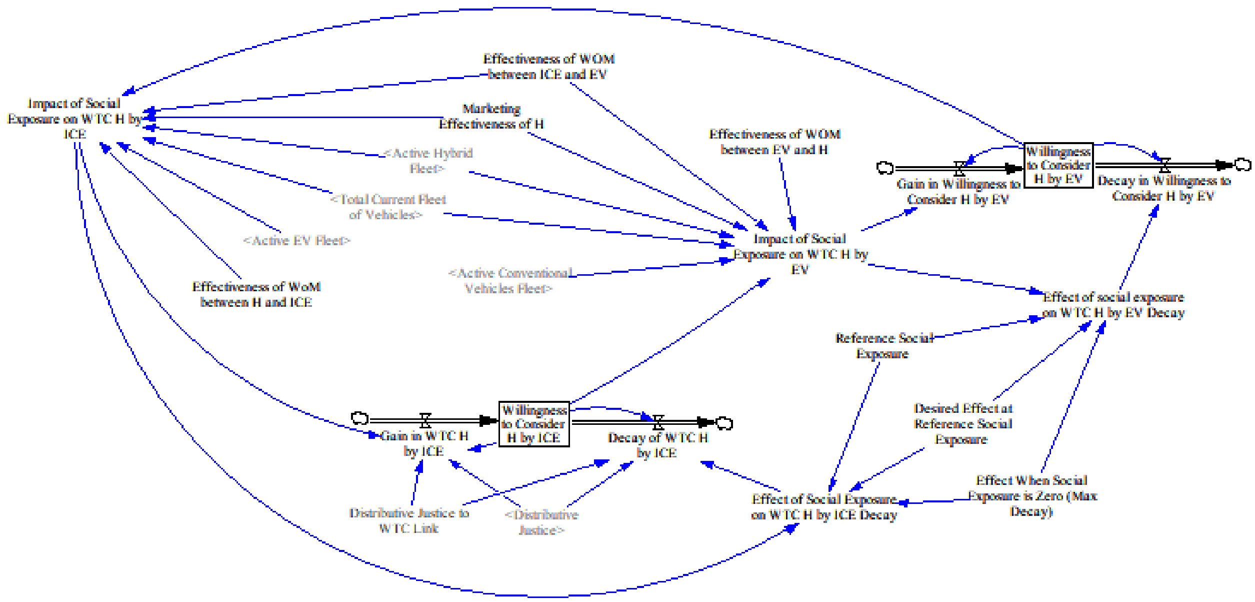


Figure A.29: Diagram of the Willingness to Consider (in this case Hybrid vehicles)

A.1.1.2 Demand and Supply Allocation Algorithm

The algorithm repeats itself in each period interval and is composed of 9 steps, where in each step we allocate some of the demand gap to some of the supply gap, update the gaps and move on to the next step. By maximum the 9th step, all of the demand gap would have been allocated to the available supplies in such a way to maximize satisfaction, i.e. drivers are allocated to their next best available alternative, while meeting supply constraints. One important assumption behind this algorithm, is that the total supply of vehicles (new and used) is always higher or equal to the total demand of vehicles. This is representative of reality, therefore this assumption is not strong and necessary.

Since we have 10 types of vehicles (5 new and 5 used) in the model, the algorithm would have maximum 9 steps. We would need the entire 9 steps in the scenario where the total demand and supply of vehicles would be equal to each other. At each time t, in each step of the algorithm, we do the following:

→ First, we determine for each type of vehicle whether we have a demand gap (i.e. the desired demand for this vehicle is higher than the available supply) or a supply gap (i.e. the supply of this vehicle is higher than the desired demand). If we have a demand gap, then some of the drivers will be re-allocated to their next best available alternative. If we have a supply gap, then if needed, drivers whose preferred alternative is in shortage would be allocated to this type of vehicle if it is their next best available alternative.

→Second, We determine the supply priority of a given type of vehicle to the total demand gap (i.e. the priority of closing the total demand gap by allocating some of it to a specific supply gap), as well as the demand priority of a given type of vehicle to the total supply gap (i.e. the priority of closing the demand gap of a specific type of vehicle based on the available sources of supply).

→Third, we determine the priorities in the different possible scenarios. For example, we could have only one type of vehicle with an excess supply (i.e. the rest all have a demand gap), or we could only one type of vehicle with a demand gap (i.e. the rest all have an excess supply). If we have one source of supply, the priority of this source of supply would be different than if we had several sources of supply. Also, the specific combination of the available sources of supply determines the priorities (e.g. If we have EV and ICE ML supplies, the priority of the EV supply would be different than if we had EV and H ML supplies). We have 31 possible cases: 1 case where all types are available (It is a combination of 5 out of 5 alternatives (${}_5C_5 = 1$), 5 cases where 4 types are available, 10 cases where 3 types are available, 10 cases where 2 types are available, 5 cases where only 1 type is available.

→Fourth, we determine at each step in which case out of the 31 possible ones we fall based on the supply gaps and accordingly determine the supply priorities. Then, based on these supply priorities allocate the demand gap to the different sources of supply and accordingly update the gaps for the next step. For example, if we had 10 excess supply units of New EV at step 1 and allocated 6 units of the demand gap to this source of supply, then in step 2 we would have 4 supply excess units of New EV and the demand gap would decrease by 6 units.

By the end of the algorithm (maximum 9 steps), all of the demand gap would be closed while meeting the supply constraints and maximizing drivers satisfaction by allocating them to their next best available alternative.

This algorithm reallocates excess vehicle demand from many demanders to many suppliers taking into consideration both demand and supply attractiveness in a way to pass important reality checks while minimizing dissatisfaction.

A.1.1.3 Production

➔ Supply (unit of Vehicle/year):

$$Supply_j = (P_j - V_j)/Sales\ Period - (P_j\ \ Outflow - V_j\ Outflow)$$

P_j is the stock of produced vehicles of type j, V_j is the stock of vehicles of type j that are currently being used. This formulation ensures that $P_j \geq V_j$. $Supply_j$ is the current inventory of vehicles j that are available to be sold to potential buyers. The stock of New vehicles is determined by the production of new vehicles. And in the case of Used vehicles, the stock is determined by the aging of the new fleet.

➔ Production of Vehicle j (Vehicle/Year):

$$Production_j = MIN(Production\ Capacity_j, Desired\ Production_j)$$

The production flow of vehicle j is constrained by the production capacity of that vehicle.

➔ Change in Production Capacity of Vehicle j (Vehicle/year/year):

$Change\ in\ Production\ Capacity_j$ = IF THEN ELSE ($Production\ Capacity_j$-ROP_j>=0, 0, MIN((ROP_j-$Production\ Capacity_j$)/Time to Adjust Production Capacity,(Maximum Yearly increase in $Production\ Capacity_j$*$Production\ Capacity_j$)/Time to Adjust Production Capacity))

The change in production capacity is determined by a desired Reordering Point (ROP) and constrained by a maximum increase of capacity in a year. The ROP is determined based on a certain desired customer service level (ROP = Demand + Safety Stock).

➔ Desired Production (Vehicle/Year):

$$Desired\ Production_j =$$

$$New\ Sales_j + Max((ROP_j - Supply_j) * Demand\ Visibility, 0)$$

The desired production is determined by the new sales plus the gap between the ROP and the current supply (i.e. inventory) of vehicles. To be realistic, the gap is only partly observed by the manufacturer since the ROP is determined based on maximum desired sales which is not fully observed by the manufacturer.

These dynamics are illustrated in Figure A.30, where the top row represents the total produced vehicle fleet P_j while the bottom row represents the vehicles in-use V_j, naturally the latter being constrained by the first.

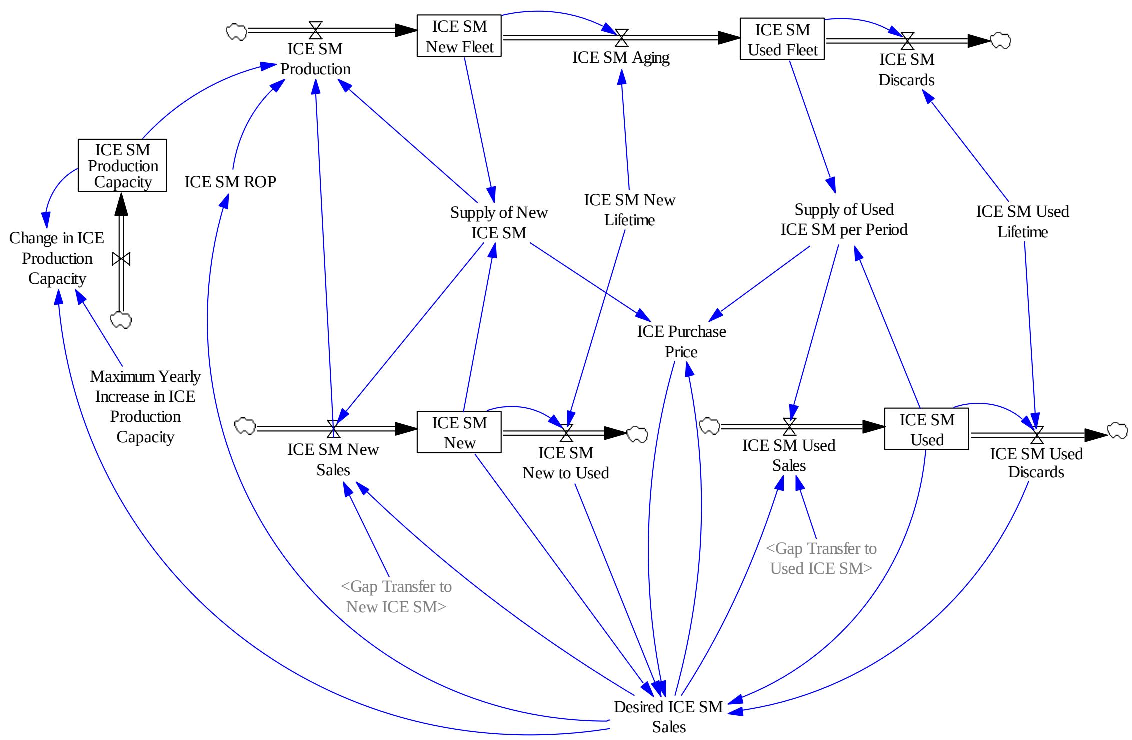


Figure A.30: Vehicle Production and Sales Diagram in the case of ICE SM vehicles

A.1.2 Infrastructure

The infrastructure is modelled to a moderate extent. We have 2 stocks for the fuel stations and 2 stocks for the charging stations.

A.1.2.1 Fuel Stations

➔ d(Fuel Station Pipeline)/dt (Unit of Station/Year)= Fuel Station to be Constructed – Fuel Stations Construction

➔ Fuel Station to be Constructed (t) = Fuel Station Gap/Time for Decision

➔ Fuel Station Gap (t) = Max (0, Maximum Desired Fuel Stations Available-Total Fuel Stations)

We use Max to make sure that is always positive.

➔ The logic behind the maximum desired Fuel Stations is as follows:

1- Profit = (Revenue/Number of Fuel Stations – Fuel Expenses/Number of Fuel Stations – Annual Capital Costs – O&M Costs) / (Fuel Expenses/Number of Fuel Stations + Annual Capital Costs + O&M Costs)
2- If we decide on a Minimum desired Profitability, then we can derive the maximum number of desired stations from it.

➔ Fuel Consumption (t) (L/Day) = Active ICE Fleet *Engine Efficiency*Driving Distance Habit + Hybrid Fleet*Engine Efficiency*Driving Distance of Hybrid on Fuel

The Fuel Consumption has 2 components. One for the ICE fleet and the second takes into consideration that the hybrid cars also consume fuel. The hybrids will drive only a certain percentage using fuel and the other using their batteries.

➔ Fuel Station Annual Capital Costs (t) (Euros/(Station*Year))= Fuel Station Capital Costs*Fuel Station Annuity Factor

➔ Fuel Station Annuity Factor (t) (1/Year)= $\frac{i}{1-\exp(-i*Fuel\ Station\ liefetime)}$

Where "i" is the yearly interest rate.

As the interest rate increase (Life time Increase), the Annuity factor increases (decreases) → Annual Capital Cost increases (decreases).

➔ Total Fuel Stations (t) = Fuel Station Pipeline + Fuel Station Available

➔ d(Fuel Station Available)/dt = Fuel Station Construction – Fuel Station Exit

➔ Fuel Station O&M Costs (t) (Euros/(Station*Year))= Initial Fuel Station O&M Costs * Effect of Ratio on Fuel Station O&M Costs

As the ratio of stations to vehicles decreases, the O&M would increase since each station would have to serve more vehicles, this is captured through the effect described below:

- ➔ Effect (Dimensionless)= a * (b^X) (exponential curve) = Effect of Ratio on Fuel Station O&M Costs (t) = Effect When Ratio is Zero*((Desired Effect at Reference Fuel Station Ratio/Effect When Ratio is Zero) ^ (Fuel Stations to Vehicles Ratio/Reference Fuel Station to Vehicle Ratio))

X = Fuel Station to Vehicle Ratio / Reference Ratio

Reference Ratio = Initial Ratio (i.e. ratio at the beginning of the simulation)

When the ratio is equal to the reference (i.e. initial) ratio, the effect would be: Desired Effect at Reference Fuel Station Ratio = a * b = 1 (It is equal to 1 since the O&M costs would be the same as the initial ones when the ratio is the same).

When the ratio is zero (no stations), then the effect would be: Effect When Ratio is Zero = a = Maximum increase in O&M costs

So, b = Desired Effect at Reference Fuel Station Ratio/ Effect When Ratio is Zero = 1 / Maximum increase in O&M costs

A.1.2.2 Charging Stations

For the Charging Stations, the "Maximum desired charging stations" is determined differently than the fuel stations. Here it is determined based on the minimum utilization necessary so that the charging stations break even (i.e. 0% profitability) (Wirges, et al., 2012).

- ➔ $Min\ t_d(t)$ (Hours/(Station*Day)) = (Annual Capital Costs of Charging Stations + "Charging Stations O&M Costs") / (("Charging Price (mark-up)"-Electricity Costs)*Charging Power of Stations*"Days/Year")

The minimum required utilization has 2 components. The numerator is the annual Costs of opening and operating a station. The denominator is the annual net revenue if the station has 100% utilization. The logic is: if the operating costs are 50% of the net revenue from fully utilizing the station, then you would need to operate the station at least 50% of the time to be profitable.

From the minimum utilization, we can determine the maximum ratio of stations to vehicles:

- ➔ Maximum $\frac{Charging\ Stations}{EV}$ (t) $=\frac{\text{Energy Consumption of EV's}*\text{Driving Distance of Hybrids on Battery}}{\text{Charging Power of Stations}*Min\ t_d}$

Numerator is the energy required to operate one electric car. The denominator is the minimum required energy to be sold per station to break even.

➔ Maximum Desired Charging Stations (t) = Maximum $\frac{Charging\ Stations}{EV}$ * Total Number of cars that need charging

Figure A.31 is a diagram of the Charging Stations dynamics:

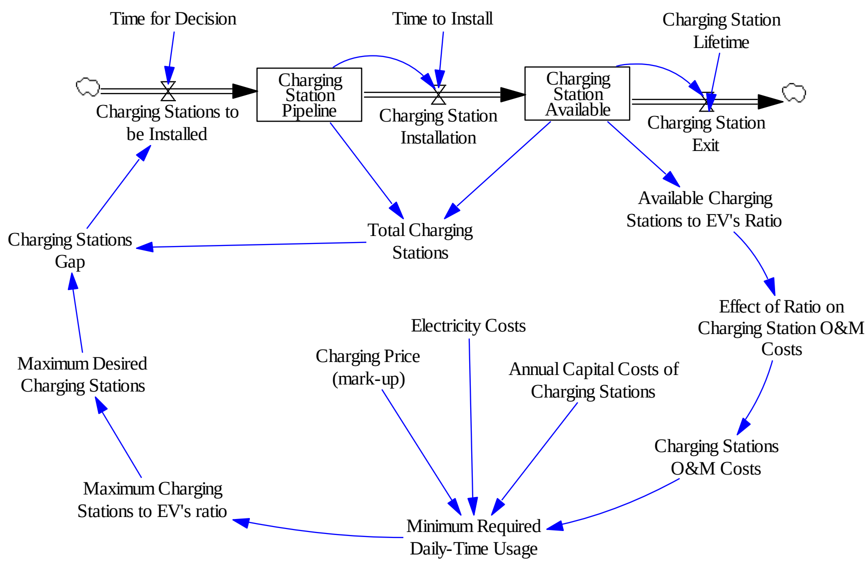


Figure A.31: Diagram of the Charging Stations Infrastructure

A.1.3 Learning

Learning is an essential part of the model since it deals with the long term dynamics of the car market. The Energy Consumption, Driving Distance of AFV's on Battery, emissions, purchase price… vary with the technological development of the batteries and of the EV manufacturing industry, so we have a learning multiplier to capture this.

The formulation is the standard learning formulation:

➔ Renewable Learning Multiplier (t) (Unitless)= $(\frac{\text{Renewable Cumulative Production}}{\text{Initial Renewable Production}})^\wedge\lambda$

➔ λ (unitless) $= \frac{\ln(1+\Delta)}{\ln(2)}$

Where Δ = Fractional Performance Improvement when experience doubles and λ = Renewable learning coefficient.

Figure A.32 is a causal Loop diagram of the simplified dynamics of the model.

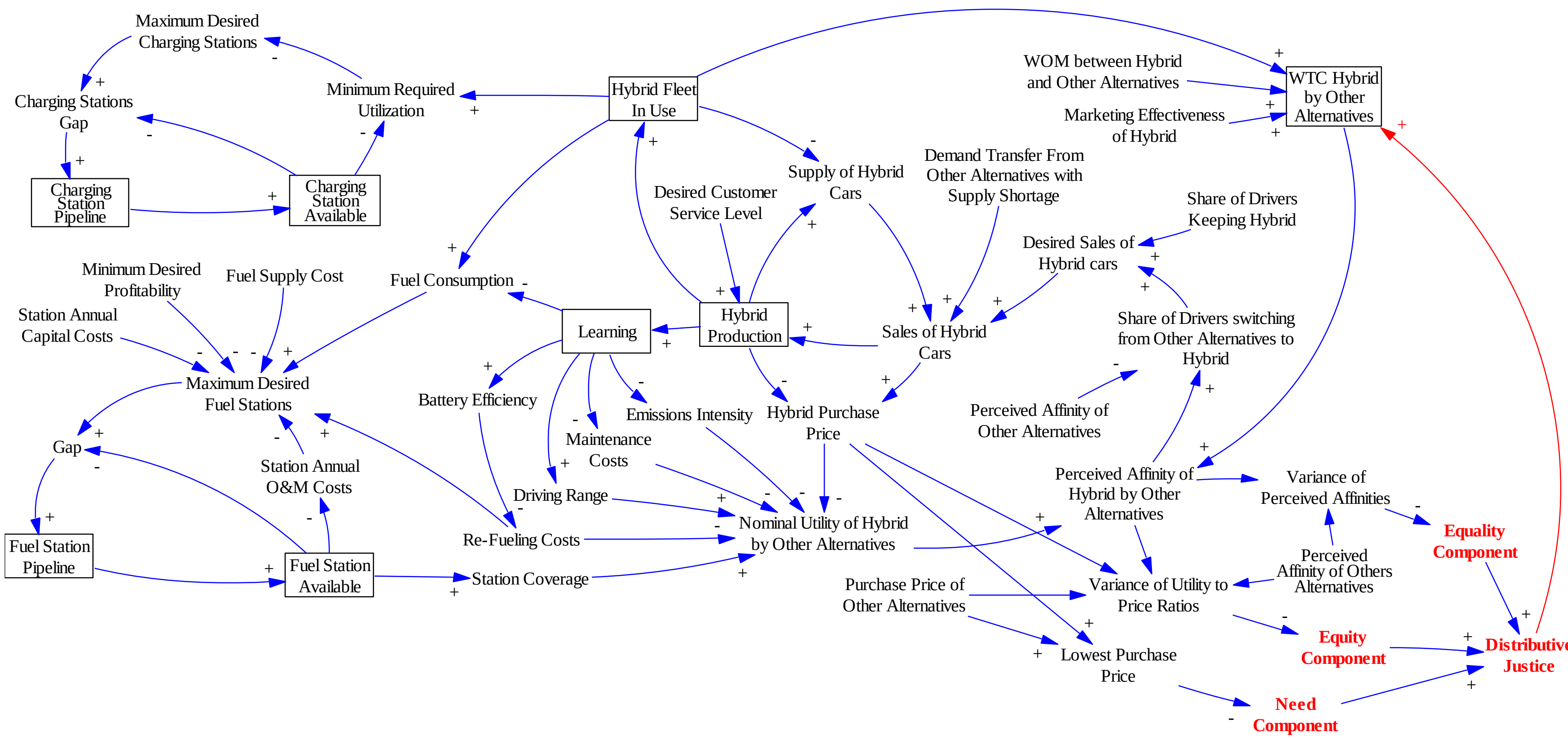


Figure A.32: Causal Loop Diagram of Model

Appendix A.2: Tradeoffs between Distributive Justice Components

It is important to note that in order to observe the tradeoffs that arise when we add distributive justice to the model, we have to do so in a ceteris paribus fashion, meaning we compare behaviors while keeping the same policy instruments whether we are trying to maximize AFV sales or distributive justice.

To investigate the tradeoffs between the distributive justice components (Equity, Equality and Need), we numerically compute their first and second derivatives with respect to time and classify their behavior at each point in time in 7 possible qualitative states listed below:

1- 1st derivative is zero ($\dot{x} = \frac{dx}{dt} = 0$): X is constant (‘X’ stands for equity/equality/need)

2- 1st derivative > 0 and 2nd derivative ($\ddot{x} = \frac{d\dot{x}}{dt}$) > 0: X is increasing increasingly

3- 1st derivative > 0 and 2nd derivative < 0: X is increasing decreasingly

4- 1st derivative > 0 and 2nd derivative = 0: X is increasing at a constant rate

5- 1st derivative < 0 and 2nd derivative > 0: X is decreasing increasingly

6- 1st derivative < 0 and 2nd derivative < 0: X is decreasing decreasingly

7- 1st derivative < 0 and 2nd derivative = 0: X is decreasing at a constant rate

Figure A.33 shows the Equality, Equity and Need behavior under each of the policy objectives. Prior to 2018, there is only one possible objective, which is the environmental one, hence the three components behave the same in both parts of figure A.33. Starting 2018 (i.e. the present), it is possible to change objectives into maximizing the distributive justice (left half of Figure A.33).

→Prior to 2018: Tradeoffs between components under the environmental policy objective

We notice that mainly the equality and equity components are moving in harmony (i.e. both are increasing or decreasing together) with respect to the environmental objective, hence no tradeoffs being made between them. However, the Need component is mostly at odds with the other two components. If Need is increasing, then the other two are decreasing, and vice versa.

So, prior to 2018, with regards to the environmental objective, the need component of the distributive justice indicator is at odds with the other two components. If lowest purchase price is increasing (Need is getting worse), then the equality and equity components are improving and vice versa. This confirms the idea that the purchase price dynamics on its own can convey additional information than simply looking at the utility dynamics, justifying the operational definition of the need component.

→Starting 2018: Tradeoffs between components under the two possible policy objectives

If we keep the same environmental policy objective (right hand side of figure A.33), then the behavior remains more or less the same until 2027, in the sense that the need component is at odds with the other two components. After 2027, the three components exhibit close behavior to each other, they are all increasing. This means that starting 2027, both the environmental and distributive justice objectives are moving in harmony.

If we change the objective and maximize distributive justice, the behavior of the need component changes drastically as shown in Figures A.33. Starting 2018, the need component starts behaving almost in harmony with the other two components, by only differing in the rate at which it is increasing. This result is expected, since if we are explicitly attempting to maximize distributive justice, we can do so only when all three components are moving in harmony and increasing, hence the behavior of the Need component changes.

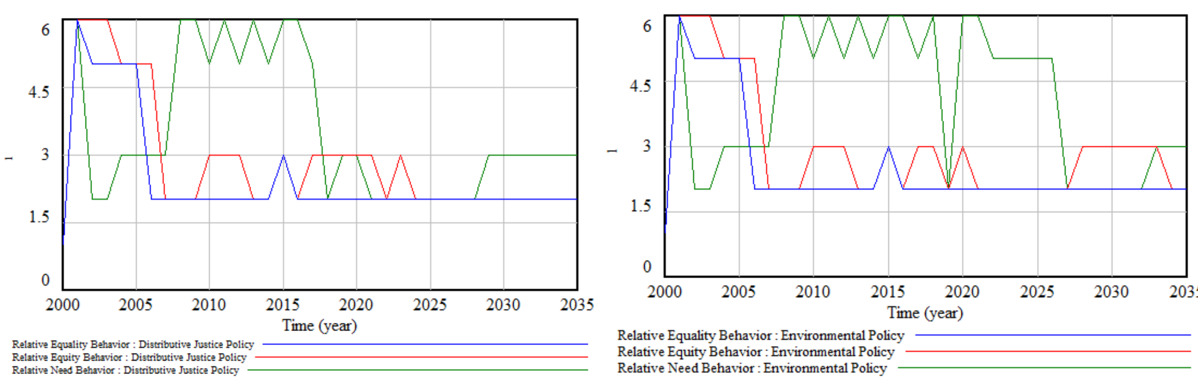


Figure A.33: Distributive Justice Components Behavior under each of the policy objectives

These results confirm that there are indeed tradeoffs between the components of distributive justice, mainly between the Need component and the other two components. If we explicitly attempt to maximize distributive justice, then we minimize these tradeoffs by bringing the behavior of the need component in harmony with the other two.

Appendix A.3: Model Behavior

As with any SD model, we need to check whether the model is able to follow the historical behavior observed in real life. By doing so, we can build confidence in the model and its ability to provide a good base to judge the outcome of potential policies. In our model, we have two main variables that we can compare their behavior to that in real life between 2000 and 2016:

1- AFV Sales (i.e. Yearly percentage of AFV sales out of total vehicle sales)
2- Active Fleet of Vehicles (i.e. total number of vehicles on the road)

These two variables summarize most of the dynamics in the model. In addition to this, when calibrating the model, we need to put in place some constraints to make sure the output passes reality checks. We have two such constraints (i.e. reality checks):

1- Available Supply of vehicles is always higher than the demand of vehicles: The total available inventory of vehicles to be sold is always higher than the total demand of vehicles. We can still have shortage in supply for specific vehicles, but the total supply is higher than total demand. This is a straightforward reality check since in real life, there are always available vehicles to sell.
2- Nominal Purchase price of full electric vehicles (EV) is always higher than the price of small hybrid vehicles (H SM): The dynamics of the nominal purchase prices of vehicles captures a significant portion of the model dynamics since it relies on the evolution of both demand and supply which are in turn dependent on the evolution of the vehicles attributes, infrastructure and policies in place. The nominal purchase prices of different types of vehicles (e.g. Purchase price of EV, purchase price of H SM…) are averages, meaning they represent the average price of the different models available in the vehicles market in real life. So it makes sense to constrain the evolution of the purchase price of EV to be always higher than that of the small hybrid vehicles, at least throughout the timeline of the model between 2000 and 2035.

These two constraints ensure that the model passes reality checks even after we calibrate it to fit historical data. The two variables (AFV Sales and Active Fleet of vehicles) along with the two constraints are grouped together in a payoff function to drive the model calibration. The payoff function is as follows:

Payoff = Relative Difference in AFV Ratio from New Sales*Weight of Relative Difference in AFV Ratio + Relative Difference In Total Active Fleet Between Model and Data*Weight of Relative Difference in Total Active Fleet + Supply and Demand Reality Check*Weight of Supply and Demand Reality Check + Difference in EV and H SM Purchase Prices*(1-Weight of Relative Difference in AFV Ratio-Weight of Relative Difference in Total Active Fleet-Weight of Supply and Demand Reality Check)

Each one of the payoff elements is multiplied by a weight which brings the four elements to the same scale, so that all four of them are given equal importance when calibrating the model.

The parameters through which we calibrate the model span across the entire model: Choice model (Beta parameters), Production of vehicles (production capacity, service levels), Sales and Learning. These parameters were allowed to vary within realistic ranges when calibrating the model while respecting logical constraints. The calibrated model behaves as in Figure A.34:

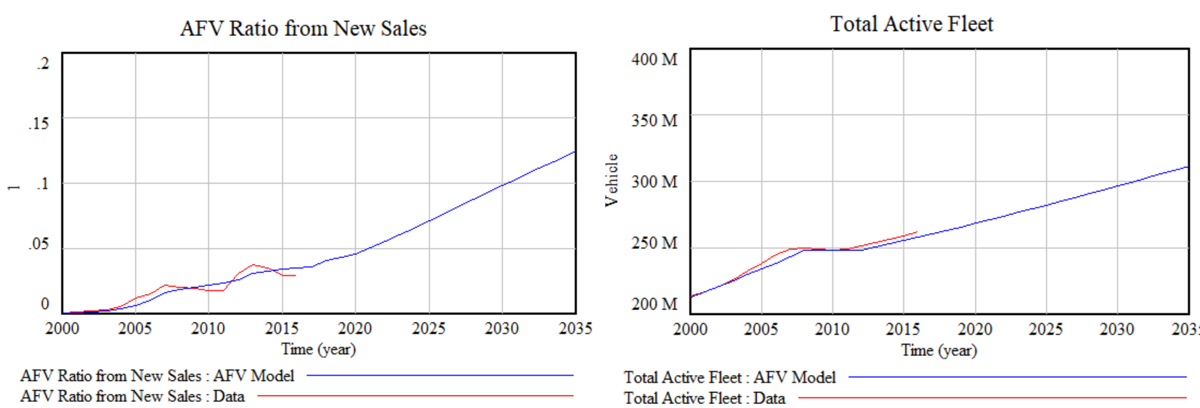


Figure A.34: AFV Ratio from New Sales and Total active Fleet of Vehicles, Model vs Data

To test the model assumptions, we ran a multivariate sensitivity analysis. Over 3000 iterations, we simultaneously varied the most important parameters in the model (spanning across Sales, Production and Policies) within large ranges (larger than realistic assumptions). Some of the results are shown in Figure A.35. Based on the sensitivity results, we can deduce that the model behaves well even under extreme conditions (i.e. parameters vary in larger than realistic ranges).

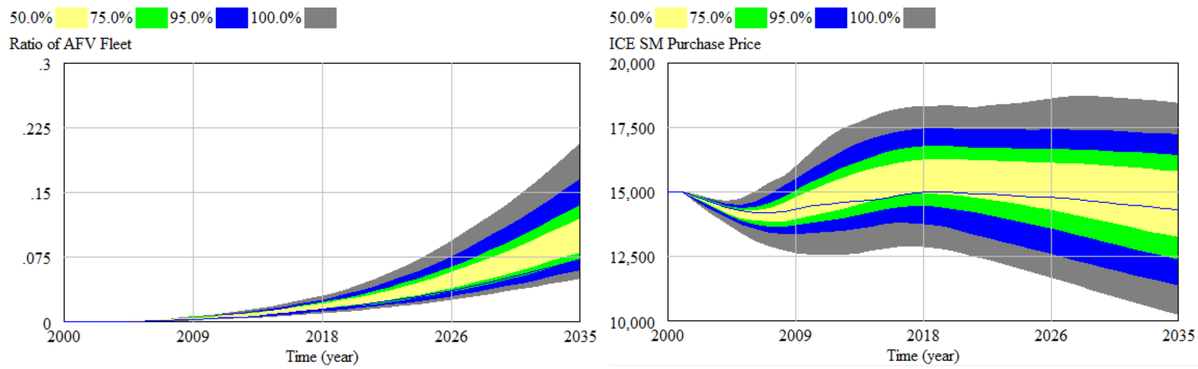


Figure A.35: AFV Fleet Ratio and ICE SM Purchase Price Sensitivity Results

Appendix A.4: System Dynamics Methodology Brief Introduction

In this section of the appendix, we will briefly introduce the System Dynamics (SD) simulation methodology. For more detailed introductory material to SD, please refer to (Barlas, 2009) and (Sterman, 2002).

We live in a world that is evermore increasing in complexity. We cannot keep track of every moving part in such a world, and as a result some of the problems we face today are nothing else than the unintended consequences of yesterday's solutions. This is policy resistance which is a well observed phenomenon, i.e. the tendency for well-intentioned interventions to be defeated by the response of the system to the intervention itself. System dynamics is a strategic approach to model complex systems in an effort to better understand their behavior and minimize unintended consequences.

AFV transition is one such complex problem which benefits from an SD approach to investigate it and minimize unintended consequences such as worsening of the social dimension while attempting to improve the environmental one.

Feedback is an important idea in SD and manifests itself through causal feedback loops which will be presented below. The relations between each of the system elements could be mathematically described. The mathematical model of the overall system dynamics structure is a system of nonlinear, first-order differential and integral equations. Computer simulation software

are used to run these models since analytical solutions to these problems are unknown. SD is a step-by-step simulation of the model structure over compressed time. Much like the operation of the real structure over real time, the model structure operates over simulated time, so that the dynamics of model variables gradually unfold.

Applications of SD cover a very wide spectrum, including economic problems, supply chains, project management, energy systems, sustainable development, politics, psychology, medical sciences, health care, and many other areas. Below, we list the main elements of SD modeling along with their definitions.

A.4.1 System

The term system refers to ‘reality’ or some aspects of reality. A system may be defined as a ‘collection of interrelated elements, forming a meaningful whole’. It is common to talk about a financial system, a social system, a political system, a production system, a distribution system, an educational system, or a biological system. Each of these systems consists of many elements interacting in a meaningful way, so that the system can presumably serve its purpose. So, systems thinking is the idea that the behavior of the whole cannot be explained by the behavior of the parts.

A.4.2 Structure

The structure of a system can be defined as ‘the totality of the relationships that exist between system variables’. In a production system, the structure would include the material and information flows related to production, where and how the various stocks are stored and shipped, how the ordering and production decisions are made, and so on. The structure of the system operates over time so as to produce the dynamic behavior patterns of the system variables. It is said, ‘the structure creates the behavior’. The structure of a system dynamics model consists of the set of relations between model variables, mathematically represented in the form of equations. The structure of a system can be extremely complicated, hence we cannot know it with certainty. However, we do know that there is a structure underneath that produces the dynamic behavior that we can see. The structure of the model we build is a representation of the aspects of the real structure that we hypothesize to be the most important in terms of driving the behavior of the specific problem we are investigating.

A.4.3 Dynamic

Variables change over time as they interact. The changes are not straightforward to predict. There are time delays involved between causes and effects and between actions and reactions. Dynamics of systems may be hard to predict by intuition even with only a few variables. Dynamic problems are naturally harder than static problems.

A.4.4 Human Dimension

Typical system dynamics problems involve human actors. So we must model not only the physics of the system (including information flows), but also how people react to situations, make decisions, set goals, make plans, and so on. This 'human dimension' adds yet another layer of complexity. Human elements are much harder to model than the mechanical/physical aspects. There are no established, tested laws of how people behave, react, or make decisions. Quite often, the modeler must rely on established decision making theories or even create his/her own theory of how the human actors would behave in the specific context of a given task and environment.

A.4.5 Causal Loop Diagrams (CLD's)

CLD's are often built before moving on to the formal Stocks&Flows models. CLD is a tool to, as the name suggests, represent the feedback loops within the system structure. By looking at CLD's, we can elicit knowledge about the system and its structure:

- What are key components of the system?
- How are components connected to each other?
- Are there feedback loops in the system structure?
- Are certain components changing in a cycle of growth or decay (i.e. polarity of loops)?

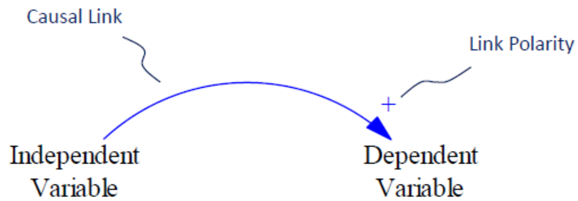
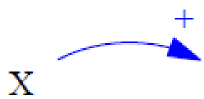


Figure A.36: Causal Link and Polarity

When determining link polarity, we must assume all other links and variables are constant, in a ceteris paribus fashion. Figure A.37 shows a Positive link:

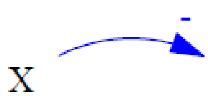


$$\frac{\delta y}{\delta x} > 0; Y(t) = Y(t_0) + \int_{t_0}^{t} x\, ds$$

Figure A.37: Positive Link

In other words, it is a positive link if cause increases → effect increases, AND if cause decreases → effect decreases.

Figure A.38 shows a Negative link:



$$\frac{\delta y}{\delta x} < 0; Y(t) = Y(t_0) - \int_{t_0}^{t} x\, ds$$

Figure A.38: Negative Link

In other words, it is a negative link if cause increases → effect decreases, AND if cause decreases → effect increases.

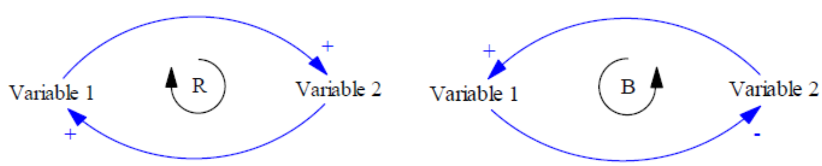


Figure A.39: Reinforcing and Balancing Loops

In Figure A.39, R stands for Reinforcing and B for Balancing. If the multiplication of the polarities along a loop is (+) then it is an R Loop. If the multiplication of the polarities is (-) then it is a B Loop (odd number of (-) polarities). A Reinforcing loop means cause & effect feed each other. A Balancing loop means that cause feeds its effect which in turns counters its cause.

A.4.6 Stocks and Flows

Stocks are elements (material, information…) of the system that you can see, count and measure at any given time. Stocks create accumulations (a historical record in the system). Stocks reflect the State of the system. Some examples of stocks/states are: Water in a bathtub system, Product inventory in a warehouse system, Workforce in an organizational system, Population in a country system and Money in a bank account system.

Flows can be classified into 2 types: Inflow (fill) & outflow (drain). Flows change stocks over time. Some examples are: Inflow from the faucet, outflow to the drainage (Water in the bathtub); Production, Shipment (Inventory); Hiring, Firing (Workforce); Births, Deaths (Population); Deposit, withdrawal (Account Balance).

Let us take as an example, the simplified population dynamics:

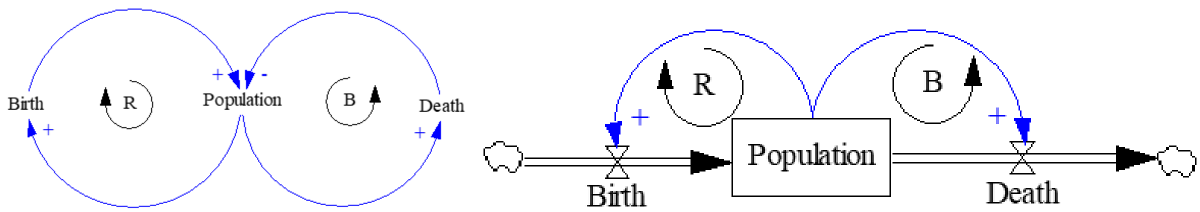


Figure A.40: CLD and Stocks & Flows representations of Population Dynamics

The dynamics in Figure A.40 can be expressed as:

$$Population(t) = Population(t_o) + \int_{t_o}^{t} (Birth - Death)\, dt$$

Keep in mind that the link polarity is relative. If births decreases, the population would still increase, however less than what it would have otherwise. The same logic holds for negative polarity: Deaths and Population.

APPENDIX B – ESSAY TWO

The prices are determined following the self-selection and participation constraints with qualities determined endogenously in the model. Given our specific model, we checked as well the following logical constraints to make sure that we prevented cannibalization between segments under all scenarios:

1- Price of Alternatives in High segment should be higher than those in Low segment:

→ (AFV High Price - AFV Low Price) ≥ 0

→ (ICE High Price - ICE Low Price) ≥ 0

→ (Lowest Price in High Segment - Highest Price in Low Segment) ≥ 0

2- From the point of view of the consumers in high segment, the quality of products targeted to high segment should always have higher quality than those targeted to low segment:

→ (Quality of AFV High to High Segment Emissions Oriented - Quality of AFV Low to High Segment Emissions Oriented) ≥ 0

→ (Quality of AFV High to High Segment Performance Oriented - Quality of AFV Low to High Segment Performance Oriented) ≥ 0

→ (Quality of ICE High to High Segment Emissions Oriented - Quality of ICE Low to High Segment Emissions Oriented) ≥ 0

→ (Quality of ICE High to High Segment Performance Oriented - Quality of ICE Low to High Segment Performance Oriented) ≥ 0