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Three Essays in Consumption and Social Dynamics

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Introduction

Exploring Social Behaviour

What drives human behavior? How do we make choices in complex environments? What factors shape our preferences in these conditions? These questions have long fascinated me and have driven generations of researchers in the social sciences. While many insights have been gained, research continues to unveil new layers of understanding. Seminal works have highlighted the bounded rationality of our decision-making, revealing that our choices are influenced not only by individual perspectives but also by the broader context of social structures. It is this interplay that drives the core of this PhD thesis.

This PhD dissertation encompasses three distinct research topics connected by the unit of analysis we will explore: our "animal" species, aka humans.

In the first Chapter, *"Interacting Cobweb Demands"* (co-authored with Prof. Giorgio Ricchiuti, University of Florence), we wanted to explore the role of consumer behaviour when choosing between the purchase of two or more goods. The methodology employed was a simple dynamical system, namely the Cobweb Model (Ezekiel, 1938). We did this by adding an element of uncertainty, namely the quality of a good. In doing so, we formulated a heuristic in which consumer choice depended on the interplay of two elements. The first is the distance of the current price from the expected price of a good, which served as a reference point, as described in Kahneman and Tversky (1979). The second element was the preference for buying the good at the lowest price, which represents the baseline of utilitarian-maximiser agents. We found that the intermediate weights between these two elements in the heuristic were responsible for complex dynamics. The interpretation of the "key element" of the heuristic, i.e., the *Reference Quality* (RQ) price, can have multifaceted views. For example, one interpretation is the luxury pricing of goods, namely the "Veblen" effect Veblen (1899). Namely, goods whose price increases with demand follow the opposite behaviour of normal goods. In detail, although not mentioned directly in the Chapter, we can observe the "positive-slope in price" effect on two parts of the Demand function , which is typical of this class of goods—namely, when the price is either too low or too high relative to the other good. Another interpretation is that consumers want to convey a signal of "trust" toward the sellers, an element existing in "fair-trade" goods. Accordingly, this could explain why consumers would be "happier" in purchasing a good above the actual price, which is also close to the concept of a "Fundamental Price" in investor heuristics in finance Brock and Hommes (1998, 1997). Our findings can be considered relevant to the literature as they employ a methodology (i.e., the Heterogeneous Agent Models) to problems that were not considered under this setting (i.e., consumer purchasing choices). Turning to the results, an overall interpretation of the analytical findings is that, as the "quality" factor enhances its relative importance, the system tends to stabilise in the direction of the RQ price, which is a positive outlook in complex dynamics settings. Finally, there are relevant mathematical results, such as the events of a Crisis of an attractor , due to the piecewise nature of the dynamical system. Concluding the comments on this Chapter, I repute this work as important for the audience of social sciences in general because it amplifies the domain of possible applications of heterogeneous agent models, as it opens new possible applications of the cobweb model that were unexplored up-to-date.

The second Chapter, differently, takes another problem with another methodology. The union with the former can be the unit of analysis, i.e., consumer behaviour. In Chapter Two *"Misperception of Norm: Smartphone Use"*, done in collaboration with the European Commission, Joint Research Center, we built a novel survey RCT to investigate a series of hypotheses concerning the use of digital devices. The topic is fascinating because digital consumers generally tend to use digital devices more than they usually would like, hence calling for exploring the consumption pattern. The latter may be due to two fundamental reasons. On one side, digital goods (particularly social media) are addictive (Allcott et al., 2022). Hence, due to a combination of habit formation and self-control issues, digital consumers may use the digital device more than they intended. Conversely, welfare measurement problems arise when a digital good is free of charge (Aridor et al., 2024). Hence, when assessing the latter, consumers may be better off reducing digital device consumption due to the former reason.

The novelty of this Chapter in the social science literature is that it analyses the problem of smartphone over-consumption from a norm perspective, with this study as the first attempt at doing it. Along the paper, our main hypothesis is that digital consumers may use smartphones more than intended because (beyond the addiction issues) they overestimate their peers' usage and underestimate their own usage. Hence, we first assess the existence of misperceptions concerning smartphone use on both sides (personally and socially). Moreover, we show that these perceptions are strongly connected with our own attitudes towards the norm (i.e. smartphone use), which is a general finding in the misperception of social norms (Bursztyn and Yang, 2022). Secondly, we show that, through the provision of an RCT information experiment, where half of the sample is informed about the "real"[1] average peers' consumption; we can derive some causal claims about the social dimension of the norm. That is, through the baseline pilot data, we show that the treatment assignment affects the intention of reducing the screen time for those respondent who were mistaking the norm "smartphone use" the most. The latter is the main contribution of this paper at this stage. Later, upon the availability of the primary survey, which is currently ongoing, we will be able to assess these findings better in a larger sample. Accordingly, we will be able to assess medium-term outcomes, like educational and well-being outcome variables, mediated by an eventual reduction of smartphone use.

In this regard, I believe this work is important for opening a new room to improve digital consumers' welfare. That is, provided the evidence of over-consumption, we give an informational tool through which consumers experience a form of self-reflection, which may induce them to reflect on their smartphone consumption load.

Finally, the ***Third Chapter***, *"Aspirations and Effort"*, considers one of "the main goals" within the PhD Thesis that I wanted to explore from the beginning, namely the topic of Inequality. For instance, the third Chapter of this work, which is not a fully developed project, first

[1] Our interpretation of "real" usage is related to the average norm usage of the device by the reference group that we considered in the study. This Chapter studies this behaviour for the population aged 18-30 from six countries in the EU.

explains some ontological reasons for the existence and endurance of Inequality over time. To achieve this "goal", I tried to reconnect the concept of "aspirations" defined as a "determinant of individual investment" (Genicot and Ray, 2020) with the structure of the society over time. That is, in a perspective where your outcomes are a function of a continuum of possible Societal combinations of effort and luck over time, Aspirations can be either self-determined at birth by your kinship unit (hence, purely exogenous from the individual standpoint) or according to the network structure, where the probability of contact (hence, integration between communities) is a determinant of your economic outcome in life. The first element is at the core of Talcott Parsons (1940) functional theory of social Stratification, while the second is the recent finding of the companions Chetty et al. (2022a,b), where they assess this relationship empirically.

The paper is divided into two main parts; the first one goes in the direction of the "History of Economic Thought" perspective. Namely, I analyse two distinct authors (Parsons (1940) and Veblen (1899)) who, even indirectly, explored the concept of action (hence, effort) over the life-cycle. In their respect, I compare their views and perspectives on this topic. Accordingly, Parsons places greater emphasis on the elements of social structure which guide individual action, while Veblen is focused on the "innate" behaviour of humankind in excelling over others. This work can be important for tracing further perspectives on the problem of inequality endurance over time, which has been unexplored from an economic perspective.

The second part of the paper, instead, attempts to formalise these concepts within a static network game with quadratic cost pay-off. Accordingly, the model's novelty is to embed agents with "aspirations", which are exogenously given. Aspirations in this scenario could be seen as a "target effort", according to which, if achieved, the agent derives enjoyment and satisfaction from it. Accordingly, I characterise the equilibrium of actions and provide some results with comparative statics for a static model version. Concluding this Chapter, the model, in a final version, shall include the dynamical evolution of aspirations over the time domain.

Now, the reader is left with the content of the dissertation.

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Chapter 1

Interacting Cobweb Demands

A heterogeneous agent model of consumer behavior

*= The present chapter is co-authored with Giorgio Ricchiuti (University of Florence), and part of it is published in the journal Computational Economics (Springer).

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Interacting Cobweb Demands

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Abstract

This paper proposes a simple, stylized two-good, two-market dynamical cobweb model. Consumers and producers are located in two countries, where they can choose to consume either locally produced or imported goods. We introduce a heuristic rule for consumers, which considers a convex combination of purchasing the cheapest good and the expected intrinsic quality of the two goods. Numerical simulations demonstrate that the interconnection between markets is a primary driver of instability, manifesting through either a flip or a Hopf bifurcation. Additionally, the dynamics depend closely on the price-quality trade-off. We identify three scenarios: when only price matters, a stable period-2 cycle arises; when only quality matters, the system converges; and in intermediate cases, complex dynamics emerge. Notably, we discovered a boundary crisis region, where there is a sudden shift from a chaotic attractor to stability. Finally, as a brief extension, we analyze the system when tariffs are considered for policy purposes.

Keywords: Interacting Markets, HAM, Trade, Consumer Choice, Consumer Heuristics Dynamical Systems.

JEL codes: C02, C62, C63, D11, D16, D91, M30, Q02, Q11.

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1.1 Introduction

In the aftermath of WWII, increasing interactions between economic regions took on a prominent role, enhancing trade flows, particularly in intra-industry exchanges (Grubel and Lloyd, 1971). In this context, empirical evidence presented both advantages and disadvantages. On the one hand, consumers benefited from having access to quality-differentiated similar goods[2]. On the other hand, greater openness magnified the risk of financial, epidemiological, and ecological shocks Schmitt et al. (2018a). These shocks can affect both sides of the market: demand and supply.

The traditional interacting cobweb market of Dieci and Westerhoff (2009, 2010) (henceforth DW, 2010) considers the presence of two goods, each represented by its respective market. The source of nonlinearity and complexity is supply-led, as producers can switch production based on the past-profit differential of the two goods sold.

This paper considers a stylized two-country, two-good cobweb-type model that emphasizes the role of the demand side within the cobweb framework. To focus on the demand effect, we keep the supply linear over time with naïve producers, allowing consumers to switch consumption between the two available goods[3]. The two goods differ only in their production location. Indeed, within the novel literature on interacting cobweb markets, a contribution that considers demand-led interaction is an interesting feature to explore[4].

We consider the presence of two switching mechanisms, one for each country under con-

[2]Explained, among others, by the pioneers of the new trade theory such as Krugman (1979) and Helpman (1981).

[3]Throughout the paper, we will use the terms quotas and shares of the two groups interchangeably. This clarification is necessary to avoid confusion for readers familiar with the concept of 'import/export quotas' in international economic literature.

[4]It is worth mentioning that such a source of interaction was already considered in Casellina et al. (2011) for an application to the credit market. However, their scenario considered consumers switching between two available financial assets and did not analyze the effects of trade costs or focus on consumers' behavioural rules.

sideration[5]. Consumers use a heuristic to evaluate the purchase of two identical goods in terms of needs satisfaction and enjoyment. In this respect, the decision rule comprises two layers: first, consumers determine which good to consume, and secondly, how much of that good to consume. This process accounts for the fact that consumers cannot observe the good ex-ante and make a purchase decision one period in advance. Consequently, in their first-layer decision, there are two main concerns. The first is that, under non-observability, they establish a "reference-focal point" (Kahneman et al., 1991) where, as the current price approaches this value, the fitness—the good's expected quality—is at its peak[6]. Consumers believe that the *reference quality*—henceforth *RQ price*—represents the value under which the type of good sold corresponds to the actual value of that good[7]. The second factor, in line with canonical consumer behaviour, is the willingness to purchase at the lowest price. The resulting heuristic is a combination of these two factors, moderated by a weighting parameter.

Compared to the related literature, we introduce non-linearities on the demand side through a switching mechanism inspired by Manski and McFadden (1981). We embed a novel heuristic that accounts for the choice of one of the two products according to a reference point. The resulting map becomes a two-dimensional piecewise-smooth system. In a similar vein, Naimzada et al. (2019) considered within a linear cobweb model the existence of a "Reference Point" evaluated by consumers directly in a demand function with loss aversion. Differently, our heuristic accounts for an aversion to purchasing a good below this value, but not above it, as quality concerns arise. The rationale is that consumers infer the quality of a given good through the observed price. Hence, a higher price than the *RQ* one does not constitute a loss in the quality sense, but only in the price sense. Moreover, for policy purposes, we analyse the system when tariffs are relevant, specifically

[5]Along with our narrative and analysis, we explore the presence of two countries, although our framework can be extended to account for a multi-country setting or a single country with two available goods.

[6]It is worth noting that consumers do not experience the good's quality ex-post. Instead, they use the reference-focal point as an ex-ante expectation of the good's quality.

[7]This scenario resembles cases where the good in question cannot be observed ex-ante. Consequently, consumers rely on this value as a reference for their purchase. A practical example can be the purchase of a wine bottle or any non-storable product that cannot be observed or sensed prior to the purchase.

considering an exogenous import tariff imposed by the importing country, with a focus on asymmetric tariffs.

Through analytical analysis and numerical simulations, we obtain the following results. When quotas are fixed over time, we generalise the canonical model of Ezekiel (1938). For the variable quotas case, we find that at least one steady state exists with both prices equal to the RQ price (Proposition 1.1). Furthermore, four additional steady states may exist depending on the distribution of consumers across the two markets (Proposition 1.3). We also show, in Proposition 1.2, that our dynamical system converges to stability (at the RQ steady state) when the *quality* factor is the sole component that matters within our heuristic. Additionally, the system could lose stability through either a Flip or Hopf bifurcation.

Moreover,through numerical simulations, along with baseline settings, we show that interconnection between symmetric markets is among the drivers of instability. Specifically, a decrease in heterogeneity (a higher intensity of choice) among consumers destabilises markets that would have otherwise been stable. This mechanism first leads to a period-doubling bifurcation, resulting in oscillations around the steady state. Moreover, further decreases in heterogeneity can give rise to more complex dynamics, including the emergence of the Hopf scenario. This key mechanism was also the main finding in Dieci and Westerhoff (2010) concerning the supply side, where a Neymark-Sacker loss of stability occurred due to market interaction.

As the final pillar of our analysis, we have found that the trade-off between purchasing at the cheapest price and at the RQ price triggers complex dynamics in intermediate cases where the cheapest price factor matters more. Conversely, when consumers prioritise the RQ price, the system converges to one of the steady states according to the initial condition of the state variable. Hence, the dynamics depend strictly on the price-quality trade-off, mediated by the weighting parameter. We identify three scenarios: when only price matters, a stable period-2 cycle arises; when only quality matters, the system converges;

and in intermediate cases, complex dynamics emerge. Interestingly, we found the existence of a boundary crisis region, where there is a sudden shift from a chaotic attractor to stability.

In the wake of asymmetric tariffs, a further destabilizing effect emerges as the distance between the two countries increases, whereas high symmetric tariffs act as a stabilizing force by making markets more segmented. Even though our framework considers exogenous trade tariffs, and thus there is no lobbying by consumers and producers as in Tuinstra et al. (2014), our results align with the stabilizing policies on profit differentials studied in extensions of the interacting cobweb model Schmitt et al. (2017, 2018b).

The remaining structure includes a literature review in Section 1.2, followed by the presentation of the baseline model in the third section. The case of variable quotas, along with its analytical properties and numerical experiments, is discussed in Sections 1.4 and 1.5, respectively. The conclusion will provide a summary and explore further avenues for extending this framework.

1.2 Related Literature

The canonical Cobweb framework has the capability to provide a theoretical explanation for price fluctuations in the commodity market. This stylised fact was prominent in the first half of the 20th century. For instance, the traditional Cobweb model emerged from contributions in the early '30s (among others, Leontief (1934) and Kaldor (1934)), which are largely encapsulated in the popularised Ezekiel (1938)[8]. The starring role of the Cobweb model in economic theory stems from the introduction of dynamics resulting from firms' naïve price expectations (namely, one period ahead) regarding the production of a non-storable commodity that takes one period to produce. Due to producers' naïvete, unstable dynamics emerges as a result of when their reaction to price changes is higher than the consumers' one. The producers' overreaction in price changes leads to fluctuations (specifically, constant up-and-down or period-two oscillations) around the long-run

[8]See Dieci et al. (2022), which provides a consistent summary of the literature on the antecedents and subsequent contributions of the Cobweb models.

equilibrium price.

Thanks to its tractability, the Cobweb framework has gathered renewed interest in being conceptualised under different settings. Among others, we can distinguish the study of different price expectation schemes such as adaptive expectations in Nerlove (1958) and its seminal extension, where chaotic behaviour emerges due to nonlinearities in Chiarella (1988). Indeed, interest in nonlinearities triggered contributions aimed at studying cobweb-type dynamics (Artstein, 1983; Hommes, 1994; Jensen and Urban, 1984).

The seminal contribution of Brock and Hommes (1997) spotlighted the Cobweb literature by embedding nonlinearities through discrete choice models à la Manski and McFadden (1981). Investors can choose between adopting a costly rational strategy or a cost-free naïve one. The nonlinearity in aggregate supply generates endogenous dynamics with chaotic behaviour. The magnitude of chaos depends on the intensity of choice, which is linked to the scale parameter of the logistic distribution (Galanis et al., 2022)[9]. However, in these frameworks, the dynamics are driven by the supply side, both in terms of firms' expectations and the strategies employed.

In our framework, however, heterogeneity concerns consumers: they compare the convenience of buying one of the two available goods. Furthermore, our work aims to refresh a branch of the literature that has yet to evolve within the Cobweb literature over the past two decades, specifically the effect of market interdependencies. On one side, Currie and Kubin (1995) shows the non-negligibility of nonlinear effects arising from market interdependencies, contrasting Schumpeter's 1954 fundamental principle of partial analysis, which posits that when effects are negligible, interrelations do not matter. Hommes and van Eekelen (1996) countered this finding by arguing that when market interdependency effects are not pivotal, the qualitative results remain unaltered, thus supporting Schum-

[9]The logistic distribution is characterised by a mean, μ, and a scale parameter, ϕ. The intensity of choice corresponds to the inverse of the scale parameter. Moreover, the variance of the logistic distribution is equal to $\frac{\phi^2\pi^2}{3}$. Therefore, an increase of intensity of choice leads to a reduction of the variance of the logistic distribution, a lower heterogeneity/dispersion or a higher homogeneity in choices.

peter's principle[10]. In this branch of the literature, Yousef et al. (2000) contributed by extending the debate to interdependent global economies, studying the effect of market interdependencies.

Secondly, our contribution belongs to the family of Cobweb models with market interactions, specifically the Dieci and Westerhoff (2009, 2010) framework. Their principal finding, as anticipated earlier, is that if two Cobweb markets are supply-linked by producers choosing to produce one of the two horizontally competitive products based on their profitability, as the degree of rationality increases, markets that would otherwise be individually and globally stable lose their stability due to this interaction mechanism. Further developments by Dieci and Westerhoff considered, for instance, the role of exporting producers and lobbying for endogenous tariffs from a two-country perspective (Tuinstra et al., 2014). While this relates to our framework from a country perspective, our approach differs by considering exogenous trade tariffs (with a focus on their asymmetry) and demand-led switching. As noted above, Casellina et al. (2011) also considered demand-side interactions with one switching mechanism and a specific application to the credit market. Further developments in the interacting Cobweb literature include the welfare effects of stabilizing policies guided by profit taxes Schmitt et al. (2017, 2018b)[11]. Another closely related contribution is Muscillo et al. (2021), which considered a dynamical model over two geographically distinct but interacting markets where the link is in trading a sector potentially affected by the spread of a disease (e.g., Cattle Market). They show that the resulting infection shock arising from market interaction is more "extreme" compared to the case of autarky.

Finally, we propose a novel heuristic rule that considers higher fitness according to the trade-off between *quality* and *price*. This type of mechanism is well-known in the literature on consumer choice. For instance, a higher concern for *quality* can be associated with "coordination mechanisms," where consumers care about the value of a good. Thus, they may have a higher willingness to pay if they believe that the quality of the good is superior. The rationale behind this mechanism can vary depending on the example given.

[10] This result was proved with the inclusion of an IID disturbance term in the model.

[11] For a comprehensive review of interacting Cobweb markets and related stabilizing policies, see Schmitt et al. (2018a)

One example is "Status Goods" (Veblen, 1899), where, according to Veblen's theory of the Leisure Class, consumption of a status good depends positively on the "exclusivity" of the good. Under certain network conditions, such as interpersonal comparisons, consumers would purchase goods with a higher price. This concept has received attention recently (Ghiglino and Goyal, 2010; Ghiglino and Langtry, 2023; Langtry, 2023). Another example relates to consumer awareness about the value of the good. In this case, awareness can take the form of "Fair Trade" mechanisms (Renard, 2003; Nicholls, 2010), which could induce consumers to be happier paying "more" knowing that a higher margin of a "non-storable" commodity, as in our case, goes to the producers. Accordingly, our model considers the *quality* effect through a parameter (w) that mediates the prominence of this factor in the consumption choice. With a lower concern for *quality*, the *price* effect increases, inducing consumers to place higher importance on the price when it is lower than the RQ price, which serves as a reference point.

Reference points are also an important component of our heuristic rule, underpinning a series of findings (among others, the studies of Kahneman and Tversky 1979; 1991) that show agents, under incomplete information, apply rules of thumb to make purchase decisions. In the Cobweb scenario, only Naimzada et al. (2019) applied such reasoning by including reference points within linear demands. They examined the role of a reference point in consumer behaviour, introducing the concept of loss aversion within the Cobweb framework. In their model, if a consumer's previous purchase was below the reference point, it was perceived positively, while a purchase above the reference point was perceived as a loss. As per their findings, losses loomed larger than gains. In our scenario, consumers use the price versus the reference price to evaluate the convenience of purchasing a given good. In conclusion, in our model, the reference point affects demand only indirectly through the consumer heuristic within the switching mechanism, which constitutes the source of non-linearity in the demand.

1.3 The Model

Relying on the Dieci and Westerhoff (2010) framework[12] of interacting Cobweb markets, we portray the consumers as the deciders of the purchase among two available goods, X and Z. As usual, within the Cobweb framework, the supplier is producing a non-storable good that takes one period to be produced. To keep the model as simple as possible, we let the aggregate supply be linear over time. In this way, we will deeply focus on the source of complexity that may arise from the nonlinearity in the aggregate demand. As anticipated in the introduction, consumers are located in two geographically distant areas, A and B. Henceforth, we assume—as a working assumption—that they are unable to migrate between the two regions. The same holds as well for the producers: we might imagine that the costs of moving for producers are so high that they have no incentives to move. Thereafter, we assume that the local good of A is X, whereas for B it is Z. Without loss of generality, the agents populating the two areas, denoted by N_A and N_B, are the same (i.e. $N_A = N_B$).

1.3.1 The Baseline Setup

In each period, consumers have a purchasing choice over one of the two goods available. However, only a fraction of them changes the product over time. Accordingly, a portion $\delta^j \in [0,1]$ for country j does not change purchasing choices over time, which can be referred to as ***conservative consumers***, $N_c^j = \delta N^j$. Instead, $(1-\delta^j)$ denotes the share of consumers that might switch consumption over time, in a dynamic fashion, henceforth denoted as ***switching consumers***, $N_{sw}^j = (1-\delta)N^j$. Throughout our analysis, δ is assumed to be the same for A and B, that is $\delta^A = \delta^B = \delta$. Consequently, the consumers' distribution in the two areas is as follows:

$$\frac{N^j}{N^j} = \frac{N_{sw}^j}{N^j} + \frac{N_c^j}{N^j} = \left[\frac{N_X^j}{N_{sw}^j} + \frac{N_Z^j}{N_{sw}^j}\right](1-\delta)+\delta = (n_X^j + n_Z^j)(1-\delta)+\delta = 1 \qquad j = \{A, B\}\,,$$

where n_i^j indicates the subset of switching consumers (with relative weight $1-\delta$), purchasing good i in country j. And $(n_X^j + n_Z^j) = 1$. It is worth mentioning that conservative

[12] Indeed, we stick to their notation as far as possible.

consumers stick to their consumption choices over time. We do assume that they are equally split in their choice between X and Z[13].

Since X and Z are available in both regions, their aggregate demand is the sum of the demands of each region:

$$D_{i,t} = \delta(D^A_{i,t} + D^B_{i,t}) + (1-\delta)(n^A_i D^A_{i,t} + n^B_i D^B_{i,t}) \qquad i = \{X, Z\} \tag{1.1}$$

where the first part represents the *conservative* consumers and the second identifies the *switching* consumers' demand that is the product of the sum between the individual demands (D^A_i, D^B_i) with their respective consumer quotas (n^A_i, n^B_i) of the two regions. The canonical linear demand functions are:

$$D^A_{X,t} = a_X - b_X P_{X,t}; \qquad\qquad D^B_{X,t} = a_X - \tau_X b_X P_{X,t} \tag{1.2}$$

$$D^B_{Z,t} = a_Z - b_Z P_{Z,t}; \qquad\qquad D^A_{Z,t} = a_Z - \tau_Z b_Z P_{Z,t} \tag{1.3}$$

where, $a_i > 0$ captures the market size for the good i and $b_i > 0$ is the demand slope. Henceforth, we consider equality between the demand slopes and the market sizes of the two goods, that is $b_X = b_Z = b$ and $a_X = a_Z = a$.

$\tau_i \geq 1$ denotes the tariff that is applied to the good i. If $\tau_i = 1$, none tariffs apply to the i^{th} good in object.

The market clearing occurs at each period as follows:

$$S^e_{X,t} = D_{X,t} = \delta(D^A_{X,t} + D^B_{X,t}) + (1-\delta)(n^A_X D^A_{X,t} + n^B_X D^B_{X,t}) \tag{1.4}$$

$$S^e_{Z,t} = D_{Z,t} = \delta(D^A_{Z,t} + D^B_{Z,t}) + (1-\delta)(n^A_Z D^A_{Z,t} + n^B_Z D^B_{Z,t}) \tag{1.5}$$

The producer's supply function, the left-hand side, directly depends on the price formation scheme. A reasonable assumption is that the producer may adopt naive expectations, as assumed in the baseline case of Ezekiel (1938) and confirmed by laboratory experiments

[13] This is a natural consequence of imposing $\delta^A = \delta^B = \delta$ over time.

related to cobweb mechanisms Sonnemans et al. (2004). That is:

$$S_i^e = sP_{i,t-1}, \;\; s > 0, \;\; i = X, Z. \tag{1.6}$$

This formulation is consistent with a quadratic cost function, that is readable through the assumption of perfect competition within the two available goods. By inserting (1.2) ((1.3)) and (1.6) into (1.4) ((1.5)), the law-of-motion of prices is as follows:[14]

$$\begin{cases} P_{X,t} = \frac{a\left(2\delta+(1-\delta)\left[n_X^A+n_X^B\right]\right)-sP_{X,t-1}}{b\left(\delta(1+\tau_X)+(1-\delta)\left[n_X^A+\tau_X n_X^B\right]\right)} \\ P_{Z,t} = \frac{a\left(2\delta+(1-\delta)\left[n_Z^A+n_Z^B\right]\right)-sP_{Z,t-1}}{b\left(\delta(1+\tau_Z)+(1-\delta)\left[n_Z^A+\tau_Z n_Z^B\right]\right)} \end{cases} . \tag{1.7}$$

It is worth noting that, given both the demands and the fixed quotas, there is no interdependence across the two prices[15]. Straightforward, the steady state ($\overline{P}_X$, $\overline{P}_Z$) is unique and it is given as:

$$\overline{P}_X = \frac{a\left[2\delta + (1-\delta)(n_X^A + n_X^B)\right]}{b\left[\delta(1+\tau_X) + (1-\delta)(n_X^A + \tau_X n_X^B)\right] + s} \tag{1.8}$$

$$\overline{P}_Z = \frac{a\left[2\delta + (1-\delta)(n_Z^B + n_Z^A)\right]}{b\left[\delta(1+\tau_Z) + (1-\delta)(n_Z^B + \tau_Z n_Z^A)\right] + s} \tag{1.9}$$

An increase in the market size, a will lead to an increase in the prices of both goods. On the other hand, an increase in the slopes (b and s) of demand and supply or in tariffs (τ_i) would decrease the prices at the steady state. Interestingly, an increase in the quota of ***conservative consumers*** results in an increase of both prices at the steady state, because it would guarantee a fixed demand towards the good in the object.

The global asymptotic stability holds whether the following conditions are met simultaneously for markets X and Z:

$$\frac{s}{b} < \left[\delta(1+\tau_X) + (1-\delta)(n_X^A + \tau_X n_X^B)\right], \qquad \frac{s}{b} < \left[\delta(1+\tau_Z) + (1-\delta)(n_Z^B + \tau_Z n_Z^A)\right] \tag{1.10}$$

[14] A necessary condition that we pose, as for having prices greater than zero $\forall t, b(\delta+1) \geq s$.

[15] We studied the case of cross-dependencies in the price of the two goods in an earlier version. Accordingly, the results correspond to a primitive form of interaction of demand-side coming from the Currie and Kubin (1995) model. The analysis is available upon request

In the case of fixed quotas, stability strictly depends on the relationship between supply and demand slopes. The right hand side is equal or greater than one if:

$$\delta \geq \frac{1 - (n_i^A + n_i^B)}{1 + \tau_i - (n_i^A + \tau_i n_i^B)}$$

Specifically, considering the absence of tariffs (i.e. $\tau_i = 1$), and given that the total fraction of consumers lies in the region $n_X^A + n_X^B \in (0, 2)$, the right hand side it is always greater than one when the share of conservative consumers (δ) is more than 0.5. Under this consideration, when the consumers' reaction (b) is greater than the one of producers (s), the steady state is stable (as in Ezekiel (1938)). In the opposite case, s greater than b, the condition for δ is more stringent. Furthermore, an increase in tariffs τ_i affects the stability of the system by segmenting markets. If the stability conditions (1.10) are not met, the resulting dynamics are in line with the up-and-down oscillations around the long-run equilibrium (1.8)-(1.9) of the canonical Ezekiel (1938) cobweb model. The up-and-down oscillations are related to the overreaction of producers to changes in demand over time.
Note that in the absence of tariffs ($\tau_X = \tau_Z = 1$), the stability condition collapses to $\frac{s}{b(1+\delta)} < 1$, which will be a useful benchmark for the non-linear demand model with interconnected markets. In the following section, we show that, for the variable quota case, stability conditions are more binding to the benchmark case.

1.4 Variable Quotas

Switching consumers choose, at every period, which good they want to purchase. Within the standard rational consumption model, the consumers' decision process depends on the existence of a utility function, where both commodities enter positively, and a budget constraint which involves both prices.
In our scenario, however, we introduce an inconsistency in consumer choice by embedding the non-observability of the good ex-ante. Contextually, ***switching consumers*** have a concern about goods' quality: they hold a belief about the intrinsic value of the good under evaluation for purchase. We refer to this as the *reference quality* (RQ) price and assume that this could be interpreted as the long-run equilibrium price (see below proposition 1.1).

The latter is necessary to account for coherence in consumer expectations[16]. Although *switching consumers* cannot observe a given good before the purchase, they rely on this value, which for them is the source of guidance towards the best purchasing choice in this context.

The existence of an RQ price, or more generally *reference or focal points*, is widely acknowledged in the literature of behavioural economics (Kahneman et al., 1991; Tversky and Kahneman, 1991; Simonson and Tversky, 1992), where scholars have documented behaviours that are now broadly accepted. Among other aspects, in the next section, we consider loss aversion as a possible extension of our model. The concept of an RQ price is quite versatile; for instance, it is common for consumers to rely on *civic coordination* mechanisms (Renard, 2003). An example is represented by the fair trade price (Dragusanu et al., 2014). Fairtrade aims to give producers a "fair" share of the face value of the product sold, as well as to establish long-term buyer-seller relationships, and is empirically observed to be a prominent component of consumer demand for non-storable goods (Gracia and De Magistris, 2008; Loureiro et al., 2001). This mechanism could induce consumers to be happier in purchasing a good that is sold at its "fair" value. Furthermore, the non-observability factor introduces cognitive uncertainty, meaning that consumers are aware they do not know what the optimal decision is (Enke and Graeber, 2023). The bias is guided by having the current price as the only relevant information for making a decision.

Accordingly, ***switching consumers*** pose a trade-off between price and - expected - quality **(RQ)**. Formally, the trade-off is of simple interpretation: it is a convex combination guided by the weight w, which we may interpret as a coordination term with producers. The RQ price, P^*_X, i.e. the "quality" factor within the heuristic, is embedded as the distance between the current price and the RQ price itself when the price at time t is lower than

[16]This way of modelling a reference point is not new in the literature of Heterogeneous Agent Models. For instance, our way of defining the RQ price is very similar to how Brock and Hommes (1998) modelled the fundamentalist price, which was the belief that the reference price was at its long-run equilibrium value.

the RQ price:

$$Q_i^j(P_{i,t}, P_i^*) = \lambda_i^-(P_{i,t} - P_i^*)^2, \quad \lambda_i^- = \begin{cases} 1 & \text{if } P_{i,t} < P_i^* \\ 0 & \text{if } P_{i,t} \geq P_i^* \end{cases} \qquad j = \{A, B\}, \ \ i = \{X, Z\}$$

Where λ^- is a dichotomous variable which assumes value one only if the current price is below the RQ price and 0 otherwise. On the other hand, consumers have the innate desire to purchase the cheapest good available, all other factors are constant.

Combining these two elements, we obtain our fitness piece-wise functions $(-V_i^j)$, which depend on the current prices, P_i, for the j^{th} region:

$$V_{i,t}^j = wQ_{i,t}^j(P_{i,t}, P_i^*) + (1-w)P_{i,t} = w\lambda_i^- \left((P_{i,t} - P_i^*)^2)\right) + (1-w)P_{i,t} \qquad j = \{A, B\}, \ \ i = \{X, Z\} \tag{1.11}$$

where $w \in [0, 1]$. When $(w = 1)$ $w = 0$, consumers comparing the two goods guide their choice on the good which is the cheapest (closest to the RQ price). To better understand how the fitness function $-V_i^j$ behaves along the price movement, we plot it in *fig.* 1.1 with different w values. It is worth noting that when $w = 1$, the fitness function V_i^j reaches the maximum when the current price P_i is at the RQ price, P_i^*. For an higher price, given λ^-, the value V_i^j remains stable. Otherwise, when $w = 0$, the peak is at $P_i = 0$. These two examples represent extreme cases. Whereas, cases with intermediate values of w could better resemble real-life decision schemes.

[***FIGURE 1.1 ABOUT HERE***]

Switching consumers, using V_i^j, compare the fitness of the two goods, hence making a decision. As in DW (2010) for the producers' case, consumers can visualize both goods' prices and thus be informed accordingly. Indeed, they are firmly located in an area, but, in each period, both goods are delivered to the market, where consumers accrue for collecting their chosen product. Thus, reasonably we consider that the consumers' choice is made one period before. We employ a switching mechanism à la Manski and McFadden (1981) for the $j-th$ country:

$$n_{X,t}^j = \frac{e^{-\beta(V_{X,t}^j)}}{e^{-\beta(V_{X,t}^j)} + e^{-\beta(V_{Z,t}^j)}}; \qquad n_{Z,t}^j = 1 - n_{X,t}^j \tag{1.12}$$

Following Brock and Hommes (1997), a useful transformation is the use of the difference between fractions of consumers. Since we are modelling two countries, we have two switching mechanisms and, consequently two differences, which are defined as:

$$m_t^j = n_{i,t}^j - n_{k,t}^j = tanh\left[-\frac{\beta}{2}(V_{i,t}^j - V_{k,t}^j)\right], \qquad (j,i,k) = \{A, X, Z\}, \{B, Z, X\} \quad (1.13)$$

with $-1 < m_t^j < 1$. As, referencing for country A, m_t^A approaches one, the local good quota of X $n_{X,t}^A \to 1$. Given the differences in fractions m_A, m_B, we can grasp the relationship of the quotas as $n_{X,t}^A = \frac{1+m_t^A}{2}$; $n_{Z,t}^A = \frac{1-m_t^A}{2}$; $n_{Z,t}^B = \frac{1+m_t^B}{2}$; $n_{X,t}^B = \frac{1-m_t^B}{2}$. Finally, note that $m_t^A = -m_t^B$, hence this makes it simpler to write the system in terms of a unique switching mechanism m^A, where the differences between the two countries, in absence of tariffs, are equivalent but with the opposite sign.

Recalling that λ^- is the piece-wise element of our model, we have all the ingredients for presenting the dynamic system with the variable quotas implemented. The system is two-dimensional piece-wise smooth, where the piece-wise element $\lambda_{i,t}^-$ is within m_t^A, namely the time-varying difference of consumer quotas, which is a direct function of the state variables at time t:

$$\begin{cases} P_{X,t+1} = \dfrac{a\left(1+\delta+(1-\delta)m_t^A\right) - sP_{X,t}}{b\left[\delta(1+\tau_X) + \frac{(1-\delta)}{2}(1+\tau_X)(1+m_t^A)\right]} \\ P_{Z,t+1} = \dfrac{a\left(1+\delta-(1-\delta)m_t^A\right) - sP_{Z,t}}{b\left[\delta(1+\tau_Z) + \frac{(1-\delta)}{2}(1+\tau_Z)(1-m_t^A)\right]} \end{cases} \quad (1.14)$$

$$m_t^A = tanh\left\{-\frac{\beta}{2}\left[w\left(\lambda_{X,t}^-(P_{X,t}-P_X^*)^2 - \lambda_{Z,t}^-(P_{Z,t}-P_Z^*)^2\right) + (1-w)(P_{X,t}-P_{Z,t})\right]\right\}$$

$$\lambda_{X,t}^- = \begin{cases} 1 & \text{if } P_{X,t} < P_X^* \\ 0 & \text{if } P_{X,t} \geq P_X^* \end{cases} \qquad \lambda_{Z,t}^- = \begin{cases} 1 & \text{if } P_{Z,t} < P_Z^* \\ 0 & \text{if } P_{Z,t} \geq P_Z^* \end{cases}$$

The dynamical system resembles the motion of the prices of the goods on the time domain. As a remark, both quota and production decisions are made one step before. Thus, the non-linear dynamics are guided by these two factors.

1.4.1 Analytical Results

Here, we provide some analytical results of our model arising from the dynamical system in equation (1.14). For analytical convenience, we also set $\tau_X = \tau_Z = 1$ to better appreciate the role of other parameters, whereas the role of tariffs in the system is treated (throughout simulations) in Section 1.5.2. For tractability, we will use a unique switching mechanism to derive steady-state distribution and stability results across the two markets. This change is meant to interpret the results without altering the qualitative side of the model. We begin by illustrating our first set of results, which consists of the steady state where both goods are at their RQ prices.

Proposition 1.1. *There exists at least one steady state of the non-linear dynamical system* (1.14)*, and it is given by* $\overline{P}_X = P_X^* = \overline{P}_Z = P_Z^*$. *With straightforward algebra, the aforementioned steady state is a combination of models parameters. Furthermore, the relationship implies that the distribution of consumers across the two countries is* $\overline{m}^A = -\overline{m}^B = 0$, *with the corresponding steady state:*

$$\overline{P}_X = \frac{a\,(1+\delta)}{b(1+\delta)+s} = P_X^*; \qquad \overline{P}_Z = \frac{a\,(1+\delta)}{b(1+\delta)+s} = P_Z^*. \tag{1.15}$$

See Appendix I for a straightforward demonstration. Before turning to the implications of this result, it is worth noting that the RQ steady state price in (1.15) exists for a specific combination of parameters of the model.

The interpretation of Proposition 1.1 is intuitive: if both prices are at their RQ prices, consumers would not have the incentive to switch their purchasing choices. Accordingly, the distribution of consumers is evenly split across the two goods. We now forward our analysis to the stability properties of our system, which includes the range of parameters for which the system at the Steady State in Proposition 1.1 is stable.

Proposition 1.2. *The steady-state* (1.15)*, in the symmetric markets case, is locally asymptotically stable where the following inequality is satisfied:*

$$\beta < min\{\beta_F, \beta_H\} \tag{1.16}$$

Where, $\Phi = b(1+\delta)+s$, *and* $\beta_F = \frac{b(1+\delta)\Phi}{sa(1-\delta)(1-w)}$ *and* $\beta_H = \frac{b^2(1+\delta)^2\Phi}{2s^2a(1-\delta)(1-w)}$. *If,* $\beta < \beta_F < \beta_H$ *varies such that* β *becomes larger than* β_F*, then a period-doubling bifurcation takes place. If,* $\beta < \beta_H < \beta_F$ *varies such that* β *becomes larger than* β_H*, then a Hopf bifurcation takes place.*

A proof is available in Appendix II, where we also show that the four regions of the piece-wise function can be analyzed using a single Jacobian matrix since their derivatives are identical. Concerning the stability results, we notice that conditions for both period-doubling and Hopf bifurcation depend on the same set of parameters.

An increase in conservative consumers (δ) stabilizes the system, as they don't switch their consumption choices over time.

The stability of the RQ steady state strictly depends on the *Price Effect* $(1-w)$. When only the RQ effect matters ($w = 1$), the system always converges.

An increase in w leads to an increase in the relevance of RQ for consumers. They react more quickly to a deviation from RQ, having a greater incentive to prioritise the good that is priced closer to RQ. This implies that a decrease in the quantity demanded of the other good does not give an incentive to switch consumption due to a decrease in prices, hence stabilizing the system.

A value of β exists such that the steady-state (1.15) is unstable. Indeed, a higher homogeneity among switching consumers (see footnote 8) will lead to higher price fluctuations in a setting that, if not linked, would be otherwise stable. Finally, both conditions are more restrictive compared with that for the fixed quota, $b(1+d) > s$ (see 1.10).

Proposition 1.3. *There are other four possible steady states* $(\overline{P}_X, \overline{P}_Z)$ *of the non-linear piecewise-smooth dynamical system* (1.14) *for the symmetric market case. They depend on both the* ***RQ*** *prices and the distribution of switching consumers across markets,* $\overline{m}^A$*:*

$$\overline{P}_X = \frac{a\left[1+\delta+(1-\delta)\overline{m}^A\right]}{b\left[1+\delta+(1-\delta)\overline{m}^A\right]+s}; \tag{1.17}$$

$$\overline{P}_Z = \frac{a\left[1+\delta-(1-\delta)\overline{m}^A\right]}{b\left[1+\delta-(1-\delta)\overline{m}^A\right]+s}; \tag{1.18}$$

Specifically,

1. *If* $\overline{P}_X < P^*_X$ *and* $\overline{P}_Z > P^*_Z$, *then* $\overline{m}^A$ *is implicitly defined as:*

$$\overline{m}^A_I = tanh\left\{-\frac{\beta}{2}\left[(1-w)\left(\frac{a\left[1+\delta+(1-\delta)m^A\right]}{b\left[1+\delta+(1-\delta)m^A\right]+s}-\frac{a\left[1+\delta-(1-\delta)m^A\right]}{b\left[1+\delta-(1-\delta)m^A\right]+s}\right)+\lambda^-_X w\overline{M}_X\right]\right\}$$

2. *If* $\overline{P}_Z < P^*_Z$ *and* $\overline{P}_X > P^*_X$, *then* $\overline{m}^A$ *is implicitly defined as:*

$$\overline{m}^A_{II} = tanh\left\{-\frac{\beta}{2}\left[(1-w)\left(\frac{a\left[1+\delta+(1-\delta)m^A\right]}{b\left[1+\delta+(1-\delta)m^A\right]+s}-\frac{a\left[1+\delta-(1-\delta)m^A\right]}{b\left[1+\delta-(1-\delta)m^A\right]+s}\right)-\lambda^-_Z w\overline{M}_Z\right]\right\}$$

3. *If* $\overline{P}_X < P^*_X$ *and* $\overline{P}_Z < P^*_Z$, *then* $\overline{m}^A$ *is implicitly defined as:*

$$\overline{m}^A_{III} = tanh\left\{-\frac{\beta}{2}\left[w(\lambda^-_X\overline{M}_X-\lambda^-_Z\overline{M}_Z)+(1-w)\left(\frac{a\left[1+\delta+(1-\delta)m^A\right]}{b\left[1+\delta+(1-\delta)m^A\right]+s}-\frac{a\left[1+\delta-(1-\delta)m^A\right]}{b\left[1+\delta-(1-\delta)m^A\right]+s}\right)\right]\right\}$$

4. *If* $\overline{P}_X \geq P^*_X$ *and* $\overline{P}_Z \geq P^*_Z$, *then* $\overline{m}^A$ *is implicitly defined as:*

$$\overline{m}^A_{IV} = tanh\left\{-\frac{\beta}{2}\left[(1-w)\left(\frac{a\left[1+\delta+(1-\delta)m^A\right]}{b\left[1+\delta+(1-\delta)m^A\right]+s}-\frac{a\left[1+\delta-(1-\delta)m^A\right]}{b\left[1+\delta-(1-\delta)m^A\right]+s}\right)\right]\right\}$$

where $\overline{M}_X = \left(\frac{a\left[1+\delta+(1-\delta)m^A\right]}{b\left[1+\delta+(1-\delta)m^A\right]+s}-\frac{a(1+\delta)}{b(1+\delta)+s}\right)^2 = (\overline{P}_X - P^*_X)^2$
and $\overline{M}_Z = \left(\frac{a\left[1+\delta-(1-\delta)m^A\right]}{b\left[1+\delta-(1-\delta)m^A\right]+s}-\frac{a(1+\delta)}{b(1+\delta)+s}\right)^2 = (\overline{P}_Z - P^*_Z)^2$.

See Appendix III for the demonstration.

Proposition 1.3 is particularly interesting. Note that these steady states cannot be computed explicitly in general and the stationary levels of the state variables depend on the intensity of choice β and the weighting parameter of RQ vs Price w. Indeed, for the four steady states, the sign of $\overline{m}^A$, representing the distribution of switching consumers between the two goods, depends on the relative magnitude of the two effects moderated by w, whereas a higher sensitivity through β increases the amplitude of the resulting distribution. It is important to note that in the first two steady states ($\overline{m}^A_I$, $\overline{m}^A_{II}$), the distribution is influenced by the comparative significance of quality versus price effects, as illustrated here with a practical example:

Corollary 1.1. *Suppose that, in the symmetric markets setting,* $\overline{P}_Z > P^* > \overline{P}_X$. *Also, consider the difference* $\overline{P}_Z - \overline{P}_X$ *over a threshold* $\Delta > 2$. *If the quality concern* w *is equal* *to:* $w^* = \dfrac{-\varphi}{\mu - \varphi}$ *With* $\mu = \lambda_X^- \overline{M}_X - \lambda_Z^- \overline{M}_Z$ *and* $\varphi = \overline{P}_X - \overline{P}_Z$*. then:*

- *If* $w > w^*$ *then* $m^A \in (-1, 0)$
- *If* $w \leq w^*$ *then* $m^A \in [0, 1)$

Corollary 1, combined with Proposition 1.3, provides insight into how the heuristic (1.11) guides the dynamics of our system (1.14). Notably, the dominance of one component of the heuristic over the other alters the distribution of consumers between the two markets when the price difference is beyond the threshold Δ. This distribution is dependent on φ, representing the price incentive, and μ, representing the quality incentive for switching consumption. In our example, it necessarily holds that $\mu \geq 0$ since $\lambda_Z^- = 0$, and $\varphi \leq 0$ by construction. Consequently, a decrease (increase) in w leads to a (dis)incentive to purchase X given $|\varphi| > |\mu|$. An increase in μ restricts the range of w required to change the sign of the distribution. This finding is particularly interesting as it underscores how the parameter w can significantly influence consumer behaviour and its distribution on the aggregate level, resulting in a wide range of equilibrium outcomes. Concluding, in the following numerical results, we also show that for a sufficiently high w, the convergence to a steady state may depend on the initial condition in prices.

1.5 Numerical Experiments

In what follows, we will investigate the behaviour of the Interacting Cobweb Demand framework through simulations. To ease the exposition, we consider that two countries are symmetric in terms of market sizes (i.e. $a_X = a_Z = a$), as well as the demand slopes ($b_X = b_Z = b$) and the exogenous tariffs ($\tau_X = \tau_Z = \tau = 1$). Furthermore, introducing friction in the market, we consider that only half of the population is *conservative* that is $\delta = 0.5$. At the same time, we assume a skewed consideration of the price factor compared to the RQ component, imposing $w = 0.2$. Finally, a consequence along the symmetry assumptions is to consider the *reference quality* value (1.15) as equal among the two goods ($P_X^* = P_Z^* = P^*$), which we recall it corresponds to the steady state price in Proposition 1.1. In brief, in Table 1, we present the baseline parameter setting (BPS):

Table 1.1: Base Parameter Setting (BPS)

Parameter	a	b	s	β	δ	w	P^*	τ
Value	50	1.5	1.1	1	0.5	0.2	22.38	1

In what follows, we will study the system varying once at time some of these parameters once.

1.5.1 Symmetric Markets

As a starting point, we are interested in showing how the system behaves according to varying intensity of choice, that is parameter β in (1.13), where an increase depicts a higher rationality (Hommes, 2013) or a higher homogeneity in choices (Galanis et al., 2022). The bifurcation diagram in *fig.* 1.2 shows that an increase in the intensity of choice leads to complex dynamics. For a low β, prices are stable at the RQ price; after a period-doubling bifurcation, a higher intensity of choice leads to an increase in the periodicity of the oscillations coming up with non-regular behaviour in the region where β approaches our baseline value 1. Furthermore, for intermediate values beyond the first chaotic region, we can observe regions where the motion is quasi-periodic. Hence, an increase in the intensity of choice β which leads to unstable dynamics tells us, in line with the claim of DW(2010), that unstable linked markets would have been otherwise stable if not linked. The latter feature was also highlighted in the stability results from Proposition 1.2. A simple interaction between these two markets, in our case consumption choice between the two available goods, leads to complex dynamics due to the non-linearity on the demand side over time.

[***FIGURE 1.2 ABOUT HERE***]

Another parameter that deserves particular attention is w, the weighting parameter between *reference quality* and *cheapest price* purchase in (1.11). *fig.*1.3 shows how the system behaves with differing values of w where, when $w = 1$ what matters is the distance to the RQ price and, conversely, when $w = 0$ purchasing the good at the cheapest price is the unique preference among consumers. When w approaches 0, a wide periodic-2 fluctuation emerges. The inner dynamic is intuitive: *switching* consumers, having a linear fitness rule where the highest the fitness the lowest the price, at the time t would almost all demand the same good, say X, since they all depict that is the most convenient to purchase. Subsequently, at time $t+1$, their switching towards X would dramatically reduce the demand for the good Z, hence lowering its price. Accordingly, *switching* consumers at time $t+1$ would decide to consume more Z since, at this period, it is the most valuable to be purchased. This process would repeat over time. Conversely, when w tends to 1, the system tends to stabilise.

The stabilising force can be interpreted as consumers who are willing to "coordinate" by buying the price closest to the RQ value, thus dividing the population of switching consumers equally or unevenly between the two goods, whose dependence depends on the initial conditions of the state variables and on the price (φ) vs the quality (μ) effect size. For example, in *fig* 1.4 (upper-panel) we show how, starting from a parameter setting where the system remains stable and where the quality incentive dominates the price incentive (i.e. $w = 0.9$), the convergence can be either to the RQ steady state (in blue) or to the asymmetric ones from Proposition 1.3 ($\overline{m}_I^A$ in green and $\overline{m}_{II}^A$ in red) with the distribution skewed towards the good that is above the RQ price (as from Corollary 1.1). On the other hand, the steady states that are both below ($\overline{m}_{III}^A$) or above ($\overline{m}_{IV}^A$) the RQ price are never observed in our numerical experiments. In the bottom panel of *fig.* 1.4 we plot, on the same space, the conditions over which w can be either greater (black), smaller (white) or equal (red) than w^*. Note that, when $w \leq w^*$, the distribution always converges to the RQ price, and the good which is below the RQ price never has the majority of consumers over the good above the RQ. Whereas, when $w > w^*$, the consumer distribution favours the good which is above the RQ price. Both of these two facts can be considered coherent with a high-quality concern within our heuristic.

[***FIGURE 1.3 ABOUT HERE***]

[***FIGURE 1.4 ABOUT HERE***]

Moving forward, for intermediate cases of w, the dynamics are more complex and intricate. Whereas the region $w \approx\in [0.42, 0.8]$ gives up-and-down oscillations, but of melded nature in comparison with the $w = 0$ case, intermediate values of $w \approx\in [0.16, 0.4)$ (where the cheapest factor plays a major role) can produce complex dynamics. The latter results can be attributed to the contrasting force of these two factors: the preference for purchasing the cheapest good and the signalling role of the RQ price as a proxy for the good quality. The incoherence just mentioned creates a trade-off according to these two forces, proceeding in an intricate way over time.

This process can be better appreciated in *fig.*1.5, where the plot (under BPS, i.e. $w = 0.2$) of the time series (after a transient phase) for $P_{X,t}(P_{Z,t})$ in blue (orange), respectively, are shown in the upper panel of the figure. The middle panel shows instead the contextual dynamics for the differences in quota $m^A_{X,t}$.

Remember that, under the BPS, the "cheapest price" factor is of higher prominence in the decision scheme. What we can see is the intuition of the trade-off between the two forces. That is, when the price is lower at time t, say for good X, consumers purchased Z at time *t-1*, and at time t they would be attracted to switch consumption of good X. However, the fact that X is distant from the RQ price would not incentivise all to switch toward X, resulting accordingly in a quasi-evenly division of consumers across the two goods at *t+1*. What makes the difference here, in the choice made at period *t+1*, is which good is the cheapest among the two. Accordingly, at time *t+2* the distribution of *switching* consumers would dramatically favour the good that was the cheapest at time *t+1*. The mentioned process would go on intricately over time, rotating in the neighbourhood of the long-run equilibrium value over time (P^* in the dotted red line).

Finally, the third panel in *fig.* 1.5 shows the same pattern of prices for a configuration of $w = 0.6$, which as mentioned refers to a greater prominence of the RQ price. What can be noticed, as the earlier bifurcation diagram of *fig.* 1.3 suggested us, is that dynamics shrink around the RQ price.

[***FIGURE 1.5 ABOUT HERE***]

To better appreciate the behaviour just described, the upper panel of *fig.* 1.6 shows the resulting attractors in the space $P_{X,t} - P_{Z,t}$ (left), $m^A_{X,t} - P_{X,t}$ (centre) and $D_{X,t} - P_{X,t}$

(right) along our BPM. The blue dot signals the position of the RQ price. Concerning the case with $w = 0.2$, the attractor shows how the dynamics are centered towards the RQ price. A first result that can be noticed, under w=0.2, is that upward price adjustments (from the RQ) are corrected quicker than downward prices. Dynamics are concentrated in the cases when fluctuations of one of the two prices are above and the other below the RQ price. When both goods' prices are above or below the RQ price, prices tend to be adjusted quickly. The upward price rigidity is likely to be due to the differential between the fitness functions of the two goods, V_i^j when the heuristic includes only the price effect, thus favouring the demand in the following period of the good that was the cheapest. Instead, the adjustment in the high-low price region can be seen as with wider fluctuation due to the asymmetric trade-off between price-quality included in the heuristic (1.11), hence slowing the switching motion in the good quotas, which can be also seen in the time series for m_t^A in *fig.*1.5[17].

Second, notice how the aggregate demand (1.1) behaves across the price domain. For instance, the change in slope in the demand is evident as the price of a given good becomes relatively lower than the RQ price. Furthermore, a second kink appears where the price of good X becomes higher than the RQ price, which is likely to be guided by the Z price when it is sufficiently lower than the RQ one. This behaviour of the aggregate demand is indeed consistent with our heuristic. In Appendix IV, we show how there exists a region where there is a change on the slope of the demand function (1.1), whose dependence is on the distance between the good in the object and the RQ price and to the consumer quotas n_i.

[***FIGURE 1.6 ABOUT HERE***]

The latter results may intuitively raise a thought in policy scenarios. Namely, if policy-makers are concerned about the "fair price", RQ, w becomes the key policy tool. Making consumers aware of the importance of paying the "fair" price for goods is one way of acting in this direction because it will lead to a higher w which stabilises the two markets.

[17] In Appendix V we show the Partial Autocorrelation Function (PACF) plot of $P_{X,t}$. Interestingly, it shows how the motion in good prices, under the BPM, is positively associated with its past realisation for a significant number of lags. Hence, capturing path-dependencies in the price motion, whereas when $w = 0$ this relationship vanishes quickly.

In this sense, the bottom panel of *fig.* 1.6 shows how the system behaves similarly for two different values of w, i.e. $w = 0$ and $w = 0.6$, but for different reasons. As we have seen, when only price matters ($w = 0$), consumers switch massively between the two available goods, depending on which good is cheaper, which explains the larger fluctuations. Instead, as w approaches 1, the consumer's decision is more skewed according to the distance of the RQ price. The latter decision scheme reduces the amplitude of fluctuations as consumers try to get closer to the RQ price.

As a last exercise for the symmetric market setting, we want to better explore -computationally- the role of β and w in the stability of the system. *Fig.* 1.7 shows the two-dimensional bifurcation diagram on the space $w \in [0, 1]$ and $\beta \in [0, 6]$ for initial price condition nearby the RQ steady state price (1.15). What we can notice is that the system is always stable whenever β is close to zero and when w approaches one, holding the other parameters constant. Recall the results from Proposition 1.2, wherein all of the conditions $(1 - w)$ interact with the region of stability, thus letting it always converge to stability whenever w approaches 1. Furthermore, what is interesting here is the existence of a very sensible region for intermediate values of β and w, which passes from complex dynamics to stability of the system. The bottom panels of *fig.* 1.8 shows how, in the space $(P_{X,t}, P_{Z,t})$ by keeping $\beta = 2$ and increasing w roughly from .49194 (left) to .4919455 (right) the system suddenly stabilises. The latter mechanism can be identified as a form of Crisis (Chian et al., 2005), more specifically, a Boundary Crisis of an attractor. Namely, following Grebogi et al. (1983), a Crisis is a global bifurcation resulting from the collision of a chaotic attractor with a mediating unstable periodic orbit or its associated stable manifold. We do better highlight this event by performing a 1D bifurcation diagram concerning the parameter w in the bottom-right panel of *fig.* 1.9. As a last remark, we notice that when the system leads to the stable manifold (*fig.* 1.9), it always ends up as mentioned earlier on the steady-state given in Proposition 1.3 ($\overline{m}_I^A$ and $\overline{m}_{II}^A$) without observing none realisation at the RQ price equilibrium.

[***FIGURE 1.7 ABOUT HERE***]

[***FIGURE 1.8 ABOUT HERE***]

[***FIGURE 1.9 ABOUT HERE***]

What about the other parameters? *fig.* 1.10 plots the bifurcation diagrams for parameter a (left panel), b (middle), and s (right) . Concerning the market size a, an increase in this parameter has a destabilising force in our dynamic system.

[***FIGURE 1.10 ABOUT HERE***]

The results of the supply (s) and demand slope (b) align with the canonical cobweb dynamics. That is, for a flatter (steeper) supply (demand) slope, the dynamics of our framework tend to stabilize, as the second and third panels of *fig.* 1.10 illustrate the mechanism.

Summarising the inner dynamics of the baseline setting with symmetric markets we have that:

- An increase in the interaction (guided by the intensity of choice β) between the two goods' markets, X and Z, is one of the two sources of instability of the 2-D dynamical system. In particular, through the bifurcation analysis shown, we can observe how this is expressed by period-doubling bifurcation first. Subsequently, further increases lead to more complex behaviour. This result is in line with the literature on interacting cobweb markets. That is, markets that would be individually stable, if not linked, lose their stability due to interaction.

- A main novelty of our work is to insert a heuristic rule for consumer choice, which mainly characterises the interacting demand framework.

  The trade-off between having the goods at the cheapest price and the closest to the RQ price creates complex dynamics for intermediate values of the moderating parameter of these two contrasting forces (w). The latter is particularly marked for low values of w. Namely, where purchasing at the cheapest price is of relatively high prominence with respect to the purchase at the RQ price. Finally, when $w = 0$ a period-2 motion appears in the system, whereas the opposite case, $w = 1$, has a stabilising force.

- We found the existence of multiple equilibria which are sensitive to initial conditions. For instance, for a high enough distance from the RQ price, with the quality factor playing a major role in our heuristic, the system converges either to the RQ price equilibrium (even with a high price incentive φ) or the asymmetric ones favouring the goods above the RQ price.

- Interestingly, there exists a crisis region where the system suddenly passes from complex dynamics to stability, and on this region, the RQ price equilibrium is not observed according to our numerical experiments.

- Coherently with the Interacting Cobweb Model (Dieci and Westerhoff, 2010), an increase in the demand (supply) slope has a (de)stabilising effect in the dynamical system.

1.5.2 Exogenous Tariffs

As Schmitt and Westerhoff (2015); Schmitt et al. (2017) for the case of profit taxes, we investigate the role of exogenous trade tariffs, τ_i, as stabilising forces. We recall that A (B) can apply a tariff to the imported good τ_Z (τ_X) (see equations (1.2)-(1.3)).

De facto, in our model τ_i acts as an amplifier of the demand sensitiveness (parameter b) for the cross-border demands (i.e. $X(Z)$ for country B (A)). Thus, still it can be considered a demand stabiliser. As a brief illustration, *fig.* 1.11 shows the 2-dimensional bifurcation diagram on the space (τ_X, τ_Z) for $w = 0.1$ (Left Panel), $w = 0.15$ (Middle panel) $w = 0.2$ (Right panel).

[***FIGURE 1.11 ABOUT HERE***]

Interestingly, we can notice how, when $w = 0.2$, high and symmetric tariffs would guide the system to stability. The latter is in line with the stabilisation policy characterised in the interacting cobweb dynamics for profit taxes (Schmitt et al., 2017, 2018b). This is confirmed in both scenarios with differing values of w but requiring a higher level of the tariff as the price concern (1-w) increases. Meanwhile, even high-symmetric tariffs are not able to stabilise the markets for $w = 0.1$, dampening further the dynamics therein. The takeaway of these graphs, although our model considers exogenous trade tariffs, is that the two regions should coordinate between themselves in imposing a higher and symmetric tariff on the two goods under study. Accordingly, this is particularly true for low values of w, through which the stabilising force of tariffs seems to be strongly dependent on the former.

1.6 Conclusions

This paper considered a two-good, two-regional Interacting Cobweb Model acting through the demand side. The source of interaction is underpinned by consumer choice: complexity emerges through the non-linearity of the demand side. The analysis was focused on symmetric markets first, to better appreciate the properties of the dynamical system. In particular, we showed that the stability of the system is strongly dependent on the magnitude of the intensity of choice, β, and on the weights given in the *price-quality* trade-off (w). Higher β indeed renders chaotic a system of two interconnected markets in a situation in which they would have been individually stable. The latter results are in line with the canonical interacting cobweb model. The *price-quality* interaction, namely w, has a chaotic effect for intermediate weights; whereas, at the extremes, the *price effect* leads to a period-2 motion and the *quality effect* guides towards stability.
We contribute to the literature on interacting cobweb markets by showing how a simple heuristic rule applied by consumers can have a destabilising effect due to the interaction of these two markets. We do highlight the importance of consumers coordinating in caring about a reference value for a given good, which can be seen as a source of stability for our system rather than being concerned about purchasing a good at a cheaper price. The latter result, putting these results in real-life contexts, may be achieved with a stronger relationship between consumers and producers. In a policy scenario, we considered the two markets as belonging to two different geographical areas, thus rendering pivotal the role of exogenous trade tariffs to stabilise the markets. Trade tariffs can stabilise the market in particular when tariffs are increasing symmetrically between the two regions.

Our framework can be extended in several directions, which we briefly mention here. The first is to merge this demand-led nonlinear model with the supply-led one of Dieci and Westerhoff (2009, 2010). In this sense, it would be possible to consider the existence of a region where both producers and consumers can switch their production and consumption choices over time. A second line of research is to better understand the role of tariffs in this framework and to explore whether tariffs could induce higher or lower average welfare effects for both consumers and producers according to our heuristics. A third line of research, which is our main contribution in this paper, is to explore different heuristics that guide consumer or producer behaviour. For example, human behaviour is inherently complex, and the decision-making process is influenced by many contextual factors that can be incorporated into simple and tractable models like the one explored here. Some directions would include further elements of prospect theory, the inclusion of learning, networks between buyers, and an explicit account of quality within the model. We leave this room for further research.

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Figures

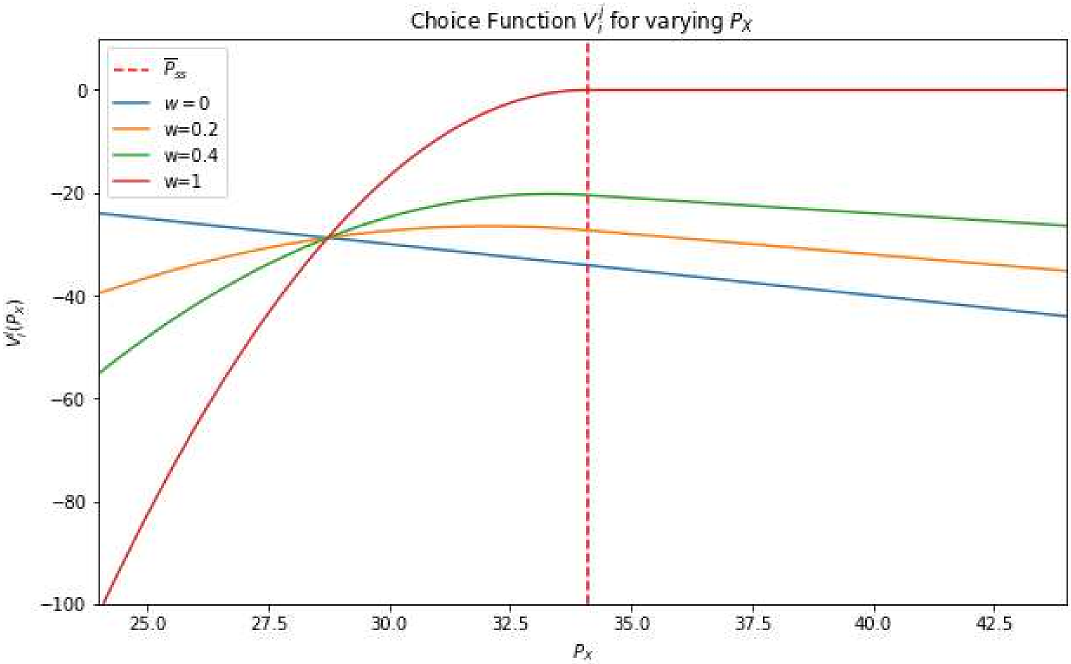

Figure 1.1: *Fitness function V_i^j in the neighbourhood of the RQ price* (1.8) *for varying w along $P_{X,t}$.*

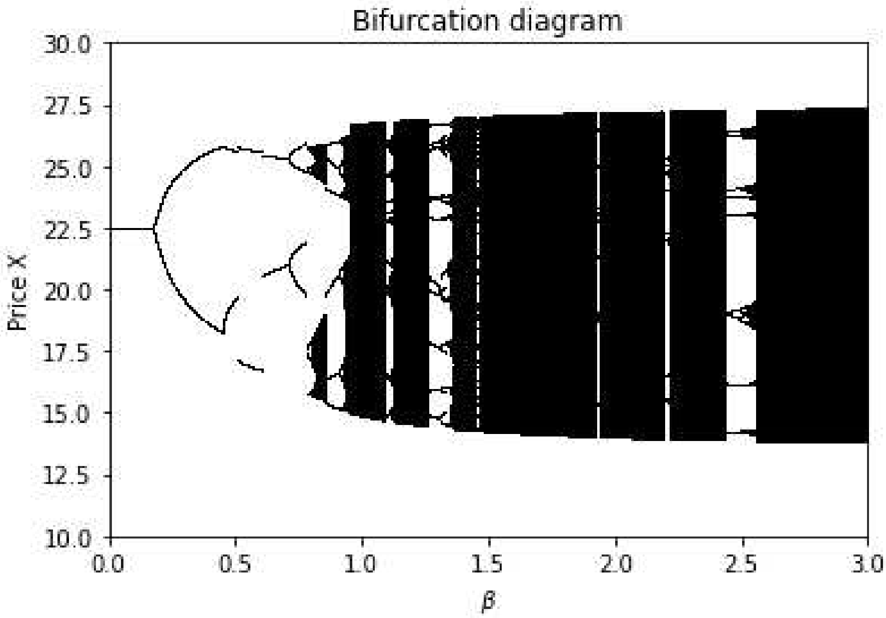

Figure 1.2: *1D Bifurcation Diagram for the intensity of choice β in 10000 steps. At each of these steps, the last 10000 observations out of 30000 Time Periods are displayed. The remaining parameter setting follows from Table 1.*

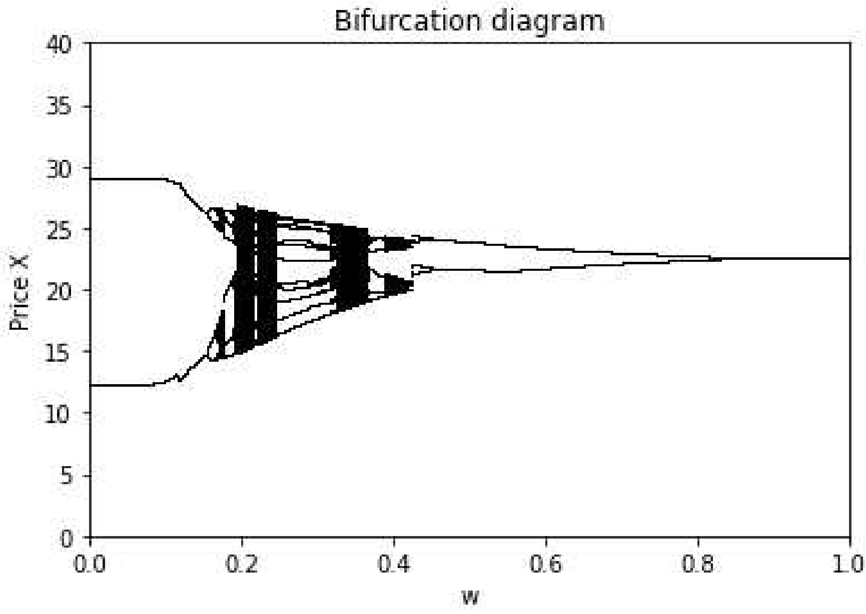

Figure 1.3: *1D Bifurcation Diagram for w in 10000 steps. At each of these steps, the last 10000 observations out of 30000 Time Periods are displayed. The remaining parameter setting follows from Table 1.*

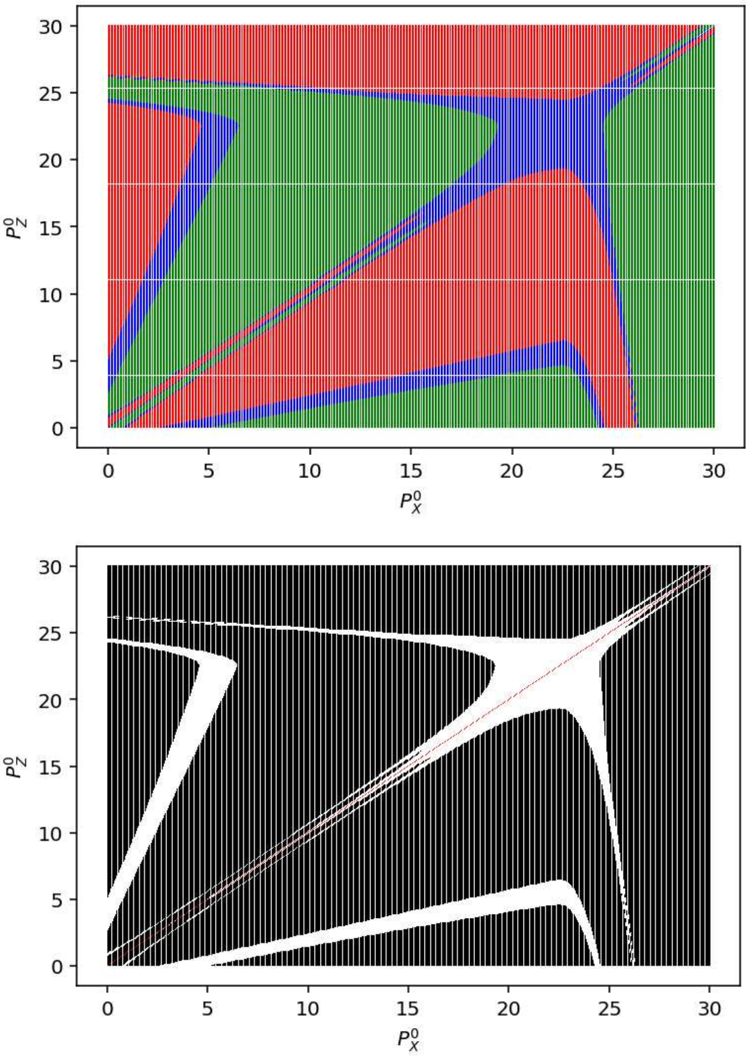

Figure 1.4: *Basin of Attraction, for initial condition in prices* $(P_{X,0}, P_{Z,0})$ *in the range* $P_{i,0} \in [0, 30]$ *from the stable region* $w = 0.9$. *Upper-Panel (Convergence to different steady states): The blue region denotes the convergence to the RQ Steady-State in Proposition 1.1. The red region denote the stationary values when* $P_X > P_X^*$ *and* $P_Z < P_Z^*$ *with* $\overline{m}_{II}^A \in [0, 1)$. *The green region denote the stationary values when* $P_X < P_X^*$ *and* $P_Z > P_Z^*$ *with* $\overline{m}_I^A \in (-1, 0]$ *from Proposition 1.3. Bottom-Panel (condition* w, w^* *in Corollary 1.1): For the same numerical exercise, we plot on the space* $(P_{X,0}, P_{Z,0})$ *whether the condition* $w > (<) w^*$ *is met in black (white) or when it holds that* $w = w^*$ *(in red).*

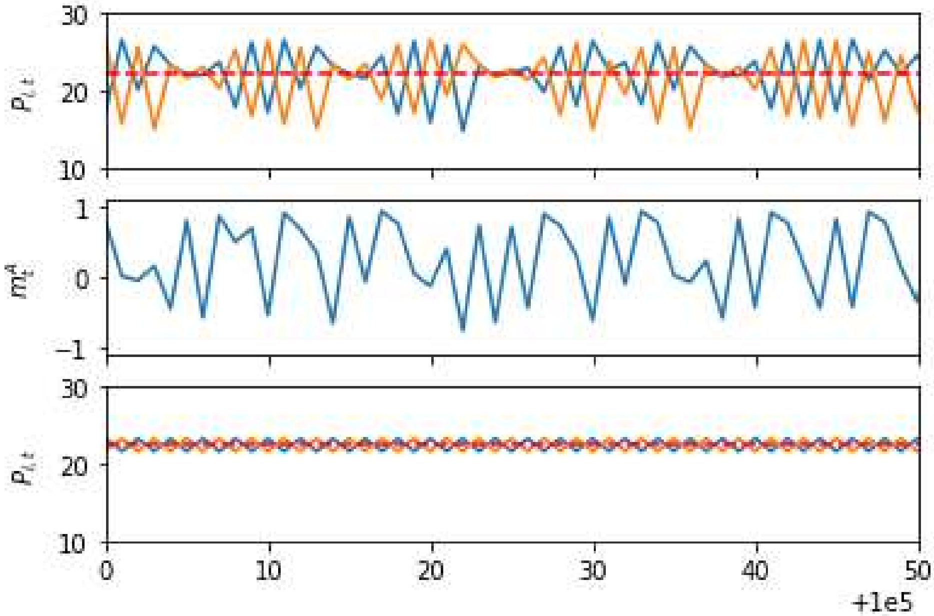

Figure 1.5: *Upper Panel: Time Series for the State Variables $P_{X,t}(P_{Z,t})$ in blue (orange) under the Baseline Parameter Setting, the red line denotes the position of the RQ price; Middle Panel: Time series for the evolution of the consumer fractions m^A (blue) under the BPS; Bottom Panel: Time Series for the State Variables $P_{X,t}(P_{Z,t})$ in blue (orange) under $w = 0.6$.*

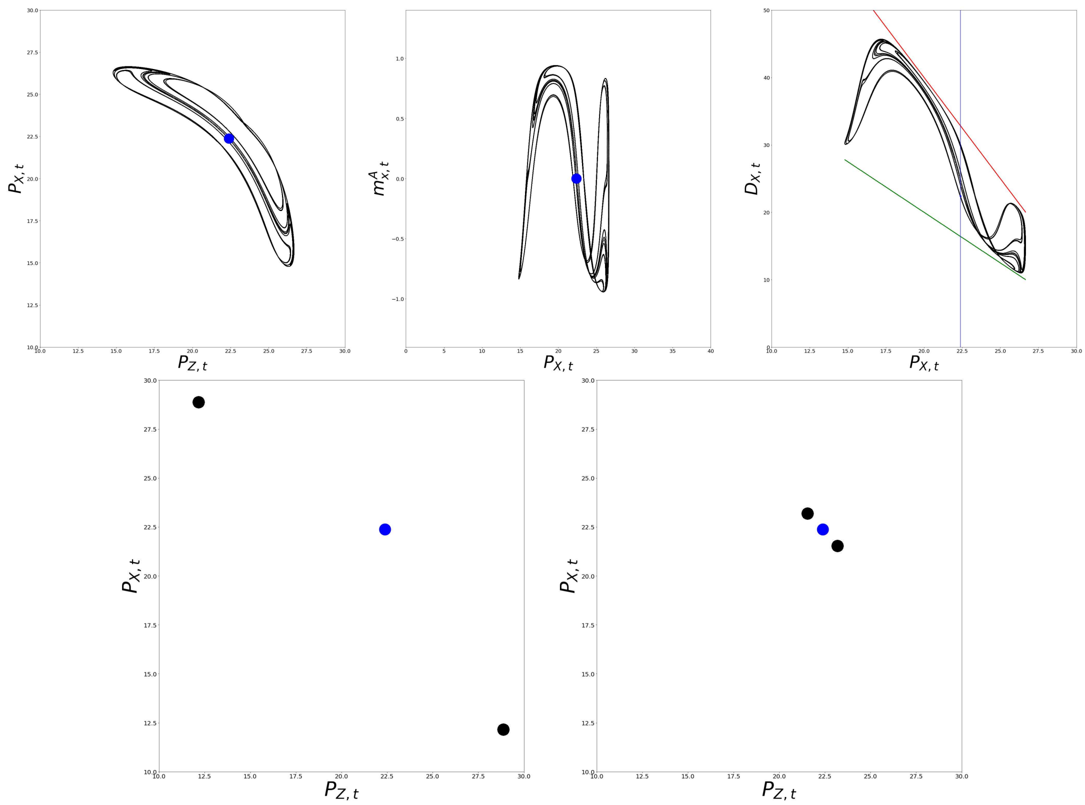

Figure 1.6: *Top panels, baseline setting: Plot of attractors in* $P_{X,t} - P_{Z,t}$ *space (left panel) and in* $m^A_t - P_{X,t}$ *(middle panel). The right panel shows the same attractor in* $D_X - P_{X,t}$ *space, where the red line denotes the maximum quantity demanded if all switching consumers were choosing* X *(i.e. with* $m^A \approx 1$*) and the green line denotes the quantity demanded by conservative consumers, which is equivalent to the case* $m^A \approx -1$*. The blue point indicates the position of the RQ price. Bottom panels: Attractors at* $w = 0$ *(left) and* $w = 0.6$ *(right) showing a period-2 motion with increased dot size.*

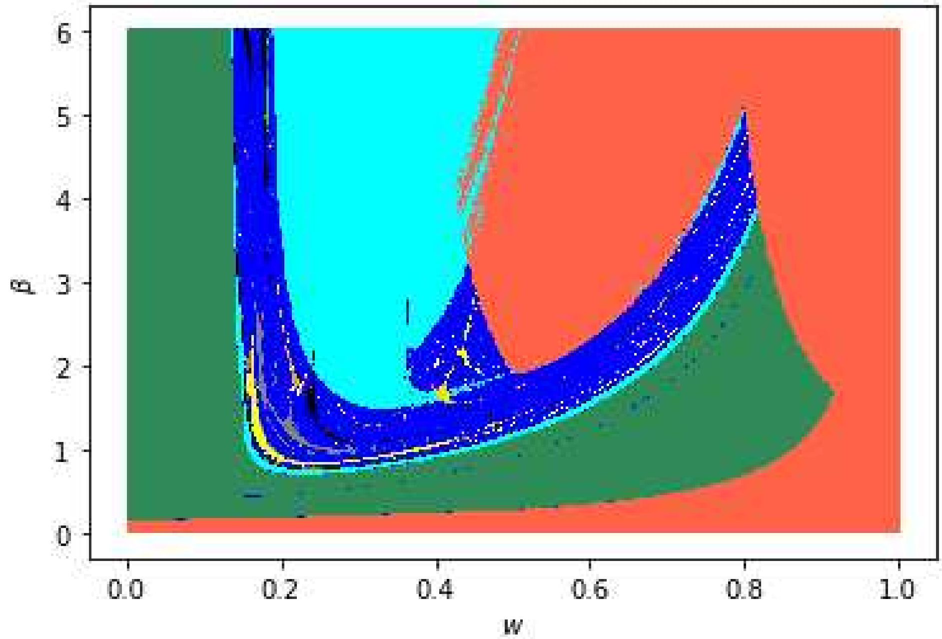

Figure 1.7: *2-Dimensional Bifurcation diagram along the intensity of choice β (vertical axis) versus the weighting parameter of the choice function w (horizontal axis) for initial condition in the state variables close to the RQ price steady states($P_{X,0} = P^* + 0.2, P_{Z,0} = P^* - 0.2$). The figure shows how, according to varying values of these two parameters, the region can be either stable (Red Region) or unstable. The instability domain has a multifaceted shape. Amongst the others, we can distinguish a periodic motion of type 2 (Green region), 4 (Cyan), and 6 (Yellow). The blue region instead denotes higher periodicity or a chaotic motion in our system.*

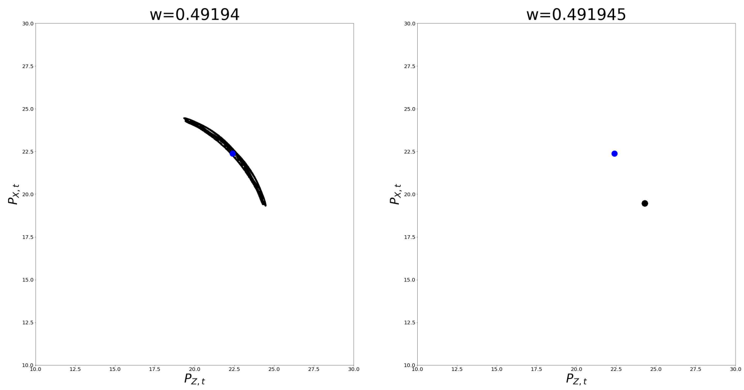

Figure 1.8: Sudden change of attractors in the $P_{X,t} - P_{Z,t}$ space for the border region between $w = 0.49194$ and $w = 0.4919455$.

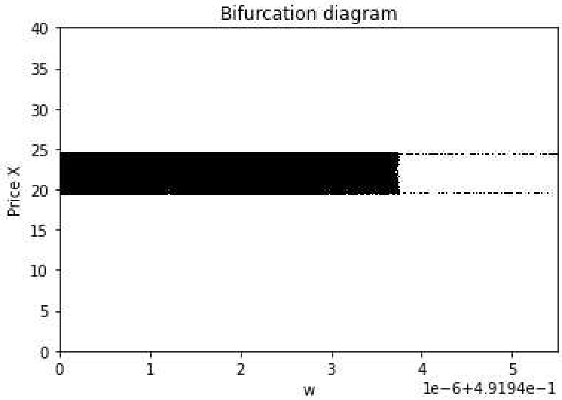

Figure 1.9: 1D bifurcation diagram for varying $w \in [.49194, .491955]$ (Horizontal Axis) for the sudden change of attractors for the border region concerning $P_{X,t}$ (Vertical Axis).

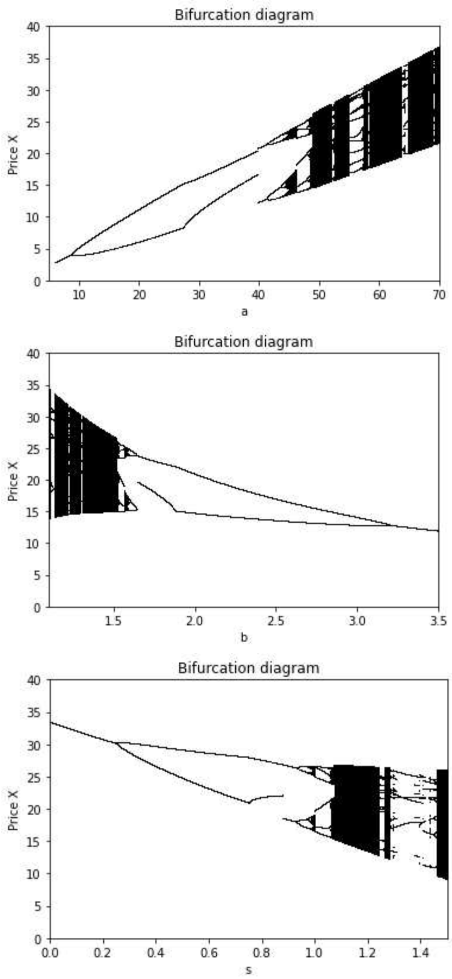

Figure 1.10: *Left Panel: Bifurcation diagram* $a_X = a_Z = a \in [5, 70]$ *with respect to* P_X. *Middle and Right: Bifurcation diagram of b (s) with respect to X's price. The Bifurcations are plotted along 10,000 steps of the parameters. For each of these steps, the last 1000 observations are displayed in the graph. (Base Parameter Setting as in Table 1).*

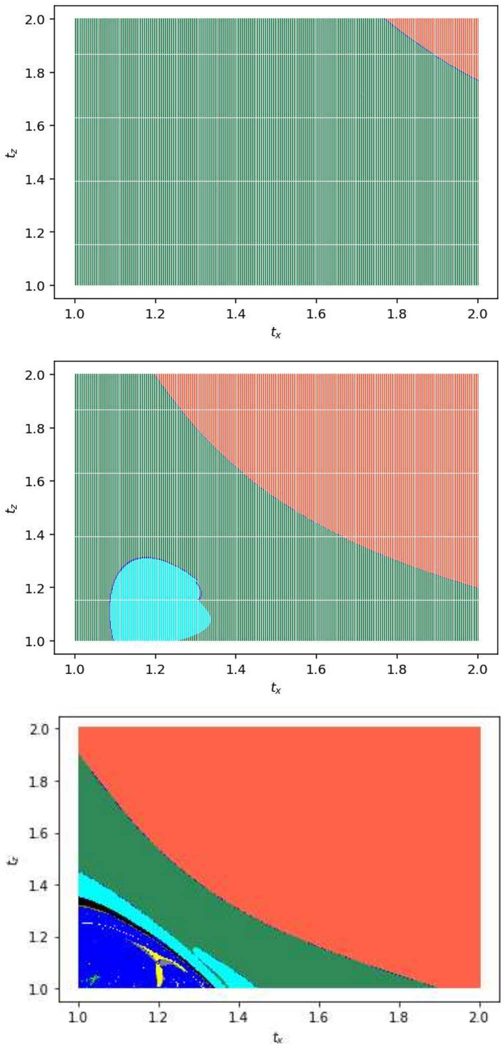

Figure 1.11: *2D Bifurcation diagram in the space (τ_Z, vertical-axis)-(τ_X, horizontal-axis) for w = 0.1 (Left panel), w = 0.15 (Middle) and w = 0.2 (Right) panel. The remainder of the parameter is the BPS in Table 1. We can appreciate the role of w, interacting with varying tariffs, in reaching stability. The figure shows how, according to varying values of these two parameters, the region can be either stable (Red Region) or unstable. The instability domain has a multifaceted shape. Amongst the others, we can distinguish a periodic motion of type 2 (Green region), 4 (Cyan), and 6 (Yellow). The blue region instead denotes higher periodicity or a chaotic motion in our system.*

I Derivation of Steady State distribution (Proposition 1)

The steady state is obtained by setting $(P_{X,t+1}, P_{Z,t+1}) = (P_{X,t}, P_{Z,t}) = (\overline{P}_X, \overline{P}_Z)$ in the dynamical system (1.14).

Hence, having the following system of equations:

$$\overline{P}_X = \frac{a\left[1+\delta+(1-\delta)\overline{m}^A\right]}{b\left[1+\delta+(1-\delta)\overline{m}^A\right]+s}; \tag{I.19}$$

$$\overline{P}_Z = \frac{a\left[1+\delta-(1-\delta)\overline{m}^A\right]}{b\left[1+\delta-(1-\delta)\overline{m}^A\right]+s}; \tag{I.20}$$

with $\overline{m}^A$ equal as:

$$\overline{m}^A = tanh\left\{-\frac{\beta}{2}\left[w\left(\lambda_X^-\left(\overline{P}_X - P_X^*\right)^2 - \lambda_Z^-\left(\overline{P}_Z - P_Z^*\right)^2\right) + (1-w)\left(\overline{P}_X - \overline{P}_Z\right)\right]\right\} \tag{I.21}$$

set in (I.21) $\overline{P}_X = P_X^*$ and $\overline{P}_Z = P_Z^*$, then all the sum of all the terms within the expression $\overline{m}^A$ is equal to 0, hence giving us (I.19)-(I.20).

II Derivation of Local Stability Conditions for the Symmetric Markets (Proposition 2)

In this appendix, we consider the stability of our system (1.14) in the symmetric case (setting $\tau_X = \tau_Z = 1.$), the time evolution of the dynamical system is driven by the iteration of the following nonlinear map (where the symbol ' denotes the unit time advancement operator). Note that, considering the absence of tariffs, $m^A = -m^B$ since $V_X^A = V_X^B$ and $V_Z^B = V_Z^A$ we can make use of this for our analysis, namely:

$$m^A = tanh\left\{-\frac{\beta}{2}\left[V_X^A - V_Z^A\right]\right\}; \qquad m^B = tanh\left\{-\frac{\beta}{2}\left[V_Z^B - V_X^B\right]\right\} = -m^A$$

Following the definition of V_i^j from (1.11), we have that m^A can be re-written as a piecewise-smooth variable, with four possible variations as follows:

$$T': \begin{cases} P'_X = F_1(P_X, P_Z) = \frac{a}{b} - \frac{sP_X}{b(1+\delta+(1-\delta)[1+m^A])} \\ P'_Z = F_2(P_X, P_Z) = \frac{a}{b} - \frac{sP_Z}{b(2\delta+(1-\delta)[1-m^A])} \\ m^{A'} = tanh\left\{-\frac{\beta}{2}\left[w\lambda_X\left(P_X - P_X^*\right)^2 - w\lambda_Z\left(P_Z - P_Z^*\right)^2 + (1-w)(P_X - P_Z)\right]\right\} \end{cases} \tag{II.22}$$

with:

$$\lambda_X = \begin{cases} 1\, if \;\; P_X \geq P_X^* \\ 0\, if \;\; P_X \leq P_X^* \end{cases}$$

$$\lambda_Z = \begin{cases} 1\, if \;\; P_Z \leq P_Z^* \\ 0\, if \;\; P_Z \geq P_Z^* \end{cases}$$

Where the piecewise-smooth nature arises from λ_X and λ_Z are equal to 1 *if* $P_X < P_X^*$ and $P_Z < P_Z^*$, respectively, and 0 otherwise. Consider the pair (λ_X, λ_Z), we can have four combination namely: $m_I^A = (0,0), m_{II}^A = (0,1), m_{III}^A = (1,0), m_{IV}^A = (1,1)$.

The first stage is to build the Jacobian matrix **J**. The first step is to compute the partial derivatives of the State variables P_X, P_Z at the equilibrium (P_X^*, P_Z^*) concerning the piecewise function m^A. Interestingly, the derivatives at the four regions defined as in (II.22) $\{m_i^A, m_{ii}^A, m_{iii}^A, m_{iv}^A\}$ are the same expression. The latter remarkably simplifies our analysis. Namely, we can make use of only one **J** since it is the same across the four regions of m^A. That is:

$$\frac{\partial m^A}{\partial P_X} = -\frac{\beta}{2}\left[2w(P_X - P_X^*) + (1-w)\right]\left(1 - tanh^2\left\{-\frac{\beta}{2}\left[V_X^A - V_Z^A\right]\right\}\right) = -\frac{\beta}{2}(1-w) \tag{II.23}$$

$$\frac{\partial m^A}{\partial P_Z} = -\frac{\beta}{2}\left[-2w(P_Z - P_Z^*) - (1-w)\right]\left(1 - tanh^2\left\{-\frac{\beta}{2}\left[V_X^A - V_Z^A\right]\right\}\right) = \frac{\beta}{2}(1-w) \tag{II.24}$$

And the partial derivatives concerning the state variables in T' we get:

$$\frac{\partial F_1}{\partial P_X} = \left(-\frac{s}{b}\right)\frac{\left[1+\delta+(1-\delta)m_t^A\right] - P_X(1-\delta)\frac{\partial m^A}{\partial P_X}}{\left[1+\delta+(1-\delta)m^A\right]^2} \tag{II.25}$$

$$\frac{\partial F_1}{\partial P_Z} = \left(-\frac{s}{b}\right) \frac{\left[1+\delta+(1-\delta)m_t^A\right] - P_X(1-\delta)\frac{\partial m^A}{\partial P_Z}}{\left[1+\delta+(1-\delta)m^A\right]^2} \tag{II.26}$$

$$\frac{\partial F_2}{\partial P_X} = \left(-\frac{s}{b}\right) \frac{\left[1+\delta+(1-\delta)m_t^A\right] - P_Z(1-\delta) - \frac{\partial m^A}{\partial P_X}}{\left[1+\delta+(1-\delta)m^A\right]^2} \tag{II.27}$$

$$\frac{\partial F_2}{\partial P_Z} = \left(-\frac{s}{b}\right) \frac{\left[1+\delta+(1-\delta)m_t^A\right] - P_Z(1-\delta)\left(-\frac{\partial m^A}{\partial P_X}\right)}{\left[1+\delta+(1-\delta)m^A\right]^2} \tag{II.28}$$

At $(P_X, P_Z) = (P_X^*, P_Z^*)$ we get:

$$\frac{\partial F_1}{\partial P_{X,P_X^*=P_X}} = \frac{-2s\left[b(\delta+1)+s\right] - sa(1-\delta)\beta(1-w)}{2b(1+\delta)\left[b(\delta+1)+s\right]} = \frac{\partial F_2}{\partial P_{Z,P_Z^*=P_Z}} \tag{II.29}$$

$$\frac{\partial F_1}{\partial P_{Z,P_Z^*=P_Z}} = \frac{-2s\left[b(\delta+1)+s\right] + sa(1-\delta)\beta(1-w)}{2b(1+\delta)\left[b(\delta+1)+s\right]} = \frac{\partial F_2}{\partial P_{X,P_X^*=P_X}} \tag{II.30}$$

From (II.29)-(II.30), the Jacobian matrix computed at the equilibrium $\mathbf{J}^*$ is symmetric with respect to the diagonal, and as just mentioned, the partial derivatives of the piecewise variable m^A are unchanged in the four possible regions, hence, the analysis simplifies to the study of the following Jacobian $\mathbf{J}^*$:

$$\mathbf{J}^* = \begin{bmatrix} \frac{\partial F_1}{\partial P_X}, & \frac{\partial F_1}{\partial P_Z} \\ \frac{\partial F_1}{\partial P_X}, & \frac{\partial F_2}{\partial P_Z} \end{bmatrix} = \begin{bmatrix} \frac{-2s\left[b(\delta+1)+s\right] - sa(1-\delta)\beta(1-w)}{2b(1+\delta)\left[b(\delta+1)+s\right]} & , & \frac{-2s\left[b(\delta+1)+s\right] + sa(1-\delta)\beta(1-w)}{2b(1+\delta)\left[b(\delta+1)+s\right]} \\ \frac{-2s\left[b(\delta+1)+s\right] + sa(1-\delta)\beta(1-w)}{2b(1+\delta)\left[b(\delta+1)+s\right]} & , & \frac{-2s\left[b(\delta+1)+s\right] - sa(1-\delta)\beta(1-w)}{2b(1+\delta)\left[b(\delta+1)+s\right]} \end{bmatrix} \tag{II.31}$$

The corresponding trace $TR(J^*)$ and determinant $DET(J^*)$ of our matrix are:

$$TR(J^*) = 2 \cdot \frac{\partial F_1}{\partial P_{X,P_X^*=P_X}} = \frac{-2s\Phi - sa(1-\delta)(1-w)\beta}{b(1+\delta)\Phi} \tag{II.32}$$

$$DET(J^*) = \left(\frac{\partial F_1}{\partial P_{X,P_X^*=P_X}}\right)^2 - \left(\frac{\partial F_1}{\partial P_{Z,P_Z^*=P_Z}}\right)^2 = \frac{2s^2a(1-\delta)(1-w)\beta}{b^2(1+\delta)^2\Phi} \tag{II.33}$$

We follow the stability conditions from Jury and Paynter (1975); Medio and Lines (2001), which can be highlighted as:

$$\begin{cases} 1 - TR^*(J) + DET^*(J) > 0 & \textit{(I) Saddle Bifurcation} \\ 1 + TR^*(J) + DET^*(J) > 0 & \textit{(II) Flip Bifurcation} \\ DET^*(J) < 1 & \textit{(III) Hopf Bifurcation} \end{cases}$$

Condition *(I)*: it is always satisfied since, from (II.32), $TR(J^*)$ is always negative with our parameter assumptions.

Condition *(II)*: For simplifying the exposition, we define $\Phi = b(1+\delta)+s$. Condition *(II)*, after some adjustment, translates into:

$$\beta < \frac{b(1+\delta)\Phi}{sa(1-\delta)(1-w)} \qquad \textit{(II)} \tag{II.34}$$

Which, if violated, *(II)* gives rise to a Flip Bifurcation.

Condition *(III)*: can be re-written as:

$$\beta < \frac{b^2(1+\delta)^2\Phi}{2s^2a(1-\delta)(1-w)} \textit{(III)} \tag{II.35}$$

Which, if violated, *(III)* translates into a Hopf bifurcation.

Notice also that, according to our parameter assumption, the condition is more restrictive than the case of fixed quotas. For instance, consider the results from (II.34)-(II.35) in terms of $\frac{s}{b(1+\delta)}$:

$$\frac{s}{b(1+\delta)} < \frac{\Phi}{a(1-\delta)(1-w)\beta} = u_F; \; \frac{s}{b(1+\delta)} < \sqrt{\frac{\Phi}{2a(1-\delta)(1-w)\beta}} = u_H.$$

If, $\frac{s}{b(1+\delta)} < u_F < u_H$ varies such that $\frac{s}{b(1+\delta)}$ becomes larger than u_F, then a period-doubling bifurcation takes place. If, $\frac{s}{b(1+\delta)} < u_H < u_F$ varies such that $\frac{s}{b(1+\delta)}$ becomes larger than β_H, then a Hopf bifurcation takes place.

III Proposition 3 and its corollary

Proof of Proposition 3: Starting from the steady-state distribution $\overline{P}_X, \overline{P}_Z$ in (1.17)-(1.18), we consider the steady state distribution of consumers across the two markets from (I.21). These steady states (similarly to the Dieci and Westerhoff case) cannot be explicitly computed but are only numerical.

First, consider the case where $\overline{P}_X < P_X^*$ and $\overline{P}_Z > P_Z^*$, then all the sum of the terms within the expression $\overline{m}^A$ is nonzero except the second term (since $\overline{P}_Z > P_Z^*$) making $\lambda_Z^- = 0$ from the piecewise function definition, and we have:

$$\overline{m}^A = \tanh\left\{-\frac{\beta}{2}\left[(1-w)\left(\frac{a\left[1+\delta+(1-\delta)m^A\right]}{b\left[1+\delta+(1-\delta)m^A\right]+s} - \frac{a\left[1+\delta-(1-\delta)m^A\right]}{b\left[1+\delta-(1-\delta)m^A\right]+s}\right)\right.\right.$$
$$\left.\left. +\lambda_X^- w\left(\frac{a\left[1+\delta+(1-\delta)m^A\right]}{b\left[1+\delta+(1-\delta)m^A\right]+s} - \frac{a(1+\delta)}{b(1+\delta)+s}\right)^2\right]\right\} = \overline{m}_I^A \tag{III.36}$$

Where the first component (with weight *1-w*) concerns the distance between the two state variables at the steady state ($\overline{P}_X - \overline{P}_Z$) and, an increase of it, favours more the consumption of the good X in the equilibrium. The second component instead (with weight w) denotes the distance between the good below the RQ price and, an increase of it favours the good which is above the RQ price, namely Z. An analogous exercise can be performed for when $\overline{P}_X > P_X^*$ and $\overline{P}_Z < P_Z^*$, hence yielding $\overline{m}_{II}^A$.

Now, consider the cases of both goods being above (below) the RQ price, $\overline{P}_X > (<)P_X^*$ and $\overline{P}_Z > (<)P_Z^*$.

When both goods are below the RQ price, all the components are active in (I.21). For the symmetric market case, the map is symmetric concerning the diagonal in all of the four regions of the piecewise map. We denote this by defining $m_t^A(P_X, P_Z) = -m_t^A(P_Z, P_X) \forall P_X, P_Z$. Concerning both goods above the RQ price ($\overline{m}_{IV}^A$), we have a nested case of m_{III}^A: The quality factors are wiped out (i.e. $\lambda_X^- = \lambda_Z^- = 0$)) and we have the price judgments only. The price differences are symmetric concerning the steady state distribution of consumers across markets in the two market prices at the equilibrium.

We combine these results with the basin of attraction derived from 1.4, where we show, for the symmetric case, their existence according to the initial price conditions of the state variables.

Proof of Corollary 1: Consider always (I.21), which denotes the steady-state distribution of consumers. Then, solve for w the argument within the hyperbolic tangent such that if w is equal to that value equation (I.21) becomes 0, which yields:

$$w^* = \frac{-(\overline{P}_X - \overline{P}_Z)}{\lambda_X^- \overline{M}_X - \lambda_Z^- \overline{M}_Z - (\overline{P}_X - \overline{P}_Z)} = \frac{-\varphi}{\mu - \varphi} \tag{III.37}$$

where $\overline{M}_X$ and $\overline{M}_X$ are defined from Proposition 1.3, $\varphi = \overline{P}_X - \overline{P}_Z$ and $\mu = \lambda_X^- \overline{M}_X - \lambda_Z^- \overline{M}_Z$. Recall that we are considering the steady state where $\overline{P}_Z > P_X^* = P_Z^* > \overline{P}_X$ from Proposition 1.3 ($\overline{m}_I^A$). The three conditions such that w lies $\in [0, 1]$ are always satisfied, namely:

$$\varphi \leq 0 \quad (a); \qquad \mu - \varphi \geq 0 \quad (b); \qquad \mu \geq 0 \quad (c).$$

concerning to our case, the price difference between the two goods (ϕ) is lower than 0 since $\overline{P}_X \leq \overline{P}_Z$ (a), the *RQ* difference is always positive since $\overline{P}_Z \geq P_Z^*$ and $P_X^* \leq P_X^*$ (b) by definition of the piecewise map and it is greater than the price difference (a). Substituting (III.37) to (I.21), the value of $\overline{m}^A$ goes to 0.

Now consider that, as from the proof of Proposition 1.2, the map is symmetric to the diagonal. Hence, the distance of the state variables from the *RQ* price $P_X^* = P_Z^*$ is symmetric. We define $\Delta = \overline{P}_X - P_X^* \in (-\infty, 0]$ as the distance from the *RQ* price of the good X and, by symmetry, we have that $2\Delta = \overline{P}_X - \overline{P}_Z$. Now, consider an increase in w in (III.37) of ϵ such that $w = (w^* + \epsilon)$, we have that the change in the distribution of consumers is equal to:

$$\overline{m}^A = tanh\left\{-\frac{\beta}{2}\left[\frac{\epsilon\left(\Delta^4 - 4\Delta^2\right)}{\Delta^2 - 2\Delta}\right]\right\}$$

The denominator is always positive since $\Delta < 0$. Studying this expression for the numerator, we study the expression within $\overline{m}^A$ such that the value $\Delta^4 - 4\Delta^2$ is greater than 0. The solution considered the negative domain of Δ is $\Delta \leq -2$. For instance, this is within the feasible set of Δ since it is always negative. So, if $\Delta \leq -2$, an increase in $w > w^*$ gives us a decrease of consumption of the good X ($\overline{m}^A \in (-1, 0]$) at the steady state. Now, consider a value of the expression such that the value $\Delta^4 - 4\Delta^2$ is lower than 0. Within the feasible set, the solution is $-2 \leq \Delta < 0$. Hence, when $w \geq w^*$ the resulting range of consumer distribution is $\overline{m}^A \in [0, 1)$. Now, consider a value of w decreased by ϵ such that $w - \epsilon < w^*$. The expression to study is:

$$\overline{m}^A = tanh \left\{ -\frac{\beta}{2} \left[\frac{\epsilon \left(-\Delta^4 + 4\Delta^2 \right)}{\Delta^2 - 2\Delta} \right] \right\}$$

The denominator is always positive. Now, we want to find the value of the expression such that $4\Delta^2 - \Delta^4 \geq 0$, which is within the feasible set $\Delta \in [-2, 0]$. If $4\Delta^2 - \Delta^4 > 0$ is true, then $\overline{m}^A$ is comprised $\in (-1, 0]$. Conversely, if we look at the value of Δ such that $4\Delta^2 - \Delta^4 \leq 0$ its range is comprised in $\Delta \in (-\infty, -2]$, which implies that the steady state distribution of consumers across markets is $\overline{m}^A \in [0, 1)$. This condition concludes the proof.

IV Non-Monotonicity in Demand according to the price value (derivation for X)

In this Appendix, we prove the existence of a region under which, according to the distance between the current price and the RQ price defined in (1.15) (from below and from above of it), there is an actual increase in the demand (1.1) given an increase in the state variable P_X from our dynamical system (1.7). Given our symmetric setting, we provide the proof for the state variable P_X, and an analogous procedure holds for P_Z. For the symmetric market case, we consider $m^B = -m^A$ and $D_X^A = D_X^B$, which implies $n_X^A = n_X^B$. We begin by writing the derivative of the demand of the good X (D_X) from (1.1):

$$\frac{\partial D_X}{\partial P_X} = 2\delta \left[\frac{\partial D_X^A}{\partial P_X} \right] + (1 - \delta) \left[2n_X^A \frac{\partial D_X^A}{\partial P_X} + 2D_X^A \frac{\partial n_X^A}{\partial P_X} \right] \tag{IV.38}$$

The partial derivatives are, respectively:

$$\frac{\partial D_X^A}{\partial P_X} = -b \tag{IV.39}$$

$$\frac{\partial n_X^A}{\partial P_X} = -\beta \frac{e^{-\beta V_X^A} e^{-\beta V_Z^A} \frac{\partial V_X^A}{\partial P_X}}{\left(e^{-\beta V_X^A} + e^{-\beta V_Z^A}\right)^2} = -\beta \frac{e^{-\beta V_X^A} e^{-\beta V_Z^A} \left[2w\lambda_X(P_X - P_X^*) + (1-w)\right]}{\left(e^{-\beta V_X^A} + e^{-\beta V_Z^A}\right)^2} \tag{IV.40}$$

Or, simply:

$$\frac{\partial n_X^A}{\partial P_X} = n_X^A(1-n_X^A)\left[2w\lambda_X(P_X - P_X^*) + (1-w)\right]$$

we insert (IV.39)-(IV.40) into (IV.38) and we set it to 0, obtaining:

$$\frac{\partial D_X}{\partial P_X} = -2b(\delta + (1-\delta)n_X^A - \beta(1-\delta)n_X^A(1-n_X^A)\left[2w(P_X - P_X^*) + (1-w)\right](a - bP_X) = 0$$

After some adjustment, we obtain a quadratic equation of the form:

$$AP_X^2 + BP_X + C = 0 \tag{IV.41}$$

where:

$$\alpha = \beta n_X(1-n_X)(1-\delta); \quad A = 2w\alpha; \quad B = \alpha\left[b(1-w) - 2w(a + bP_X^*)\right];$$

$$C = \alpha(2wP_X^* - (1-w)) - 2\left[b(\delta + (1-\delta)n_X^A\right],$$

We compute the value of P_X such that a (decrease) increase of it gives a (positive) negative sign in the derivative. In this regard, we use the parametrization employed in the simulation of the manuscript from Table 1. Furthermore, since P_X is within n_X^A we compute this value for all feasible values of $n_X^A \in (0,1)$. We do this to test the robustness of our findings to any combination of P_X and n_X^A since both depend on P_Z which we are not considering, and any change in P_Z that affects P_X is funnelled through $n_X^A = 1 - n_Z^A$ defined in (1.12). The solution to the problem can be re-written as:

$$P_X = \frac{-B \pm \sqrt{B^2 - 4AC}}{2A} \tag{IV.42}$$

The discriminant in (IV.42) is always positive when $P_X > (<) P_X^*$ for our BPM and for

$n_X^A \in (0,1)$. Hence, we have two real solutions, in the range $n_X^A \in (0,1)$, which can be computed numerically. We plot the two solutions in *fig.* IV.12, where we show the value of P_X such that the slope of the demand function (1.1) is equal to 0 within the range $n_X^A \in [0.01, 0.99]$, where as n_X^A approaches its limit values 0 and 1, the solution goes converges towards $-\infty$.

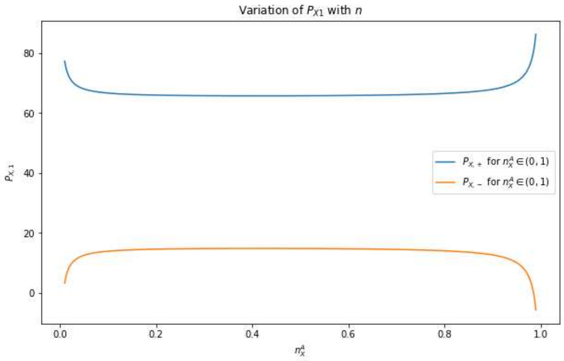

Figure IV.12: Relation between the state variables P_X and the consumer quotas n_X^A by moving in the space $n_X^A \in [0.01, 0.99]$. The blue solution is not achievable since $P_{X,t} < P_X^*$ by construction. The orange solution approximates the region in which the demand function from the right-panel of 1.6 changes the slope in the $P_X < P_X^*$ space.

V Partial Auto-Correlation Function of P

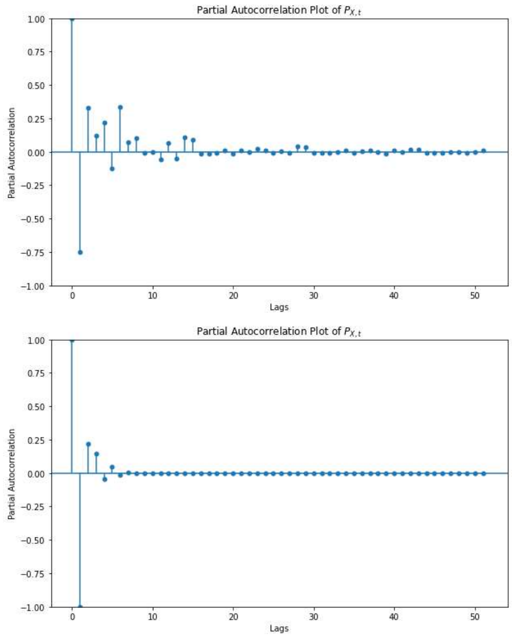

Figure V.13: *Partial-Auto-correlation Function (PACF) plot, which it shows the relationship between the state variable $P_{X,t}$ and its realizations up to 50 lags $(t-50)$. The left-panel depicts the motion under the baseline setting $(w = 0.2)$ and the right panel with $(w = 0)$.*

Chapter 2

Misperception of Norms: Smartphone Use

An Information Experiment from a pilot-test survey.

Misperception of Norms: Smartphone Use. Evidence from a Pilot-Test.

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Abstract

Misperception of Norms are widespread across social contexts. The implications of misperceiving own and others' behavior is typically associated with distorted responses by those who are affected by. In this paper, we employ an online survey to test the existence of misperceptions concerning smartphone use. We first assess the existence of them, and we examine the source of misperceptions distinguishing the own from the peers' usage. We found evidence of systemic reference group overestimation of usage, which is positively associated with own screen time, and active usage of social media platforms (SMP). Concerning the misperception of the own usage, the direction is unclear. Notwithstanding the latter fact, those who reported higher screen time are more likely to underestimate their own usage. We include, as a policy intervention, an information experiment which aims at providing truthful information about others' smartphone use. We found that, a 2.4% underestimation of own use is associated with a willingness to reduce screentime smartphone consumption by 1%. Furthermore, showing the truthful value of smartphone peers' consumption to those who overestimated peers' consumption led us to estimate an ATE of 0.119 S.D. points among our subjects.

Keywords: Behavioural Economics, Misperceptions, Social norms, Digital addiction, Smartphones, Social Media.

JEL codes: C21, C83, C90, D12, D83, D91.

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2.1 Introduction

Smartphones have become essential and pervasive tools in our daily lives because of their multi functionality and constant access to the internet. Research in multiple disciplines has linked excessive use of smartphones and social media[1] with a higher risk of digital addiction problems, unhealthy behaviours, and reduced well-being (Griffiths, 1996; Griffiths et al., 2014; Allcott et al., 2022; Braghieri et al., 2022).

The problem of the unhealthy use of SMP's has received considerable attention recently by researchers and institutions worldwide[2]. Amongst others, the European Union is expressing concern about these topics and exploring new regulations to address issues such as digital addiction. For instance, during the plenary session of the European Parliament at the end of 2023, the speaker for the Internal Market and Consumer Protection Committee, Kim van Sparrentak, said: *«We set rules for slot machines, but every time we open our app, scroll down, or refresh our social media, the same thing happens in our brains.»*. Hence, calling for new guidelines, and regulations on the modalities through which digital users are experiencing their consumption.

Examples like these are vast, and many institutions worldwide are raising similar concerns and implementing measures to mitigate the negative impacts of social media on mental health and well-being. In economics, the debate on the implications of extensive smartphone and social media use from an economic perspective is relatively recent (Aridor et al., 2024). The existing evidence underpins an increase in subjective well-being after embracing treatments curbing extensive social media use (Allcott et al., 2020, 2022; Braghieri et al., 2022). For instance, in Braghieri et al.

[1] Concerning social media platforms (SMP), the definition follows from Aridor et al. (2024). Namely, *"Social"* refers to interaction between users; *"Media"* refers to two-side markets (Tirole and Rochet, 2003), where we do distinguish between the information providers and their consumers; and *"Platform"* refers to the online internet-based applications which uses algorithms to deliver content.

[2] For example, Australia, China, and Norway have already applied age-restrictions on their use.

(2022) one explanation for the reduced well-being following social media introduction in US colleges was unfavourable social comparisons that might occur on SMP.

Among the leading causes of digital addiction, it is established that the Fear-Of-Missing-Out (FOMO) (Kuss and Griffiths, 2017; Oberst et al., 2017) plays a key role. Particularly, younger users, by observing their peers' frequently posting content related in social media platforms, they may be tempted to check these platforms to avoid feeling excluded. This behaviour is central to the definition of FOMO (Przybylski et al., 2013). Using economic terminology, it can create a strategic complementarity effect in using SMP. Under this perspective, the use of SMP it can also be considered a norm, in the sense that the expectation over others' use may have an incidence over the own behavioral pattern in using the same device. Accordingly, misperceiving others' use may prompt individuals to engage in social media (and smartphone use in general) more than they originally intended.
Furthermore, the addictive nature of digital products may put uncertainty also about own use, which may raise unawareness on the time spent using the digital device. We distinguish the peers' misperception from the own use misperception. The own misperception, instead, can be driven by cognitive biases on how the norm of using smartphone can be seen. For instance, if smartphone use is seen as a "bad"[3], respondents could be inclined to underestimate their own consumption. The latter can be seen as a form of projection bias, which depends on how the norm "smartphone use" is seen among subjects, which could depend on environmental factors, such as family, and friends opinions concerning the norm.

In this study, we conduct a two-wave online RCT survey on students enrolled in tertiary education to address some research questions on smartphone consumption

[3]In this sense, we interpret the excessive smartphone use bas as the interplay between the injunctive pressure of the norm, in Cialdini et al. (1991) or in Bicchieri and Xiao (2009) words, the normative expectations over the norm, and the personal way of defining appropriate a certain screentime, which constitutes the personal norm reflection.

dynamics, both socially and personally. This paper focuses on the results of the pilot testing at the baseline survey. Accordingly, this paper will focus on the existence of misperceptions and the short term effects of correcting them. In particular, we measure the average treatment effect (ATE) on correcting misperception when respondents are shown with information concerning both peers', and own usage against showing only the own usage *(Self-Reported + Own Guess)*. We measure the latter by asking the willingness to declare their ideal smartphone consumption when we correct the misperceptions. Meanwhile, the broader goal of this project is to consider also the medium-run effects of the same policy at the follow-up survey, namely, one month later than the baseline survey. In the follow-up we will collect the outcome variables listed in Section 2.3.4, with the empirical strategy shown in Appendix V. The sample size of the pilot testing comprises the analysis of the results on $N_p = 665$ subjects from six EU countries (*Belgium*, *France*, *Ireland*, *Italy*, *Poland*, *Sweden*). Our population target consist on tertiary education enrolled students aged from eighteen to thirty years old.

First, we want to assess whether there exists a systematic misperception of their own, and reference group use of smartphones across our respondents, and we want to investigate the possible drivers which can affect such perceptions. Accordingly, we distinguish between drivers which could arise from the descriptive side of the norm, and the ones that could be derived from the social stigma of the same norm (i.e. injunctive or normative expectations, what you think others we ought to do).

Second, we deliver at the baseline survey a treatment assignment aimed at embracing willingness to reduce smartphone consumption. After eliciting their ex-ante own and peers' perceptions of smartphone use, we provide to our respondent a guideline to provide a screen capture concerning their own objective consumption. Subsequently, we randomly divide our population in two groups where we correct perceptions about own and others' use by giving to respondents objective information about their own and reference group consumption as a treatment assignment and to the control group only own consumption objective information.

Our primary outcome of interest, at the baseline, is the willingness to reduce smartphone consumption as a matter of receiving the information. At the follow-up, our primary outcomes are smartphone use, subjective well being, and educational variables. Due to data availability, this paper focuses on the short-terms effects of providing calibrated information of peers' smartphone usage, and the study of the determinants in the willingness of revising consumption.

Concerning the pilot phase of the baseline survey, we found the following results: 74% of our respondents overestimates peers' usage. The average estimation is of 43.3% higher than the true value. Furthermore, we show that the overestimation of peers' usage is strongly associated with own smartphone screen time. After controlling for baseline screentime use and covariates, we show that when we provide the information treatment, users with greater misperceptions concerning peers' usage have a marked willingness to reduce their smartphone consumption—correcting misperceptions among those overestimating by 100% corresponds to an intention to reduce consumption of at least 11.40% (*0.119 S.D. units*) compared to the control group. Concerning own usage, the direction of perceptions is unclear, users both may under or overestimate their own usage. However, the direction of the perceptions is strongly connected to the screen time of a user: As the screen time increases, (heavy) users are more likely to underestimate their own usage. With the information treatment, and after controlling for baseline usage and covariates, we show that 2.4% underestimation of own usage, leads to an intention to reduce own consumption by 1%, which implies an effect size of greater magnitude than the peers' overestimation case. We note that, at the pilot testing, we cannot test directly the effect of the self-reflection. Hence, at the moment we cannot derive any causal claim. For measuring it, at the main survey, we will provide an identification strategy for such an effect which corresponds to ask about the ideal consumption prior to uploading the screencapture, and of the information treatment provision.

Finally, with the pilot data, we want to investigate possible causes of Peers' overestimation. Namely, first we show that respondents who have higher in-degree in SMP is correlated being actively engaged the same space (e.g. by posting multimedia content). Afterwards, we show that the latter is related with overestimating peers' usage.

Concerning the first relationship, there might be reverse causality issues. Namely, users with higher in-degree may be such because they were already active users, conjecting that active usage of social media is associated with higher appeal to have in-degree (i.e. higher exposure to others' users). Conversely, it may be true that users are active because, outside of social media, have many real friends, and hence they are active because they value sharing content with their real-life friends. However, we cannot directly relate the direction of causality since, in the testing phase, we had not a proxy of neither real-life friends, and of SMP friends attributes. Finally, we found that actively engaged users in SMP are less likely to reduce consumption, also conditional on the treatment provision, hence not finding treatment effects. The latter indicates that active users perceive higher welfare gains in using smartphone compared to passive users.

Concerning the second relationship, the causality nexus cannot identified since we do not have a network of SMP friends. Accordingly, two explanation are possible. Here, the direction of the relationship is conditional according whether active users' out-degrees are with other active users, hence they "misperceive" global reference group use because their local reference group actually is a driver of misperception, which may indicate an assortative relationship. For instance, we did not find a significant relationship between being more passive, and misperceive others' use. Rather, being passive is robustly associated with higher out-degree, and lower in-degree albeit of a lower extent.

The second relationship, if true, may indicate the existence of a Friendship Paradox (FP) effect (Feld, 1991; Jackson, 2019). That is, users' are active because they perceive higher gains from the activity, and tend to be matched with those who are mostly active, hence overestimating others' use. The FP theory, formalized by Jackson (2019), has been developed also thanks to the intuition of Perkins and Berkowitz (1986) for an addictive behaviour with a similar population target (US students on a college campus), namely binge drinking. Their main finding was the observation that the majority people tend to overestimate how often their peers engage in binge drinking, and the ones who overestimate their peers were also more likely to do it more often.

It is worth noting that these results stand from a pilot-testing phase. The sample characteristics of the main baseline survey would include $N = 12000$ respondents from 5 EU countries (*Belgium, France, Germany, Italy, and Sweden*), with a sample balanced in terms of gender, age, and Country representativeness. With the final sample, we expect an attrition rate of around 50% from the baseline, which would allow us to study the effect of the outcome variables in the medium run, collected one month after the baseline of approximately 6000 subjects. With the current study, we have been able to identify a set of potential drivers of own screen time use, which poses the premise of the information treatment. Accordingly, the information treatment, ideally, has an effect on the outcome variables in the medium run. Even if we not have the results concerning the follow-up survey, we present the hypothesis thereby.

The paper proceeds as follows, in Section 2.2, we do clarify our contribution to the literature. In synthesis, our paper contributes to the branch of studies which analyses the impacts of digital consumption. We reconnect to the literature of addiction and the impacts of smartphone consumption on well-being. Secondly, our paper merges this literature with the one of social norm definitions (Cialdini et al., 1991; Bicchieri and Xiao, 2009), and interventions (e.g. Perkins and Berkowitz (1986)). For instance, this study constitutes the first attempt in exploring the impact of SMP (and of smartphone use in general) from a social norm perspective. That is, we conject that others' behaviour, or expectations concerning own behaviour can have an impact on own attitudes towards this norm. Each of the three possible norms' influences (descriptive, injunctive, and personal) are explored within our main survey. While, in this version, we focus mostly on the descriptive side of the norm.

In Section 2.3, we briefly describe the dataset first (2.3.1), then we present the experimental design (2.3.2), the information provision procedure (2.3.3), and the main outcome variables that will be used (2.3.4).
In Section 2.4, we present the set of our hypothesis with the corresponding results. We distinguish between the analysis on Misperceptions (2.4.1), the treatment effects of providing truthful information treatment at the Baseline (2.4.2)[4]. Section 2.5 will follow with the conclusions.

2.2 Contribution to the Literature

The research topic areas which this paper contributes to can be divided into two parts: The first includes works which examined the impact of consumption of digital devices in real-life outcomes, while the second concerns the misperception of norms and the provision of information treatments as a mean to correct them.

[4]While the survey is structured in two distinct time-frames, the current analysis focuses on the baseline results of the baseline pilot-testing phase. The empirical strategy at the follow-up, with a brief description of the outcome channels is presented in the Appendix V.

2.2.1 Impacts of Digital Consumption

Research from many disciplines explored the role of the consumption of smartphone in general, and its consequences specifically on subjective well-being dimension. A non exhaustive list of contributions in this topic is provided here, although an extended review about the consumption aspect of SMPs in particular can be found in Section 4 of Aridor et al. (2024).

In economics, the primary studies which have explored the impact of digital consumption in terms of welfare are Allcott et al. (2020, 2022); Braghieri et al. (2022). All of the studies agree that, after embracing treatments aimed at reducing consumption of digital devices, users generally increase subjective well-being (SWB) measures. SWB can be effective in assessing the extent of welfare among consumers under biases. The reason stands on the addictive nature of the digital good under consideration, which is the premise of our intervention. For instance, addiction problems, amongst the others self-control issues, may overestimate the welfare gains from using social media.

Allcott et al. (2020) examined the welfare effects of deactivating Facebook (one of the leading SMP) for one month in an experiment. They found that deactivation led to increased real-life interaction (with family and friends), reduced political polarization, increased subjective well-being, and reduced valuation of Facebook during the deactivation period. The latter can be considered a signal that the perceived welfare of social media consumption may be overstated. In relation to our study, it can be that the perceived welfare of using digital devices can be related to the expectation over others' use. Hence, we test the eventual presence of this effect by comparing those who received factual information about others' smartphone use with those who do not received the same (controlling for the wedge in the perceptions).

Braghieri et al. (2022) examined, through an event study, the staggered introduction of Facebook in US campuses and its implication in mental health of college students. They found sizable effects of mental health issues, such as depression, which amount in S.D. points to 22% of losing a job. Their justification was related to the unfavourable social comparison that might occur within the platform, hence giving a social perspective of the digital addiction problem. Allcott et al. (2022), inspired by an earlier framework of Gruber and Köszegi (2001), decomposed the addiction to SMP in two components: Habit Formation and Self-Control Problem. Through a structural model of addiction, they estimated that, on average, self-control problems may account for 31% of social media consumption for a user.

Outside of economics, SWB explorations includes the study of Brautsch et al. (2023), which surveyed over 50 studies to investigate the connection between smartphone screentime with eight sleep outcomes in students ranging from 16 to 25 years old. concluding a negative association between these two dimensions. Later bedtime and daytime tiredness were associated with mobile phone use at night. However, in the surveyed studies, there was a lack of causal interpretation without the inclusion of the possible underlying channels. Nesi and Prinstein (2015) reported a strong association of popularity and gender with depression, where the moderator was acting as an enhancer through the technology-based social comparison. Specific Randomised Control Trials on academic students tailored at examining the effect of Digital Self-Control Tools (DSCT), such as Holte and Ferraro (2023), showed that simply changing the colour tonality of the smartphone was effective in reducing screen time by 37.9 minutes per day on a sample of academic students. However, this has not influenced wellbeing outcomes, suggesting a sub-optimality of the intervention. Other attempts, at least to induce an appealing reduction in smartphone use by academic students, included performing tasks prior to opening the target app (Kim et al., 2019), and changing the newsfeed and including goal-reminders (Lyngs et al., 2020). Overall, these studies motivate the need of searching for tools which may be proven effective in reducing smartphone consumption, with the premise that standard welfare measurements are overstating the gains that consumer have from their consumption.

Other interventions aimed at curbing the "dark-side" effects from digital consumption comes from Digital Literacy programs at primary, and secondary school. The need for these interventions arises from the non-desirability of total removal of digital devices; hence, the answer is to promote healthy co-living habits with these devices among younger subjects.Weinstein and James (2022) systematically reviewed them and classified the objectives of these interventions into three main goals: *(i)* Critical awareness; *(ii)* Self-reflection; and *(iii)* Strategies for behavioural change. Our study, by correcting both own and reference group perceptions of smartphone usage, aims at directing the *(ii)* (own), and the *(iii)* (peers') goals. While, concerning the *(i)* goal, a qualitative measure, for example a Vignette study reflecting the problem of extensive smartphone use, would go on the direction of reflecting on the consequences of extensive smartphone use.

Jeong et al. (2012) meta-reviewed 51 media literacy (ML) interventions, finding an overall positive impact and suggesting that an interactive mediating role for students (active vs. passive involvement) helped increase the efficacy of these policies. Jeong and coauthors found no significant difference in ML programs according to place, age group and subject of the intervention. Furthermore, the effect was more important in enhancing critical thinking than active behavioural change. For instance, the Jeong et al. findings are coherent with our statement concerning the Weinstein and James (2022) classification. However, none of the interventions reviewed relied on a proper causal assessment of these interventions and were limited to a mere correlational analysis of the outcomes considered.

Moreover, another element which has been explored in association to smartphone use is the measurement of educational outcomes. A state of the literature on academic achievement and smartphone use starts from Amez and Baert (2020), who correctly argued that the relationship between smartphone use (primarily measured as self-reported or objective time use) and academic achievement (mostly self-reported or actual GPA) how there is a limited causal interpretation in the aforementioned studies. For instance, the main empirical approach is limited to linear regression, correlational or logistic analysis. However, in all the studies considered by Amez and Baert, the results overall agree that a confirmed none or a negative relationship (specifically, in 18 out of the 23 studies considered) exists.

In recent years, studies with more consistent causal interpretations came from Baert et al. (2020), who surveyed first-year university students from two Belgian universities. They found how, through an IV approach, smartphone use was determined mainly through measures of multitasking (result also confirmed by Lau (2017)) and of internet quality of usage. Correcting for this endogeneity allowed them to give a substantial estimate of the impact of smartphone use on academic achievement (measured as the number of exams passed) that, if not controlled for these measures, was substantially underestimated. Their estimates indicate that a 1pp increase in the Standard Deviation of smartphone use leads to a decrease in the GPA of about 5pp (1 out of 20 on the Belgian scale). Later, Amez et al. (2023) confirmed the same result by observing the same sample with a longitudinal analysis of 2016-2018. Furthermore, they advocated for further research to find specific behavioural foundations underlying the effect between these two forces.
Concluding, the studies mentioned warns about the potentially overestimated welfare effects of smartphone consumption, whose difficulty to estimate relies also in the fact that consumption of digital goods, such as SMP, is generally free. Second,

treatments aimed at reducing consumption generally work in a direction of increase subjective well-being and better outcomes in terms of academic achievement.

2.2.2 Norm Misperceptions and correction through Information Experiments.

Concerning norms misperceptions, there are both observational and theoretical elements to be considered. We begin by describing the stylised aspects of misperception and their implications on economic outcomes.

Bursztyn and Yang (2022) provided a meta-review analysing 79 studies on misperceptions published after 2000, from which they gathered four conclusions about misperceptions: *(I) Misperceptions about others are widespread across domains, and they do not merely stem from measurement errors. (II) Misperceptions about others are very asymmetric, namely, beliefs are disproportionately concentrated on one side relative to the truth. (III) Misperceptions regarding in-group members are substantially smaller than those regarding out-group members. (IV) One's own attitudes and beliefs are strongly, positively associated with (mis)perceptions about others' attitudes and beliefs on the same issues.*

Reconnecting them to our study, respondents' have a systematic belief of overestimating reference group smartphone consumption, averaging 43.3% of reference group overestimation (Figure 2.4). The data collected refers to in-group members, which may suggest that if asked the perception concerning out-group members, the percentage could be even higher[5]. Furthermore, the fact of overestimating reference group consumption seems to be related also to own attitudes. In Figure 2.5, we show clearly how the tendency to overestimate others' use is associated with higher own screentime, which may suggest a channel of "misperceived" complementarity in our respondents.

[5]In the survey, we ask perceptions about the subsample of their population of interest (i.e. *students of your age*).

Turning to the state of the art of the contributions, concerning (I) norms misperceptions encompasses a widespread range of topics. To mention a few, Gimpelson and Treisman (2018), where they found that people tend to misperceive their position in the income distribution: Those who are below of the 5th decile tend to overestimate their position and those above to underestimate it. Bursztyn et al. (2020) studied the overall approval of women working outside home (WWOH) in Saudi Arabia, finding that there was a systemic underestimation about the actual level of approval. A possible cause was standing in the social stigma of discussing the matter publicly.

Concerning addictive behaviors, our specific norm intervention, efforts have been spent in understanding determinants of binge drinking (Baer et al., 1991; Prentice and Miller, 1993; Miller and Prentice, 1994; Perkins and Berkowitz, 1986; Haines and Spear, 1996). Perkins and Berkowitz (1986), amongst the others, observed that people tend to overestimate how often their peers engage in binge drinking, and the ones who overestimate their peers were also more likely to do it more often. Their result, for instance, motivates in some way our research. In the sense that, concerning an addictive behaviour, the perception over others' behaviour may give internal consistency about own behaviour. In light of these findings we may conclude that peer' effects can generate an incentive for inducing habit formation, and then cause addiction.

Possible explanations to this result (and to our study), may reside in theoretical grounds. Jackson (2019), based on an intuition of Feld (1991), found a justification which was grounded on the "Friendship Paradox" (FP). The FP can be defined as the stylized network fact that "your friends' have more friends on average than you". Being overexposed to people who are, on average, more popular with you, could be a cause of driven misperceptions. Hodas et al. (2013) found that, in SMP, more than 98 per cent of users had fewer followers than the people they followed; typically, a user's "friends" had 1,000 per cent more followers, or more, than the user. Alipourfard et al. (2020) show how the FP drives local perceptions about the prevalence of topics of discussion, hence exposing more some topics more than others. In our study, we partially explain this relationship by showing the link between active use of social media and misperception. Furthermore, active use is associated with (self-reported) in-degree of SMP. The latter may reflect a connection between the taste for an activity, and the effort in creating social connections, which may further amplify the FP effect.

An alternative way of seeing the overestimation of others' use rather than the own resides in Davison (1983), that is "the third communication effect". The third communication effect can be seen as a form of projection bias where people see the others' more affected by a phenomenon more than they actually are. At the same time, people tend to believe that they are not so affected by the same phenomenon. In our study, we observe that around 78.8% of the sample tend to think that their reference group uses the smartphone more than them. At the same time, 41.2% of our sample is above the norm, and of whom 57.6% thinks they use it less than the average. Concluding here, the third communication effect can be a fashionable explanation of the relationship between own smartphone use and the misperceptions concerning the same activity. The latter may suggest a possible explanation of our respondents' biases.

Finally, our paper aims at checking whether, by correcting misperceptions, respondents' embrace a higher willingness to revise their behavior. We do this by using an information treatment which provides truthful information concerning reference group usage, and own usage. Exhaustive reviews concerning the effect of correcting misperceptions can be found in Bursztyn and Yang (2022); Haaland et al. (2023), and in Stantcheva (2023). Information experiments aimed at understanding the impact of social norms are trending in recent years. Generally, there is overall agreement that information provision works well in the short-run, by having moderate to high treatment effects on respondents. However, in longer time spans, if not accompanied by qualitative measures (e.g. Vignette studies), it is difficult to find persistence in the results.

For instance, in Bursztyn et al. (2020) they shown how informing the actual percentage of people agreeing on WWHO changed the attitudes in husbands in subscribing wives for signing for an outside home job. After one month, the attitude was persistent beyond labour market outcomes. For example, there was a reported increase of wives signed to driving lessons. Haines and Spear (1996), based on Perkins and Berkowitz (1986) findings, they showed that by implementing an awareness campaign focused on correcting misperceptions can effectively reduce binge drinking: A 5-year intervention on a university campus led to a reported reduction of 18.5% of students who perceived binge drinking as the norm (from 69.7% to 51.2%) and an actual self-reported reduction of 8.8% (from 43.2% to 34.2%) of effective binge drinking.

In our study, we do not provide such a pervasive measure, which may anticipate that, in the follow-up we would not find a consistent persistence in the treatment effects concerning out of device measures. However, our preliminary findings can be interpreted as an area of intervention for reducing screentime use. If the effectiveness of the intervention is connected to its persistence, more structured interventions intuitively can be helpful in achieving consistent results. For example, we may image to include a device-based application which pervasively exposes subjects to their smartphone consumption pattern.

2.3 Data and Methods

This section presents the sample characteristics, the experimental design, the survey structure, the treatment assignment, and the construction of relevant variables for hypothesis testing.

2.3.1 Description of the Sample

Descriptive statistics of the sample from the pilot testing are available in Table 1, while the distribution of respondents is shown in Figure 2.1.

[TABLE 1 ABOUT HERE]

[FIGURE 2.1 ABOUT HERE]

From Table 1, we can observe that among the main covariates in our pilot analysis, there is a relative balance between the two treatment groups. Namely, the two groups—one that receives information about peers' average usage and one that does not. None of these variables differ significantly in a two-tailed t-test.

However, a note should be made regarding the main survey, which began on February 24^{th}, 2025. The gender distribution of the sample is clearly skewed toward female subjects (71.8% for Treated units and 74.1% for Control units). The pilot data collection did not restrict the achievement of target quotas; specifically, the online survey platform did not limit access to the survey for specific groups. Accordingly, the goal for the main data collection will be to avoid such imbalances through data provider controls. Furthermore, the descriptive statistics show that the Operating System (OS) of our respondents in the treatment (control) group is divided between 54.2% (50.94%) for iOS and 46.6% (49.06%) for Android, which makes it reasonable to provide two different guidelines for presenting the screen time weekly average data.

Concerning parents' education, the majority of respondents have parents with tertiary education (55.8%), while 41.61% have parents with secondary education[6]. Finally, Table 2 shows the distribution of the outcome variables, which we will use for hypothesis testing in both the baseline and follow-up surveys.

[TABLE 2 ABOUT HERE]

2.3.2 Survey Overview

Figure 2.2 shows the experimental structure of the survey and its timeline. We refer to the baseline survey as $t = 1$ and the follow-up survey, administered four weeks later, as $t = 2$. Before the baseline survey (from *December 4th, 2024* to *January 07th, 2025*), we conducted a pilot survey with an eligible final sample size of N_p=665 participants. The empirical results in this version are on the basis of the latter. The complete structure is available in detail in the Supplementary Material of this document, upon request.

[FIGURE 2.2 ABOUT HERE]

Recruitment: Participants were invited to take part through a commercial survey company, *Bilendi*. Participants gained access to and completed the survey via the platform *LimeSurvey*, whose access was controlled by *Zeta Research s.r.l.*. The survey title did not explicitly reveal its aim *(Survey of Youths' Media Engagement and Digital Use)*.

Population Target: The online survey target population consists of students aged 18 to 30 from six countries in the European Union (Belgium, France, Ireland, Italy, Poland, and Sweden)[7], with the survey translated into the official languages of each country. More specifically, our planned sample comprises approximately 12,000 students (at baseline) currently enrolled in a university program (Bachelor's, Master's,

[6] Since we are considering tertiary education students, we do not exclude that socio-economic factors may influence the distribution of this variable in our survey.

[7] Concerning the main baseline study, we removed Ireland and Poland, and included Germany.

or PhD) or in a vocational program that began in 2018 at the latest. The resulting sample is expected to be representative in terms of EU countries' population areas (NUTS-1), gender, and age[8]. Since the survey is administered to tertiary education students, we do not expect coverage error or any self-selection issues, as the age bracket of our target population exhibits homogeneous levels of internet usage in the areas considered (Stantcheva, 2023).

Exclusion Criteria: We exclude tertiary education students younger than 18 or older than 30. The enrollment year of the current program must fall between 2018 and 2024. Respondents who are not enrolled in a university or vocational program during the survey period, and those who do not own or use a smartphone, are excluded from our study. If a subject does not meet the inclusion criteria, they are screened out. The respondent cannot re-enter the survey or attempt to participate again due to the quality controls implemented by the provider. Additionally, the provider displays a message to all participants before they begin the questionnaire[9]. This message is intended to verify their availability to participate in both waves of the study. Participants who do not wish to accept are excluded from participating in both waves:

"By completing this questionnaire, you will subsequently be contacted to participate in the second phase of this survey. By confirming your participation in the second questionnaire, the information provided in both questionnaires will be recorded and associated with each other."

- **I accept ⇒ SURVEY BEGINS**
- **I do not accept ⇒ SCREENOUT**

[8]If our final sample does not meet one of the following criteria, we will use sampling quotas to adjust the distribution of our respondents.

[9]During the pilot testing phase, another exclusion criterion was failing an attention check, in which users had to report the correct screen time shown in a screen capture (see Appendix I.2). However, we opted to remove this screen out because it led to unreasonable drop-out rates.

Attrition Rate: Concerning the attrition rate, we have two options for measuring it.

The first option measures attrition from recruitment by comparing the first wave of participants' responses ($N = 12,000$) with those in the second wave. According to the surveying company, this approach would yield a final attrition rate of approximately 25% of the initial baseline sample. In this scenario, we expect that the attrition rate could reach up to 50% relative to the initial survey, while an attrition rate of around 30% aligns with similar online experiments[10].

The second option involves sending a reminder between the first and second waves to confirm willingness to participate in the follow-up survey. This strategy measures attrition based on the response rate of those who confirmed their participation, similar to the approach used by Allcott et al. (2022) in a multi-wave study, though they achieved an attrition rate of about 5%.

In conclusion, we will adopt the first option, as our survey is structured in two parts. We anticipate a uniform attrition rate between treated and control units, preserving the representativeness of both groups.

When considering attrition rate, we reasoned possible heterogeneous effects between treatment and controlled units. Since our information-treatment design does not implement an invasive intervention in our respondents, we do expect to have a uniform attrition rate between treated and control units, thus not undermining the nature of our results in terms of the representativeness of the two groups.

Incentives: During the survey, participants receive a fixed monetary incentive upon completing each of the two questionnaires. Consequently, there is no incentive for providing correct responses when participants are asked to state their preferences

[10]See, for instance, Hoy and Mager (2021) and Stantcheva (2023) for best practices in survey construction.

and expectations.

Pilot-Test: During the pilot test, participants answered a set of forty-five questions. The average completion time during the pilot-testing phase was 18 minutes and 52 seconds. As stated, the aim of the pilot test is to provide information from a restricted sample ($N_P = 665$), a subset of whose questions will be included in the Baseline survey. The pilot survey serves as the foundation for the analysis hereby discussed.

Survey 1 (Baseline): Participants will complete the baseline survey starting on February 24^{th}, 2025 (with soft-launch data collection) once the sample size target is reached. The treatment assignment is provided at the beginning of the baseline survey via a hidden variable. The survey starts by collecting demographic and education covariates. Subsequently, we ask participants to report their perceptions of smartphone use for themselves and their peers. Finally, before the information treatment, we collect objective data on smartphone use by asking respondents to upload a screen capture of their smartphone's screen time. First, we instruct them to navigate to the screen time section of their smartphones and record the objective time use, whose procedure is explained in Appendix I.1. This procedure allows us to double-check the reported data against the screen capture for the previous week's usage. Furthermore, the screen capture provides information on the most-used categories/apps, allowing us to, for example, observe the time iOS users spend on social media and verify if this category is among the top three for our respondents. Additional details on guiding respondents to provide the screen capture are available in Appendix I.1, and in Appendix I.2 we provide some statistics concerning the upload, and of the truthfulness of the information provided by our respondents[11].

[11] In this regard, we provided an ancillary intervention which divides the sample between 50% who have a mandatory assignment of uploading a figure, while the other 50% does not. The reader is referred to Appendix I.2 for details concerning the screen capture upload, compliance with the procedure, and reliability of the self-reported screen time.

We provide different guidelines based on the operating system (iOS vs. Android), which covers 99% of the overall smartphone market. This procedure is also followed in the follow-up survey. To facilitate the screen capture process, we include an attention check by displaying an example image of the data that respondents should subsequently provide.

Survey 2 (Follow-up): Participants will complete the second survey four weeks after the first battery of questions. The follow-up survey is designed to collect outcome variables, which can be grouped into dimensions of subjective well-being, educational outcomes, and smartphone usage patterns. Definitions of these variables are provided in Section 2.3.4.Furthermore, in Appendix V, we do provide the empirical strategy for estimating the ATE of the information treatment.

Randomisation: The treatment assignment is stratified by key covariates—namely, Age (below and above twenty-two), Gender, and the Country in which the survey is completed—to ensure comparability across groups. The assignment is random, with specific probabilities attached to each treatment, as summarized in Figure 2.2. The design features a *2X1* information treatment, whereby subjects are randomly allocated at the baseline survey to either: (i) view only information about their own use (both perceived and actual), or (ii) view information about both their own use (as in (i)) and their peers' use[12].

2.3.3 Treatment Description (Information):

In this part, we provide a detailed description on how we provide the information treatment. We start by eliciting perceptions on our respondents concerning smartphone usage on both own and reference group usage. Then, we show how we guided respondents' to provide the average weekly usage screen capture. Finally, we show

[12] At this point, we further highlight the existence of two additional randomization layers: one related to the provision of Nudge Tips, and the other concerning the mandatory upload of the screen capture. However, in this thesis chapter, we not focus on these additional randomizations, as our primary aim is to analyze the role of misperceptions in smartphone use.

the visual of the I treatment.

As mentioned in the introduction, we provide a qualitative motivation which is the premise of our intervention. The reader is referred to Appendix IV for some evidence of willingness to reduce consumption, encompassing data privacy, fear of addiction, and institutional factors.

Information Treatment (I): The first active treatment group *[i]* receives information about both their objective and perceived smartphone screen time. The second group *[ii]*, in addition to receiving their own usage information, is provided with factual data on peers' smartphone consumption, collected from a survey reporting average usage for the reference age group.

Hence, if confirmed, the treatment effect will emerge from comparing respondents' own "smartphone use" in group *[i]* and, for those in group *[ii]*, a comparison that also includes peers' usage. Before delivering the information treatment, we elicit ex-ante empirical expectations regarding both their own and peers' time usage from all respondents, using a slider in the survey.

Own perceptions: *« How much time do you use your smartphone daily? Provide your best estimate in hours and minutes»*

Peers' Perceptions: *«How much time do students of your age use their smartphones daily? Provide your best estimate in hours and minutes ».*

We identify a specific reference group for the norm *"Time spent on Smartphone"*: that is *"students of your age"*. The underlying reason is that, if smartphone use can be considered a social norm, we conjecture that the resonance of others' use depends on what people of your age do, rather than a wider age bracket. The latter can be considered most effective under younger cohorts, who are more inclined to conform to risky behaviors' due to social comparisons with their peers.

Moreover, our social perspective suggests that social networking sites are the primary source of misperceptions regarding smartphone time use. Consequently, one might wonder why we ask about overall smartphone use rather than social media use specifically. The reason is that collecting precise data on the time respondents spend on social media is challenging, especially given the need to harmonize data across different operating systems. However, it is worth noting that social media use is a subset of overall smartphone screen time. Therefore, if we hypothesize that the main variation stems from social media, then smartphone use estimation can serve as an upper-bound estimate of social media misperception.

Concerning the measurement of the self-reflection effect[13], we ask our participants to indicate, after reporting their perceptions, their ideal screen time as follows (from the survey):

Ideal Use: *«What would be your ideal smartphone screen time?»*

This approach enables us to assess the willingness to modify behavior by comparing respondents' actions immediately before checking their screen time statistics with their responses after being presented with a comparison between their perceived usage and the actual data. Accordingly, by comparing this variable with the Ideal Use Change variable presented in Section 2.3.4, we will be able to provide a within subject effect of the self-reflection effect concerning the own use. Namely, the ideal use before the screen capture upload versus after visualising the information. The latter will constitute our mean to quantify the self-reflection effect in the main base-

[13]This procedure is not present in the pilot survey phase.

line survey.

Moreover, we ask respondents to elicit their perceptions of their average daily usage, since we subsequently collect a screen capture of their previous week's usage. This is done to avoid incomplete data from the current week's consumption. In Appendix I.1, we provide the guidelines given to users on how to upload the screen capture correctly. To assess the robustness of our data collection, Appendix I.2 presents evidence regarding the validity of the screen captures provided by our respondents. An issue arises when a respondent does not provide an exact estimation of the previous week's usage. For example, if the survey is taken on Monday or Tuesday, the current week's consumption would include only one or two days of screen time, yielding unreliable data because idiosyncratic daily variations may be smoothed out over an entire week. Hence, to ensure comparability between subjective and objective use, we use the previous week's consumption as the basis.

In cases of incomplete previous-week consumption data, the strategy to recover such information varies by operating system. For iOS users (approximately 51*p.p.* of our sample), recovery is straightforward, as the current week's screen time consumption provides the variation compared to the previous week, as shown in Figure I.1 below. For all Android users, except those using Samsung devices (accounting for the remaining 20*p.p.* of the sample), we will control for missing data in our estimation strategy when necessary.

The elicitation of the priors of empirical expectations over the norm is essential, as in the information provision treatment studies, to identify whether the change in the behavior can be considered the highest to those who were mistaken the most the norm ex-ante, both personally and socially. Hence, the information treatment can be considered as a mean to correct a misperception of a norm (Bursztyn and Yang, 2022; Haaland et al., 2023) whose effectiveness relies on both the willingness to adjust behavior in the short run and the behavioral change that the respondent embraces after the information provision in the medium run.

For instance, we assume that the information treatment has an effect for the subjects who were mistaking the most the empirical expectations (as we will show in the results), and the expectations concerning own usage.

The treatment provision is relatively simple, as can be seen from Figure 2.3.

[FIGURE 2.3ABOUT HERE]

The information treatment distinguishes the own+peers' group *[ii]* (top panel) from the own-only group *[i]* (bottom panel) by providing, in addition to their own consumption information, objective data on smartphone consumption for their reference group. Moreover, on the right side of the treatment, we display a standing score designed to prevent unintended backfire effects among respondents who fall below the norm. This measure is consistent with our premise that habitual screen time use, potentially harmful in terms of addiction, justifies the intervention. Additionally, we assess the self-reflection effect for all subjects by asking them to indicate their ideal consumption after receiving the information. The ideal screen time, defined in Section 2.3.4, will be our measure to quantify the treamtent effect of being exposed to truthful information concerning peers' usage.

Our treatment, which is light in pervasiveness as it is shown only once, aims to reduce smartphone consumption—especially among those consuming above the norm—without inducing a taste for conformity among those below the norm. We implement this by classifying respondents based on their average use (y) relative to the reference group's average (100, in percentage points) using a buffer zone x (in our case, for the pilot testing, 10p.p.). Specifically, if a respondent's average use satisfies $(100 - x) < y < (100 + x)$, their consumption is considered "good"; if it is below $100 - x$, it is deemed "Great"; and if it exceeds $100 + x$, it is labeled as "Above Average". Accordingly, we chosen y to be 5.2. hours, which was also the result of a survey with similar from the GWI. The latter number is coherent with our sample mean (5.17 hours), and the sample median (4.5 hours). To give higher consistency with our population, and to divide our subjects more equally in the two groups, we chosen the sample median at the pilot testing as of our value of the norm for the main baseline survey. We drew inspiration from a similar setting described in Allcott (2011) for U.S. household energy consumption, where incorporating such information into households' bills effectively reduced consumption among those above the norm.

2.3.4 Outcome Variable Construction

In this part, we define a set of outcome variables that will be used in our analysis. We divide this subsection into two parts: the first distinguishes the outcome variables measured in both waves to examine whether changes can be mediated by smartphone use, and the second describes other relevant variables that can be auxiliary in hypothesis testing. In the first part, we begin by constructing a composite indicator that captures subjective well-being (the Well-being Index). We then build a variable of Ideal Use Change to determine whether there is a self-reflection and norm-reflection effect regarding the desired usage pattern. Furthermore, we present a short version of the Internet Addiction Scale (Lopez-Fernandez, 2017) and a validated version of the FOMO scale incorporating elements from Abel et al. (2016); Przybylski et al. (2013). The sum of these four components generates the Welfare Index, which is defined below. Finally, we define the activity/passivity social media scale, adapted from a validated scale (Escobar-Viera et al., 2018). Items followed by (-1) indicate that an affirmative response enters with the opposite sign in the index computations.

Ideal Use Change: While providing the Information Treatment, we ask our respondents whether they would like to adjust their screen time in the following way:

«Upon viewing your smartphone consumption in the above figure, what would be your ideal smartphone consumption?»

The ideal use change variable is the answer to this question, in percentage to the self reported objective screen time use. Indeed, we put as an initial value the self-reported screen capture (see the slider in Figure 2.3). As in Allcott et al. (2022), this question is designed to capture the perceived extent of overusage of the smartphone device.

Formally, we define the ideal use of the i^{th} respondent at time $t = 1$ as SM_i^*. The Idea use change of the i^{th} respondent at time $t = 1$ ($\Delta C_{i,1}$) is defined as the difference between the ideal use and the baseline consumption, $SM_{i,1}$, divided by the baseline consumption:

$$\Delta C_{i,1}^* = \frac{SM_i^* - SM_{i,1}}{SM_{i,1}} \tag{2.1}$$

In the follow-up, at $t = 2$, we measure the realisation of smartphone consumption by re-collecting the screen time capture, and we measure the actual use change outcome variable as follows:

$$\Delta C_{i,2}^* = exp(\Delta C_{i,1}^* - \Delta C_{i,2})$$

where $\Delta C_{i,2} = \frac{SM_{i,2} - SM_{i,1}}{SM_{i,1}}$ represents the actual change in smartphone consumption across the two periods. In this way, if $\Delta C_{i,2}^*$ equals one, it implies that the actual change in smartphone consumption between the two periods is equal to the change declared in the first period. Otherwise, a value of $\Delta C_{i,2}^*$ greater (or lower) than the one it implies, taking as an example a user that wished to reduce consumption in the following period, that the respondent had a decrease in consumption which was not close enough to the Idea or that she increased the consumption as opposed to the declared change.

Subjective Well-being (SWB) Index: Following (Allcott et al., 2022), we define a set of variables that are entailed at capturing the relationship between smartphone use patterns and measures of subjective well-being in line with other studies concerning digital good consumption. If the treatment could act in a direction towards behavioural change of smartphone use, and of social media, we want to measure whether the change in consumption of digital goods has a mediating role with well-being measures.

***Happiness**: «Taking all things together, how happy would you say you are?».*

People were instructed to text back their answers on a scale from 1 (Extremely unhappy) to 10 (Extremely happy), which we coded, respectively, from -1 and 1 passing through at each of the ten steps for the SWB index construction.

***Loneliness(-1):** «During the past week, how much of the time have you felt lonely?».*

Possible answers are coded ranging from None of the time (0), Almost none of the time (0.25), Some of the time (0.5), Most of the time (0.75) to All of the time (1).

Activities: From the question activities, we took some of items which are related to subjective well-being, the question is *«How much time do you spend.. »* and we considered the following items for the construction of the welfare index: *Exercising*, *Eating unhealthy food(-1)*, *Sleeping*, *Spending time with friends*, and *Spending time with family*. Answers were coded as "too little" (-1); "just about the right amount" (0); and too much (1).

Smartphone Addiction Scale(-1): We use the scale adapted from Lopez-Fernandez (2017), which was quite appropriate for cross-country comparison, as it is the case for our study. The addiction scale comprises 10 items, and it is a shortened version if compared to others used for similar studies (Andreassen et al., 2012; Bianchi and Phillips, 2005; Griffiths, 2005). In essence, the core reason for using such scale is to relate the use of the smartphone to the six elements which embeds addiction: salience, mood modification, tolerance, withdrawal, conflict, and relapse. Questions initiate with *"In the past two months, how often have you"* and include elements such as *"Missing planned work due to smartphone use"* or *"Constantly checking my smartphone so as not to miss conversations between other people on social media"*. Each of these questions was coded ranging from answering *Never (0)*, *Rarely(0.25)*, *Sometimes(0.5)*, *Often (0.75)*, and *Always (1)*. The resulting Smartphone addiction scale is the sum of these components, and it is valued as negative about the computation of the Welfare Index. The complete specification is available in Appendix III.

FOMO Scale (-1): For measuring Fear-of-Missing-out, we use the validated scale version of Przybylski et al. (2013) adapted with elements from (Abel et al., 2016), which resembles the salience of social anxiety, self-esteem, and social interactions. The FOMO scale that we will make use of is available in Appendix III, and it comprises a list of ten items. Each of these questions was coded ranging from answering *Never (0), Rarely(0.25), Sometimes(0.5), Often (0.75), and Always (1).* The sum of the scores reflects the extent of FOMO. As for the Addiction index, the FOMO scale is valued negatively for the computation of the Welfare Index.

Welfare Survey Index: The Welfare Survey Index score of a respondent is defined as the sum of its components weighted by the inverse-covariance matrix as in (Anderson, 2008). The elements included are the items within the SWB index, the Addiction scale, the FOMO scale, and the elicited Ideal Use Change.

Activity-Passivity Social Media Scale: We generate an activity-passivity social media scale within the survey. We do this by asking to answer a battery of 12 questions from a list of activities which can be considered as "Active" (A) or "Passive" (P) while using social media. The full list is in the Appendix III. Each of these questions was coded ranging from answering *"Never"* (-1), *"Rarely"* (-0.5), *"Sometimes"*(0), *"Often"* (0.5), to *"Always"* (1). Accordingly, we provide an average of the scores. The activity and passivity scale ($A_i \in [-1, 1], P_i \in [-1, 1]$) is hence the average score among the active and passive components, respectively.

2.3.5 Other Variables

Here, we refer to the creation of additional relevant variables that can serve as mediators in our analysis for hypothesis testing. We aim to assess whether there is also an injunctive effect of the social norm regarding "smartphone use" by creating a composite index for it, the Injunctive Norm Strenght (ISM). The ISM includes elements adapted from both LaBrie et al. (2010), and Baer (1994). Their application was concerning a similar addictive behaviour. That is, binge drinking. It is worth noting that this question was not included in the pilot testing. Accordingly, this variable will be crucial in testing whether the underreporting of own smartphone screen time can be related to normative pressures from relatives. Finally, we collect information about the in, and out-degree of the two most used SMP, TikTok and Instagram, within a directed network structure. We do the same for the platform with an undirected network structure, Facebook, by asking the number of friends.

Injunctive Norm Strength (ISM): *Imagine that the people in your life are aware of your daily habits, including your social media use. How would the following people react if they knew that you were using social media about six hours per day?*

- Parents or Caregivers.
- Closest friends

- Friends from your course of study.

People were instructed to text back their answers on a 7-point scale from Very uncomfortable (1) (not at all) to strongly comfortable (7).

Followers: (From the survey): *On social media, how many of the following do you have?*

- *Instagram followers (following) [NUMERIC]*
- *TikTok followers (following) [NUMERIC]*
- *Facebook friends [NUMERIC]*

Socio-Demographic Controls: When performing a regression, we will control for the following variables, whose values are shown in Table 1: *Gender*, *Age*, *Country (NUTS-1)*, and *Parents' Education*.

2.4 Hypotheses and Results

We divide the empirical analysis of the paper into two parts. The first part shows the existence, and the relationships linked to misperceptions, which is purely observational and associative. The second part shows the channels at which the policy intervention through Information generate treatment effects among subjects, accompanied by the moderators. In particular, we show that treatment effects can be measured in terms of interaction with key variable concerning misperceptions, which is robust to the inclusion of the interaction between social media variables (i.e. Activity in Social Media and Instagram followers) with the treatment assignment. In the appendix V instead, the focus is on the methodology employed to test our hypotheses subsequently concerning the the follow-up analysis.

Finally, for enhancing robustness in the results, we drop-out of the analysis the subject that we considered as "defiers" in responding to the survey. In particular, we dropped-out those who declared of having zero hours of screentime, those who have a misperception of the own use higher than 2.5 standard deviations of the mean. We dropped these observations out as we considered these options as unrealistic. The resulting sample characteristics are highlighted in Tables 1 and 2. In the main study, we plan to drop, as further robustness check, the 5% of respondents who responded to the survey the fast, remove or interact with students who did not upload the screenshot, remove or interact with students who did not pass the attention check, and using population weights if the sample is not balanced[14].

2.4.1 Hypotheses concerning Misperceptions

H1 Misperception about others smartphone use: The first hypothesis concern the existence of misperception of reference group usage. Namely, the existence of an asymmetry in perceptions about peers' smartphone use. In detail, peers' smartphone usage tend to be overestimated concerning their smartphone use in absolute terms. Define $E(S_j)$ as the expected time spent on smartphone by the reference group for individual i^{th} individual. It is worth noting that individual i, which belongs to our sample $N = (1, \ldots, i-1, i, i+1, \ldots, n)$ forms perceptions based on local projections of her reference group j, with $j \in N_i \notin N$ which may be referred as real-life and virtual friends of the i^{th} respondent (N_i). In this sense, the expectations by i over j constitute the perception about reference group objective $(\overline{S}_j)$ social media use, which constitutes the empirical expectations of our subjects over the -descriptive- norm. Define the reference group social media use by the population S_{-i}, which constitutes the actual descriptive norm. Hence, we define the Misperception of social media use $M_i(S_{-i})$ as the difference between the ex-ante elicited perception about reference group usage and the actual difference. H1 can be seen as a (positive) asymmetric distribution of the misperceptions (in terms of the true value) of our population target concerning

[14] Due to limited observations, these procedures were not possible at this stage given the limited sample size.

their reference group as follows:

$$M_i(S_{-i}) = \frac{\left(\mathbb{E}(\overline{S}_j) - S_{-i}\right)}{S_{-i}} > 0, i \in N, j \notin N \tag{2.2}$$

To test this hypothesis, we employ a non-parametric test by plotting, for each respondent, the wedge between the subjective perception of smartphone use concerning reference group usage ($\mathbb{E}(S_j)$) against the value of the norm (S_{-i})=*5.2 hours*, which was obtained by a survey of the GWI[15]. The results are shown in Figure 2.4.

[***FIGURE 2.4 ABOUT HERE***]

From Figure 2.4 we can see a clear overestimation made by the majority of the sample. In detail, the average misperception about reference group usage in our sample is about 43.3% of the actual value.

Drivers that are associated to reference group overestimation (or underestimation) in general is a goal associated with this family of studies (Bursztyn and Yang, 2022). The possibility of understanding the consequences of misperceiving others' behavior creates also the base for an intervention aimed at correcting the behavior of those who are misperceiving it.

Accordingly, a first claim that can be advanced is whether this error in estimating others' behavioral norm is associated with own attitudes and behavior accordingly. To understand this source, we want to understand whether the misperception about others can be linked with excessive smartphone use. In Figure 2.5 we plot the relationship between the own reported screen time and the Peers' misperception already shown.

[***FIGURE 2.5 ABOUT HERE***]

[15]We remark that in the main survey, we changed this value to the median value of the reported screen time in the pilot testing phase (S_{-i})=*4.5 hours*.

Figure 2.5 shows how that the correlation between peers' overestimation and own screen time use is non-negligible *(corr = 0.38)*, which may indicate that there is a complementarity effect between others' expectation behavior and own attitudes concerning the norm. Although this result exhibits a strong relationship between the two variables, a casual analysis is needed to explore the actual extent of which correcting misperceived information could actually push towards intention to treat in reducing the smartphone consumption. We better explore this aspect in the Section 2.4.2 where we explore the information treatment baseline effect in revising consumption, proxied by the ideal use change variable defined in Section 2.3.4.

H2 Misperception about own smartphone use: Similarly to H1, we provide an hypothesis which could help us to better understand whether there is a source of asymmetry behind the perception of own usage. In this sense, we conject that individuals have an asymmetry towards underestimation of own use. If this hypothesis is true, we attempt to justify it through the main survey by relating it with the strength of social pressure to the i^{th} respondent, through the ISM variable as earlier mentioned. Accordingly, H2 can be summarised as:

$$M_i(S_i) = \frac{(\mathbb{E}(S_i) - S_i)}{S_i} < 0 \tag{2.3}$$

We test H2 by plotting the distribution of the wedge between perception and the actual value, as for H1. Figure 2.6 shows us the results.

[***FIGURE 2.6 ABOUT HERE***]

What we can see is that our sample is divided between the majority that overestimates the own smartphone use (57%) and a still consistent fraction which underestimates own use (36%), with around 7% of our sample that have correct guesses concerning their own use. The own smartphone use misperception has an average of 29% (median 8.6%) of overestimation of own use. Accordingly, we reject the hypothesis that users systematically underestimate own use. However, it is worthwhile to check the relationship between the own perception about own use and the own attitude, as we did for H1. Namely, the relationship between the own misperception and the own screentime use. We check this by showing the scatterplot between the two variables, and the results are shown in Figure 2.7.

[***FIGURE 2.7 ABOUT HERE***]

The graph shows how, as smartphone consumption increases, respondents have a tendency to underestimate the own smartphone consumption, which partially supports our initial hypothesis. However, there is not a systematic relationship with underreporting. Rather, underreporting of own smartphone use is more frequent among those who have higher usage *(corr= 0.41)*, as opposed with the Peers' estimation, which is associated with overreporting.

The findings, as for now, suggest a great deal of relationship between own attitudes and the direction of the misperceptions. The latter is true for both case, own and others' use. Overall, a challenge within these family of studies analysing misperceived outcomes concerns in finding their source, and especially if interventions aimed at correcting them work as intended. Namely, in our case the targeting goal is to embrace a willingness to reduce consumption, especially for those who can be considered as "heavy users". We devote the remainder of this part to find plausible explanation of the misperceptions, and the following part whether intervention aimed at correcting them work as intended.

H3 Misperception about others use: The Friendship Paradox: The relationship between Peers' Misperceptions and the Friendship Paradox can be a meaningful hypothesis for testing a possible "natural" explanation of the phenomenon arising from the social structure. The conjecture is that the Friendship Paradox, especially in directed network social media structures (e.g. Instagram, X, TikTok) compared with undirected SNS network structures (e.g. Facebook) can be strongly associated with someone experiencing misperceptions since the probability of being exposed to heavy users could be higher. To test H3, we do not have a network of relationships and activities of the friends of our respondents. However, previous studies found that there is a strong (negative) relationship between the in-degree of the respondent (the number of followers) and the probability of being exposed to it (see for instance Alipourfard et al. (2020)), namely those who you follow have more followers than you, and this probability is decreasing with the in-degree of a respondent. As an identification proxy, to be relevant in information aggregation, influential nodes (those with the highest in-degree) should be also the ones who have the highest level of activity.

We check this by testing the relationship between in-degree of a respondent (proxied by the self-reported number of followers on Instagram), and the activity components of the index, which are indexed in section Appendix III. We also reasoned that higher out-degree is associated with the passive components of the index, which comes from the same index. The explanation is that more out-degree signals a willingness to watch passively others' contents. Whether, higher in-degree can proxy social effort in establishing connection, which we connect to the taste of being active social media.

We chosen to explore this relationship with the Instagram information since it is the social media most used among our respondents, as it can be observed from Figure 2.8. The empirical strategy concerns performing a simple OLS regression with the following structure:

$$\theta_i = \beta_0 + \gamma\, ln(IG_i^{fs}) + \rho\, ln(IG_i^{fg}) + \beta \mathbf{X_i} + \epsilon_i, \;\; \theta_i \in \{A_i, P_i\} \tag{2.4}$$

Where $A_i(P_i)$ refers to the average of the scores of the Active (Passive) actions that a respondent reported to do, and $ln(IG_i^{fs(fg)})$ are the log-transformation of the self-reported followers (following) that an user has on Istangram. We chosen to use a log transformation since we assume a decreasing scaling effect as the number of both in and out degree increases. Finally, $\mathbf{X}_i$ comprises the socio-demographic controls listed in Section 2.3.5.

The results of Activity in social media in equation (2.4) are shown in Table 3 for the active use of social media with different specifications:

[***TABLE 3 ABOUT HERE***]

The log transformation coefficient implies the associative effect of increasing roughly by 2.7 times the number of followers (following).

We can see a strong positive connection between the way of using social media and the in-degree of the respondent in the same platform, which is robust to all the specifications. An interpretation can be that the perceived value of being active on social media platform increases as the number of people who can visualise your content produced increases. Conversely, having higher out-degree is associated with lower active engagement in the Instagram social media platform. It is worth noting that the relationship in this case is weaker. The standardized coefficient, concerning the in(out)-degree in the third specification, indicates an associative increase of S.D. 0.33 (-0.12) points, which indicates a small-to-medium (small-to-none) association size.

Hence, this descriptive evidence can argue that active users are likely to be also be among the popular users who propagate information. As a robustness check, in Table 4 we also check whether there is a relationship with the passive variables. Accordingly, the relationship in this case is non-exisiting for the in-degree case, which strenghts the argument in favour of the activity hypothesis. Meanwhile, the higher the out-degree, the greater the association with a passive use of social media, which is coherent with our previous explanation, and of results in 3.

[***TABLE 4 ABOUT HERE***]

If active users tend also to be the more popular, a statement that can be made is about the relationship between active users and the misperception direction. That is, if the active users will also tend to misperceive more others' use (in overestimating), a statement that can be made is that there is assortativity between active users. In other words, active users could be connected, in out-degree terms, with other active users and then have misperceived belief about the population, but not about their sample. Otherwise, if non-active users, who can be regarded as "non-popular", have higher misperceptions, the relationship goes from passive users who observe the content produced by active users, hence forecasting a higher usage in the population. We test this relationship by connecting the peers' misperception wedge to both the active and passive components of the Activities in Social Media index with this OLS specification:

$$M_i(S_{-i}) = \beta_0 + \rho A_i + \varphi P_i + \beta \mathbf{X}_i + \epsilon_i \tag{2.5}$$

where $M_i(S_{-i})$ is defined as from (2.2), A_i and P_i are the active and passive component defined in Appendix III. The results of specification (2.5) are shown in Table 5.

[***TABLE 5 ABOUT HERE***]

From Table 5, we observe a considerable relationship between overestimating others' usage and being active on SMP, which is robust to all the specifications. Part of the result is explained by the baseline smartphone use which, if not controlled for, would lead to an overestimation of the effect size of being active. Interpreting the result, it could be the case that active users may tend to interact with other active users, implying an assortativity in the relationship of the usage. We cannot directly test for this relationship, as already said. However, some formal interpretation can be linked to the Assortativity Neglect Equilibrium (ANE) in Frick et al. (2022). That is, active users are such because they are matched with other active users. Hence, by observing mounting activity in their social media feed, they may forecast a higher usage of their sample, which implies an overestimation of their reference population accordingly.

The latter statement could be combined with the fact that Peers' Misperceptions have a non-existent association with the passive activities reported. However, the results in Tables 3, 4, and 5 should be taken with a grain of salt since if we do not have an exact network structure (as in our case), peer-effects are not identified. Hence, no causal claims can be advanced from the results.

H4 Misperception about others use: FOMO **(To be tested in the main Baseline Survey)**. The hypothesis concerning this relationship regards the identification, in a different manner from the FP hypothesis, between the FOMO and Peers' Misperceptions. In particular, the interpretation here is that, by expecting a higher usage over others' use in SMP, a user is likely to check more often the smartphone to avoid missing out on the content posted by the peers. Hence, the main idea is to test whether there is a positive relationship between the FOMO index, whose components are defined in Appendix III, and the Peers' Misperceptions defined in equation (2.2).

$$M_i(S_{-i}) = \beta_0 + \rho FOMO_i + \beta \mathbf{X}_i + \epsilon_i$$

Where ρ is expected to be greater than 0 according to the FOMO hypothesis. $M_i(S_{-i})$ is defined as in (2.2), and $\mathbf{X}_i$ is the usual set of controls from Section 2.3.5.

H5 Misperception about own use; Injunctive norms (**To be tested in the Baseline Survey)**: The idea here is to check the existence of a channel which justifies the existence of misperception in underreporting own screen time usage, hence explaining H2. In this case, the idea is that a person who feels social pressure in "not" using the smartphone in certain places (hence, normative pressures), would tend to underreport its own use. The latter would be an interior mechanism to not feel the fear of social sanctions from others. Hence, H5 can be summarized as a "positive" relationship between the strength of the Injunctive (Normative) norm, and the level of underreporting of the own use of the smartphone.

We test this by re-adapting a question from Baer et al. (1991) which was aimed at testing the strength of the injunctive norm of binge drinking for US college campus students. From the survey, we begin by asking to respondents imagining that some key figures (i.e. Parents, Intimate friends, and University Peers') in their life can observe their consumption of social media, and how they would react accordingly. The ISM strength is the average score of the three items listed in Appendix III. Hence, H5 hypothesizes a negative relationship between this measure and the own misperception of smartphone use. That is, the more uncomfortable would feed the people close the more you have a tendency to under-report your consumption. In other words, by defining ISM_i the injunctive norm strenght of the i^{th} respondent, we test this relationship as follows:

$$M_i(S_i) = \beta_0 + \rho ISM_i + \beta \mathbf{X}_i + \epsilon_i$$

Where ρ is expected to be lower than 0 according to this hypothesis. $M_i(S_i)$ is defined as in (2.3), and $\mathbf{X}_i$ is the usual set of controls from Section 2.3.5.

2.4.2 Hypotheses concerning Information treatment: Baseline Analysis

At the baseline survey, we test the short-run effect of providing truthful information to our subjects concerning peers' smartphone use, namely the social norm treatment. We distinguish between subjects who received the information about own consumption only and subjects who received information about peers' consumption, which in our empirical estimates we define as a dichothomous variable $D_i \in \{0, 1\}$. Either the own and own+peers' groups compare this information with their perception.

We outlined in Section 2.3.3 the way through which the I treatment should act to direct a change in the behavior. Here, we provide some evidence of the respondent' reaction to the information treatment provided. Finally, before proceeding, it is worth to note that, during the pilot phase, we cannot measure the self-reflection effect directly in our subjects since we do not have the pure control group. At the pilot stage, we can only measure the information treatment effect of showing the peers' smartphone consumption.

The first element to explore is whether the intervention targets heavy smartphone users in declaring a willingness to change behaviour. Hence, when showing the information, we ask to respondents what is the corresponding ideal screen time that they would like to have. Respondents' may either declare a willingness to increase or reduce consumption. Figure 2.9, in the top panel, shows the corresponding relationship with screentime.

The nice feature from the top panel of Figure 2.9 graph is that, irrespectively of the treatment group, is that we can observe a relationship, as the screentime increases, in willingness to reduce consumption. Furthermore, looking at the bottom panels of Figure 2.9, we can see that another moderator is at play, irrespective of the treatment assignment. Namely, there is a marked difference in declared ideal use change between those who were underestimating (left-panel) and overestimating (right-panel) their smartphone consumption. The different reaction is intuitive: those underestimating their consumption are faced with the true information that actually are consuming more than they actually thought to do. Accordingly, the reaction is to desire an adjustment which aims at correcting the consumption to the point of the own expected behaviour. Meanwhile, those who were overestimating their consumption they may not have the same attitude, given the fact that they are consuming less than they thought. At the same time, in the bottom panels of

Figure 2.9 is difficult to detect an exact relationship with the peers' overestimation (Y-Axis). For instance, we aim at checking, conditional on the social norm treatment assignment, whether those who were overestimating the most are keener to reduce their consumption pattern, compared with those who did not received such information. The latter will be our ATE estimation.

[***FIGURE 2.9 ABOUT HERE***]

We investigate this factor by running a linear regression and, as a dependent variable, we use the Ideal Use Change, $\Delta C^*_{i,1}$, defined at $t = 1$ in (2.1) Section 2.3.4. Our main specification is the following:

$$\Delta C^*_{i,1} = \beta_0 + \gamma D_i + \rho M_i(S_{-i}) + \varphi D_i \cdot M_i(S_{-i}) + \mu M_i(S_i) + \varsigma SM_i + \beta \mathbf{X}_i + \epsilon_i \quad (2.6)$$

Where $\Delta C^*_{i,1}$ comes from Section 2.3.4, $M_i(S_{-i})$, and $(M_i(S_i))$ are defined in equations (2.2), and (2.3), respectively. SM_i instead, refers to the self-reported baseline use. Finally, D_i is the Social norm treatment assignment described in Section 2.3.3, and shown in Figure 2.3. The social norm treatment effect is measured through the coefficient φ, which considers the interaction effect between the treatment assignment (D_i), and the Peers misperception wedge $(M_i(S_{-i}))$. One may wonder why the treatment effect could not be measured by the treatment assignment solely. Accordingly, we argue that an effect on willingness to revise consumption, proxies by our dependent variable, does not depend on visualizing peers' information per se. Rather, it is strongly connected to the ex-ante empirical expectations concerning the information shown. That is, controlling for all the relevant covariates, as in (2.6), the ATE is increasing in the higher ex-ante overestimation of our respondent.

The results of (2.6) are shown in Table 6.

[***TABLE 6 ABOUT HERE***]

From this specification, we are able to quantify the causal effect of the I treatment. On one hand, the coefficient of D_i shows how there is a null effect per se of showing the peers' smartphone consumption average on the willingness to revise own consumption. The latter is coherent with our argument concerning the peer' effect channel.

On the other hand, our measure of ATE is given by the coefficient φ, which is the interaction between the Peers' Misperception wedge, in percentage terms, and the treatment binary variable. For instance, we can observe that, for each 1 p.p. of overestimation of Peers' usage $(M_i(S_{-i}))$, having corrected the misperception (D_i) corresponds to a willingness to reduce smartphone consumption by 0.114 % in the (4) specification, which includes all the controls. The latter, in S.D. units corresponds to an ATE of -0.119, with a 95% of ATE $\in [-0.211 - 0.028]$. We may see this result as an estimation of the perceived overusage due to complementarity effects in others' usage: Once respondents' are faced with true information concerning reference group usage, they are keener to reduce consumption accordingly, conditional on having overestimated the reference group usage.

In terms of policy implications, the immediate effect of having a comparison between your usage, and the reference group (or population in general) corresponds to an affirmative reception of the respondent, conditional on an overestimation of the ex-ante expectations of reference group usage. That is, if a sole snapshot of your consumption comparison has an effect, a more pervasive exposure[16] to this information would lead to greater treatment effects. The latter, surely, it can be a channel to be better explored in future research.

We further investigate this effect, as a robustness check, by checking whether there is some heterogeneity by dividing the sample in below versus above the median of

[16]For example, this can be achieved by showing the information contained in Figure 2.3 when unlocking the phone, in the home screen.

some key variable related to smartphone use. In Figure 2.10 we show the ATE results of specification (4) in Table 6, where the red (black) CI refer to the below (above) the median population of the referenced variable.

[***FIGURE 2.10 ABOUT HERE***]

In Figure 2.10, we can notice that the effect of correcting misperceptions, conditional on the imprecise expectations, is higher and non zero for the users below the median of most of the variables considered. While there is not a significant difference between having under or overestimated the own use (second graph from the top), users who have lower Baseline use of smartphone, Addiction Index score or are less actively engaged on social media, and have a fewer followers on Instagram have a higher willingness to reduce smartphone consumption upon receiving the peers' information treatment. We can interpret the latter as that the misperception is clearly not the only source of having consumed more than intended digital devices, as the literature clearly states, but rather it can be a further channel which, up to date was not explored. For instance, two different interpretations can be given to the results in Figure 2.10, which can be applied according to the variable considered. On one hand, users who have higher screntime, and higher addiction, can be revealed as addiction constraints, in the sense that the perceived self-efficacy on reducing consumption is lower among the subjects who have a higher habit formation (i.e. *Baseline Use*), or/and have a higher self-control problems (i.e. *Addiction Index*), which is at the base of the Allcott et al. (2022) findings on addiction concerning digital products. Another explanation, which was unexplored up-to-date (to the best of our knowledge) is that those who are above the median of some variables concerning social media variables (i.e. being an active user in SMP and/or having higher in-degree) value higher the smartphone usage, hence generating a further constraint in reducing smartphone consumption.

We further show, in Table 7, that the ATE conditional on having misperceived peers' usage is robust to including other possible sources' of correction. For instance, in all of the specification neither of the interactions between the Treatment and being Active on Social Media ($ActivitySM \cdot D_i$), and the log transformation of Instagram followers ($ln(IG(fs)){\cdot}D_i$) are not as relevant as the ex-ante peers' expectations in the decision of either reducing or increasing consumption. Conversely, we can see that being actively engaged in SMP ($ActivitySM$) per se is a significant constraint in not reducing consumption, as for the Own Misperception ($OwnMisp\%$) that play a relevant role in reducing (or not reducing) the current consumption pattern.

[***TABLE 7 ABOUT HERE***]

As just discussed, being actively engaged on SMP ($ActivitySM$) could be a constraint in reducing consumption can be interpreted as users who are mostly active perceive greater welfare gains. Hence, not willing to revise consumption. When considering the difference between overestimating (i.e. $OwnMisp\% > 0$) and underestimating consumption($OwnMisp\%$ <0), the effect size varies.

For instance, in Figure 2.11 we plot, in S.D. units, the coefficient size of some of the relevant covariates distinguishing between those who underestimated (in red) or overestimated (in black) their own use, using the specification **(4)** from Table 6. For instance, the $M_i(S_i)$ varies according to the direction of the misperception. Namely, combining both the results in Figure 2.9, and the effect size in the Figure 2.11, 1^{st} panel in the bottom figure, we can notice that respondents who had an overestimation of their own consumption (i.e. $M_i(S_i) > 0$) have an opposite direction concerning those who underestimated the consumption (i.e. $M_i(S_i) < 0$). Namely, overestimation is related to a resistance in willingness to reduce consumption, while underestimation is greatly associated in willingness to reduce consumption, even if of a lower magnitude than the former.

Furthermore, increased baseline screen time plays a higher effect in those who underestimated consumption, coherent with the correlation between the underestimation of own use and the baseline screen time. While, for the ATE ($M_i(S_{-i}) \cdot D_i$), and the rest of the variables included, it may be noticed that there is no substantial heterogeneity. Please, notice also the reduced sample size, and that at this stage robustness checks are not valid as they would be in the main baseline analysis. To show the latter fact, in Figure, 2.12 we show that heterogeneous effect by gender (top figure) and by country (bottom figure) are difficult to assess due to the limited size (and representativeness) of our sample. For instance, the results that we presented are mainly driven by the female population (top-panel of Figure 2.12), which yield intuitive relationships between our explanatory, and treatment variables. Conversely, when taking into account country heterogeneity, it is evident that our results are mostly driven by the countries with greater representativeness (i.e. *France*, *Italy*, and *Poland*).

[***FIGURE 2.11 ABOUT HERE***]

[***FIGURE 2.12 ABOUT HERE***]

2.5 Conclusions

This paper studied, and assessed, the existence of misperception of smartphone use, and its relationship with the behavioural attitudes. Moreover, we included in our novel survey an intervention which was aimed at correcting misperceptions among our respondent. Accordingly, we found that the effectiveness of the intervention is strongly dependent on the ex-ante expectations about reference group norm, and on personal attitudes towards the norm itself.

The analysis was focused on the pilot results of the baseline analysis of our survey. We found evidence of misperceptions concerning both the reference group, and own usage. Namely, 74.1% our respondents' overestimates how much their reference group makes usage of smartphone by 43.3% on average (including underestimations). While, concerning their own use the direction goes in either directions: 57.59% of our respondents overestimates their smartphone use, with 6.9% of correct guesses[17]. Furthermore, we shown that perceptions concerning both own and peers' norm is correlated to own attitudes: for instance, higher smartphone use is correlated with higher (under)overestimation of (own) peers' usage. Both relationships are coherent with our hypothesis. We tried to describe respondents through some further hypothesis, which were connected through aspects of their social structure, and the way of using SMP. Namely, through mere association, we described that active users in SMP may be such because of their higher in-degree. However, it could be also the reverse. That is, higher in-degree is function of being active, which would be inherently correlated with some unobserved respondent characteristics (e.g. higher social effort in real life). Furthermore, active users are also more likely to misperceive upwards others' use, suggesting an assortative mating between active users, according to our theory. Notwithstanding the missing causal link, it is true that active users in SMP they value higher their use of the smartphone. For instance, they are less willing to reduce their consumption of smartphone. This result, combined with the findings in Allcott et al. (2022), may provide an additional explanation concerning the welfare gain sources in using digital products.

Concerning the social norm intervention, we found that showing the truthful reference group information induced a willingness to reduce consumption among those who were overestimating their reference group smartphone use, with an Average Treatment Effect of 0.119 S.D. units, while having received the information solely does not have an effect. The latter is coherent with preceding research concerning

[17]Notice that this value is connected to the self-reported values of screen time statistics. Hence, by using imputed values from Appendix I.2, the own misperceptions statistics may vary accordingly.

that the behavioural change is conditional on ex-ante expectations concerning the norm (Bursztyn et al., 2020). We showed that this result is robust to alternative sources of willingness to change like being more an active-content user on social media, or having a higher number of followers on Instagram, the most used platform among our subjects. The latter result opens a novel way on treating the problem of extensive smartphone use among our reference population. That is, if smartphone use is also dependent on the expectations over others' use, then policy implications should focus in making this information more pervasive across devices. For instance, around 90% of our sample is aware of the existence of the screen time digital wellbeing & parental control tools (Figure IV.8). However, the majority of our respondent does not have concrete expectations concerning either the own, or the others' use.

This study contributes to the literature of misperceived social norms identification, and intervention. We do this by providing an unexplored context where this phenomenon appears and, concurrently, we provided a mean to correct them by looking at the average treatment effects. Finding that it is increasing in function of the ex-ante misperceptions. Furthermore, we contributed to the literature in digital addiction, by finding that there may be further sources in consuming more than intended the digital goods, which originates from social covariates, and perceptions on them.

Finally, this study presents some limitations, which are mostly related to the nature of our sample. Namely, we have a sample which is unbalanced in terms of gender (over 70% of the sample is made by females), which may drive our results. Furthermore, the sample size is limited ($N = 665$), which refers to the sample of the baseline pilot test. Accordingly, upon availability of the main baseline sample (i.e. $N = 12000$ expected in May 2025), we can have a higher confidence concerning ATE's, and especially concerning heterogeneous treatment effects. Furthermore, this study does not explores the follow-up persistence in effects concerning smartphone use. Accordingly, respondents who have declared a willingness to reduce consumption in our baseline, it is not guaranteed whether they would actually follow their revealed intentions. For instance, information treatment studies are mostly known to be well-performing in the short-run, while the medium-run effects are not as strong (see Haaland et al. (2023); Stantcheva (2023); Bursztyn and Yang (2022)). However, the short-run effects tells us something about a further source of extensive smartphone use. That is, the complementarity effects conditional upon others' use. Hence, if the latter is true, a possible effective policy is to make more pervasive this information. For example, by applying a widget in the home screen of the users', such that they are forced to see their own comparison with the reference group.

In these respects, further research could go in the following directions. First, the Friendship Paradox channel is an important avenue to see whether social network structure (i.e. in,out-degree individual characteristics) can be casually linked with perceptions concerning reference group usage. For example, the fact of being assortative matched with other active users can be identified as a source of mispercpetions about reference group use, we can identify the casual link between misperception and extensive smartphone usage, provided independence with smartphone use between active, and passive users.

Second, this work has provided an assessment the effectiveness of exposing our respondents' to truthful information on reference group usage. However, while the short-run effect are identified, there are no results yet concerning its persistence in the medium run (i.e. one month later). For instance, the intervention pervasiveness is very low, and information treatments are generally known in performing well in the short-run, while in the medium-run if not accompanied by qualitative/pervasive measures (e.g. Vignette studies), the effect tend to be reduced over time. Accordingly, further area of research may be aimed at checking whether a higher exposure over time to this information is more effective in reducing smartphone consumption over time.

Third, the empirical results provided here could be developed here to explore whether, by employing a deviation from the Jackson (2019) framework, we are able to explain the reason why users', given their taste fro social media, may be more active through the exposure to other active users'. For instance, the action of being active in SMP may depend also on the in-degree, where users tend to give higher value to being active. Furthermore, their action could be distorted by the fact of being assortatively matched with other active users (in out-degree terms), hence providing a novel explanation of differentiated behaviour among SMP users.

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Figures

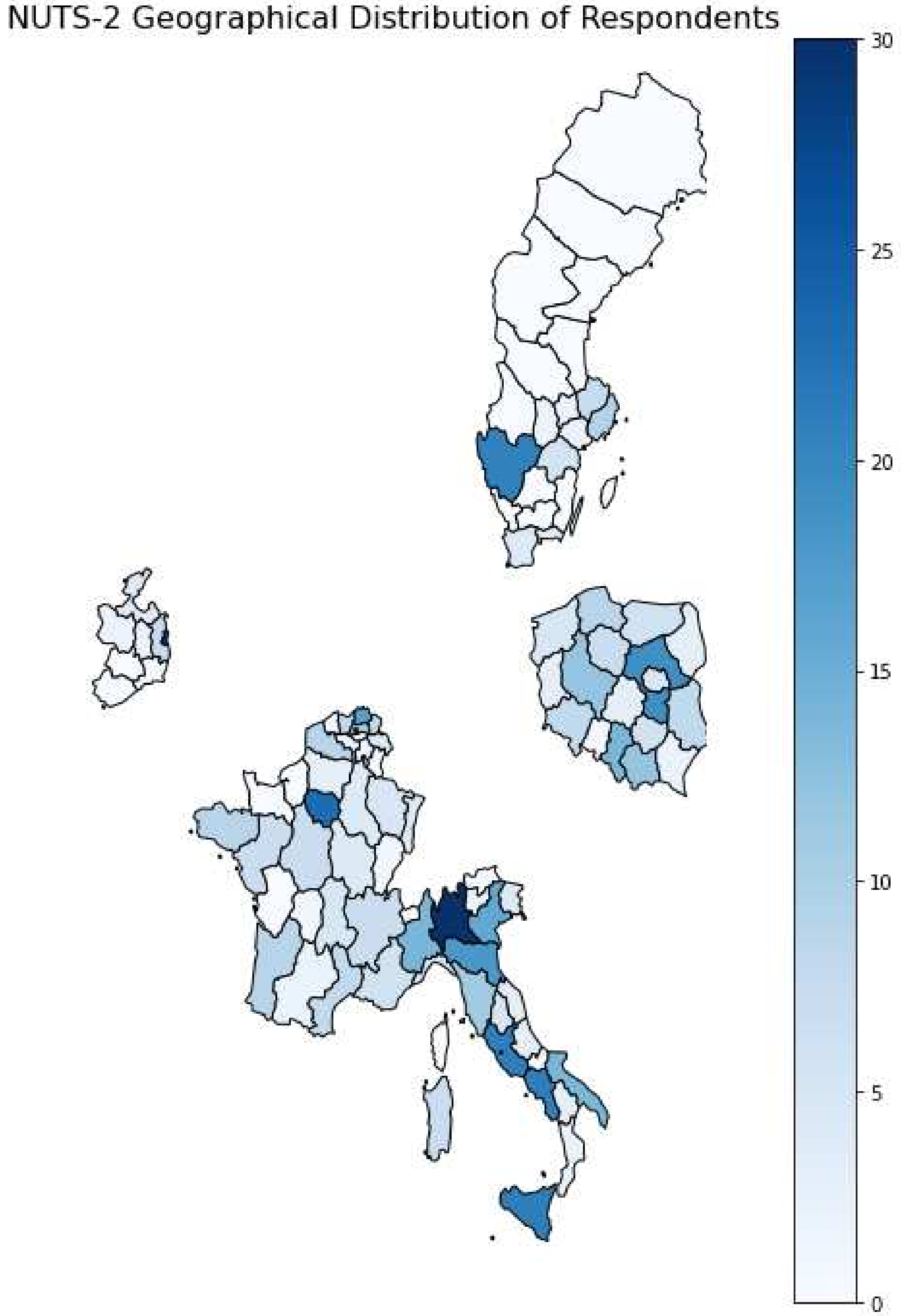


Figure 2.1: *This figure shows the geographical distribution of the pilot sample at the Nuts-2 level. Notice that, in the main baseline analysis the countries "Ireland" and "Poland" will be replaced by "Germany" due to panel provider availability.*

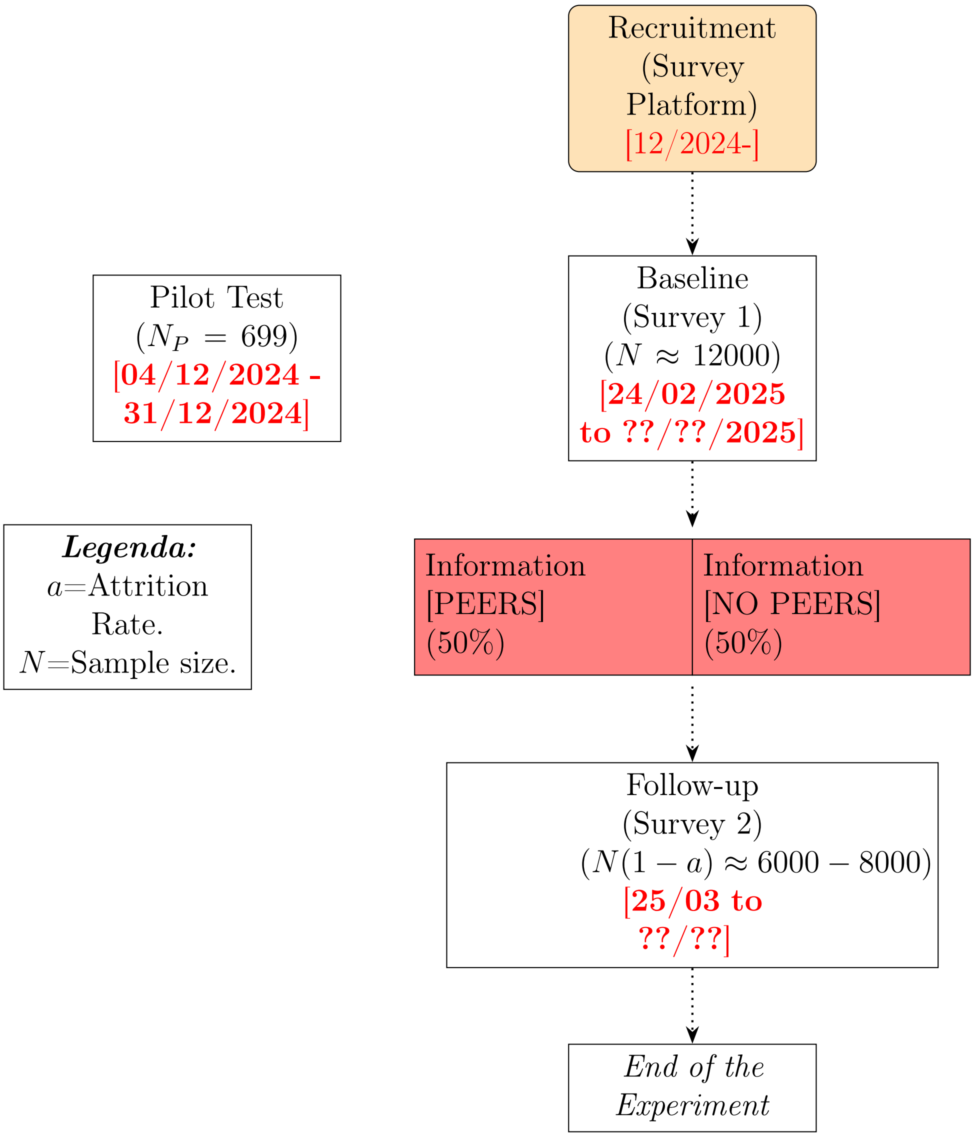


Figure 2.2: *Experimental Structure and Timeline. Exact ending dates will be updated accordingly.*

Figure 2.3: *Information Treatment Visual Overview for (top-panel) peers' social norms treatment, and (bottom-panel) the own-reflection (active) control group. The box in the right side of the peers' treatment is designed to place a score compared to the norm and to avoid backfire effects on the treatment who place themselves below the norm, as in Allcott (2011).*

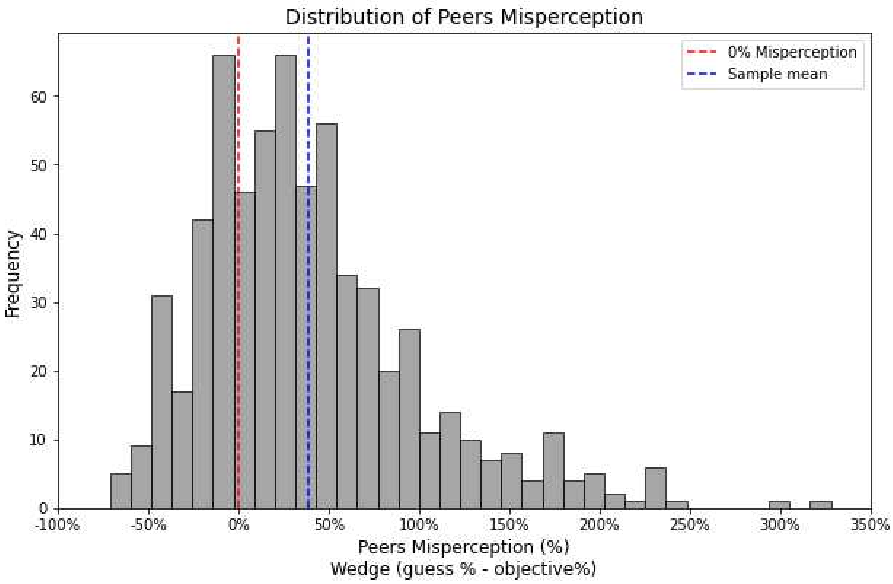


Figure 2.4: *This figure shows the distribution of the answer to the question :«How much time do students of your age use their smartphones daily? Provide your best estimate in hours and minutes ». The 0% point refers to the reported average for a survey conducted by the Global Web Index (GWI) with a similar population. The x-axis values are defined from equation (2.2). The sample mean displayed amounts to* 43.3%. *The Peers' Misperception variable is divided between* 74.14% *of users overestimating their reference group use, and* 25.86% underestimating it.

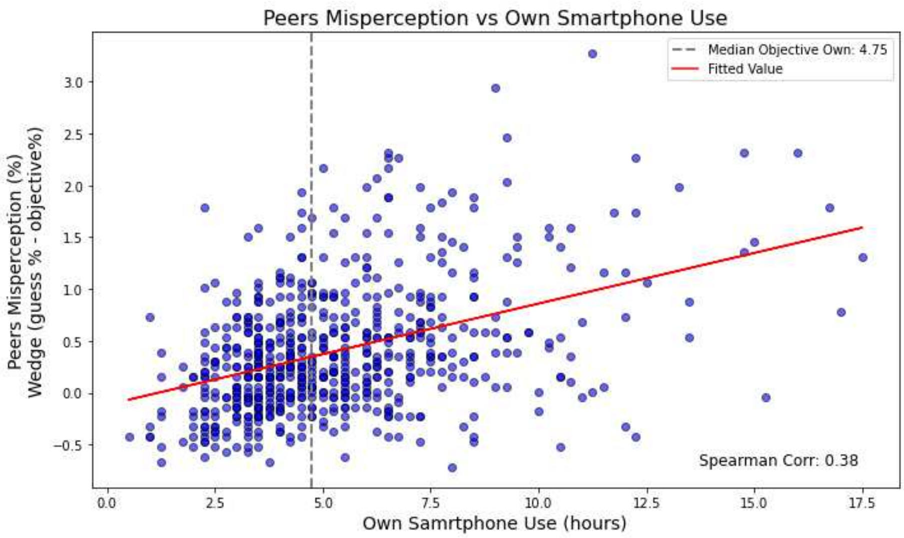


Figure 2.5: *Scatter plot showing the relationship between the Misperception of Peers' (y-axis) (Equation (2.2)) and the own self-reported screen time (x-axis). The gray line shows the median value of Own reported screen time, while the red line represents the fitted line between the two variables, which exhibits a positive relationship (as shown from the Spearman Correlation in bottom-right side).*

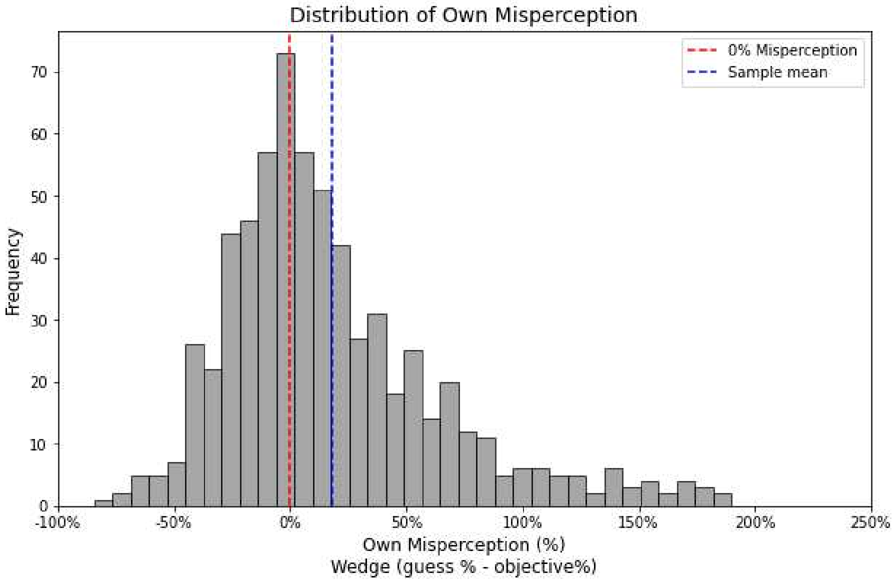


Figure 2.6: *This figure shows the distribution of the answer to the question :«How much time do you use your smartphone daily? Provide your best estimate in hours and minutes ». The sample mean displayed amounts to* 29.72% *computed in terms of the Baseline screen time of a respondent. The Own Misperception variable is defined as in equation* (2.3)*, and it is divided between* 6.9% *of correct guesses,* 57.59% *of users overestimating their use, and* 35.48% underestimating their use.

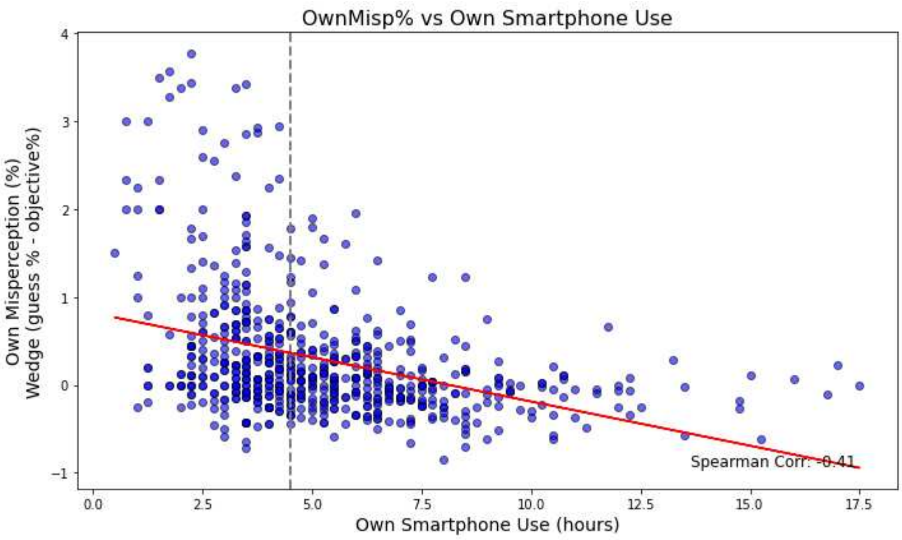


Figure 2.7: *Scatter plot showing the relationship between the Misperception of Own usage (y-axis) (defined as in equation* (2.3)*), and the own reported screen time (x-axis). The gray line shows the median value of Own reported screen time, while the red line represents the fitted line between the two variables, which exhibits a negative relationship (as shown from the Spearman Correlation in bottom-right side).*

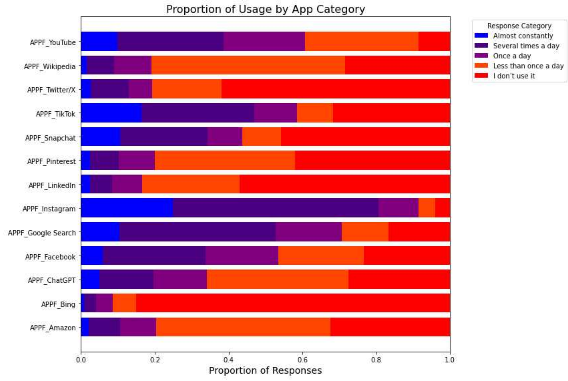


Figure 2.8: *Bar plot showing the distribution the answers of each apps listed in the vertical axis, to the following question: « How often do you use these digital platforms? ». Possible answers were indexed in five items, with the legend available in the upper-right side of the figure.*

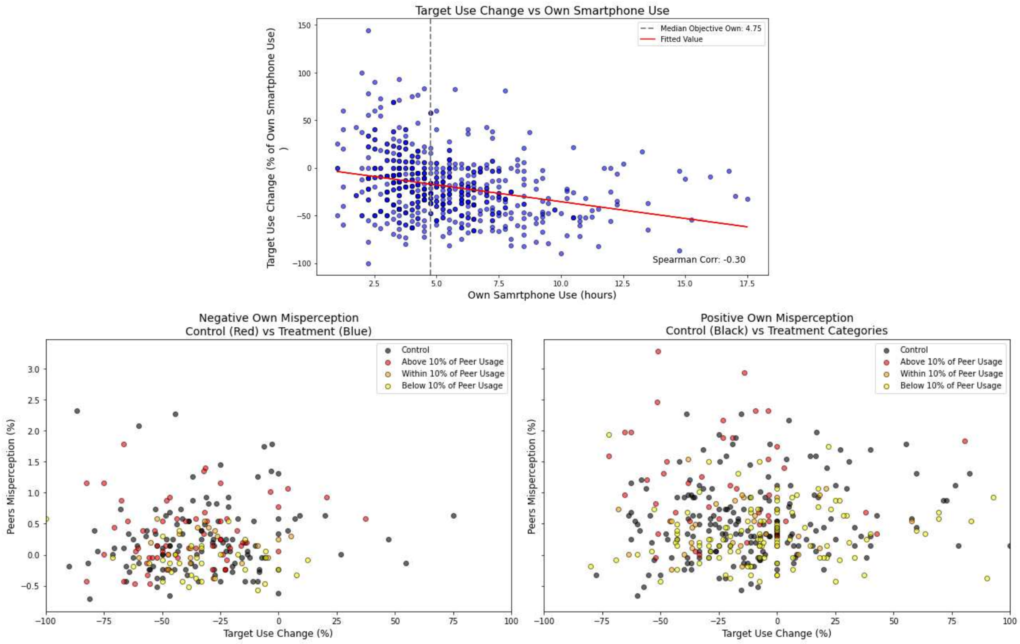


Figure 2.9: *Ideal Use Change (defined as in equation* (2.1) *in Section 2.3.4) from respondents showing, in the top panel, the relationship between Ideal use change (Y-axis) and own self-reported screentime (X-axis). The gray, and red lines are defined as in Figures 2.5-2.7. In the bottom panels we distinguish the Ideal use change (X-axis) by those who were underestimating their smartphone consumption (i.e.* $M_i(S_i) < 0$ *in* (2.3)*) (bottom-left) from those who were overestimating it (i.e.* $M_i(S_i) > 0$*) (bottom-right), while on the Y-Axis there is the Peers' Misperception wedge defined as in* (2.2)*, where the value of 0 indicates correct perceptions about the reference group usage. The colour of the dots differentiate the control group from the positioning of the treated units, according to their reported screen time (above-within 10%-below average).*

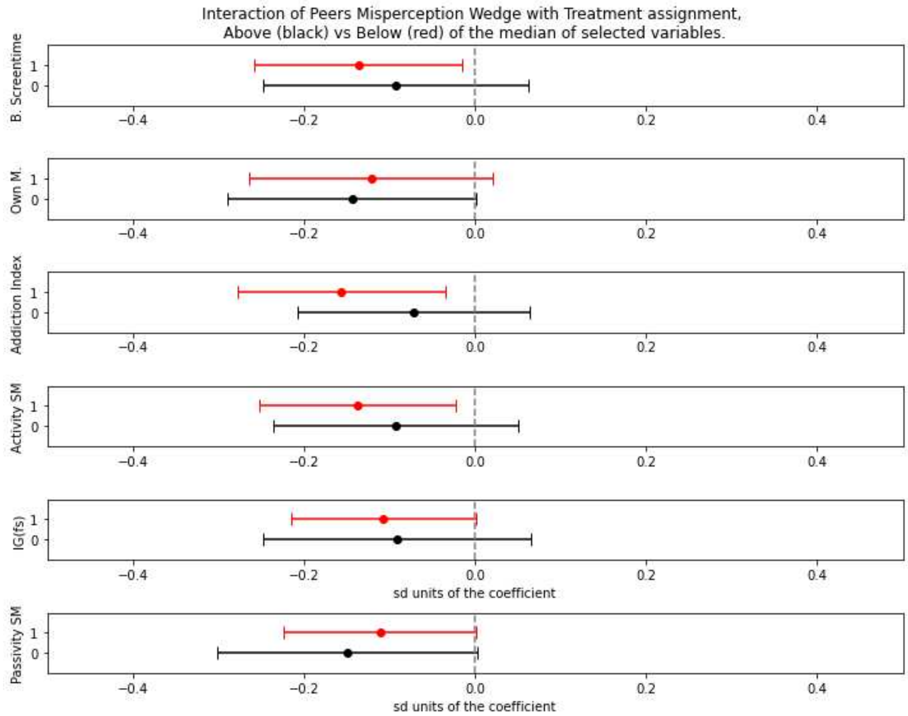


Figure 2.10: *Robustness check for the coefficient "Peers Misp, Wedge(%) · T" of specification **(4)** in Table 6. The figure shows the varying treatment effect (conditional on the overestimation of Reference group smartphone use belief) of correcting misperceptions on the elicited Ideal Use Change. We divide the samples (from top to bottom) in above (**in black**) and below (**in red**) of the median of: (1) Baseline Use; (2) Own Misperceptions (Wedge %); Addiction Index; Activity Social Media; Instagram Followers; Passivity in Social Media. All sample ATE: S.D. Coefficient = -0.119, Confidence Interval = [-0.210 -0.028]*

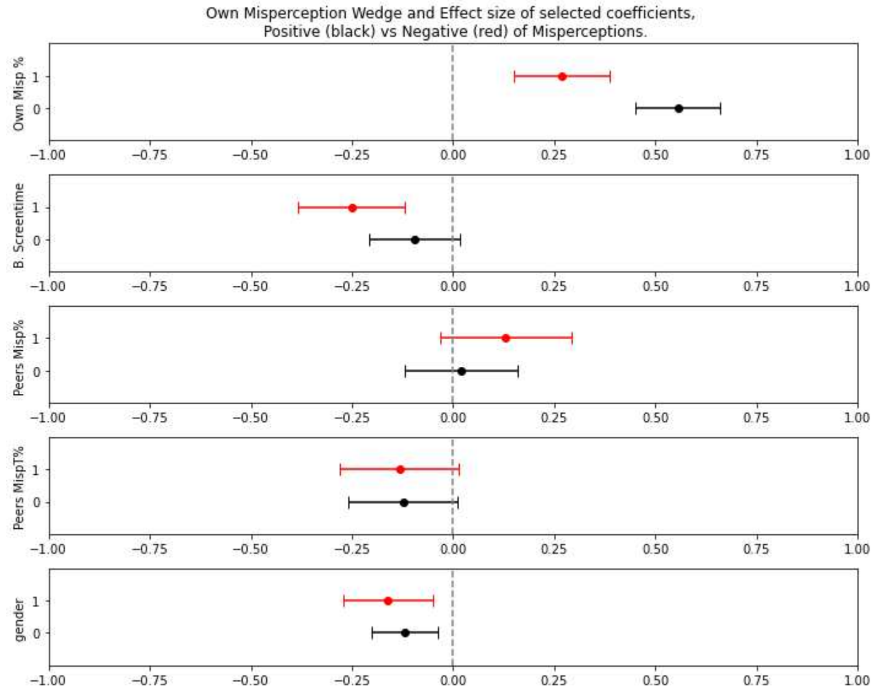


Figure 2.11: *Heterogeneous effect size for selected coefficient of specification **(4)** in Table 6: We divide the sample between those who overestimated (**in black**, N=383) and those who underestimated (**in red**, N=236) their own smartphone use.*

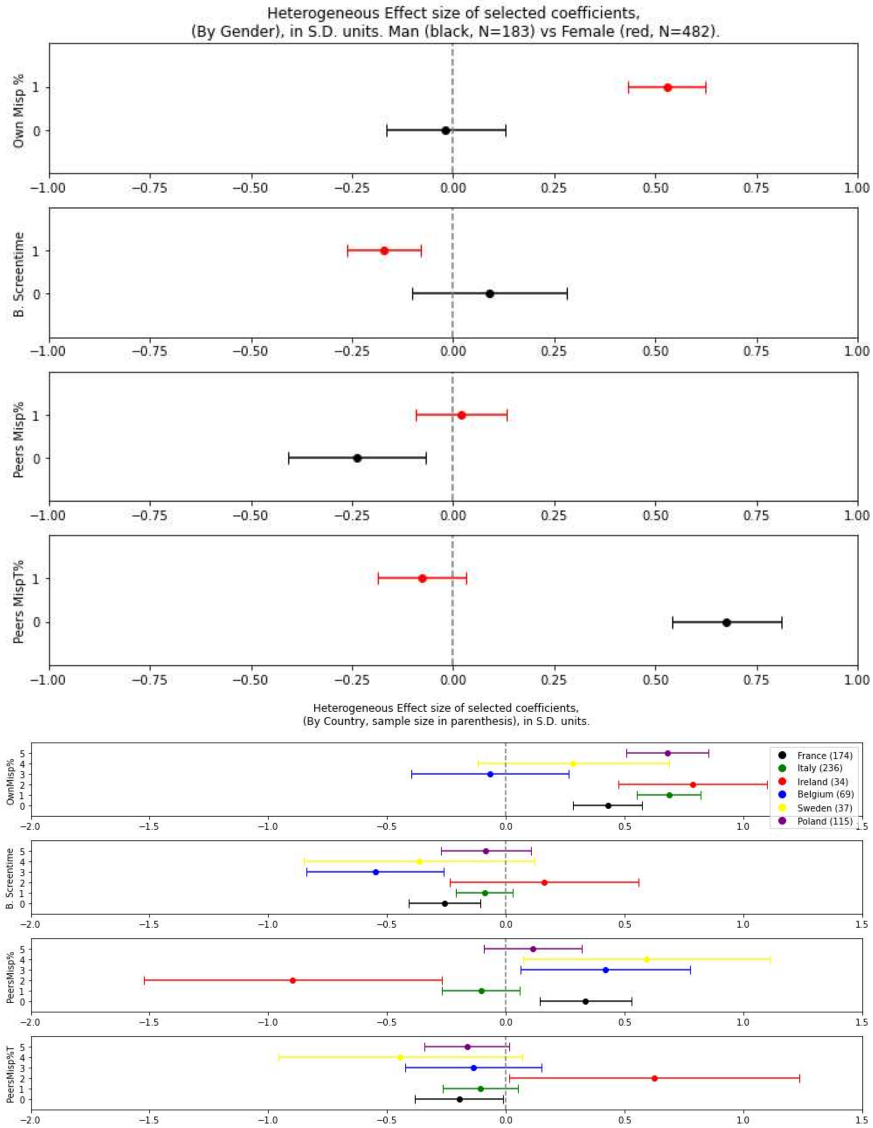


Figure 2.12: *Heterogeneous effect size for selected coefficient of specification **(4)** in Table 6. Upper figure: We divide the sample between males (**in black**) and females (**in red**). Bottom figure: we examined heterogeneous effects by country. From both figures it can be noted that the resulting effects are mostly driven by the Female sample (upper figure), and the most representative country of our sample (France, Italy, and Poland). The reduced sample size of the pilot testing does not allow us to recover robust conclusions.*

Tables

Table 1: Summary Statistics: Information Experiment (Covariates).

Variable Name	**Treatment**		**Control**	
N=665	(330)		(335)	
	Mean	**Min/Max**	**Mean**	**Min/Max**
Gender	0.7121	0/1	0.7373	0/1
	(0.4535)		(0.4408)	
Age	23.1788	18/30	22.9493	18/30
	(3.1150)		(3.2344)	
Grade (Quartile)	2.5478	0.00/4.00	2.5078	0.00/4.00
	(1.1322)		(1.1376)	
Brand:				
Apple	0.5333	0.00/1.00	0.5045	0.00/1.00
	(0.4996)		(0.5007)	
Google	0.0061	0.00/1.00	0.0119	0.00/1.00
	(0.0777)		(0.1088)	
Motorola	0.0182	0.00/1.00	0.0149	0.00/1.00
	(0.1338)		(0.1214)	
Other	0.0879	0.00/1.00	0.0657	0.00/1.00
	(0.2835)		(0.2481)	
Samsung	0.2606	0.00/1.00	0.2866	0.00/1.00
	(0.4396)		(0.4528)	
Xiaomi	0.0939	0.00/1.00	0.1164	0.00/1.00
	(0.2922)		(0.3212)	
Baseline Use	5.2114	0.50/17.50	5.1366	0.75/16.75
	(2.6522)		(2.5990)	
Own Misp, Wedge(%)	0.2834	-0.71/3.78	0.3108	-0.84/3.50
	(0.6987)		(0.7425)	
Peers Misp, Wedge(%)	0.4124	-0.62/2.94	0.4546	-0.71/2.51
	(0.6335)		(0.6520)	
Parents' education:				
Primary	0.0273	0.00/1.00	0.0209	0.00/1.00
	(0.1631)		(0.1432)	
Secondary	0.4152	0.00/1.00	0.4627	0.00/1.00
	(0.4935)		(0.4994)	
Tertiary	0.5576	0.00/1.00	0.5164	0.00/1.00
	(0.4974)		(0.5005)	
Country:				
Belgium	0.0970	0.00/1.00	0.1104	0.00/1.00
	(0.2964)		(0.3139)	
France	0.2455	0.00/1.00	0.2776	0.00/1.00
	(0.4310)		(0.4485)	
Ireland	0.0576	0.00/1.00	0.0448	0.00/1.00
	(0.2333)		(0.2071)	
Italy	0.3667	0.00/1.00	0.3433	0.00/1.00
	(0.4826)		(0.4755)	
Poland	0.1727	0.00/1.00	0.1731	0.00/1.00
	(0.3786)		(0.3789)	
Sweden	0.0606	0.00/1.00	0.0507	0.00/1.00
	(0.2390)		(0.2198)	

Notes: Baseline summary statistics of the pilot testing. Standard Error in parenthesis. If present, asterisks in the treatment column refer to p-values from two-tailed t-tests of equality with the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Summary Statistics: Treatment vs. Control (Outcome Variables)

Variable Name	**Treatment**		**Control**	
N=665	(330)		(335)	
	Mean	**Min/Max**	**Mean**	**Min/Max**
Happy	6.6994	1.0 / 10.0	6.4063	1.0 / 10.0
	(1.8174)		(1.7592)	
Loneliness	0.1408	-1.0 / 1.0	0.1063	-1.0 / 1.0
	(0.5070)		(0.5468)	
Well-being Index	-0.1557	-1.0 / 0.6	-0.1806	-1.0 / 0.6
	(0.2944)		(0.2881)	
Minimize	5.7532	1.0 / 10.0	5.5250	1.0 / 10.0
	(1.9196)		(1.9458)	
Distract	0.6028	0.0 / 1.0	0.6352	0.0 / 1.0
	(0.2522)		(0.2281)	
Satisfaction	6.4494	1.0 / 10.0	6.1594	1.0 / 10.0
	(1.9025)		(1.9158)	
PassivitySM	0.4040	-0.67 / 1.0	0.3896	-1.0 / 1.0
	(0.3684)		(0.3813)	
ActivitySM	-0.1304	-1.0 / 1.0	-0.1950	-1.0 / 1.0
	(0.3651)		(0.3948)	
Ideal Use Change	-18.0365	-100.0 / 300.0	-17.9439	-90.0 / 144.4
	(36.9350)		(33.1072)	
IG(fs)	690.87	0.0 / 51164.0	599.08	0.0 / 10000.0
	(2917.15)		(1203.51)	
Addiction Index	-0.4131	-0.975 / 0.0	-0.4119	-0.9 / 0.0
	(0.2111)		(0.2118)	

Notes: Treatment and Control group statistics for baseline pilot testing outcome variables. Standard deviations (in parentheses) are below the respective means. Min/Max values represent the observed range within each group.

Table 3: **Ordinary Least Square (OLS) regression: Social Media Activity**

Variable; mean y=-0.1603	**Activity SM**	**Activity SM**	**Activity SM**
Constant (β_0)	-0.3562^{***}	-0.3628^{***}	-0.4440^{***}
	(0.045)	(0.113)	(0.117)
ln(IG(fs))	0.0670^{***}	0.0672^{***}	0.0666^{***}
	(0.014)	(0.014)	(0.014)
ln(IG(fg))	-0.0290^{**}	-0.0240^{*}	-0.0264^{*}
	(0.015)	(0.015)	(0.015)
Baseline Use	–	–	x
Socio-Demographic Controls	–	x	x
Adj. R-squared	0.049	0.086	0.094
F-statistic	18.18	7.214	7.284
N	665	665	665

Notes: Linear regression for SMP (*Activity SM*). The dependent variable refers to the average score of frequencies in performing activities in Social Media platforms regarded as Active **(A)**, as shown in Appendix III.

ln(IG(fs)) (ln(IG(fg))) reflects the number of self-reported followers (followings) on Instagram by a respondent in its logarithmic form. Hence, the coefficient reflects the association of increasing by 2.7 the size of the explanatory variable to the dependent variable. Baseline Use refers to the self-reported screen-time by the respondent. Socio-Demographic Controls refer to the demographic variables listed in Section 2.3.5. Asterisks refer to p-values concerning the student-t test of coeffcient significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Standard errors in parentheses.*

Table 4: **Ordinary Least Square (OLS) regression: Social Media Passivity**

Variable; mean y=0.3939	**Passivity SM**	**Passivity SM**	**Passivity SM**
Constant (β_0)	0.1738^{***}	0.0593	0.0435
	(0.044)	(0.114)	(0.114)
ln(IG(fs))	0.0095	0.0055	0.0054
	(0.014)	(0.014)	(0.014)
ln(IG(fg))	0.0309^{**}	0.0349^{***}	0.0345^{***}
	(0.015)	(0.015)	(0.015)
Baseline Use	–	–	x
Socio-Demographic Controls	–	x	x
Adj. R-squared	0.037	0.050	0.049
F-statistic	13.72	4.511	7.284
N	665	665	665

Notes: Linar Regression for SMP (*Passivity SM*). The dependent variable refers to the average score of frequencies in performing activities in Social Media platforms regarded as Passive **(P)**, as shown in Appendix III.

ln(IG(fs)) (ln(IG(fg))) reflects the number of self-reported followers (followings) on Instagram by a respondent in its logarithmic form. Hence, the coefficient reflects the association of increasing by 2.7 the size of the explanatory variable to the dependent variable. Baseline Use refers to the Objective screen-time reported by the respondent. Socio-Demographic Controls refer to the demographic variables listed in Section 2.3.5. Asterisks refer to p-values concerning the student-t test of coeffcient significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Standard errors in parentheses.*

Table 5: **Ordinary Least Square (OLS) regression: Peers' Misperceptions.**

Variable; mean y=0.4337	**(1)**	**(2)**	**(3)**
ActivitySM	0.2859^{***}	0.2842^{***}	0.2171^{***}
	(0.066)	(0.067)	(0.064)
PassivitySM	-0.0061	-0.0119	-0.0202
	(0.065)	(0.066)	(0.060)
Constant (β_0)	0.4819^{***}	0.5374^{***}	0.0694
	(0.040)	(0.175)	(0.184)
Baseline Use	–	–	x
Socio-Demographic Controls	–	x	x
Adj. R-squared	0.026	0.043	0.145
F-statistic	9.885	4.013	11.21
N	665	665	665

Notes: Regression results for Peers' Misperceptions (dependent variable), defined as the wedge between the objective data of the population mean and the answer to the question *«How much time do students of your age use their smartphones daily? Provide your best estimate in hours and minutes »*. *Activity SM* (*Passivity SM*) refers to the average score of frequencies in performing activities (passivities) in Social Media platforms regarded as Active **(A)** or Passive **(P)**, respectively. The list of these activities is available in Appendix III. Baseline Use refers to the Objective screen-time given by the respondent. Socio-Demographic Controls refer to the demographic variables listed in Section 2.3.5. Asterisks refer to p-values concerning the student-t test of coeffcient significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses.

Table 6: Regression Results: Ideal Use Change (OLS)

Variable	**(1)**	**(2)**	**(3)**	**(4)**
Constant (β_0)	18.6933***	14.9773***	−15.4039***	−12.7140
	(3.802)	(4.122)	(4.116)	(11.568)
Baseline Use (ς)	−6.0664***	−7.7200***	−1.8893***	−2.2198***
	(0.655)	(0.665)	(0.697)	(0.699)
$M_i(S_{-i})$ (Peers, %) (ρ)	–	27.0950***	1.7488	2.7116
	–	(3.676)	(3.613)	(3.622)
$D_i(\gamma)$	–	6.8233*	5.4314	4.8913
	–	(3.972)	(3.442)	(3.417)
$M_i(S_{-i}) \cdot D_i(\varphi)$	–	−14.0035***	−11.7286***	−11.4069***
	–	(5.129)	(4.446)	(4.435)
$M_i(S_i)$(Own, %) (μ)	–	–	38.4647***	38.0485***
	–	–	(2.591)	(2.572)
S.D. Controls	–	–	–	X
Adj. R-squared	0.113	0.187	0.390	0.402
F-statistic	85.66	39.25	85.90	35.37
Observations	665	665	665	665

Notes: OLS regressions for Ideal Use Change (defined as in equation (2.1)). The mean of the dependent variable is $\overline{y} = -12.69$. Standard errors are in parentheses. Baseline Use (SM_i) refers to the Objective screen-time self-reported by the respondent. D_i refers to the binary treatment indicator where, if $D_i = 1$, a respondent is assigned to the social norm treatment group, as shown in Figure 2.3. $M_i(S_{-i})$ (Peers, %) refers to the percentage wedge that is defined in equation 2.2. $M_i(S_{-i}) \cdot D_i$ refers to the interaction between the peers' misperception and the treatment indicator. $M_i(S_i)$(Own, %) refers to the misperception of the own smartphone use, which is defined in (2.3).
Socio-Demographic Controls refer to the demographic variables listed in Section 2.3.5. Asterisks refer to p-values concerning the student-t test of coeffcient significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Regression Results: Ideal Use Change (OLS).

Variable	**(1)**	**(2))**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Constant (β_0)	17.8898	−14.9641	26.7861***	−5.6417	−11.2701	−11.4275	−11.1931
	(7.041)	(6.176)	(5.961)	(4.077)	(6.550)	(12.366)	(12.616)
Baseline Use (ς)	−6.1058***	−2.4022***	−6.4883***	−2.7889***	−2.1938***	−2.5168***	−2.5467***
	(0.659)	(0.591)	(0.648)	(0.588)	(0.691)	(0.697)	(0.705)
$D_i(\gamma)$	−6.5975	4.7327	−2.4760	−0.9866	9.5399	10.9706	12.0476
	(10.248)	(8.566)	(3.653)	(3.069)	(9.133)	(9.165)	(9.235)
$ln(IG^{fs})$	0.2183	0.6951	–	–	0.2017	0.8150	0.8916
	(1.163)	(0.969)	–	–	(0.963)	(0.986)	(1.005)
$ln(IG^{fs}) \cdot D_i$	1.1438	−0.8175	–	–	−0.7934	−1.1530	−1.3458
	(1.807)	(1.510)	–	–	(1.528)	(1.536)	(1.548)
ActivitySM **(A)**	–	–	26.7861***	18.0287***	16.8285***	14.6843***	14.4345***
	–	–	(5.961)	(5.032)	(5.083)	(5.123)	(5.136)
$ActivitySM \cdot D_i$	–	–	−5.7585	−3.5041	2.3647	1.9479	2.3077
	–	–	(8.825)	(7.411)	(7.696)	(7.667)	(7.695)
$M_i(S_i)$(Own, %) (μ)	–	36.6643***	–	35.4253***	37.8568***	37.6067***	37.3403***
	–	(2.148)	–	(2.128)	(2.564)	(2.552)	(2.568)
$M_i(S_{-i})$ (Peers, %) (ρ)	–	–	–	–	1.2308	2.4015	2.7011
	–	–	–	–	(3.574)	(3.594)	(3.613)
$M_i(S_{-i}) \cdot D_i(\varphi)$	–	–	–	–	−12.9137***	−12.6152***	−12.5677***
	–	–	–	–	(4.482)	(4.480)	(4.490)
S.D. Controls							
	–	–	–	–	–	X	X
Brand FE							
	–	–	–	–	–	–	X
Model Statistics							
R-squared	0.116	0.387	0.153	0.404	0.415	0.430	0.433
Adj. R-squared	0.110	0.382	0.148	0.399	0.407	0.415	0.413
F-statistic	21.60	83.15	29.87	89.33	51.58	28.70	22.24
Observations	665	665	665	665	665	665	665

Notes: OLS regressions for Ideal Use Change (defined as in equation (2.1)). The mean of the dependent variable is $\overline{y} = -12.69$. Standard errors are in parentheses. Baseline Use (SM_i) refers to the Objective screen-time self-reported by the respondent. T D_i refers to the binary treatment indicator where, if $D_i = 1$, a respondent is assigned to the social norm treatment group, as shown in Figure 2.3. $M_i(S_{-i})$ (Peers, %) refers to the percentage wedge that is defined in equation 2.2. $M_i(S_{-i}) \cdot D_i$ refers to the interaction between the peers' misperception and the treatment indicator. $M_i(S_i)$(Own, %) refers to the misperception of the own smartphone use, which is defined in (2.3).
Activity SM refers to the average score of frequencies in performing activities on social media platforms regarded as Active **(A)**, as shown in Appendix III. *ln(IG(fs))* reflects the number of self-reported followers on Instagram by a respondent in its logarithmic form. *Activity SM* $\cdot D_i$ and *ln(IG(fs))* $\cdot D_i$ are the interactions between the just mentioned explanatory variables and the treatment indicator D_i . $M_i(S_{-i})$ (Peers, %) refers to the percentage wedge that is defined in equation 2.2. $M_i(S_{-i}) \cdot D_i$ refers to the interaction between the peers' misperception and the treatment indicator D_i. $M_i(S_i)$(Own, %) refers to the misperception of the own smartphone use, which is defined in (2.3).

Socio-Demographic Controls refer to the demographic variables listed in Section 2.3.5. Brand Fixed Effects (FE) refers to a set of dichotomous variables which controls for the list of brand (from Table 1) which the respondent reported. Asterisks refer to p-values concerning the student-t test of coefficient significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

I Screen Capture Assessment

In this section, we evaluate the effectiveness of the screen capture upload. Accordingly, we divide this section in two parts. In the first part, we show how we guided our respondents on providing the screen capture of their screen time. In the second part, we are interested in whether users have self-reported the correct data requested by us. In this regard, we provide some "rules" that we applied to verify whether the data uploaded were reliable for our analysis.

I.1 Screen Capture Upload (Guideline)

Before uploading the objective screen time capture, we get the users familiar with the information that we need through an attention check. Accordingly, Figures I.1 and I.1 show them a screencapture which includes the data that they will have to subsequently upload to the platform.

The attention check procedure in the main survey collection will be kept. However, we abandoned the idea of screen out respondents' who were not able to provide the correct information.

We ask users to report the daily average users in a capture that we provided them, as we can see in Figure I.1 for Android (left) and IOs (right). Once passed the attention check, we provide the guidelines on provide the same capture from their own device.
Once users have completed the attention check, we provide the screencapture upload guideline in the following way for Android (IOs in the right):

- Now, check the screen time on your smartphone and provide the Daily Average Screen Time following the instructions below:
- see Figure I.1 where users are shown which is the data that they should share

to us.

- See Figure I.3 where it is shown the panel where users' can upload the screen capture of the average week screen time. The upload is mandatory for half of the sample.

Attention Check

For Android:

Please look at the screenshot below from a smartphone showing the Digital Wellbeing & Parental Control. What is the Daily Average Screen Time displayed in the image?

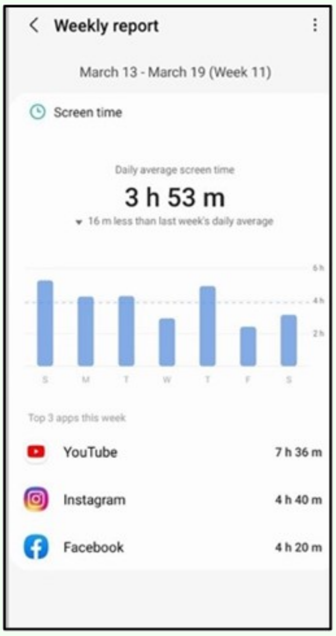


Figure I.1: *Screenshot of Android Digital Wellbeing & Parental Control section.*

Daily Average (hours)

$x \in [0, 24]$

Daily Average (minutes)

$x \in [0, 60]$

For iOS:

Please look at the screenshot below from a smartphone showing the Screen Time. What is the Daily Average Screen Time displayed in the image?

Figure I.2: *Screenshot of iOS Screen Time section.*

Daily Average (hours)

$x \in [0, 24]$

Daily Average (minutes)

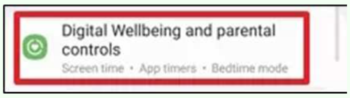
$x \in [0, 60]$

Screen-Capture Guideline

For Android:

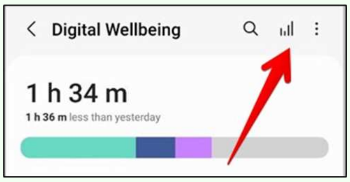
Access Digital Wellbeing & Parental Control Tools:

1. Find the Settings app
2. Scroll down and tap on Digital Wellbeing & Parental Controls.

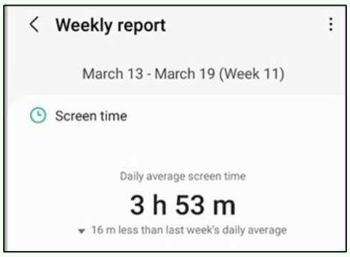


View your Weekly Report:

1. On this section, tap on the bar chart on the upper-right corner of the screen.



1. A bar chart with your daily average screen time is displayed.



Your answer (converted):

Enter your average screen time

For iOS:

Access Screen Time:

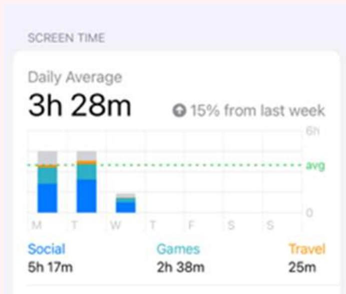
1. Unlock your iPhone and find the **Settings** app.
2. Scroll down and tap on section.

View your Weekly Report:

1. In the Screen Time, you will see a graph showing your daily usage. Top on **See All App & Website activity** to get a detailed report.
2. Ensure that the top tab is set to **Week** to view your weekly screen time data.

Note the Total Screen Time:

1. Look for the section **Daily Average** (within the graph). This shows your average daily screen time for the past OR this week.



Your answer (converted):

Enter your average screen time

Figure I.3: *This figure shows the panel of the survey, subsequently to the guideline in Figures I.1 for Apple and Android users, where respondents have to upload the screencapture. Fifty percent of the sample is obliged to do it, while for the other half of the sample it is possible is to proceed with the survey completion without the upload. In Table I.1 we highlight the resulting upload statistics. It is worth noting that, in the first row of the dark blue box, there is the labelling of the panel (i.e. uploadNotMandatory). The figure comes from a testing phase of the survey effectiveness.*

I.2 Screen Capture (description & imputation)

In this part, we provide a brief assessment of the effectiveness of the survey in guiding respondents' to effectively provide a screen capture of their guideline. Moreover, we look at whether the screen capture, provided by our respondents, corresponds to the correct data required, with a logic that we explain here. Finally, we also show the consistency between the data correctly uploaded to the self-imputed data that we used along our analysis.

Before proceeding with the analysis, we mention that we divided, as an ancillary intervention, the eligible sample in two groups.
The first group was assigned to the "mandatory" screen time upload. Namely, respondents assigned to this group were not able to go further with the survey unless they provide an upload of an image concerning the screen time. Conversely, the second group, whose assignment was "non mandatory" were able to go further with the survey, even by not uploading any image.

As mentioned, the imputed baseline screen time data we should be able to collect at least the average consumption of a week. Accordingly, in Figure I.4 we show the process that brings us to obtain the data with weekly usage data. Furthermore, In Table I.1, we provide a summary of some of the key relevant statistics concerning the effectiveness in uploading the smartphone screen time.

Accordingly, to allow us to impute the data, a first requirement is trivially that respondents' upload a figure in the survey platform. The capability of proceeding in the survey, if the respondent' does not upload the figure is conditional on the ancillary assignment to the mandatory Figure Upload. Namely, if the subject does not upload the figure, and has a mandatory requirement the only possible action is to not complete the survey. Among those assigned to this treatment, 76.89% uploaded a figure in the platform (282 out of 371). Hence, this passage implied a drop-out rate of $0.5 \cdot (1 - 0.7689) = 11.55\%$ of the sample. Moreover, among those not assigned to the mandatory treatment, around 46.85% of the sample complied with the assignment. Combining the two sources of upload, we were able to collect 468 uploads, of whom 431 with actual data (92%). To be considered an observation, the figure must be a ***screencapture*** (including the entire screen of a smartphone). Hence, the figure must not be taken as an external photo, and it should contain the page of Screen time for iOS users, and of Digital Wellbeing & parental control tools for Android operating systems, this requirement lead us of having 431 screen captures.

Now, the following passage is pivotal in determining how we impute the screen time weekly usage data. In particular, across Operating Systems, we may have at least one of the following data points:

(1) *Average Screen Time Statistics ($Week_{i,t}$)*: The Average screen time of a respondent on a weekly basis.

(2) *Average Screen Time Statistics ($Daily_{i,t}$)*: The Average screen time of a respondent of up to four days.

(3) *Previous Week Change ($\Delta Week_{i,t}$):* The Average screen time variation in comparison to the previous week.

Accordingly, (1) and (2) are mutually exclusive events. We are able to recover the data if the events (1); (1) $\cap$ (3); (2) $\cap$ (3) are true. Namely, if the week variation is available, the imputed screen time of the i^{th} respondent is:

$$ScreenTime_i = Week_{i,t} \tag{2.7}$$

where $Week_i$ is the imputed weekly usage provided by the respondent.
If a respondent has data on $Week_{i,t}$, and $\Delta Week_{i,t}$, the imputed screen time is:

$$ScreenTime_i = 0.5 \cdot Week_{i,t} + 0.5 \cdot \frac{Week_{i,t}}{(1 + \Delta Week_{i,t})} \tag{2.8}$$

Where the first term (with weight 0.5) corresponds to the current week as in (2.7), and the second one imputes the previous week screen time. For example, if the current week consumption had increased by 40%, the imputed value for the previous week would be $Week_{i,t}(1-(-0.40))$. This scenario cover 36% of the respondents who uploaded the entire week consumption (2), consequently 64% of those who uploaded week consumption refer to case (1).
Finally, if the i^{th} respondent has a daily observation with previous week variation we are able to impute a weekly usage with the following formula:

$$ScreenTime_i = Daily_{i,t} \frac{Week_{i,t}}{(1 + \Delta Week_{i,t})} \tag{2.9}$$

where $Daily_{i,t}$ is the aforementioned event (3). In this case, from Table I.1 we can see that this case corresponds to the 54% of those who uploaded a non-entire week screen capture.

The resulting sample satisfying one of the three characteristics ((2.7)-(2.8)-(2.9)) is of 300 observations.

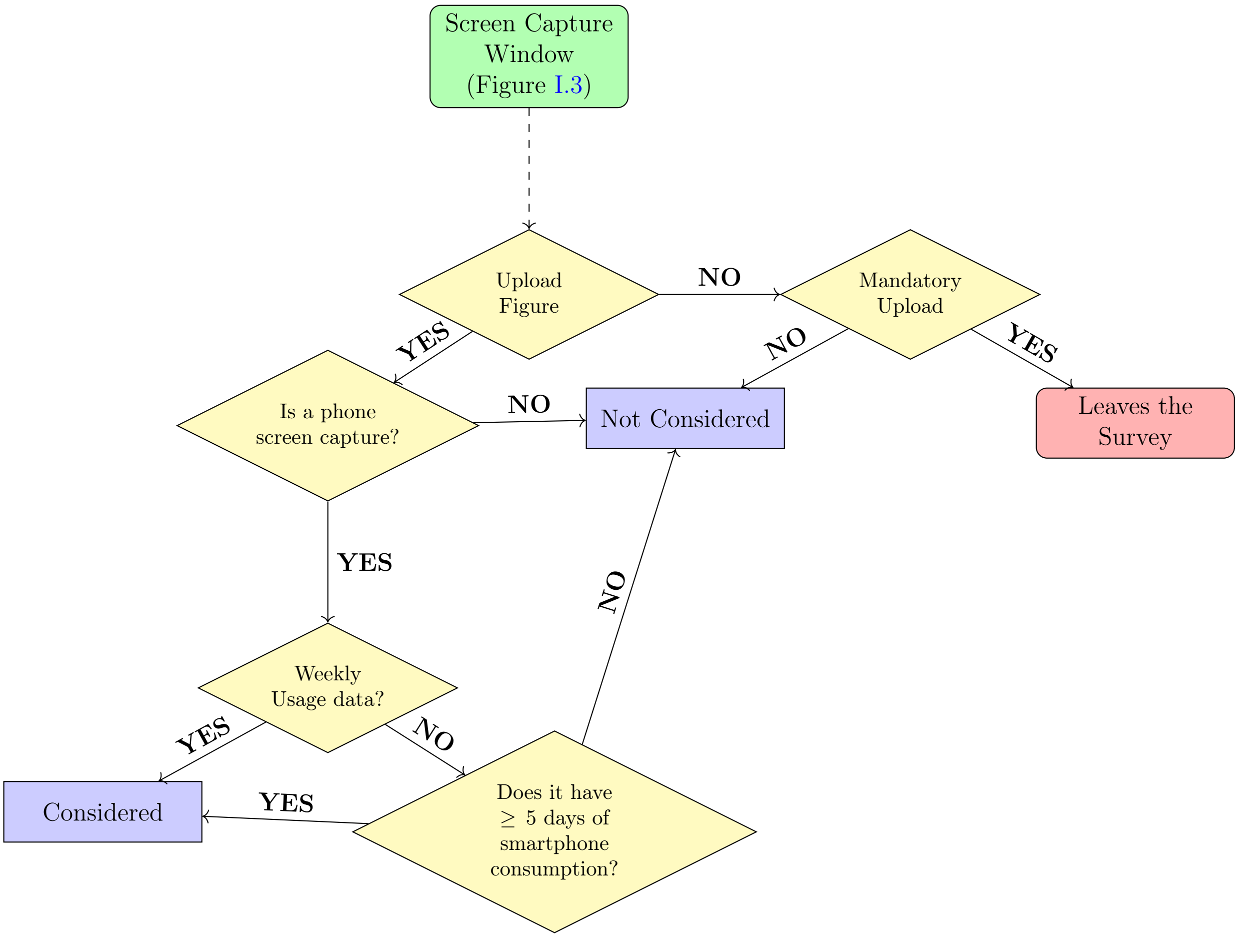


Figure I.4: *Logic of the data with screen capture to be considered as truthful measures of smartphone*

Table I.1: Sample characteristics of Screen capture uploads (Subsample of those who completed the survey)

Characteristic	**Value**
Obliged to provide screen capture	282
Not obliged to provide screen capture	397
Not obliged uploading a screencapture	46.85%
Total uploads	468
Uploads:	
with data	431 (92%)
with average week consumption	147 (31.41%)
with daily average consumption (up to 4 days)	284 (60.4%)
with variation to previous week	207 (44.23%)
Δ previous week (daily)	54%
Δ previous week (weekly)	36%

Concluding this part of the appendix, we show some relevant figures for assessing the reliability of our data.

In Figure I.5, we show the limitations in certain brands in providing the correct information. In particular in the left panel we see that only the majority of respondents' week data usage from Samsung were able to provide the correct information (around 60%), while Apple, and Xiaomi had tinier percentages of around a fifth of their users. Moreover, it is interesting the Google, and Motorola users were not able to provide the correct information. Accordingly, their brand does not provide at all the weekly usage information.

In the right panel of Figure I.5 instead, we show that only 80% of Apple users, and around 10% of Samsung users were able to provide information concerning previous week usage. The latter may be alarming according to our theory, in the sense that users' are not able to keep track of their smartphone consumption overtime.

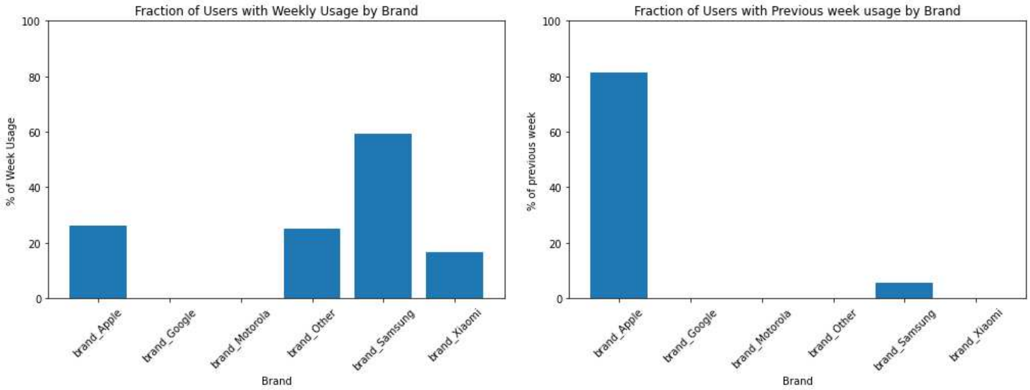


Figure I.5: *This Figure shows, on the left panel, the fraction of users, for each brand, that were able to provide information concerning their week usage. While, the right-panel shows the fraction of users, for each brand, that were able to give information concerning their previous week smartphone consumption.*

To conclude, we provide a comparison on the reliability of the self-reported data versus the imputed data. Figure I.6 shows the distributions of the Baseline screen time of all the sample from Table 1 (upper-left); and, for those who satisfy conditions (2.7)-(2.9) we show their self-reported screentime (upper-right); their screentime after the imputation procedure (bottom-left); and the absolute difference between self-reported and imputed screen time (bottom-right). We can see visually how, in the first three figures, the three distributions are overlapping. The imputed screen time, accordingly, are in line with the self reported values by the respondents.

Concerning the absolute differences, in the bottom-right panel we can see how some outliers have a great difference between imputed and self-reported. Concerning this information, the average error is of 1.73 hours in reporting the corrected value, and of 0.99 hours of median error. We may conclude that, apart some outliers, which for future analysis must be taken into account, the overall compliance in digitizing the correct information is high among our respondents, which makes our data employed reliable.

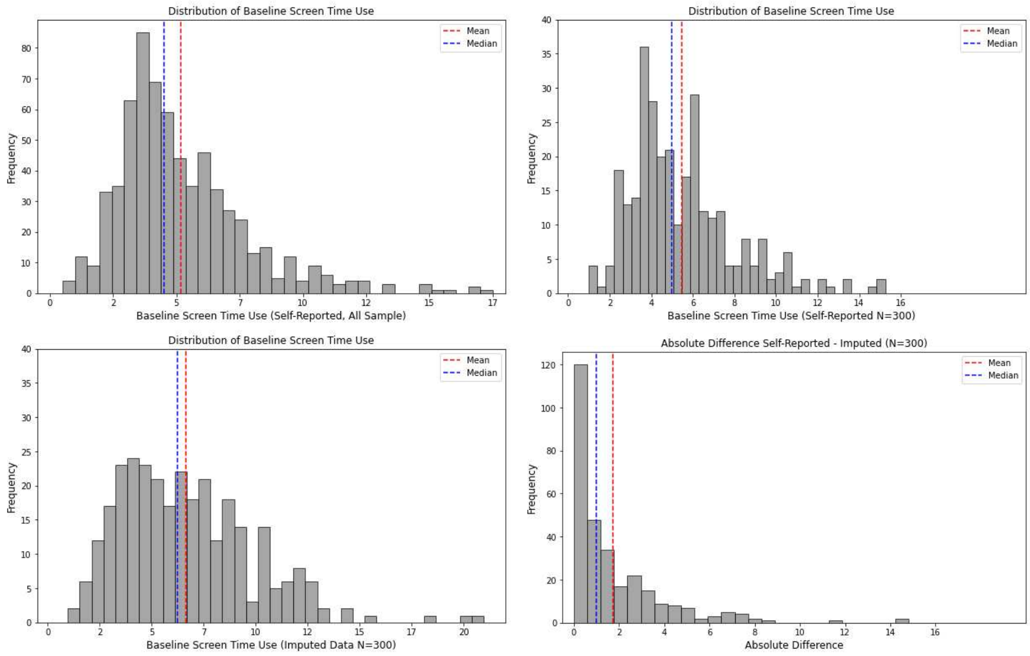


Figure I.6: *This Figure shows: (upper-left) The distribution of the entire sample (from Table 1) of the self-reported smartphone consumption; (upper-right) the self-reported consumption of users who provided week smartphone usage; (bottom-left) the imputed consumption of the same users (through* (2.7)-(2.9)*); and (bottom-right) the absolute difference between self-reported (as in upper-right), and imputed (as in bottom-left) for the same users.*

II Survey Structure

II.1 Baseline Survey

We divide our baseline survey into 8 sections, where we collect self-reported data about (in chronological ordering) *(i)* Pre-Treatment Covariates; *(ii)* Education Information; *(iii)* Smartphone Use Information; *(iv)* Smartphone Apps; *(v)* Well-being Information; *(vi)* Digital Activities and Productivity; *(vii)* Attitudes towards Social Media; and *(ix)* Other Covariates. In the Supplementary material of the thesis, we provide the complete characteristics of the questionnaire. Here, we highlight the variables that we want to elicit to test our hypothesis. We begin by indexing them:

- ***Covariates (Pre and post-Treatment):*** The set of pre-treatment covariates includes (and is not limited to) demographic characteristics that will be used for stratifying the assignment to the treatment. These include Age; Gender; Place of residence (NUTS-3 level); living situation (parents, alone, apartment with other students, student dorm, parent-spouse), post treatment covariates include birth country, language spoken at home; parents' education; and easiness in managing expenses.

- ***Education-related information:*** Concerning education, we ask to self-report the beginning of current higher educational studies (year); level of enrolment (e.g. BSc., MSc, Ph.D.); Field of Study (ISCEFD-13) number of completed courses; Main financial source of education (family support, student loan, scholarship/grants, part-time job, personal savings); Secondary School Grade; Attendance Type (presence, remote, combination of both), and current Gross-Product-Average (GPA).

- ***Subjective Well-Being Information:*** Self-reported variables such as Happiness; Loneliness; self-reported frequencies of activities (e.g. Exercising; time with family, time with friends); life satisfaction.

- ***Smartphone and social media related information:*** Concerning smartphone use, and social media, in particular, we ask to self-report the age of first smartphone ownership; privacy concern on the use of data by third parties; operating system (needed to give the guideline for the screen-capture); awareness about the existence of "screen time" management options; perception on the smartphone use concerning own and others; frequency of usage of a battery of apps; followers and following for three social network platforms (Facebook, Instagram and Tiktok); way of using social media (list of active vs passive actions); wtp for deactivating selected platforms for one month (FB, IG, X and ChatGPT); Short version of 10 items of the digital addiction measure; self-perception about distractions from social networks; multitasking with social media while studying; caregivers restrictions in social media use and, if affirmative, which action they have taken to restrict it.

- ***Pro-Regulation information:*** Concerning the regulation attitudes, we do ask about the perception of the impacts of social media on reference group (positive/negative); if negative, we do ask in which way social media negatively impacts peers'; perception about students' being addicted to social media (positive/negative); perceived transparency of social media algorithms; Approval of "Government intervention" to regulate social media use" in selected ways and, if affirmative, in which way the governments should act.

II.2 Follow-up Survey

Four weeks later, we do collect outcome variables entailed at verifying the effectiveness of our treatment provision (I). The follow-up survey contains a restricted version of the baseline variables, and we do include some new variables which collect relevant information for our analysis. We do classify the outcome variables in three strands, namely Smartphone, Well-Being and Educational outcome variables:

- ***Smartphone Outcomes:*** Perceptions on smartphone use concerning own and reference group ("Students' of your age"); Self-perceptions about screen-time change in the previous four weeks; Activity in social media; Injunctive norm strength for social media use; Short version of 10 items of the digital addiction measure; self-perception about distractions from social networks; multitasking with social media while studying.

- ***Education Outcomes:*** Learning Satisfaction; Completion of exams in the previous four weeks + GPA; Planned Exams.

- ***Well-Being Outcomes:*** Happiness; Loneliness; self-reported frequencies of activities (e.g. Exercising; time with family, time with friends); Fear-Of-Missing-Out (FOMO) Index.

III Variable Definitions

Smartphone Addiction Scale(-1) (Lopez-Fernandez, 2017):

How often have you:

- Missing planned work due to smartphone use.
- Having a hard time concentrating in class, while doing assignments, or work due to smartphone use.
- Feeling pain in wrists or at the backneck while using a smartphone.
- Won't be able to stand not having a smartphone.
- Feeling impatient and fretful when I am not holding a smartphone.
- Having my smartphone in mind when not using it.
- I will never give up using my smartphone, even when my daily life is already greatly affected by it.
- Constantly checking my smartphone so as not to miss conversations between other people on social media.
- Using my smartphone longer than I had intended.
- The people around me tell me that I use my smartphone too much.

Options: Never (0); Rarely (0.25); Sometimes (0.5); Often (0.75); Always (1).

FOMO Scale(-1) (Przybylski et al., 2013; Abel et al., 2016):

Please, tell us to what extent do you agree with these statements:

- I fear others have more rewarding experiences than me.
- I fear my friends have more rewarding experiences than me.

- I get worried when I find out my friends are having fun without me.
- I get anxious when I don't know what my friends are up to.
- Sometimes, I wonder if I spend too much time keeping up with what is going on.
- It bothers me when I miss an opportunity to meet up with friends.
- When I have a good time, it is important for me to share the details online (e.g. updating status).
- When I miss out on a planned get-together it bothers me
- If I am unable to check my favorite social media when I want to, I do frequently feel nervous.

Options: 5-likert scale from 1=Strongly Disagree to 5=Strongly Agree.

Social media Activity Scale (Escobar-Viera et al., 2018): *On social media, how much time do you spend doingthe following activities?*

- Interacting with friends/family **(A)**.
- Checking the news **(P)**.
- Sharing updates or information about yourself **(A)**
- Chatting/messaging **(A)**
- Meeting new people **(A)**
- Reading through conversations without actively engaging **(P)**
- Watching videos **(P)**
- Posting videos **(A)**

- Expressing your views. **(A)**

Options: Never (-1); Rarely (-0.5); Sometimes (0); Often (0.5); Most of the time (1).

Injunctive Norm Strenght (INS) (Baer, 1994; LaBrie et al., 2010):

Imagine that the people in your life are aware of your daily habits, including your social media use. How would the following people react if they knew that you were using social media about six hours per day?

- Parents or Caregivers.
- Closest friends
- Friends from your course of study.

Options: Very uncomfortable (1), moderately uncomfortable (2), mildly uncomfortable (3), neutral (4), mildly comfortable (5), moderately comfortable (6), strongly comfortable (7).

IV Qualitative Evidence for the Intervention

In this section of the Appendix, we make use of some survey responses to motivate our intervention.

Namely, in Figure IV.7, we show that users, in their majority, have a concern about the collection of their personal data. Concurrently, respondents perceive the transparency of SMP' content distribution as skewed towards not being transparent.

In Figure IV.8, we show that both contextual social influence and in-device factors play a weak role in limiting consumption. Concerning the first, we refer to the availability of DSCT monitoring the screentime. Concerning the second, we refer to whether our respondents have faced parental restrictions during their teenage years.

In Figure IV.9, we show that, among our respondents, there is a perception of overconsumption of SMP, which may signal that general consumer welfare measurements could be overestimated when relating them to social media use. Moreover, in Figure IV.9, we also show that there is a high concern regarding the reference group's addiction, while the overall impact of SMP on their reference group remains unclear in terms of direction.

Finally, in Figure IV.10, we show that over 90% of our respondents agree with a governmental intervention concerning SMP. Among them, opinions on how the intervention should take place are relatively divided between those who prefer guidelines over strict regulations. Below this information, Figure IV.10 shows the approval of our respondents (in terms of prioritisation) among a list of possible interventions.

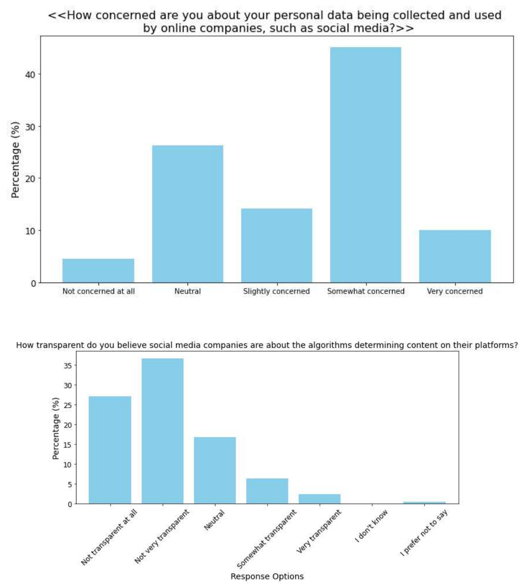


Figure IV.7: *Qualitative evidence of intervention: Data Privacy.*
The top panel shows how the majority of respondents' are concerned about the usage of their own data by online companies. The bottom panel shows how the perceived transparency of social medias (by our respondents) in personalizing the content viewed is low.

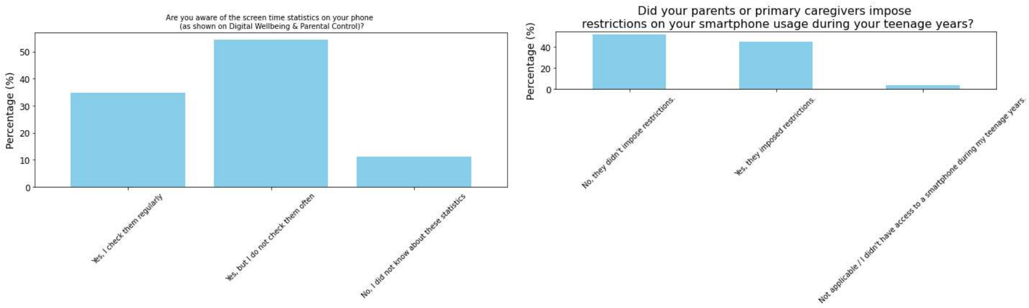


Figure IV.8: *Qualitative evidence of intervention: Consumption Restrictions and Control. The left panel shows how most of our respondents' are aware about the existence of Digital Self-Control Tools such as the screen time statistics. However, more than the majority do not use them regularly (center bar). The right panel shows how the majority of respondents' did not received limitations in smartphone consumption by parents.*

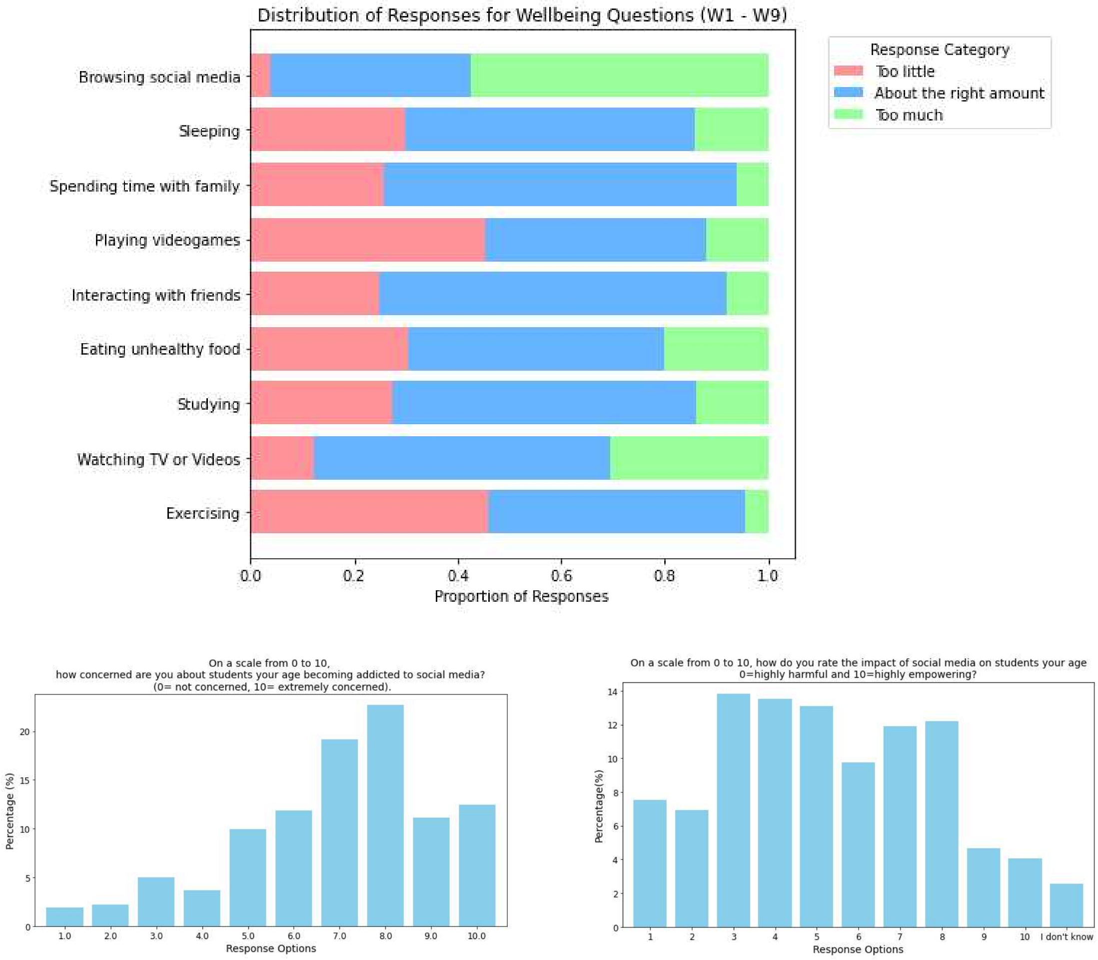


Figure IV.9: *Qualitative evidence of intervention: Overconsumption.*

The top panel shows the answers the perception of spending some general activities: «How much time do you spend». It is clear how "Browsing Social Media" is the activity with the highest frequency of being done "Too Much".

The bottom-left panel asks about being concerned on reference group addiction to social media, and the bottom-right panel asks about the perceived impact of social media on the reference group. Both of the bottom figures shows an inclination towards apprehension on reference group' impacts on social media consumption.

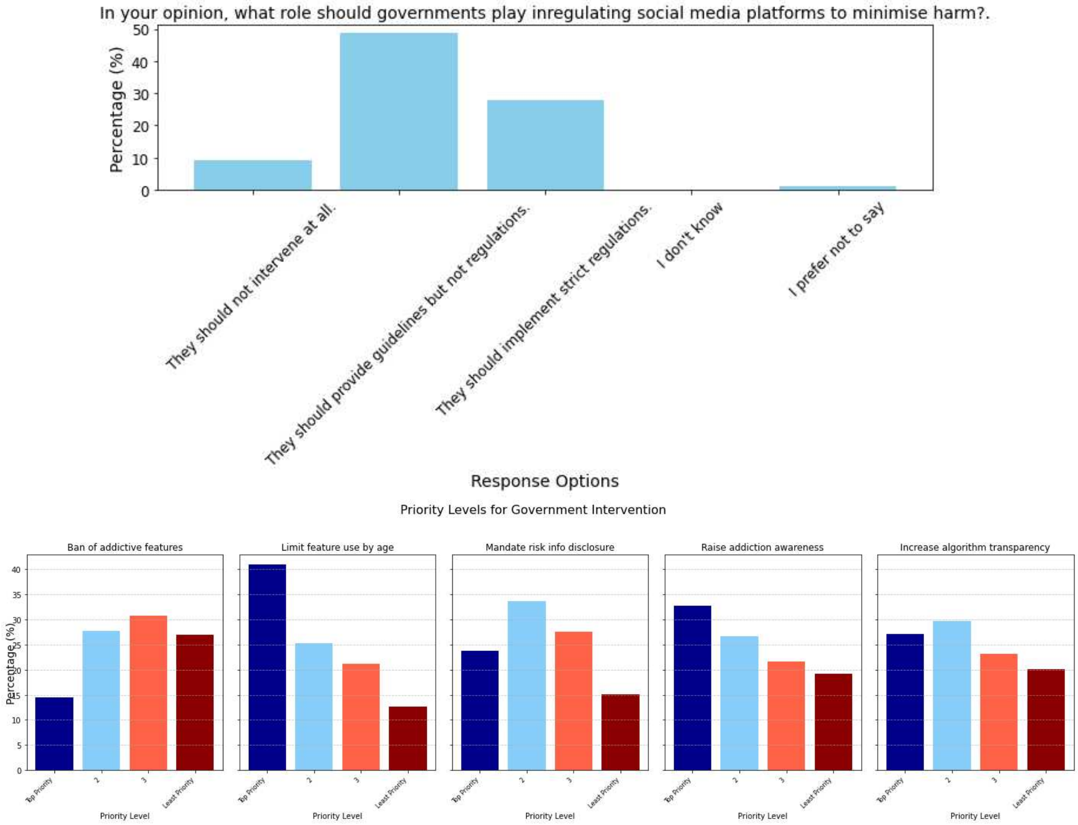


Figure IV.10: *Qualitative evidence of intervention: Institutional Factors.*
The top panel shows the answers to which role should play the government in regulating social media. Accordingly, there is overall agreement concerning institutional intervention, whose majority is inclined towards providing guideline (48%) and the rest is supportive of strict regulations (27.8%).
The bottom panel shows the degree of prioritization for certain features with a more detailed description of the question here (starting from the left):
1: Banning certain features, such as infinite scrolling, auto-play, or push notifications.
2: Limiting the use of certain features to specific age groups.
3: Mandate SMP toprovide information about the risk of addiction.
4: Raising awareness about the risk of addiction.
5: Increase transparency about the algorithms determining social media's content.

V Empirical Strategy: Follow-Up Survey.

As described in the paper, our online survey concerns the provision of the information treatment outlined in Section 2.3.3. The analysis along the paper is about the baseline pilot survey. As mentioned, our main analysis will consist also in collecting the treatment effects at the follow-up survey. Thus, here we present the empirical strategy of the follow-up survey. The main conjectures are two. The first is that upon seeing the peers' smartphone consumption, users may declare a willingness to reduce consumption. Moreover, also those who underestimated their smartphone consumption may declare the same intention. Hence, the follow-up goal is to see whether effectively these users reduced their consumption. Moreover, we want to establish between smartphone consumption and well-being outcomes. Hence, our main conjecture is that smartphone use (or other measures concerning its usage experience) mediates the treatment effect between the treatment assignment and the well-being outcomes.

We define a general outcome of the i^{th} respondent as $Y_{i,t}$ where $t \in \{1, 2\}$ is the outcome measured at the baseline and at the follow-up survey, respectively. For example, $Y_{i,t}$ at $t = 1$ may refer to the ideal use change measured at the information provision (Regression in Tables 6 and 7). At the follow-up survey, $Y_{i,2}$ refers to smartphone consumption, and to a series of well-being measurements mentioned in Section 2.3.4. We also define the row vector $\mathbf{X}_i$ the set of pre-treatment covariates mentioned in Section 2.3.5 above. Hence, our average treatment effect ATE for the information treatment (I_i) can be written as a multivariate linear regression. Namely:

$$Y_{i,t} = \gamma Y_{i,t-1} + \tau^{I}_{i,1} I_i + \tau^{\cap}_{i,1} I_i \cdot SM_{i,1} + \rho SM_{i,1} + \beta \mathbf{X}_i + \epsilon_{i,t} \tag{2.10}$$

Where $\tau^{I}_{i,1}$, and $\tau^{\cap}_{i,1}$ refers to the ATE of receiving the information treatment, and of interacting the information treatment with key smartphone related variables (SM_i), respectively. For example, SM_i can be related to ex-ante perceptions in own (peers') smartphone use $M_i(S_i)$ ($M_i(S_{-i})$), to the self-reported frequency of social media use, the social media in-degree (i.e. followers), or to the activity (and) passivity in way of usage of social media in a similar fashion to how we estimated in Table 7.

When we do regress for a variable other than smartphone use, we employ an Instrumental Variable approach (IV). Consequently, we endogenise the smartphone use in the follow-up survey ($\eta_{i,2}$) as a function of its lagged value ($\eta_{i,1}$), and of the treatment assignments (and interactions) shown in (2.10). This approach goes closely to Allcott et al. (2022), which can be summarised in the following way:

$$Y_{i,t=2} = \gamma Y_{i,t-1} + \sigma\eta_{i,t} + \beta\mathbf{X}_i + \epsilon_{i,t} \tag{2.11}$$

$$\eta_{i,t} = \beta\eta_{i,t-1} + \tau^I_{i,1} I_i + \tau^{\cap}_{i,1} I_i \cdot SM_{i,1} + \rho SM_{i,1} + \beta\mathbf{X}_i + \epsilon_{i,t} \tag{2.12}$$

As in Allcott et al. (2022) experiment, the IV exclusion restriction not necessarily holds. There might be other channels through which the treatments could affect an individual willingness to change behaviour.

Accordingly, we measure, at the follow-up the ATE of the I treatment (mediated by smartphone use) concerning the following variables:

- Welfare Survey Index (and its components individually) defined in Section 2.3.4.
- Activity-Passivity Social Media Scale..
- Perceived Usage Difference (New Follow-up survey).
- Self-Reported Frequency of Apps usage.
- Smartphone Use.

Moderators: We run the model in 2.10-2.12 also by checking the presence of heterogeneous effects among the respondents. We distinguish respondents by being below or above the median category of selected moderators. We plan to test for heterogeneous treatment effects by splitting the sample above versus below the median values of age, gender, baseline objective smartphone use, addiction index, activity index, Social Media Followers (Following), FOMO scale, Socio-Economic Status (Estimated), Parents Education, Immigrant Status (Estimated).

Chapter 3

Aspirations and Effort

A Sociological Exercise

& a Social Network Model.

The Rise of Influence: On the determinants of Aspirations, and their inclusion in a Network Game

Lorenzo Pinna[‡]

Abstract

This paper has a twofold objective. The The first one discusses the determinants of aspirations through the lens of two XIX-century economist-sociologists: Talcott Parsons and Thorstein Veblen. In particular, we discuss the works of *"Stratification"* in Parsons (1940), and of *"Pecuniary Emulation"* in Veblen (1899) to analyse the determinants of action. Accordingly, we combine their conclusions to draw the conditions under which aspirations emerge in human societies. The second objective includes aspirations in a network game with strategic complementarities inspired by Ballester et al. (2006) and Ushchev and Zenou (2020). Agents take an action in relation to their aspirations. In this sense, preferences are modelled in two directions. In the first scenario, agents want to convey to a social norm which states that agents with the highest aspirations are expected to exert higher effort concerning their peers. As a consequence, lower aspirations agents have a higher weight in pursuing an action. In the second scenario, agents prefer "emulating" the highest peers' aspiration behaviour. We characterise an equilibrium of action and provide some comparative statics. Finally, we show the conditions at the equilibrium, where aspirations are reached.

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Keywords: Social Networks, Action, Social norms, Pecuniary Emulation, Stratification.

JEL codes: B21, B31, D01, D91, Z13 .

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3.1 Introduction

In the last decades, income (and Wealth) inequality has gained an outstanding position in economic research. Understanding the relationship between the persistence of this phenomenon and the economic (and social) consequences at the individual (and society) level is an ambitious goal that most actors aim to study and evaluate. In economics, the latter has included distinct approaches (Piketty, 2014, 2020, 1995; Alesina and Angeletos, 2005; Alesina and La Ferrara, 2005; Bowles and Gintis, 2002; Bowles and Fochesato, 2024; Corak, 2013, 2016; Hauser and Norton, 2017; Bavetta et al., 2019; Genicot and Ray, 2017; Ray and Genicot, 2022; Bergman et al., 2019).

In this respect, an element neglected until recently in inequality-economic- research was how individuals' surrounding social relationships shape their perceptions and behavioural attitudes. In this respect, novel empirical evidence (Chetty et al., 2022a,b, 2024) found[1] that higher -local- exposure to diverse Socioeconomic Status (SES) networks shapes income mobility and perception of the same phenomenon, but not its demand for redistribution (Domènech-Arumí, 2025). The latter explains, for instance, how the misperception of the income distribution is a widespread phenomenon across countries (Gimpelson and Treisman, 2018; Engelhardt and Wagener, 2014; Niehues, 2014), with people below (above) of the median of the distribution generally over (under) estimating their position within it. Surprisingly, experimental evidence of informing respondents about the true value of income inequality or income mobility does not have a clear effect on the demand for redistribution (Mollerstrom et al., 2015; Fehr et al., 2024), irrespectively of the own standing in the distribution. The missing link is in clear contrast with the Meltzer and Richard (1981) theory of redistribution according to the median voter income position or the preferences for inequity aversion over time Fehr and Schmidt (1999), which may lead to a reaction for higher redistribution.

[1]The two studies of Chetty et al. 2022a; 2022b successfully provided this evidence with a sample composed of 84.1M of US citizens. They show how cross-social interactions by Socioeconomic Status are the main responsible for upward income mobility.

Fehr et al. (2024) for instance, gave an explanation that: <<.. *people view parental influence as a legitimate reason to justify some inequality.*>>, which may, for instance, generate an interplay on the various forms of inequality acceptance. According to their findings, Fehr et al. (2024) shows that it does not correlate to whether a respondent believes that income is determined by "effort" or "luck". The latter poses our premise for the following chapter. Namely, this paper attempts to look at possible relationships between the existence of aspirations, defined as "determinants" of individual investments (as from Genicot and Ray (2017, 2020)), and own behavioural attitudes, here considered as the effort in reaching a goal that a unit of analysis poses to herself. We divide this writing into two parts.

In the first part, we attempt to provide a normative-behavioural- explanation of the phenomenon, which draws from elements of social structures and an innate tendency to have distinction over others. To characterize this concept, we distinguish the determinant of individual action, given how aspirations are determined. We proceed to this objective by reviewing concepts from theories of two earlier economists/sociologists from the late XIX century to the first half of the XX century. Namely, Talcott Parsons and Thorstein Veblen.

In the second part, we show a simple model where we contribute in a network game with strategic complementarities à là Ballester et al. (2006), a model of aspirations, where aspirations are determinant of effort.

Thus, the contribution of this essay is twofold. In Section 3.2, this work analytically explores aspirations' role in determining the action (or effort) at the individual level. To do this, we explore two authors who had a role in investigating the relationship between human action and the surrounding social structure. It is worth noting that neither of the authors explicitly used the word "aspirations". However, their writing on these two distinct issues can be linked to this concept, as we can see throughout the paper.

The first author is Talcott Parsons, and we provide a critical analysis concerning his writing on *"An analytical approach to the theory of social stratification"* (1940). Accordingly, we conclude that Parsons drew a continuum of possible societies, which can be observed at the two extremes. On one side, a Society may reward individuals at birth by making aspirations purely exogenous or, conversely, the reward may be according to achievements, hence making aspirations endogenous and depending on the social structure. Finally, concerning Veblen, we will see how the author tried to describe how human beings have an innate tendency to excel over others. Namely, the tendency of humankind to exhibit "predatory behaviour". By doing this, we go beyond its contribution to the more popular writing on conspicuous consumption; we will analyze what Veblen called "Pecuniary Emulation", which is Chapter 2 of the "A Theory of the Leisure Class" (1899). This chapter can be considered prominent in the formulation of aspirations because Veblen takes, as for Parsons, the analysis of why individuals do take action. Veblen argues that this process is the fruit of an innate tendency of showing *"invidious distinctions"* over their fellows. Accordingly, *Veblen* argues that, in Societies where there is a system of private property, this is channelled through the accumulation and the subsequent display of wealth. In conclusion, it is worth making a distinction between the two authors since, according to Parsons, aspiration formation is conditional on the process of the reward of the action. That is, he emphasizes the institutional setting. According to Veblen, aspirations are part of an innate tendency to "privilege" over others. Hence, we can conclude that aspirations, according to Veblen, are always endogenous to the individual.

In the second part, we present, in Section 3.3, through a game-theoretical framework, a simple network model where individuals take an action. The novelty of the model is that agents are endowed with *goals* (or *aspirations*, which we will make use of the two terms interchangeably) and interact through a - *goal* weighted- network of which they derive a social norm. Accordingly, agents may follow those with the lowest or highest goals according to a parameter that regulates the interaction. The agents' choice is a level of effort, given a quadratic pay-off. The model is quite similar to the Ballester et al. (2006) and Ushchev and Zenou (2020) model of social norms. The aim of the model, in this preliminary phase, is to show how aspirations can influence determining an action.

Hence, being the first contribution to include aspirations in a network game with strategic complementarities.

3.2 On the determinants of Aspirations

3.2.1 Talcott Parsons's view

To explain Talcott Parsons perspective on the determinants and the influence of *Aspirations* in pursuing an action, we will make use of the writing in Parsons (1940), which provides a characterisation of the theory of action under *Stratification*. According to Parsons, Stratification is defined as the division of individuals in *social ranks*, which implies a hierarchical ordering. This analysis will be useful to understand which situation a unit of analysis has a scope for "Achieving Status" given the social circumstances.

A key emergent aspect in Parsons writing is, without doubt, the prominence of social comparisons. According to Parsons, units of analysis are classified in "social ranks"[2]. For instance, what he calls *"moral evaluation"* is simply the comparison (conditional on the social rank) between a subject (i.e. a unit of analysis) and its counterparts, which could be a group of social connection, given the Status (or qualities) that an individual attains to.

For Parsons, the quantification of the *moral evaluation* principle given a social rank varies according to the "action" that a person undertakes. Most importantly, the *moral evaluation* process is conditional on the normative pattern[3] of the Society, which is based on a classification of the "Action Opportunity" set through which a unit belongs. Given a normative pattern, there is also the case where individuals can be ranked equally, regardless of their actions. For instance, as Parsons argues:

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[2] The social rank can be seen as a hierarchical ordering of occupational structure, whose classification can be superior or inferior when relating two occupational statuses. It is worth remarking that Parsons never classified these occupations. However, he claimed its existence.

[3] A normative pattern can be seen as a Social Norm. That is, Parsons (1940) defines it as :<< *There is, in any given social system, an actual system of ranking in terms of moral evaluation. But this implies in some sense an integrated set of standards according to which the evaluations are, or are supposed to be, made. Since a set of standards constitutes a normative pattern, the actual system will not correspond exactly to the pattern.* >>

The theoretical possibility exists that not only any two individuals but all those in the system should be ranked as exact equals. This possibility, however, has never been very closely approached in any known large-scale social system. And, even if it were, that would not disprove the fundamental character of Stratification, since it would not be a case of "lack" of of Stratification but of a particular limiting type. (Parsons, 1940), pp.843.

With this assertion, Parsons wants to pin an Institutional aspect on the relevance of human action. That is, the latter increases its relevance as the *moral evaluation* of social ranks increases. For instance, Parsons puts clearly that, to commit to the discussion about social ranks *moral evaluations*, he puts a reference to (italics added): <<*The main factual references will be to the type of system of Stratification where, as in our own, there is a rather wide scope for, in Linton's term, the "achievement" of Status.* >> *(Parsons, 1940) pp 844.* That is, Status or qualities of a unit can be morally evaluated according to Parsons through different lenses, which they will discuss here subsequently.

Now, the discussion turns to the analysis unit, which is why humans take action. Parsons defines them as part of *"goal-directed"* entities, which by satisfying them, they gain a source of *"hedonic satisfaction"*. This source of satisfaction gives a sense of the self of *respect*, whereas a missing achievement of it gives a sense of *guilt* or *shame*. Interestingly, Parsons already had in mind a concept of "conformity" to social norms, which is implicitly in line with the "keeping up with the neighbours" theory of Veblen (1899). Since an agent's action is directed towards the goal, an agent is interested in achieving it, enjoying hedonic satisfaction from it, and gaining respect and recognition from the "*generalised other*". For instance: << *.. the other individuals become important to anyone; what they do, say, or even subjectively think and feel cannot be merely indifferent to him.*>> *Parsons (1940), pp. 845.* In this sense, for Parsons, the validation or recognition from others' becomes even more important than attaining the role he plays in Society. This can be a first instance of aspiring towards the achievement of one's own goal, conditional on the comparison with others:

.. this common pattern is applied on the judgments of higher and lower as applied to individuals, which thus form a convenient point of reference for systematising the normative pattern itself.

Self- respect, which, it may be said, is in the first instance a matter of living-up to the moral norms the individual himself approves, becomes secondarily a matter of attaining or maintaining a position in terms of the scale of Stratification. Failure to conform with institutionalised norms thus injures the individual's self-interest by leading to withdrawal of help and satisfactions; it can easily lead further into the "negative" reactions. (Parsons, 1940) pp 845.

And still:

... loss of moral respect for a person makes it at least difficult to maintain a high level of affection for him. Loss of either or both tends also to entail withdrawal of sources of hedonic satisfaction as far as these are dependent on the actions of others.(Parsons, 1940) pp 846.

Few considerations can be made from these sentences. First, a Society that attains to Status seeking activities, success or failure of aspirations is subjected to a moral authority, which is represented by the connection of the agent to which she is connected. Second, the reaction, conditional on the achievement or the failure of pre-determined goals, generates a reaction which goes in either direction. That is, an agent could gain esteem and respect from the connections, otherwise having a loss from it. These considerations go very close to the concept of aspirations as described in Genicot and Ray (2017), self-esteem (Kőszegi et al., 2022), and of theories which make a desire for social conformity in status (Bernheim, 1994), which had gained renewed interest in economic theory.

Moving further, Parsons (1940) characterises Societies according to the element that confers Status. In its broadest sense, this can be distinguished between considering whether Status can be conferred through the *Ascribed* elements of an individual (i.e. the kinship unit, exogenously given), or from the *Achievements*, which are the fruit of actions that an individual undertakes during the lifetime. A Society whose valuation of Status lies between these extreme characterisations has different implications concerning the importance of action towards achieving Status. Full adherence to kinship units would imply a Society of Castes, like in India. Hence, your achievements would not confer a higher status, authority, or power. On the other extreme, it would imply a full "Equality of Opportunities" Society, which would approach the "American dream" case[4], or in more abstract terms,

[4]Likely, Parsons was referring to the first half of the XX century concerning such type of Society, where economic mobility prospects were higher due to the rise of the Society of Mass Consumption.

the description that Rawls (1971) resembles in his writings.

The full characterisation of *moral evaluation*, according to Parsons (1940), is based on these six dimensions: *(i) Membership in a kinship unit*; *(ii) Personal Qualities*; *(iii) Achievements*; *(iv) Possession*; *(v) Authority*; and *(vi) Power*. This multidimensional characterisation of social ranks, weighted by their importance, characterises a reward system within our Society.

Such a differentiation implies varying "degrees of freedom" in the possibility of advancing between social classes, according to the action. For instance, Parsons talks openly about the high-income mobile Society of the first half of the XX century[5] as follows:<<*..this dominant pattern of the occupational sphere requires at least a relatively high degree of "equality of opportunity", which in turn means that Status cannot be determined primarily by birth or membership in kinship units. Parsons (1940) pp 852.* >>. While, in a Caste system, the element of birth is the sole component which determines Status.

Combining the latter with the pieces of evidence of Corak (2013, 2016), which describes a positive relationship between the level of inequality and the correlation between parent-child earnings, we can draw a relationship also between the incentives of pursuing an action aimed at achieving a differentiated "Status" in Society. That is, action-oriented to the achievement of Status is drawn on the prospect of having "room" for obtaining it. The room in an object may be interpreted in diverse ways. One, for instance, can be interpreted as an informational opportunity barrier (Chetty et al., 2022a,b). For instance, Chetty et al. found that higher Economic Connectedness (EC), defined as the number of links above the median Socio-Economic Status (SES) connections, can inform better about the prospects of income mobility than inequality itself. The latter is done for the US adult population, which is robust even after controlling for racial segregation measures, poverty rates, and other relevant economic barriers.

[5]Particularly, the reference to the after World War I, which coincides with the end of the "Belle Epoquè".

In Figure 3.1, we summarise the acyclical relationship between the type of Societies and the corresponding rooms for action to ease the understanding of this concept.

[***FIGURE 3.1 ABOUT HERE***]

Once this distinction is made up, namely the one between *Ascribed* and *Achieved* Status, within the two extremes, it is possible to draw a continuum of elements of action within each "possible" Society.

In a Society which approaches a Caste System, the emergent element of *moral evaluations* is certainly the kinship unit when pursuing an action. It is not easy to imagine that, once Status is conferred to the part of the kinship, the unit has to do nothing to keep it. For instance, we can image the black line in Figure 3.1 as a line which depicts the "Freedom" in pursuing an action which goes from the left ("Full Freedom of Choices") to the right ("Bounded Choices"). The latter can be seen as a concept which closely follows Amartya Sen's works on the Capability Approach.
For instance, a person may have the "qualities" to achieve a given position in a social rank scale but cannot if the room of action becomes "Bounded". The latter does not imply that the unit of analysis, given a "Bounded" action set, is not exempted from having aspirations. Instead, as Parsons argues, aspirations are ascribed at birth and are a function of the elements other than *(i)*. These elements are relevant in determining how that person will behave throughout the lifespan:<< *.. the essence of the matter is that a combination of element other than birth becomes part of the ascribed pattern to which the incumbent of the Status is socially expected to "live up." Parsons (1940) pp 855.*>>.

Conversely, when Society approaches higher Freedom of choices, the *moral valuations* are conditional on the adherence between the "target status" and the action that the agent has taken to achieve it. In this case, Parsons argues about the limitations of our Society concerning the measurement of this criterion. The latter probably explains why, in economics, this concept of measuring aspirations has never been brought to analysis. A part of the "résidus", as Pareto (1923) has defined all of what cannot be directly quantified in the science. Hence, up to now, the concept of adherence it is not demonstrable empirically.

Notwithstanding the measurement problem, the distinction that Parsons poses in drawing a line between *"Caste Societies"* and *"Equal Opportunity Societies"* is important for two reasons. First, it helps to understand how individuals' life outcomes are determined by institutional factors (in this case, kinship relevance in achieving "status"). The second factor of interest in Parsons is the need for individuals to adhere to a "social norm" when pursuing an action, which is also on the basis of Veblen (1899) writing.

3.2.2 Thorstein Veblen's view

Considering Veblen's perspective, we will make use of the writing in Chapter 2 of the book "The Theory of the Leisure Class" (1899). This book is mainly known for the topic of "Conspicuous Consumption", from which it gained a relevant interest in recent times, concerning microeconomic theory (e.g. see Ghiglino and Goyal (2010); Ghiglino and Langtry (2023)). The interest in this part of the survey is to look at the primitive aspects of conspicuous consumption. Namely, the effort motive which brings up a person to achieve it– what Veblen (1899) called "Pecuniary Emulation".

Direct measurements of this phenomenon include Bowles and Park (2005), where they found that higher inequality in a country was a driver to higher working hours in the same unit of analysis. For instance, their finding confirmed Veblen's theory, which we will explain throughout this part of the essay. However, their findings were considered to be aggregated. Veblen's arguments, instead, were directed towards an innate human tendency towards predatory behaviours in excelling over others. Hence, success is determined by "invidious comparisons" where the ground posed by the latter is relative to achievements.

In the chapter of *Pecuniary Emulation*, Veblen (1899), Veblen distinguishes the three distinct phases (and their measurements) under which the accumulation of resources takes place. Namely, barbaric institutions, private property institutions, and advanced industrial societies. Under all of these phases, Veblen emphasises the innate nature of humankind to excel over others, which he calls *"invidious distinction"*. *Invidious distinction*, as we will see in this part, is quite a flexible criterion of measurement according to Veblen. Moreover, this conceptualisation in the *Pecuniary Emulation* writing is the most important if related to *"human action"* as Parsons (1940) argues. The latter because Veblen is implicitly arguing that there is a scope for achieving status within all these societies: Parsons advances claims on the social structure process which leads to the outcome of status, while Veblen emphasises the "preferences" (i.e. the instinct of predatory behaviour), and on the unit of measurement for aspiration success/failure. The latter, by Veblen, is defined as the process of excelling in terms of possessions (or wealth, generally speaking) over their fellows.

Concerning the first phase, Veblen paves out the way on which the *"normative patterns"* in ancient (western) Societies lead to the beginning of the institution of ownership. In this aspect, Veblen puts evidence first on the rising "custom" of barbarian societies of appropriating women's enemies as "trophies", which was then extended to a form of slavery to all the enemies, which includes:<<*... an extension of slavery to other captives and inferiors, besides women, and by an extension of ownership-marriage to other women than those seized* >>. Moving further, in this phase there is a common need to achieve a reward, which is the:<<*... the desire of the successful man to put their prowess in evidence by exhibiting some durable result of their exploits* >> Veblen (1899) (pp.19). The latter, according to Veblen, is the outcome of Emulation and of a primitive stage of having appropriation of "things". On the last remark, in this phase, the men's prowess and achievements were considered more broadly at a "community" level, which was then abandoned in favour of more individualistic form of identifying achievements.

Once this phase is concluded, Veblen emphasises Societies where *"The institution of private property is found" (pp.20).* In this phase, there is a dynamical process of technological progress, which takes the form of a *"Industrial Efficiency"*, and it confers the possibility of affording more than a *"bare livelihood"* to those who are engaged in. Furthermore, this phase of Society also coincides with the detachment from the *"physical need of subsistence"*, which Veblen defines as *"physical wants"*. Accordingly, for Veblen this is the moment where accumulation takes place:

The end of acquisition and accumulation is conventionally held to be the consumption of the goods accumulated — whether it is consumption directly by the owner of the goods or by the household attached to him and for this purpose identified with him in theory. This is at least felt to be the economically legitimate end of acquisition, which alone it is incumbent on the theory to take account of. Such consumption may of course be conceived to serve the consumer's physical wants — his physical comfort — or his so-called higher wants — spiritual, aesthetic, intellectual, or what not; the latter class of wants being served indirectly by an expenditure of goods, after the fashion familiar to all economic readers. But it is only when taken in a sense far removed from its naive meaning that consumption of goods can be said to afford the incentive from which accumulation invariably proceeds. The motive that lies at the root of ownership is emulation; and the same motive of emulation continues active in the further development of the institution to which it has given rise and in the development of all those features of the social structure which this institution of ownership touches. The possession of wealth confers honour; it is an invidious distinction. Nothing equally cogent can be said for the consumption of goods, nor for any other conceivable incentive to acquisition, and especially not for any incentive to accumulation of wealth. Veblen (1899), pp 20-21.

The latter sentence, in the Veblen 's writing, is a crucial passage in establishing a link between the earlier stages of human development (i.e. barbaric western societies), with the -industrially- developed ones, where wealth is established itself as a concept of "*achievement*". Hence, it can be argued that humans, defined as directed goal units, in later stages of development of Societies, may measure their degree of "self-respect" or "esteem" based on their achievements, and hence of "wealth", instead of physical "predatory instincts", which were belonging to earlier stage societies. Accordingly, the easiest way to recognise one's esteem or achievements becomes an individual's possessions. Veblen makes this passage clear, and it explains it not as a matter of change in purpose but rather as a change in incentives that are provided to a unit in gaining distinction from the others:

With the growth of settled industry, therefore, the possession of wealth gains in relative importance and effectiveness as a customary basis of repute and esteem. Not that esteem ceases to be awarded on the basis of other, more direct evidence of prowess; not that successful predatory *aggression or warlike exploit ceases to call out the approval and admiration of the crowd, or to stir the envy of the less successful competitors; but the opportunities for gaining distinction by means of this direct manifestation of superior force grow less available both in scope and frequency. At the same time opportunities for industrial aggression, and for the accumulation of property, increase in scope and availability. And it is even more to the point that property now becomes the most easily recognized evidence of a reputable degree of success as distinguished from heroic or signal achievement. It therefore becomes the conventional basis of esteem. Its possession in some amount becomes necessary in order to any reputable standing in the community. It becomes indispensable to accumulate, to acquire property, in order to retain one's good name.* Veblen (1899) *pp 23.*

Accordingly, the basis of esteem is in one's own possessions, which is embedded in a social norm. For instance, in this passage, Veblen converges to Parsons view in the concept of Aspirations "Success/Failure", namely: << *In order to stand well in the eyes of the community, it is necessary to come up to a certain, somewhat indefinite, conventional standard of wealth; just as in the earlier predatory stage, it is necessary for the barbarian man to come up to the tribe's standard of physical endurance, cunning, and skill at arms. A certain standard of wealth in the one case, and of prowess in the other, is a necessary condition of reputability, and anything in excess of this normal amount is meritorious. Those members of the community who fall short of this, somewhat indefinite, normal degree of prowess or of property suffer in the esteem of their fellow-men...* Veblen (1899) *pp 24.* >>. In this respect, the relationship of economic success/failure is clearly highlighted by Parsons (1940). However, Veblen 's innovation stands on attaching a specific reference point for comparison. Namely, the wealth or possessions in general. Finally, in these respects, Veblen makes clear the link between the normative behaviour under which the unit engages in the process of "achievement":

Under the regime of individual ownership the most available means of visibly achieving a purpose is that afforded by the acquisition and accumulation of goods; and as the self-regarding antithesis between man and man reaches fuller consciousness, the propensity for achievement — the instinct of workmanship — tends more and more to shape itself into a straining to excel others in pecuniary achievement. Relative success, tested by an invidious pecuniary comparison with other men, becomes the conventional end of action. The currently accepted legitimate end of effort *becomes the achievement of a favourable comparison with other men; and therefore the repugnance to futility to a good extent coalesces with the incentive of emulation. Veblen (1899) pp 26.*

And

Purposeful effort comes to mean, primarily, effort directed to or resulting in a more creditable showing of accumulated wealth. Among the motives which lead men to accumulate wealth, the primacy, both in scope and intensity, therefore, continues to belong to this motive of pecuniary emulation. Veblen (1899) pp 26.

What is interesting in this passage, beyond the highlighting of the "conditional success", which is tested as "an invidious comparison", makes interesting the story of *achievement* to how we present the model in the next section. That is, the link between the accumulation and the comparison is the "effort" whose utility is towards accumulating and only then making the comparison. The latter is the so-called *"instinct of workmanship"*. In these two passages, Veblen emphasises the "action" which comes through the form of *"purposeful effort"*, which is meant to be a more creditable way to show wealth. Accordingly, this aspect of Veblen's theory of emulation can be linked with the one of Parsons (1940) by the diagram in Figure 3.1. That is, Veblen's focus is mainly on Society, which approaches an incentive in *"Achieving Status"*, hence on tendentiously mobile Societies. The mobility across individuals overtime is not openly discussed in Veblen (1899).

Beyond this, the Veblen (1899) contribution in the motives of accumulation does not focus on the relative positioning towards social classes. In this respect, the stylistic choice is coherent according to how he is describing the phenomenon[6]. That is, Veblen (1899) describes the fact of humans excelling over the others' "*invidious distinction*" which is attached to the process of accumulation and ownership. Hence, Veblen makes general the concept of "aspiration" as a distinct element of humans of having recognition by others in terms of their esteem and respect from them.

[6]Veblen, in this respect, deepens the difference between social classes in the taste of consumption. This is done in Chapter 4, where he discusses "Conspicuous Consumption".

Concluding, both theories of Veblen (1899), and Parsons (1940) present distinct elements which, if combined, may constitute an improvement towards modeling aspirations endogenously over time. A first step towards achieving this goal is to provide a model where aspirations are determinants of human action. The latter is the goal of the following section.

3.3 A Network Model of Aspirations

This section presents a model whose attempt is to introduce a framework, under the literature presented on Network games in Section 3.3.1, which considers the role in aspirations when providing effort. Prior to proceed with the structural aspects of the model in Section 3.3.2, we do a brief re-cap of the literature of network games with quadratic pay-off structure.

3.3.1 Network Games

The model presented in this section is a network game with strategic complementarities. A substantial review of network games is available in Jackson and Zenou (2015), while here we do provide the closest contributions to the model hereby presented.

Accordingly, the first model in considering the quadratic pay-off structure in providing strategic complementarities in effort comes from Ballester et al. (2006). In their model, i.e. the local aggregate (LA), the novel feature was the characterisation of the equilibrium according to the centrality in "reaping" the complementarities from the network structure. Namely, the Katz-Bonachich Centrality (from Bonacich (1987) and Katz (1953)). Accordingly, in the LA model, the action magnitude is proportional to this network measure, which considers all possible paths (with decaying weights) that an agent attains from her/his network. Further developments of this model encompass a wide range of topics[7]. For instance, we can consider policy implications varying to the sign of the peer effects, and according to the budget (Bramoullé et al., 2014; Galeotti et al., 2020), biases in social norms (Jackson, 2019), social effort in legislative activity (Canen et al., 2022), peer effects

[7]Originally, this model was idealised as a measure of identifying the network structure of criminal organisations and how criminal actions are distributed among "gangs".

in education (Calvó-Armengol et al., 2009), among the others.
From an inspiration of Ballester et al. (2006), our closest contribution comes from Ushchev and Zenou (2020). In their model, namely the Linear-In-Means (LIM), the action, under a quadratic-cost pay-off, does not look forward at the aggregate action of the network but rather at its mean level. Consequently, the results in Ushchev and Zenou (2020) differ from Ballester et al. (2006): an agent takes an action above (below) the social norm only if his/her productivity is above (below) the weighted average productivity of the network. The result is quite interesting since in Ushchev and Zenou (2020), the equilibrium effort is a weighted combination between the own productivity and the mean level of the social norm. Reconnecting it to our model, we find that by embedding aspirations on both the own "private" return and on the social comparison motive, the equilibrium effort is either increasing the private returns or decreasing the peer effects from higher aspirations. To microfound our result, an interpretation can be that higher aspired agents, to receive the same peer effects as relatively lower aspired individuals, must be assortatively connected to the same type of individuals (i.e. highly aspired).

Moreover, in the first stage, our work also wants to explore the implications in terms of inequality, conditional on the distribution of aspirations. Accordingly, network models that explored inequality arising from the network structure include Calvo-Armengol and Jackson (2004) for effects on unemployment (hence focusing on the informational flow) and Calvó-Armengol and Jackson (2009) for correlations of parent-child behaviour. Calvó-Armengol and Jackson (2009) found a particularly interesting result: without directly linking the parent to the offspring, their action is highly correlated, given that the offspring inherits the parents' network. Hence, the inter-generational correlation in behaviour may be underestimated if only the parent information is considered.

Finally, this work is not the first to consider sociological concepts in orienting behaviour, particularly Veblen. For instance, the topic of "Conspicuous Consumption" and externalities in consumption from a social network perspective has been widely explored in Ghiglino and Goyal (2010); Ghiglino and Langtry (2023); Langtry (2023). Accordingly, their findings relate to the signal of a "conspicuous" good about how many others consume it. In our case, the inclusion of a Veblen concept relates to the "Pecuniary Emulation" motive. Namely, agents peer effect is more sensitive to highly aspired individuals, conditioning on whom agents are following. Accordingly, we interpret this result as the fact that, if the peers' highly aspired are providing effort, the perception of the return to effort is higher.

3.3.2 Model Baseline: Local-Average Model with exogenous Aspirations

Throughout this section, we will make use of bold notation to indicate matrices and vectors, while normal notation is used to indicate scalar values. A typical player $i \in N = \{1, ..., n\}$ has an inner (ex-ante exogenous) heterogeneous characteristic: An aspiration $k_i \in [\underline{k}, \overline{k}]$, with $\underline{k} > 0$. An aspiration k_i of a player describes the level of consumption or the minimum required effort to attain to that aspiration.

We can state that $\underline{k}$ is a subsistence consumption level, which ensures survival, whereas $\overline{k}$ could represent the highest consumption level (in monetary terms) of that category (e.g. *Veblen*'s goods). To comply with the aspiration, each typical player i selects a level of effort $e_i \in \mathbb{R}_+$, whose collection of is a column-vector $\mathbf{e} = (e_1, ..., e_i, ..., e_n)$[8]. Effort can be considered as an action aimed at achieving a given consumption level, which depends on the aspiration posed. Effort and aspirations are measured on the same scale. Hence, the definition follows:

Definition 3.1. *(Aspirations: Satisfaction and Failure). Given an aspiration for the i^{th} player k_i, we say that k_i is satisfied if the chosen effort e_i exceeds the aspiration level k_i, namely $e_i \geq k_i$. Otherwise, we say that the aspiration is failed.*

For simplicity, agents have the same level of productivity, namely α, this allows us to focus on the role of aspirations in pursuing an action. Furthermore, an agent is part of an undirected network, described by a $n \times n$ adjacency matrix $\mathbf{G}$. An element of $\mathbf{G} = [g_{ij}]$ describes the relation between typical agent i and peers' j with $\{0, 1\}$ entries. We say

[8] We can see k_i as an aspiration or consumption goal and $\mathbf{e}$ the chosen level of effort or induced consumption to achieve that aspiration. Another example can be that an individual has an occupational aspiration which implies a series of actions, where the effort to achieve that aspirations is linearly increasing in the difficulty of achieving the aspiration itself.

that i and j are connected if $g_{ij} = g_{ji} = 1$ and 0 otherwise. A position of i in an undirected network $\mathbf{G}$ defines her position concerning the social norm $\tilde{e}_{-i}$ which is given by her connections. $\mathbf{G}$ does not contain self-loops (i.e. $g_{ii} = 0$), namely it is a zero-diagonal nonnegative square matrix. With these ingredients, now we can define the $n \times n$ interaction matrix $\mathbf{W} = [w_{ij}]$, which is the row-normalised matrix of $\mathbf{G}$. An element of $\mathbf{W}$ is defined as $w_{ij} = \frac{g_{ij}}{d_i}$ if $d_i > 0$ and $w_{ij} = 0$ otherwise. At this point, we model how the j^{th} agent influences agent i. Before defining the social norm peers influence, we define the matrix $\tilde{\mathbf{W}} = [\tilde{w}_{ij}]$, which is a $n \times n$ goal-weighted interaction matrix. An element of $\tilde{\mathbf{W}}$, $\tilde{w}_{ij}$ is equal to $\tilde{w}_{ij} = \left(w_{ij} k_j^{\beta}\right)^{\frac{1}{\beta}}$ where the size, and the sign β redirects the influence as becomes greater, and positive (negative) to the highest (lowest) aspiration of the agent. It can be noticed that, we model an element of $\tilde{\mathbf{W}}$ through a well-known functional form, that is the Constant Elasticity Substitution (CES). With all these ingredients, we can define a social-norm, for a player i, which is the effort vector $\mathbf{e}$ weighted by $\tilde{\mathbf{W}}$.

Accordingly, the intensity of the relationship from j to i arises from $j's$ aspirations (k_j), and vice-versa. Hence, the interaction matrix is non-symmetric. Formally:

Definition 3.2. *(CES Aspirations Social Norm): A Social Norm that a player i observes from the set of players j ($\tilde{w}_{-i}$) is a weighted relationship of how other players efforts (e_j) are influenced by their players goals' (k_j). That is:*

$$\tilde{e}_{-i}(\beta, k_{-i}) = \left(\sum_{j=1}^{N} w_{ij} k_j^{\beta}\right)^{\frac{1}{\beta}} \cdot e_j = \tilde{w}_{-i} \cdot e_j \tag{3.1}$$

which represents the weighted average about the relation over the i's connections on how much effort peers' are exerting in relation to their aspirations. Namely, agents' influence arises solely in $i's$ connections ($j \in d_i$) and not from the whole population.

For simplicity, the current-stage of the model considers a full-information game. A further development of this framework may postulate alternative expectation formation schemes concerning the others' aspirations, which could not be known by a player.

Modeling the social norm (3.1) is general, since it allows for any level of $\beta \in \mathbb{R}$. Furthermore, the expression (3.1) is not entirely new. For instance, Boucher et al. (2024) captured the CES social-norm relationship with respect to effort. In particular, when $\beta = 1$ we do obtain the Linear-in-Means (LIM) model (Ushchev and Zenou, 2020) where peers' effort do not influence i's social norm differently in the own effort choice. Conversely, as β approaches large (small) numbers, the i^{th} player defines the social norm concerning the highest (lowest) agent effort. In our case, the effort effect remains unvaried. Rather, the same effect varies according to the goal of the j^{th} agent that i observes. Formally, by setting the limit of β approaching $+\infty$ we do have that in (3.1):

$$\lim_{\beta \to +\infty} \tilde{e}_{-i}(\beta, k_j) = max\{k_j\}e_j$$

Which implies that i is following the highest goal-directed agent. This case allows to consider the case of *emulative* behaviour, where an agent "emulates" the agent with the highest goal. Conversely, when β approaches $-\infty$ we have that:

$$\lim_{\beta \to -\infty} \tilde{e}_{-i}(\beta, k_j) = min\{k_j\}e_j$$

Which it implies that the agent is more sensible to the agent with the lowest goal. Notice that this latter behavior could be consistent either with altruistic or power motives. Also, as Trigg (2001) argues, this way of imaging the behavior (i.e. downward influence) is consistent with the Bourdieu (1984) argument about the "habitus" of the upper class in being forward looking to the working class. That is, the trickle-round approach.

Consequently, the relationship between the two agents is not reciprocal, implying an asymmetric interaction pattern between agents, that is captured by the element $\tilde{w}_{-i}$ in (3.1).

This novel approach in formulating a social norm relates to an agent that influences the action of the others in terms of effort e, and this effect is weighted by the aspirations that an agent has (through $\tilde{\mathbf{W}}$). For instance, an increase in aspirations poses higher self-expectations on effort. The latter can be interpreted as an increase in self-esteem (as in Kőszegi et al. (2022)). In this simple framework we want to capture two aspects regarding the action taken, which are both conditional on the aspirations posed. First, the self-commitment in posing effort, and second the social expectations over your aspiration, which capture the social pressure for exerting higher effort, given a high aspiration. The latter is captured through decreasing cost in social comparison, due to an increase in aspirations.

Hence, the bi-lateral pay-off is described by a function which yields utility $U_i(e_i, k_i, \tilde{e}_{-i})$:

$$U_i(\mathbf{e}, \mathbf{K}, \mathbf{W}) = \left(k_i\alpha - \frac{c}{2}e_i\right)e_i - \frac{\gamma}{2}\left(\frac{e_i}{k_i} - \tilde{e}_{-i}(\beta, k_{-i})\right)^2 \tag{3.2}$$

From (3.2), notice some aspects of the game, which takes elements from both Ballester et al. (2006) and Ushchev and Zenou (2020). First, the aspiration k_i factor enters twice into the computation of the optimal action. In the first case, it has an analogous effect that productivity α has in this class of games with a quadratic setting. Conversely, it also sets a ground concerning the social norm, in the sense a player with a higher aspiration should exert higher level of effort to comply with the social norm, otherwise paying the penalty $-\frac{\gamma}{2}\left(\frac{e_i}{k_i} - \tilde{e}_{-i}(\beta, k_{-i})\right)^2$ for not doing so. We can also consider k_i itself as "productivity". For instance, a justification can be that peers' j, by knowing that the i^{th} agent has higher capabilities in performing a given task, it is -socially- required that i performs more on that task than others should.

Second, it constitutes a network-quadratic game with strategic complementarities (i.e. $\frac{\partial U}{\partial e_i \partial e_j} > 0$)[9]. Hence, the role played by k_i constitutes an application of the relationship between the role of aspirations, and the action taken e_i to achieve it. By setting $\frac{\partial U}{\partial e_i} = 0$, we obtain the best-response to the game (3.2), namely:

$$e_i^* = \max\{0, a_i + \gamma z_{ij} e_j | i \neq j\} \tag{3.3}$$

where $a_i = \frac{\alpha k_i^3}{ck_i^2 + \gamma}$ and $z_{ij} = \frac{k_i}{ck_i^2+\gamma}\tilde{w}_{-i}$ are scaling factor functions, and are monotone increasing transformations in k. Now, we turn on to some specifics of the utility function (3.2). Spillovers are mediated by the relative role of aspirations, namely:

[9]Where, if we consider a matrix of cross-effects Σ from Ballester et al. (2006), its decomposition sets to 0 the global substitutability component γ, where $\gamma > 0$ if there exist some strategic substitute effects across players (i.e. $\underline{\sigma}_{ij} < 0$, which is not our case at this stage.) with $\gamma = -min\{\underline{\sigma}, 0\}$ where $\underline{\sigma}$ is the highest strategic substitutability effect across of the population.

$$\frac{\partial U}{\partial e_j} \geq 0 \iff e_i \geq k_i \tilde{e}_{-i}(\beta, k_{-i}) \tag{3.4}$$

where the ground posed by own aspirations (k_i) in relation to others' says that spillovers are positive the lower the peers' aspirations are, and they decrease as the own aspirations are increasing. The latter could be considered as a declining peer' effect due to higher aspirations. With uniforms aspirations (k_i), this statement collapses to the findings of Ushchev and Zenou (2020).

In light of the formulation of the best-reply (3.3), now we turn to some parsimonious equilibrium analysis.

3.3.3 Results

Now, we turn to the equilibrium analysis of the game (3.2), we start by augmenting a Nash Equilibrium, which it will be our benchmark equilibrium point for the comparative statics. Considering the Best-Reply in (3.3), we define, in matrix notation, some elements which will be useful for the next result.

First, denote $\mathbf{a} = [a_i]$ the $n \times 1$ vector of individual aspirations. We define also the matrix $\mathbf{Z}$, with $\mathbf{Z} = [z_{ij}]$ observed in (3.3). $\mathbf{Z}$ is a $n \times n$ zero-diagonal matrix of own-aspiration comparison-effects multiplied by the diagonal $n \times n$ matrix of peers'-aspiration effect.

The latter two components can be decomposed between $\mathbf{B}$, and $\tilde{\mathbf{W}}$. $\mathbf{B}$ is a $n \times n$ diagonal matrix, where an element of $\mathbf{B}$ is $[b_{ii}] = \frac{k_i}{k_i^2 c + \gamma}$. Accordingly, the best-reply in (3.3) can be re-written as:

$$\mathbf{e} = \mathbf{a} + \gamma \mathbf{Z} \mathbf{e} \tag{3.5}$$

where, by solving for $\mathbf{e}$ in (3.5), the following result holds:

Lemma 3.1. *(Nash Equilibrium):*

(i) There exist an interior Nash equilibrium of the game (3.2)*. The equilibrium is given by the following expression:*

$$\mathbf{e} = [I - \gamma \mathbf{Z}]^{-1} \mathbf{a} = \mathbf{a} \sum_{m=1}^{\infty} \gamma^m \mathbf{Z}^m = a_i \phi_i \tag{3.6}$$

Moreover, if the matrix $\gamma\mathbf{Z}$ is invertible, the nash equilibrium (3.6) is stable and it constitutes the unique interior solution if the spectral radius of the matrix $\gamma\mathbf{Z}$, namely $\rho(\gamma\mathbf{Z})$, is lower than one.

(ii) The social norm equilibrium ($\tilde{\mathbf{e}}$) is equal to:

$$\tilde{\mathbf{e}} = \mathbf{a}\sum_{m=1}^{\infty}\gamma^m\mathbf{B}^m\tilde{\mathbf{W}}^{m+1} = a_j\phi_j \tag{3.7}$$

(iii) The Pay-off equilibrium is:

$$U^*(k_i,\gamma,c,\alpha,\mathbf{e}) = a_i\phi_i\left(\underbrace{k_i + \frac{\gamma}{2k_i}a_j\phi_j}_{Benefit} - \underbrace{a_i\phi_i\left[\frac{c}{2}+\frac{\gamma}{2k_i^2}\right]}_{Costs}\right) - \underbrace{(a_j\phi_j)^2}_{Pure\ Externalities} \tag{3.8}$$

Note that, the equilibrium characteristic can be interpreted as the combination of two factors.

Namely, higher aspirations increase the effort level at the equilibrium (from $\mathbf{a}$) and are increasing in the aspirations of peers (from $\mathbf{Z}$). That is, being connected to higher aspirations agents gives higher peer' effects at the equilibrium. The latter can be interpreted as an additional complementarity effect arising from an agent's inner characteristic. Note also, given an increase in private cost (c), that higher aspiration individuals reap lower complementarities from the other agents (from the element b_{ii} in z_{ij}). The latter, in this model, is a key element because, as we will see in a while (in Proposition 3.3), aspiration success/failure is a function of social norm behaviour in effort when private costs (c) are higher than private benefits (α).

Now, we turn to show some features of the static model. In particular, we show first in which direction some key parameters of the model modify the action at the equilibrium. Subsequently, we show the conditions under which the aspirations "success" (as in Definition 3.1) are reached at the equilibrium effort.

We begin by examining the effect of a marginal increase in productivity α. Accordingly, we relax for the moment the assumption of uniform productivity levels α. Since its dependency is strictly related to aspirations, we draw the following results:

Comparative Statics of α:

Proposition 3.1. *The effects of a marginal increase in productivity of an individual (α_i) is depending in the aspiration k_i. Namely:*
(i) The effect of an increase in own productivity on peers' action is positive, and smaller than one provided that $\forall k_i \in [\underline{k}, \overline{k}]$:

$$\left[0 < \frac{\partial e_j^*}{\partial \alpha_i} < 1,\right]$$

with the threshold $\overline{k}$ defined implicitly by

$$\left.\frac{\partial e_j^*}{\partial \alpha_i}\right|_{k_i = \overline{k}} = 1.$$

(ii) The effect of an increase in own productivity on the own pay-off (U_i^*) depends on the size of α, and on the own aspirations k_i. That is:

$$\lim_{k_i \to +\infty} \frac{\partial U_i^*}{\partial \alpha} = \frac{k_i^2}{c}(1-\alpha)$$

Where: If $\alpha = 1$, then $\lim_{k_i \to +\infty} \frac{\partial U_i^*}{\partial \alpha} = 0$, and if $\alpha > (<) 1$ then $\lim_{k_i \to +\infty} \frac{\partial U_i^*}{\partial \alpha} = -\infty(+\infty)$

Given the interaction between α and k_i, it is not surprising that an increase in productivity crucially depends on the latter. From Proposition 3.1, we can see that an increase in productivity increases the action profile of peers at the equilibrium. Furthermore, the effect on the own pay-off (U_i^* from (3.8)) crucially depends on whether α is greater (smaller) than a unity. That is, since α enters quadratically in the social costs, $\alpha > 1$ entails a more than proportional increase in cost at the equilibrium pay-off than the benefits, hence -marginally- decreasing the pay-off. That is, the social pressure effect dominates the private benefits.

Now, we explore the role of other two key parameters on equilibrium effort: the private cost of the action c, and the conformity parameter γ. Their effect on the effort at the equilibrium is complex. As we can see here:

Comparative Statics of c:

Proposition 3.2. *Define the expressions* $A_i = \left(1 - \gamma \frac{k_i}{k_i^2 c + \gamma} \cdot \tilde{w}_{-i}\right)^{-1}$, *and* $a_i = \frac{\alpha k_i^3}{k_i^2 c + \gamma}$. *The effect of a marginal increase in private costs c on the equilibrium is given by:*

$$\frac{\partial e^*}{\partial c} = \underbrace{\frac{\partial a_i(c)}{\partial c}}_{<0} \times \underbrace{A_i(c)}_{>0} + \underbrace{\frac{\partial A_i(c)}{\partial c}}_{<0} \times \underbrace{a_i(c)}_{>0} < 0$$

The negative effect of private cost c at the Nash Equilibrium e^{NE} in (3.6) is trivially negative. Accordingly, this depends on two expressions which the private costs enter in (3.6), namely a_i, and A_i. The first is an increasing transformation of aspirations k_i, namely $\mathbf{a}$, which also interacts with the productivity α. At the same time, the second one regulates the intensity of peer effects through $\mathbf{B}$. Both of these expressions are decreasing in c.

As a final result for the static model, we do present, at the Nash Equilibrium, the condition under which an agent can achieve the aspiration (given the Definition 3.1):

Proposition 3.3. *(Aspiration at the NE):*

Consider $c \geq \alpha$. *Then, at the equilibrium effort* e_i^{NE} (3.6) *for a typical agent i:*

1. *If* $\gamma \tilde{w}_{-i}^2 > 4(c-\alpha)$ *then aspirations are reached at the points:*

$$\frac{\gamma \tilde{w}_{-i} - \sqrt{\gamma^2 \tilde{w}_{-i}^2 - 4(\alpha - c)\gamma}}{2(c-\alpha)} \leq e_i^{NE} \leq \frac{\gamma \tilde{w}_{-i} + \sqrt{\gamma^2 \tilde{w}_{-i}^2 - 4(\alpha - c)\gamma}}{2(c-\alpha)}$$

2. *If* $\gamma \tilde{w}_{-i}^2 = 4(c-\alpha)$ *then aspirations are reached at the point:*

$$\frac{\gamma \tilde{w}_{-i}}{2(c-\alpha)} = e_i^{NE}$$

3. *Otherwise, if* $\gamma \tilde{w}_{-i}^2 < 4(c-\alpha)$ *is true, aspirations are never reached.*

Conversely, if $c < \alpha$ *is true, aspirations are always reached* $\forall i \in N : k_i \geq 1$.

The result in Proposition 3.3 is interesting. First, note that in the absence of social comparisons (i.e. $\gamma = 0$), the unique point where aspirations are reached is when $\alpha \geq c$).

Conversely, when $\gamma > 0$, we can see how the definition of "success" and of "failure" (from Definition 3.1) is dependent upon the social incentives in providing effort. For instance, if "private net-cost" (i.e. $c-\alpha$) is greater than the "social incentives" (i.e. $\gamma \cdot \tilde{w}_{-i}$), that is the benefit of being connected with highly aspired individuals, then aspirations are consistently failed for the player (from 3. in Proposition 3.3). Moreover, this result replicates the main findings of aspirations in Genicot and Ray (2017), concerning the first result in Proposition 3.3, but for a different reason from them[10]. That is, one's own aspirations that are too distant from the peers' aspirations lead to failure (as in Point 1-3 in Proposition 3.3). Hence, the latter statement is true whenever $\alpha < c$. Meanwhile, uniformity in aspirations leads to success in situations where private costs dominate private incentives. Conversely, aspirations are always reached if private incentives are greater than private costs. We visualize the four cases in Figure 3.2 where we show, by varying the parameter α, how the aforementioned conditions guide the change.

[***FIGURE 3.2 ABOUT HERE***]

3.4 Conclusions

This paper had a dual goal.

On the one hand, the aim was to explore the determinants of aspirations in economic outcomes, which can be considered part of the "*residues*" (in Pareto (1923) terminology). To achieve the first goal, we analysed two prominent authors who contributed to Economics and Sociology: Talcott Parsons and Thorstein Veblen. Both authors contributed significantly to understanding aspirations' role in human action, albeit their approach is quite different. Parsons focuses on the role of social structure to arrive at a characterisation of Aspirations, while Veblen's focus was prevalently on the innate tendency to excel over others, the so-called "invidious distinction".

On the other hand, the aim was to provide, through a parsimonious network-game theoretical framework, how social norms and peers' aspirations could determine the success

[10] They use the cognitive window as a relationship between own economic situation, and the whole economy. While, in our case, it is the relationship between aspirations and the social network.

or failure of one's own aspirations. To show this phenomenon in a static framework, we provided a quadratic-cost pay-off network model, which borrows elements from Ballester et al. (2006) for the quadratic cost pay-off (which assures a closed-form solution) and from Ushchev and Zenou (2020) which considers the relevance of peers' social norm aspirations. We characterised a Nash Equilibrium and provided some comparative statics on it. Accordingly, we showed that the reach of one's aspirations depends on the trade-off between social conformity and the private net costs of pursuing an action. That is, when private costs are higher than the benefits, aspiration success depends upon the social benefits of conformity.

On both sides, this paper presents an early-stage exploration of studying the formation of aspirations by individuals. Accordingly, there is clear room for improvement on both sides.

On one side, the analysis of the two contributions by Parsons and Veblen can be further enriched by comparing them with further contributors to the thought of this phenomenon. Pursuing the first part of this paper in this direction could constitute a stand-alone contribution to understanding aspiration formation heuristics. The latter aspect, in economics, is practically unexplored, as Genicot and Ray (2017) argued.

Conversely, to be consistent with the formulation of aspirations over time, the network-game theoretical framework should consider the results provided in an evolutionary context. For instance, as in Genicot and Ray (2017), aspiration "success" can be considered as an element corresponding to the achievement of a "milestone", which hence provides additional utility to the agent. This latter element is not considered in this paper since the framework is static. Hence, if we consider a time-evolving framework, aspirations should give a kink in the utility function according to whether the same is reached or not. Second, they should be treated as endogenous since they may depend on previous aspirations, past achievements, and the resulting social structure.

Enriching the contribution in both the sociological and the evolutionary aspects of aspirations would undoubtedly contribute to the literature in further understanding how their evolution influences action and, consequently, their distribution over time.

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Figures

Type of Societies
(Normative)

Fully Mobile System
(Endogenous Aspirations) $\longleftrightarrow$ Caste System
(Exogenous Aspirations)

$\longleftarrow$
Scope for Achieving Status
(Relevance of Action)

$\longrightarrow$
Kinship Moral Evaluations
(Ascribed Status)

Figure 3.1: *Type of Societies (Normative). Personal Elaboration from Parsons (1940) conceptualisation.*

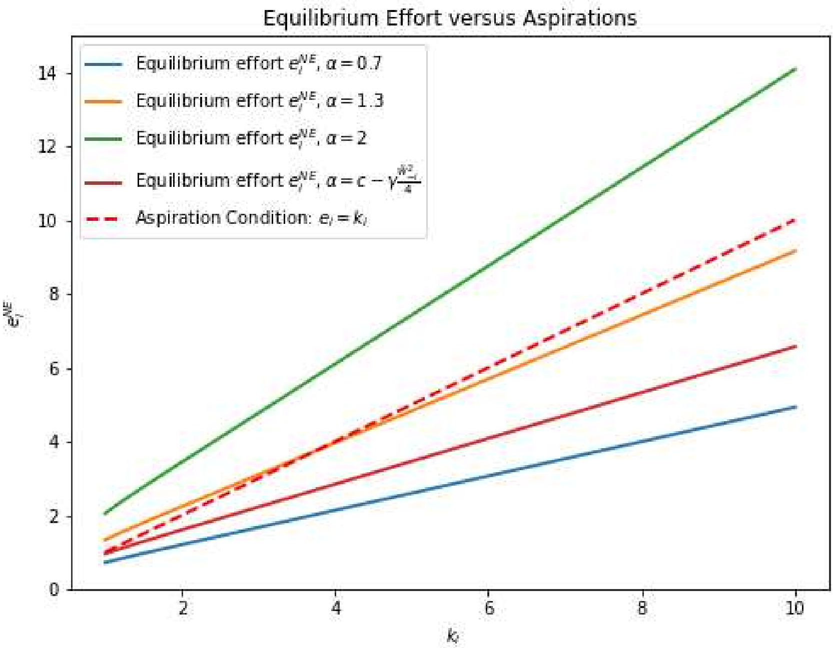

Figure 3.2: *Aspiration condition: If above the 45° degree line (red-dashed) means success. The figure illustrate the four cases with varying α, where each of the four scenarios in Proposition 3.3* are shown. The other parameters are $\beta = 1$; $c = 1.5$; $\overline{k}_j = 2.75$; $\gamma = 0.3$

I Proofs

Proof of Lemma 1:

To prove the existence, and the uniqueness of the interior Nash Equilibrium, we do rely on known results from linear algebra. Accordingly, the main results come from Debreu and Herstein (1953), and Battigalli et al. (2023). We consider a square-matrix $\mathbf{Z} \in \mathbb{R}^{n \times n}$ such that the diagonal elements are 0, i.e. $z_{ii} = 0, \forall i \in \{1, ..., n\}$. We denote as $\mathbf{I}$ the identity matrix, $\lambda_{max}(\mathbf{Z})$ the largest eigenvalue of $\mathbf{Z}$, $\rho(\mathbf{Z})$ the spectral radius of the largest absolute value of the eigenvalues of $\mathbf{Z}$, $\mathbf{1}$ the vector of all 1's, and $\mathbf{0}$, the vector of all 0's, and $\gg$ the strict partial ordering between vectors, and $\gamma < 1$ be a scalar smaller than one. Accordingly, the condition for existence, and of uniqueness of the interior Nash Equilibrium can be written as follows:

Proposition 3.4. *Consider a square matrix $\mathbf{Z} \in \mathbb{R}^{n \times n}$ such that (i) $\rho(\mathbf{Z}) < 1$, (ii) for each $i \in I$, $z_{ii} = 0$ and (iii) for each $j \neq i$ $0 < z_{ij} < 1$, and (iv) $\gamma < 1$. Then $(\mathbf{I} - \gamma \mathbf{Z})^{-1} \cdot \mathbf{1} \gg 0$.*

This result is always reached for sufficiently low values of γ, such that the social multiplier does not dominate the personal costs of taking action. Otherwise, the equilibrium would diverge. This is a sufficient, and necessary condition for proving (i) in Lemma 3.1. To proove (ii) it is sufficient to insert (3.6) in (i) into (3.1), so that we obtain (3.7). Finally, to proove (iii), it is sufficient to insert (3.6) into the pay-off function (3.2) .

Conclusions

What's Next?

Along the PhD journey, I had the chance to explore distinct topics related to the research union between Economics and Social Sciences, in general. I am grateful for this opportunity.

However, as I shall argue, I have also left many research questions.

In the first chapter, namely the union between consumer behaviour and system dynamics, it is possible to further explore consumer choice with varying heuristic rules or endogenous reference points and look at their evolution over time. Moreover, another interesting element to explore is whether the modeling of a "Conspicuous Good" into the interacting cobweb framework may change the dynamics and its stability conditions.

Concerning the second chapter, the exploration goes first with the entire dataset of the RCT survey at disposal. Namely, if short-run outcomes are confirmed, and we can see persistence in the medium run, it would be appealing to derive prominent policy implications. For example, in the paper, I argued that the causal claims would be more substantial in the medium run if the respondents were highly exposed to both information concerning their own and peers' smartphone consumption while using it. A field experiment through an on-device app would be interesting such as to strengthen the results hereby presented.

Concerning the third chapter, the two explorations, namely the thoughts of prominent figures in Social Sciences and the Network Game, can also be considered standalone research. Accordingly, two independent papers may explore, in the first instance, how Parsons and Veblen viewed aspirations. In the second phase, a network model with endogenous time-varying aspirations would be interesting to explore to see how these influence behaviour and how the social network structure affects the long-term equilibrium outcomes.