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Time allocation inequality: An economic analysis of digital leisure*

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CONTENTS

Abstract

Recent concerns about time invested in digital leisure have attracted research in behavioral sciences and economics. This work explores the time allocation economics of smartphone leisure activities using Becker's (1965) theory of the allocation of time. The theoretical adaptation is applied to the Korean context using the Korean Smartphone Overdependence Survey for 2023-2024. The econometric estimation describes statistically significant negative associations between the wage and (i) smartphone time share on leisure, (ii) short-video share of video consumption and (iii) misalignment between actual and desired leisure allocation. These estimations depict a gradient among economic groups who have unequal allocation of time in smartphone leisure activities. These findings can be used to argue about potential unequal effects found in the literature on the use of these technologies among the population.

1. INTRODUCTION

The intensive use of digital entertainment has recently raised concerns due to its potential harmful effects on the mental health of users (New York State Assembly, 2025; Jo et al., 2021). Some of the explanations for the patterns of consumption for these technologies have been attributed to their design which makes them highly engaging, as is the case of algorithmic recommendation features in social media and online video platforms. These designs, it has been argued, create consumption behaviors similar to addiction; therefore, several of the approaches studying these concerns are related to human behavioral fields (Allcott et al., 2020, 2022). A complementary approach is the study of the economics of time allocation and how this influences consumer choice of time spent on these digital products. It is a convenient approach due to the fact that the low monetary entry cost for the use of these technologies has made evident that the real cost of their consumption is the time invested in their use, especially when their design features allow time-intensive usage, such as "doomscrolling". Moreover, if harmful effects of extensive exposure to these products exist, it is of interest to assess whether the time allocation is equal across the population or whether there exist societal groups that allocate more time to such leisure activities.

To explore by how much time allocation for digital leisure products varies across socioeconomic groups, I use the theoretical framework introduced by Gary Becker in 1965 in his seminal work, *A Theory of the Allocation of Time*. I develop an adaptation of the theory to explore the allocation of smartphone leisure time and its composition across digital products with different engagement characteristics. The theoretical analysis is then applied to the South Korean context through the use of the Korean Smartphone Overdependence Survey, a dataset which measures consumption patterns of digital entertainment products across society. This rare dataset offers an interesting opportunity to explore detailed patterns of consumption by digital products in highly connected societies.

The theoretical framework describes a setting in which the allocation of time among different activities is determined by the opportunity cost of time, which is approximated by the wage rate. This leads to distinct responses to digital product consumption at different levels of opportunity costs for the representative individual. The prediction of the model is that an increase in the wage rate will induce a reduction in all smartphone leisure activities with a disproportionate adjustment of activities that exhibit a slower rate of decrease in marginal benefits, or higher engagement characteristics.

Due to data limitations, the predictions offered by the theory are only explored descriptively in the Korean setting. This empirical analysis focuses only on the full-time working population between ages 19 and 59, as they more closely illustrate the effects of changes in wages described in the theory. I found a statistically significant negative relationship between smartphone leisure time and wages, a statistically significant negative relationship between the probability of being a high short-video format consumer and wages, and finally, a statistically significant negative relationship between wages and the probability of displaying a misalignment between actual and desired smartphone leisure use. Specifically, the misalignment rate is defined as the share of respondents whose actual main leisure activity is smartphone use but whose desired leisure activity is something different. These findings coincide with the type of relationships predicted by the theoretical framework; however, it is possible that this relationship could be driven by other factors such as particular preferences or differences in leisure time availability.

This work relies on the following strands of literature. The time-allocation economics literature was first introduced by the seminal theoretical work of Becker (1965), which introduced time as one of the resource constraints, coupled with the income constraint, that determine the rational choice of consumption for economic agents, and elaborated the idea that households do not merely consume market goods; rather, they use them as inputs together with time to produce commodities, which they combine to maximize their utility. Both perspectives marked a more realistic approximation of the behavior of households regarding their allocation of resources and labor supply. This work was later complemented by Gronau (1977), by the explicit division of the use of time into home production and leisure, distinguished by their output, the former being home goods that substitute market goods, while leisure time enters directly into the utility function. The theoretical framework of time allocation has inspired literature mostly focused on empirically assessing the relationship between market work time and leisure time across socioeconomic groups and through time. Some early evidence of the mid twentieth century relates the decrease in market hours of men in the U.S. and Japan to new developments in television (an activity directly related to leisure) such as diverse programming and broadcasting in color, in particular for the most educated men between 1965 and the late 1970s in the U.S. In time data from the U.S. and Sweden, individuals reported variation in satisfaction levels from different time usage: activities that occurred in interactive contexts were more satisfying than those performed in solitude. Particularly, the satisfaction of market working time was rated higher than most leisure activities. This suggests that time cannot be considered only as an input in the production of commodities, but preferences over how this time is experienced are also at play (Juster and Stafford, 1991).

In parallel, some of the main applications of the theory of allocation of time have been developed in macroeconomic evaluations of changes in trends of the supply of market labor in the last decades and its association with inequality. There is evidence that in the U.S. between 1965 and 2003 the number of hours dedicated to leisure rose about 6-9 hours per week for men and 4-8 hours for women, driven mainly by a reduction in the amount of time spent at market work for the former, and by less time allocated to home production for women. These changes are accompanied by a growing cross-sectional dispersion in the time allocated to leisure, where less educated groups and low-wage workers experienced greater increases in leisure time (about 7.3 hours) compared to more educated groups and high-wage workers (Aguiar and Hurst, 2007). The increasing aggregated trend in leisure time is explained by the growth of total factor productivity in the market sector which increases wages and generates an income effect that pushes households to afford more leisure time. The cross-sectional divergence among socioeconomic groups is accounted for by an intertemporal substitution effect of labor, where households who experienced larger wage increases invest more time working, while households whose wage level stayed constant or decreased decided to work more at the beginning of the period and then devoted more time to leisure (Boppart and Ngai, 2021). By aggregating multiple time allocation records in the U.S. and focusing on age groups, Ramey and Francis (2009) found that between 1900 and 1980, individuals between ages 24 and 54 experienced an increase in their leisure time of about five hours per week; however, by 2005 they returned to the 1900 level. This same group displayed the same number of working hours in 2005 as in 1900, mainly driven by the rise in female working hours offsetting the decline of male hours. On average, from 1900 to 2005, people over 14 years old experienced an increase of four hours per week of leisure time.

More recently, the theories of allocation of time have been of use to explain patterns of consumption of time-intensive goods, particularly digital products, whose main component is the time invested in their consumption—as in the case of gaming, online video and social media, and whose consumption is principally related to leisure. This framework has been used to analyze firm competition in online leisure markets, where the monetary price is near zero and time is the significant cost of consumption. The amount of time invested in the consumption of a particular digital good and its share of the total, aside from its particular features, have been argued to be the main determinants of the substitution pattern between time-intensive commodities, assuming activities requiring mostly time to be close substitutes. In particular, in the event of diversion in consumption, commodities with higher time shares and time intensity tend to receive larger time reallocation, instead of money-intensive goods. The empirical evidence shows that offline activities absorb 39% and 29% of the time diverted in an experimental case where the consumption of Facebook and Instagram, respectively, is reduced through a financial incentive (Goodman et al., 2026). Some part of the literature has been focused on assessing how different socioeconomic groups reallocate time in response to the introduction of recent digital technology innovations. According to this research strand, the digital technological development has had particular effects on younger groups and in low-income populations. The massive affordability of the internet has created differences in usage, where conditional on internet adoption, less educated and low-income people are more likely to spend more time online, especially in leisure activities such as chatting or online gaming, explained partially by differences in the opportunity cost of leisure time (Goldfarb and Prince, 2008). There is also variation in the type of news acquisition, where less educated groups tend to have larger time allocation in the consumption of local news, in contrast with more educated groups that tend to consume news from national and international sources. These differences are driven by the opportunity cost of time, which drives the amount of time devoted to news consumption, and by differences in preferences between groups (Bang and Sieg, 2025). In the case of younger groups, in particular, men from 21 to 30 years old, the quality improvements in video-gaming and recreational computer activities since 2004 have been one of the contributors to the decrease in market hours among this segment of the population. According to the American Time Use Survey (ATUS), from 2004 to 2017, the recreational computer time for young men rose 60%, while total leisure time only rose 4%. At the same time, the market hours for this population declined by about 2%. This has been attributed to an increase in the marginal value of leisure time (Aguiar et al., 2021). Using the Korean Smartphone Overuse Survey, Park (2025) found an *inverted-U* pattern between household income and digital overuse from 2019 to 2022. Park defines perceived digital overuse through a measure of smartphone addiction which accounts for behavioral salience, control failure and negative outcomes in well-being. This measure appeared to increase with household income up to a point, and then decreased. They suggest that these results can be driven by higher-income groups' ability to regulate their digital behavior.

The analysis of different time allocations across socioeconomic groups for digital products has led to assessments of the welfare effects of these technologies, an approach that is linked with the growing literature related to the concerns of the intensive time usage of digital media, including social media and video entertainment platforms. The concerns related to welfare vary from concerns about effects on consumer surplus to mental health issues. It has been argued that the choice of time-use of social media and video platforms is influenced by behavioral biases, such as self-control problems, projection bias, habit formation and naïveté. Some experimental evidence suggests that self-control problems cause 31% of social media use, and evidence from younger segments signals that deactivation of social media increases subjective well-being, and reduces future valuations of its use, suggesting habit formation and an overestimation of its consumer surplus (Allcott et al., 2020, 2022). Moreover, there are findings that attribute a decrease in mental health (22% of the effects of losing one's job) among the student population at U.S. colleges to the introduction of Facebook, ultimately increasing the likelihood that students reported impairments to academic performance (Braghieri et al., 2022). In general, most of the literature recognizes that despite these setbacks, digital media offer an overall positive consumer surplus. However, some more recent findings that include in the analysis externalities and network effects—inherent in the main digital platforms—indicate that by accounting for these aspects, there is a possible negative aggregate welfare outcome, suggesting that there could be disutilities among some non-user groups, who may experience social exclusion or fear of missing out (FOMO) by not using such digital products (Bursztyn et al., 2025).

This project contributes to the literature as there are no recognized works that apply Becker's theory of allocation of time to the more recent technological innovations in the features of social media, such as the algorithmic short-video format. It also contributes to the study of patterns of consumption of digital content in the working segment of the population, as most of the research is focused on the younger population. Lastly, it complements the study of consumption trends of digital products using time-use data from the Republic of Korea's Smartphone Overdependence Survey, an understudied context as the majority of studies rely on U.S. or European time-use data.

The rest of the thesis is structured as follows: Chapter two develops the theoretical framework relying on Becker's theory of allocation of time applied to digital leisure products; Chapter three applies this theory to the Korean setting using the Korean Smartphone Overdependence Survey; Chapter four describes the results of the econometric estimations; Chapter five discusses the results according to the theory and other potential explanations; Chapter six concludes.

2. THEORETICAL FRAMEWORK

2.1 Becker's theory of time allocation

The work of Becker (1965) and his theory of allocation of time is a useful theoretical framework to make a first assessment of the underlying mechanisms that guide the consumption of digital products across different socioeconomic groups. According to his work, people face a shadow price of time that determines their allocation of time among non-working activities such as leisure. This shadow price measures the opportunity cost of time. Becker describes that any activity can be decomposed into goods and time devoted to perform it; he names such an activity a *commodity*. The full cost of a commodity, then, is the monetary cost of the goods used and the opportunity cost of invested time. For example, for a commodity called "eating at home", the costs are the ingredients of the dish and the time invested in cooking. The time cost will be determined by how much time the consumption of the commodity needs and the individual's shadow price of time. Becker approximates this shadow price by the loss of earnings that the individual incurs by devoting time to consuming and not working. Individuals will maximize their utility by choosing a bundle of commodities which depend on the market price of goods and the time needed to produce them, which are subject to two different constraints, a time and an income constraint. The time constraint expresses the fact that time is a finite resource (i.e. there are only twenty-four hours per day to be allocated among different sets of activities), and the income constraint, which states that the price of goods used in the production of commodities must be equal to labor earnings and other income. The alternative approach that Becker introduces is the definition of *full income*, a unification of time and income constraints through the wage rate, specifically that time can be transformed into income by using it to obtain earnings, and income can be converted into time, by working fewer hours and freeing up time. This turns both constraints into a single resource constraint in monetary terms, where time has value measured by the wage rate, or the foregone earnings from not working. So, the constraint will depict the maximum income achievable when all the time is devoted to work. At the optimum, the allocation of resources will depict that the utility of an additional unit of any commodity is equal to its full cost valued at the marginal utility of full income. As full income is dependent on the allocation of time to obtain earnings, changes in the wage rate will determine how different individuals decide to allocate time among different commodities. So, in general, what determines consumption is the relative full price of commodities, and that price will vary as a function of the opportunity cost of time of the individual, which is given by her wage. So, depending on the level of her wage, the individual will choose between time-intensive and goods-intensive commodities.

Becker's analytical framework has three elements that are of interest to explain the mechanisms relevant to the current analysis of digital products. First, by allowing agents to decide their consumption according to their shadow price of time, it is possible to obtain different consumption choices of goods with the same market price but different full prices for each individual, reflecting differences in their opportunity cost of time. Second, the consumption choice will be, according to Becker, the result of two opposing forces, substitution and income effects, one inducing the individual to restrain herself from time-consuming activities, given the greater opportunity cost, and the other pushing the individual to consume more of all normal goods because of her greater real income. Third, the wage-elasticity of products allows the differentiation of goods that are more sensitive to changes in the opportunity cost of time. In general, this theory is a useful asset for evaluating patterns of consumption between agents with different opportunity costs of time, which are primarily determined by their wages, and hence their economic status.

2.2 Application to digital consumption choices

To apply the rational framework of Becker to the current choice of digital entertainment consumption, there are some elements to consider. First of all, the usage of these technologies nowadays has entry costs that are accessible to almost all of the population: internet plans, devices, and subscriptions are close to universal, especially in highly connected societies. Secondly, the consumption of digital entertainment products has the property that consuming one more unit of entertainment has basically a marginal monetary cost of zero, as is the case of consuming one more video on YouTube, one more reel on Instagram or TikTok, one more session of online-gaming, or one more episode of a series on Netflix or other streaming-video platform. However, the amount of time that these activities require can be substantial, which depends, among other things, on the individual's decision of how much time to invest in this consumption. Moreover, the common characteristic of smartphone-based entertainment is that the design of platforms is focused on keeping the user engaged, so it is more salient that the time invested in these platforms is mostly determined by the user's stopping decision and not the content itself. In the following lines, these elements are taken into account to develop the adaptation of the rational Becker model to smartphone-based digital entertainment consumption.

To perform this analysis, it is useful to define two smartphone commodities indexed by $i \in \{A, B\}$ that the individual produces using only time as input. The utility level of the individual, holding everything fixed, will be determined by the choice of the amount of Z_i commodities, such that $U = U(Z_A, Z_B, Z_o)$, where Z_o represents non-smartphone commodities. It is assumed that U is increasing and concave for each Z_i, it is additively separable across commodities, and that preferences are well-behaved (complete, transitive and continuous). The individual will maximize her utility facing the two previously mentioned constraints, a time and an income constraint. The time constraint is expressed as the allocation of a fixed amount of time T across labor time T_L, smartphone time devoted to consumption T_u, and non-smartphone activities T_o, such that $T = T_L + T_u + T_o$. Smartphone time is composed of the different time allocations among the two different commodities Z_i, such that $T_u = T_A + T_B$. As mentioned at the start of this section, it is possible to assume that current digital commodities are composed principally of time costs. This means that the income constraint can be expressed simply as $p_o x_o = I$, the value of the market goods used in producing non-smartphone related goods, where p_o and x_o measure the value of the expenditure on non-smartphone related goods (food, rent, transport, non-smartphone entertainment), which must be equal to the labor income I[1]. Labor income can also be expressed as $I = wT_L$, where w is the wage rate and T_L the amount of time invested in earning income. Following Becker's definition of full income, there is a single resource constraint obtained by substituting the time constraint, expressed as $T_L = T - T_u - T_o$, into the income constraint, such that $p_o x_o = (T - T_u - T_o)w$, which, after rearranging, gives the expression

$$p_o x_o + wT_u + wT_o = wT \tag{1}$$

This expression illustrates how expenditures are related to the maximum income attainable if all the time is devoted to work. This expression is useful because it allows assigning a monetary value to the time invested in different activities, such as wT_u, which can be interpreted as the opportunity cost of using time in smartphone activities and not earning income.

One important element to introduce in the analysis is the difference in the rate at which the marginal utility of an additional minute of consumption declines across commodities. As an example, the short-form video format is characterized by its algorithm, which delivers the user novel content that can make the session of consumption highly rewarding. Watching a series on a streaming platform can also be rewarding; however, due to the longer video format, the novelty between each new piece of content is more spaced. The rate of satisfaction between these two digital entertainment products can be expressed as two different rates of diminishing marginal utility of time, where the streaming content will exhibit faster decreasing marginal utility of time in contrast to the platform with short-video formats, because the novelty of the former will deplete faster. Expressing differences

[1]Non-labor income is not taken into account for simplicity.

in the rates of diminishing marginal utility of time allows the comparison of consumption choices among different digital products that have open-ended time requirements. For this analysis, both commodities A and B will be characterized by having open-ended time requirements and they will differ only in their rate of diminishing marginal utility of time: the marginal utility of a minute declines proportionally more slowly for commodity A. Formally, it is assumed that the elasticity of the marginal utility of time ε_i will be lower for commodity A for all $T_A, T_B > 0$, such that $\varepsilon_A(T_A) < \varepsilon_B(T_B)$[2].

People will choose the optimal allocation of time by maximizing their utility $U(Z_A, Z_B, Z_o)$ subject to the full income constraint. The solution of the optimization problem of the individual, developed in Appendix A, shows that the optimal allocation of time for the Z_i commodities is given by the expressions[3]

$$\frac{\partial U}{\partial Z_i} f_i'(T_i) = \lambda w, \qquad \frac{\partial U}{\partial Z_o}\frac{\partial g}{\partial T_o} = \lambda w \tag{2}$$

The expression on the left denotes the optimal condition for smartphone-related commodities, and the one on the right for the other non-smartphone commodities. Both conditions imply that the marginal utility of one more minute invested in the commodity Z_i equals the marginal cost of one more minute invested in that commodity. In general, at the optimum the marginal utility of one more minute must be the same across all smartphone and non-smartphone commodities, i.e. the utility of one extra minute of scrolling on TikTok must be the same as that of one extra minute of eating at home.

To complete the optimal allocation of resources, the optimal choice of goods consumption for non-smartphone commodities will be given by

$$\frac{\partial U}{\partial Z_o}\frac{\partial g}{\partial x_o} = \lambda p_o. \tag{3}$$

This shows that the cost of one more unit of non-smartphone goods is simply determined by its price.

The optimal conditions[4] allow observing the effects of a change in wages. An increase

[2] ε_i is defined as $\varepsilon_i \equiv -\frac{T_i MU_i'(T_i)}{MU_i(T_i)}$, where $MU_i = \frac{\partial U}{\partial Z_i} f_i'(T_i)$ and $Z_i = f_i(T_i)$, where f_i indicates the production function of the smartphone commodity i, which is assumed to be increasing and concave.

[3] $Z_o = g(x_o, T_o)$ is the production function of the non-smartphone commodity, assumed to be increasing and concave.

[4] The interpretation of these conditions is, as in the original Becker model, based on the assumption of a wage rate independent of hours worked.

in wages, as shown in all the time-related conditions, will increase the cost of any minute invested in that commodity. In this case, all smartphone-related commodities will become more expensive as their costs are assumed to be entirely composed of time. So, as $\frac{\partial U}{\partial Z_i} f_i'(T_i)$ is a decreasing function of T_i, the adjustment to an increase in wage is a reduction of the time allocation T_i in the commodity i until the marginal utility of an additional minute is again high enough to justify the higher cost of time. The elasticity of the marginal utility of time, ε_i, will determine the necessary adjustment of the time allocation for the marginal utility of a minute to reach the new level of λw. Commodities with lower decreasing marginal utility of time will receive larger proportional time adjustments; hence, they will exhibit higher elasticity to wages. This change in wages will also induce a shift in consumption from time-intensive commodities toward goods-intensive ones, i.e., goods become relatively cheaper than time.

To analyze how the change in wages affects the consumption of smartphone commodities, it is useful to recall the assumption made about the difference in the rate of diminishing marginal utility of time of the digital commodities. These commodities are entirely composed of time, so in contrast with other non-smartphone commodities which use time, they cannot exchange time for expenditure on goods. As an example of this, there is the case of the time invested in commuting, where the time taken in public transport can be exchanged for a greater expense on goods, such as a more expensive cab ride, but there is no alternative to save time in watching a movie through buying goods, as the complete consumption of the content depends only on the time invested in the activity. Secondly, the assumption is that A is the function with the lower diminishing marginal utility of time, that is, $\varepsilon_A(T_A) < \varepsilon_B(T_B)$: commodity A's marginal utility of time declines proportionally more slowly than B's. This is mainly driven by the general tendency of digital entertainment products to focus on maximizing the time in which a consumer is engaged. So, an increase in wages will generate a larger proportional fall in T_A, compared to the other digital commodity B, enough to restore the optimal condition, $\frac{\partial U}{\partial Z_A} f_A'(T_A) = \lambda w$. As an example, the reduction of time will be larger for the production of a commodity called "watching reels on TikTok", in contrast to a commodity "watching news online", because the latter will exhibit faster diminishing marginal utility of time.

There will be a substitution effect, as there is a reallocation of time from the most time-intensive activities, A and B, to less time-consuming activities Z_o and to labor.

However, it is important to acknowledge that there are also income effects: the increase in wages increases full income, and hence should induce an increase in the consumption of all normal goods. Nevertheless, as argued before, digital commodities are made up mostly of time resources, so the income effect will operate only through the marginal utility of income, λ, because there is no goods channel through which consumption can rise. These two opposing forces will determine the level of consumption of all commodities, and provided λ falls less than proportionally with the wage—so that the shadow price of time λw remains increasing in w—it should be expected that the substitution effect induces a reduction in the time invested in the smartphone activities because of the higher price of a minute, or $\frac{dT_A}{dw} < 0$ and $\frac{dT_B}{dw} < 0$. Then, a first prediction of this model inspired by Becker's theory will be that people who face higher opportunity costs derived from higher wages will exhibit less time invested in activities that exhibit pure time requirements, while people with lower income, and hence lower opportunity costs, will display higher consumption levels of this type of commodity.

2.3 Using a functional specification

To observe the mechanics of the previous general model and the optimal quantity of time allocation for commodities A and B, it is useful to implement a functional specification for these commodities following the Becker adaptation. Utility will be defined in the following form:

$$U = Z_A^{\gamma_A} + Z_B^{\gamma_B} + u(Z_o) \tag{4}$$

where $\gamma_i \in (0, 1)$ and the production function of both commodities is assumed to be linear in time, such that $Z_i = T_i$. The engagement parameter γ_i will capture the differences in the marginal utility of time, and as described earlier in the chapter, the assumption is that $\gamma_A > \gamma_B$, characterizing commodity A as the digital commodity with slower diminishing utility of time.

The optimal allocation of time for both commodities will be given by the expressions[5]

$$T_A^* = \left(\frac{\gamma_A}{\lambda w}\right)^{\frac{1}{1-\gamma_A}}, \qquad T_B^* = \left(\frac{\gamma_B}{\lambda w}\right)^{\frac{1}{1-\gamma_B}} \tag{5}$$

They illustrate that the optimal level of time allocation will be determined negatively by

[5] Derivation in Section 7.2 of Appendix A.

the shadow price of time λw, and its responsiveness to that price will be determined by the curvature parameter, γ_i. This mechanism is useful to analyze graphically. As shown in Figure 1, the marginal utility of time is a decreasing function of T_i. Both commodities have different values of γ_i, which create a difference in the speed at which the satisfaction from each additional minute decreases in the consumption of the given commodity Z_i.

To analyze how a change in wage influences the adjustment of the level of time invested in these commodities, it is useful to observe the elasticity of the optimal time allocation with respect to the shadow price of time λw, given by the following expressions[6]

$$\eta_A = -\frac{1}{1-\gamma_A}, \qquad \eta_B = -\frac{1}{1-\gamma_B} \tag{6}$$

A percentage change in wage will induce a percentage change in the time allocation, whose magnitude is positively related to the engagement parameter γ_i. An increase in the wage, followed by an increase in the shadow price of time, as depicted in Figure 1 in the movement from λw_0 to λw_1—provided the shadow price still rises after the fall in the marginal utility of income, λ—will generate a disproportionate adjustment of time in both A and B. As there are different levels of γ_i for both commodities A and B, the required time adjustments will be larger for the commodity A, which has the slower rate of decreasing marginal utility of time, a high γ_A, for which the reduction in time invested must be larger to meet the new shadow price of time, in the figure ΔT_A. Furthermore, the time adjustment observed for the commodity with the fastest diminishing marginal utility of time will be smaller, in the figure ΔT_B, as a reduction in time increases the marginal utility of time faster, meeting the new level of the shadow price of time.

3. DATA & EMPIRICAL ANALYSIS

The Republic of Korea's Smartphone Overdependence (KSO) survey is a nation-wide survey carried out by the Ministry of Science and ICT (MSIT), and the National Information Society Agency (NIA) since 2004. It gathers information at the household level about smartphone and internet usage across the Korean population aged 3-69, that has used the internet at least once within the past month. The survey explores the adverse effects of the use of smartphones and internet, for the design of public policy aimed at

[6] $\eta_i = -\frac{1}{\varepsilon_i}$.

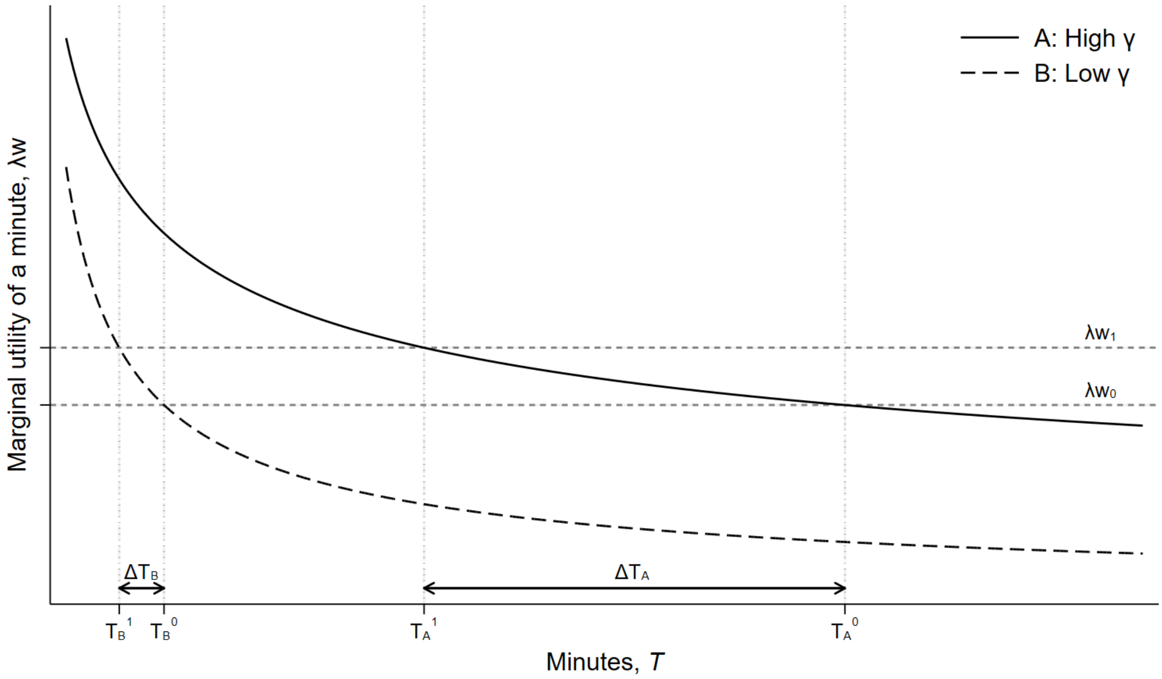

Figure 1: Decreasing marginal utility of time and time adjustments to changes of shadow price of time

the prevention and mitigation of overdependence on these technologies (Ministry of Science and ICT and National Information Society Agency, 2024). To develop this research project, the 2023 and 2024 waves have been used, which include questions focused on the consumption of algorithmic short-video formats, the smartphone feature argued to have the highest engagement property.

The empirical application of the model elaborated in Chapter three is developed under the following adaptations. First, the shadow price of time will be approximated by the wage rate, which is obtained by taking the mid-point of each of the ten different categories of individual income established in the KSO dataset, and then dividing it by the average working hours, which, according to the Korean Survey on Labor Force at Establishments (Ministry of Employment and Labor, 2025), was 156.2 hours for all workers in 2023 and 154.9 hours in 2024. Second, the sample is reduced to only the full-time working population, as it is expected that this set describes more naturally the mechanics of the predictions. To obtain this sample for the analysis, people are excluded who earn below the minimum wage, are younger than 19 or older than 59[7], and those who have reported a non-working occupation, such as student or homemaker. The descriptive statistics of

[7] 19 years old is the age of majority in Korea and 60 years old is the statutory age of retirement.

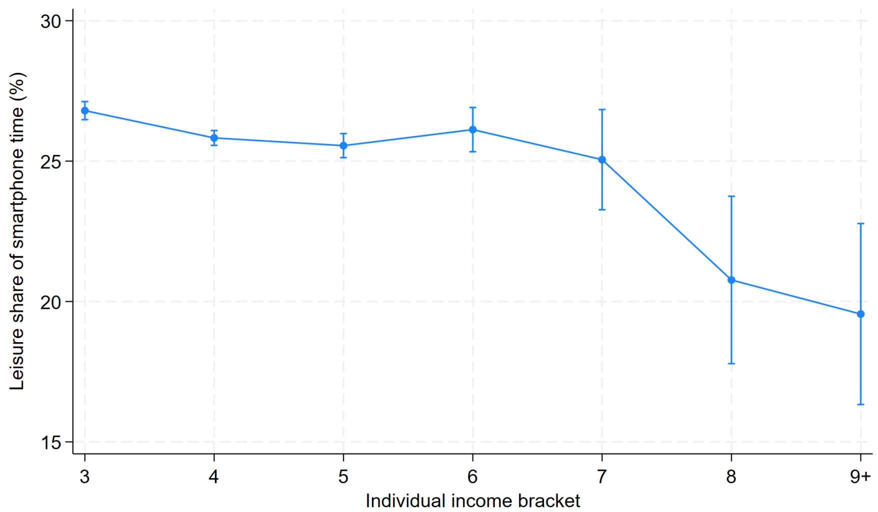

Figure 2: Relation between individual income and share of smartphone time on leisure

the sample are illustrated in Table 1.

To perform a first descriptive approximation of the relationships of the model, the reported share of smartphone usage time devoted to leisure is used[8]. It is expected that as leisure is an unproductive activity which consumes mainly time, there will be a negative relation between income and the proportion of time invested in this type of activity. Figure 2 plots the relation between the income brackets of the survey (excluding 1 and 2 because they are below minimum income levels) and the share of smartphone time spent on leisure. The plot depicts a negative relation that potentially supports the theoretical mechanisms of the previous chapter.

The adaptation of Becker's theory of allocation of time to digital entertainment consumption generates predictions about unequal consumption patterns for different socioeconomic groups. This chapter will perform a descriptive assessment of the relationships implied by the theoretical framework, using the Korean context of smartphone and internet usage.

The KSO survey permits observing the allocation of time performed by individuals among smartphone activities. To first evaluate the relations outlined by Becker's adaptation to digital commodities, the reported share of smartphone usage time in leisure will be exploited. As depicted in the model, higher levels of shadow price of time, λw, induce an adjustment of the optimal allocation of time which reflects the equalization of

[8]According to the survey, smartphone leisure activities encompass: Games, film/TV/video (YouTube, Netflix), music, radio and podcasts, webtoons, web novels, books, photography, drawing, adult content, and gambling.

Table 1: Descriptive statistics, KSOS 2023–2024

	Mean	SD	Median	Min	Max
Age	42.6	10.2	43.0	20.0	59.0
Female (%)	41.60	49.29	0.00	0.00	100.00
Household size	3.1	1.0	3.0	1.0	6.0
Hourly wage (₩)	22,219	5,980	22,407	16,005	61,330
Household income (₩M/month)	5.8	2.0	5.0	3.0	11.0
Leisure share of smartphone time (%)	26.1	12.4	25.0	0.0	95.0
Observations			24,791		

Notes: Survey-weighted. Sample: workers aged 19–59 earning above the statutory minimum wage, KSOS 2023–2024 pooled. Hourly wage constructed from individual income bracket midpoints divided by average monthly working hours (156.2 in 2023, 154.9 in 2024), Korean Labor Force Survey at Establishments. Household income reported at bracket midpoints (six brackets of ₩2M width; top bracket ≥₩10M assigned ₩11M).

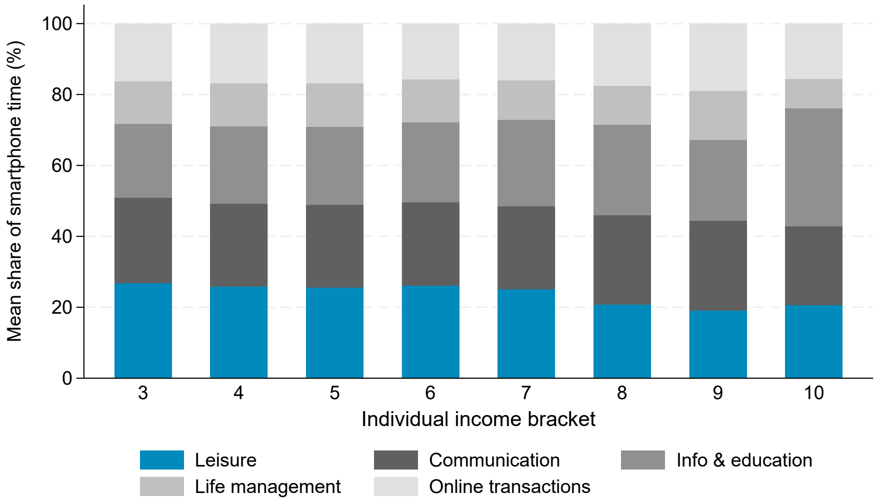

Figure 3: Share of smartphone usage time by individual income bracket in sample

the utility value of a minute invested in unproductive activities to productive ones. As a higher income represents a higher opportunity cost of putting time into non-productive activities (given a rise in the shadow price with increases in wages), it is expected that time invested in these activities will be lower for richer socioeconomic groups. The Korean dataset measures the share distribution of smartphone usage time among five categories: Communication, Online transactions, Leisure, Life management, and Information search & education. Figure 3 plots the distribution of the shares of the five different categories of smartphone time usage in each of the seven income categories of the sample used. To start the analysis, an initial hypothesis is defined:

- H1: The share of smartphone usage time devoted to leisure will be larger for lower income groups and lower for higher income groups.

To assess H1 formally, the following baseline specification is defined:

$$s_i^L = \beta_0 + \beta_1 \ln w_i + \mathbf{x}_i' \boldsymbol{\beta} + \tau_t + u_i \tag{7}$$

This estimation describes the share of smartphone leisure time of an individual s_i^L, where the main explanatory variable is the log of the wage. Baseline controls are included, such as gender, age, household size, level of education, city size and year fixed effects. Individuals are clustered at the household level and observations carry sampling probability weights. Two additional specifications are added to this first estimation model. A second specification controls for the occupation of the individual, which takes into account job characteristics that could influence the shares of smartphone time use, such as a manual worker whose phone use is limited only to leisure and communication, compared to an office worker whose use of smartphone can include other categories, which makes the share of leisure smaller. The third specification adds household income as an approximation of income effects; in particular, it aims at holding λ fixed to describe only the substitution effects in the time allocation choice. A richer household could allow the individual to invest less time in smartphone leisure not only because it is more expensive (in terms of its personal opportunity cost), but because the household has the resources to allow the individual to invest time in other types of offline leisure, so this specification aims at directly describing substitution effects arising from an increase in the price of time for the individual. The estimated coefficients of these specifications are descriptive semi-elasticities, which aim at testing the sign restrictions of the theoretical model. The results of these estimations can be observed in Table 2.

The KSO Survey allows filtering the dataset to only video users and exploiting the reported usage of short-video formats, argued to be the most engaging smartphone feature nowadays. Specifically, it is possible to observe the share of short-form content within online video use, which allows the comparison between a commodity A with a higher engagement parameter γ_A, in this case the short-form video format (TikTok, Reels), and a commodity B, the long-form format (Netflix streaming), with the lower engagement

Table 2: Share of smartphone usage time in leisure and wage rate (H1)

	(1)	(2)	(3)	(4)
Log hourly wage	-2.411***	-1.790***	-2.068***	-1.503***
	(0.417)	(0.425)	(0.428)	(0.437)
HH income 4–6M won			0.213	0.302
			(0.287)	(0.285)
HH income 6–8M won			-0.914***	-0.787**
			(0.336)	(0.335)
HH income 8–10M won			-0.888*	-0.722
			(0.498)	(0.497)
HH income 10M+ won			0.416	0.456
			(0.927)	(0.920)
Demographic controls	Yes	Yes	Yes	Yes
Occupation indicators		Yes		Yes
Year FE	Yes	Yes	Yes	Yes
Observations	24,791	24,791	24,791	24,791
R^2	0.015	0.021	0.017	0.022

Notes: Survey-weighted OLS; standard errors in parentheses, clustered on household. Column (1) is the baseline estimation, (2) controls for occupation, (3) controls for household income, (4) controls for occupation and household income. Sample: workers aged 19–59 earning above the statutory minimum wage, KSOS 2023–2024 pooled. Household income reference category: 2–4M won. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

parameter γ_B. Following the same reasoning from above, it is expected that higher levels of wage rate will induce a lower share of short-form video consumption by the mechanism of the adjusting value of the shadow price of time. According to that reasoning, a second hypothesis is defined:

- H2: People in lower income groups will exhibit a higher share of short-form video while higher income groups will exhibit a lower share, within online video formats.

The share of short-video format is reported in four intervals: (1) 0–25%, (2) 25–50%, (3) 50–75%, (4) $\geq$ 75%. To test H2 formally, an ordered probit model is estimated in which there exists a latent share s_i^V underlying the reported interval, of the form

$$s_i^V = \beta_1 \ln w_i + \mathbf{x}_i' \boldsymbol{\beta} + \tau_t + u_i \tag{8}$$

s_i^V falls within one of the response intervals, so the individual responds with interval k

according to this latent share. Then, to observe the probability that individual i responds with interval k, three cut points are estimated that define the four intervals of the response, assuming $u_i \sim N(0,1)$. So, the probability of observing interval k is given by

$$\Pr(s_i^V = k \mid \mathbf{x}_i) = \Phi(c_k - \beta_1 \ln w_i - \mathbf{x}_i'\boldsymbol{\beta} - \tau_t) - \Phi(c_{k-1} - \beta_1 \ln w_i - \mathbf{x}_i'\boldsymbol{\beta} - \tau_t) \quad (9)$$

This expression is estimated using maximum likelihood, where c_k denotes the thresholds dividing each interval of the distribution, and Φ, the standard normal CDF. An estimated $\beta_1 < 0$ is expected, which will move the probability mass out of the high-frequency intervals into low intervals. As β_1 is expressed on an arbitrary scale of the latent index, for its interpretation, the weighted average marginal effect of a change in wage on the probability of being a heavy short-video consumer, i.e., being at the top interval of the short-video format consumption share, measured in percentage points[9], is computed. Under this specification, it is expected that the probability of having a high share of short-form video consumption will be lower for higher income groups, by the same mechanisms as the previous econometric model. For this model, the two complementary specifications are also added, one controlling for occupation and the other controlling for household income. Table 3 depicts the results of this estimation.

To finish the analysis, it is useful to exploit the reported main leisure activity and the desired leisure activity offered by the survey to do a complementary reading of the relationships expressed by the rational theoretical framework. According to the framework, the decision of digital entertainment consumption is optimal for the different socioeconomic groups, which select their levels of digital entertainment consumption subject to the opportunity cost of time. Then, if an individual reports a misalignment between her main leisure activity and her desired leisure activity, it could be related to the full-income constraint, which may restrict the feasible set of leisure activities. If this relation exists, then a final hypothesis can be explored:

- H3: The share of individuals whose main leisure activity is smartphone use but whose desired activity is a different one will be greater for lower income groups and smaller for higher income groups.

To explore this hypothesis, misalignment is defined as smartphone use being the main

[9]For each individual, $\frac{\partial \Pr(s_i^V=4)}{\partial \ln w}$ is computed.

Table 3: Share of short-form content within online video and wage (H2)

	(1)	(2)	(3)	(4)
Log wage	-0.116***	-0.110**	-0.125***	-0.118***
	(0.042)	(0.043)	(0.044)	(0.045)
HH income 4–6M won			0.008	0.006
			(0.029)	(0.029)
HH income 6–8M won			0.058*	0.057*
			(0.034)	(0.034)
HH income 8–10M won			0.035	0.033
			(0.050)	(0.050)
HH income 10M+ won			-0.086	-0.086
			(0.082)	(0.083)
Demographic controls	Yes	Yes	Yes	Yes
Occupation indicators		Yes		Yes
Year FE	Yes	Yes	Yes	Yes
Observations	19,648	19,648	19,648	19,648

Notes: Survey-weighted ordered probit of the short-form share of video time (four ordered intervals); standard errors in parentheses, clustered on household. Column (1) is the baseline estimation, (2) controls for occupation, (3) controls for household income, (4) controls for occupation and household income. Sample: video users, workers aged 19–59 earning above the statutory minimum wage, KSOS 2023–2024 pooled. Household income reference category: 2–4M won. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

reported leisure activity while the desired leisure activity is a different one. Then, these differences are plotted as the mean misalignment rate by individual income bracket, in Figure 4. The relation suggests a negative gradient in the share of people experiencing a misalignment across economic groups. This relation is formally explored with the following linear probability model:

$$m_i = \beta_0 + \beta_1 \ln w_i + \mathbf{X}_i' \boldsymbol{\delta} + \tau_t + u_i \tag{10}$$

This expression estimates the joint probability that the individual reports smartphone as her main leisure activity and that it does not correspond to her desired one. As in the previous models, the main explanatory variable is the log of the wage, and the controls include demographic variables, occupation and household income. The results of this estimation can be observed in Table 4.

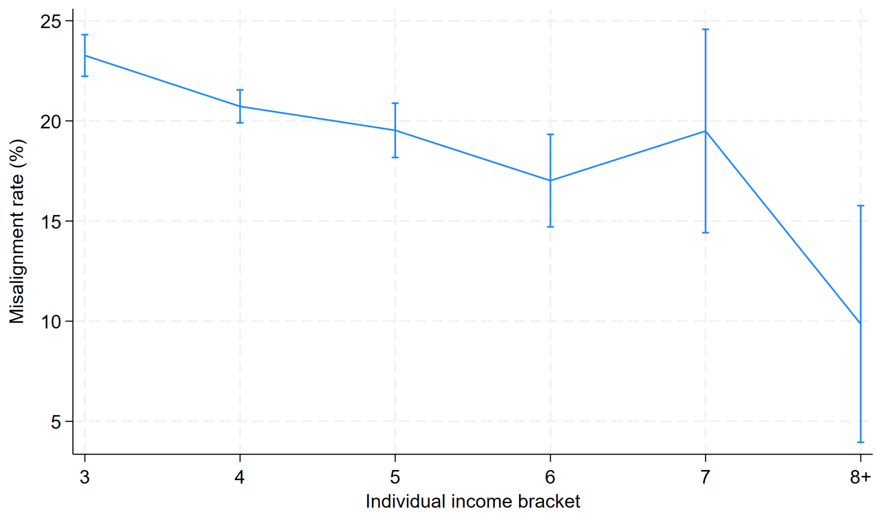

Figure 4: Misalignment reported vs desired preference for smartphone leisure and individual income bracket

4. RESULTS & DISCUSSION

4.1 Results

The empirical models allowed an approximation to the mechanisms of Becker's theory of time allocation applied to the context of current digital leisure consumption in Korea. The first estimation results, depicted in Table 2, are a more general treatment of the relationship between people's allocation of time among smartphone-related activities and the level of wage rate. The baseline estimation shows that the difference across the income distribution is $\ln(9.5) - \ln(1.5) \approx 1.85$ log points, which implies a decrease of $1.85 \times (-2.41) \approx 4.5$ percentage points in the share of smartphone leisure from the lowest income bracket to the top one, significant at 1%. The mean share of smartphone leisure is 26.1%, so the consumption gap for this type of commodity amounts to $\frac{4.5}{26.1} \approx 17\%$ of the mean share. By controlling for occupation, which allows us to observe the wage relation within occupation categories, it is observed that the association of wages is attenuated, $\beta_1 = -1.79$; however, it maintains its significance and sign. It is important to note that individuals in occupations which potentially do not largely rely on the use of smartphones exhibit a larger share of leisure time, as shown by the coefficients for the occupation categories of skilled agricultural and elementary workers, 7.9 and 6.0 percentage points respectively ($p < 0.01$), with respect to the reference category (Managers) and conditional on wage and other controls, while individuals in other occupations that may

Table 4: Leisure misalignment and wage (H3)

	(1)	(2)	(3)	(4)
Log wage	-8.501***	-7.829***	-7.945***	-7.366***
	(1.295)	(1.322)	(1.332)	(1.359)
HH income 4–6M won			-2.208**	-2.163**
			(0.877)	(0.876)
HH income 6–8M won			-3.504***	-3.394***
			(1.033)	(1.032)
HH income 8–10M won			-4.440***	-4.299***
			(1.468)	(1.469)
HH income 10M+ won			5.499**	5.586**
			(2.559)	(2.561)
Demographic controls	Yes	Yes	Yes	Yes
Occupation indicators		Yes		Yes
Year FE	Yes	Yes	Yes	Yes
Observations	24,791	24,791	24,791	24,791
R^2	0.024	0.025	0.026	0.027

Notes: Survey-weighted LPM; where misaligned indicates that smartphone use is the actual but not the desired leisure activity. Weighted baseline misalignment rate: 21.2%. Standard errors in parentheses, clustered on household. Column (1) is the baseline estimation, (2) controls for occupation, (3) controls for household income, (4) controls for occupation and household income. Sample: workers aged 19–59 earning above the statutory minimum wage, KSOS 2023–2024 pooled. Household income reference category: 2–4M won. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

use smartphones for activities different from leisure exhibit a smaller association, such as the categories of Professional and Office worker, whose coefficient reaches 1.6 percentage points ($p < 0.05$)[10]. Column (3) describes the results of an estimation that controls for the household income, the proposed approximation for holding fixed the income effects of changes in wage. The variation of the coefficient from the baseline is small, $\beta_1 = -2.07$. It maintains its sign and significance. The relationship between household income and share of leisure time does not show relevant magnitudes with a consistent pattern across brackets, which potentially supports the idea that household affluence does not clearly determine a higher or lower leisure smartphone time allocation. Finally, putting both controls in the estimation maintains the negative relation, $\beta_1 = -1.5$, and significant.

The second model allowed observing the relation of a change in wage on the proba-

[10]The tables with the complete coefficients are located in Appendix B.

bility of being in the top interval of the share of short-video format consumption. This specification summarizes the theoretical model described in Chapter three. According to the model, it is expected that a change in the shadow price of time, approximated by the wage, will be associated with a larger time adjustment for the commodity with a higher engagement parameter γ_i. In this case, the short-video format is the digital commodity with the highest engagement parameter, so it is expected that it will receive the larger time adjustment among online video formats, i.e. $\eta_{\text{short-video}} - \eta_{\text{long-video}} < 0$; then, the share of this commodity within online video consumption will be reduced. The baseline specification depicts a negative relation at the 1% significance level, supporting the negative relation between the shadow price of time and the consumption of this type of content. The model-predicted average probability of being at the top interval is $\Pr(s_i^V \geq 75\%) = 2.4\%$, and the marginal effect for individual i of a log-point increase in wages is $\beta_1 \times \phi(c_3 - s_i^*)$, where s_i^* is the predicted latent share and ϕ the standard normal density; the average of the marginal effect across the sample is -0.65 (SE 0.24) percentage points. Then, a wage twice as high is associated with a decrease in the probability of being a heavy short-video consumer of $0.65 \times 0.69 \approx 0.45$ percentage points, which amounts to $0.45/2.4 \approx 19\%$ of the average probability of being in the highest interval. Controlling for occupation and household income does not affect the direction and significance of the association of wages with the consumption of short-form video.

The results for the estimation of the association of a change in wage with the probability of experiencing misalignment between the reported and the desired leisure activity and reporting smartphone as the main leisure activity complement the explored relation between the opportunity cost of time and smartphone-related leisure activities. A one-log-point increase in the wage is related to a decrease of 8.5 percentage points in the probability that smartphone use is the main leisure activity while a different one is desired, which, relative to the weighted baseline rate of 21.2%, is 40% lower. Controlling for occupation and household income does not significantly change the magnitude of the coefficient. The relationship of household income is as expected: the greater the resources, the less binding the full-income constraint, and hence the lower the probability of being in misalignment, potentially related to the possibility of achieving the desired leisure activity. This behavior is observed in the coefficients, which decline monotonically from the 4–6M won bracket to the 8–10M won bracket, with the exception of the last income bracket (3% of the sample) which displays the opposite relation.

4.2 Discussion

The results of the estimation that relates smartphone leisure time and wage, and the estimates of the relation between share of short-video format and wage, complement each other. As the theoretical framework predicts, a higher opportunity cost will drive downward the amount of time invested in time-intensive commodities. The fact that this relation survives in both specifications suggests that the mechanism could be operating in both scenarios. Furthermore, the fact that this negative relation is maintained after controlling for type of occupation, which influences the use given to smartphones, and household income, which affects the resources of the individual, reinforces the interpretation that wages could be driving the consumption of leisure smartphone time and its allocation between time-intensive products.

One possible limitation of this theoretical interpretation of the results could be the argument that, for the majority of people, choosing their working hours freely is not possible, because of, for example, fixed working schedules. However, people can still devote hours to raising their potential future wages, through learning and job switching.

The relationships found in Chapter three could be affected by some potential measurement errors. Wages are obtained through bracket mid-point classification, which can erase variation within each individual income bracket, thereby potentially reducing precision. The use of an average monthly measure of hours worked can bias the estimates if the real hours vary across groups; for example, if higher-income workers work longer hours than lower-income groups, then their wage would be overstated, ultimately attenuating the negative relation shown in the three estimations. Lastly, the time allocation data is self-reported, which can also affect the precision of the estimates.

The econometric analysis is a descriptive assessment, limited by the reach of the dataset used; this prevents the causal evaluation offered by the theoretical model of Chapter two. However, it is an opportunity to evaluate alternative mechanisms that may be related to the mechanism inspired by Becker's theory of allocation of time. In the following, explanations related to the relationships found in the econometric analysis are discussed.

The negative correlation between leisure smartphone time and wage found in Chapter three and explained by the theoretical framework as the result of the variation of the opportunity cost of different economic groups can be driven by other mechanisms, such as the role of preferences driving the individual income gradient; in other words, people having different tastes over the time allocated to leisure could influence their productivity or capacity to produce income. Another explanation could be related to the increasing leisure time trends for low-income groups found by Aguiar and Hurst (2007) and Boppart and Ngai (2021), which could suggest that the differences in time allocation on smartphone leisure arise only because of differences in available leisure time. Variation in educational levels appears to be operating only through its effects on wages, as in all specifications its estimates are not significant, and because the estimation also controls for occupation, the possibility that differences in digital skills are the main mechanism, by allowing the use of these technologies for purposes other than leisure, is less likely.

The results of the estimation of the relationship between the share of short-video format and wages reflect the time reallocating mechanism of the theory, whereby a higher wage level induces a larger time reduction for the commodity with the higher engagement parameter, in this case a reduction of the share of the format with higher engagement in total video consumption, which in the theoretical model corresponds to a reduction of time devoted to this type of product. However, similarly to the previous result of leisure time and wages, preferences and leisure time availability can be driving these results. In this particular case, another explanation is the behavioral biases described by Allcott et al. (2020; 2022), suggesting that perhaps low-income groups experience more self-control problems preventing them from regulating their consumption of this type of engaging content. This same mechanism can be a possible interpretation of the results for the misalignment of smartphone use as the reported activity differing from the desired one. In that case, a behavioral bias could be preventing the individual from attaining her desired leisure activity.

The results of the estimations in Chapter three could have some normative interpretations. Braghieri et al. (2022) and Bursztyn et al. (2025) document welfare effects of continuous exposure to social media, which generate a reduction in well-being; if this holds in this scenario, lower-income people that consume more smartphone leisure commodities, such as short-video formats, are being exposed to a greater degree than higher-income groups to the potential harmful effects of exposure to heavy smartphone usage. This unequal result is more evident for people whose desire is to consume less smartphone leisure but are constrained by full-income, in the form of time or money. This is an interesting interpretation that would imply inequality in the welfare obtained from currently highly engaging digital products.

5. CONCLUSION

This project relates how different socioeconomic groups allocate time with respect to wages. It has been shown theoretically and empirically that there exists a social gradient in the consumption of these digital products. What does this mean in terms of well-being and for future policy design? There are several possible options. First of all, inspired by Boppart & Ngai (2021), who conclude that the fact that lower-income populations have more leisure time can partially offset the welfare effects of rising income and consumption inequality in some parts of the world, the unequal exposure to smartphone leisure can offer opportunities to these population groups by allowing cheap access to information and opportunities through this type of media content, such as social events, jobs or education. Moreover, this type of content can offer cheap relief during contexts of stress and economic hardship. However, recent evidence suggests that prolonged exposure to these technologies can be welfare decreasing (Allcott et al., 2020, 2022; Braghieri et al., 2022; Bursztyn et al., 2025). Then, if an individual has easier access only to this type of leisure, there are unequal circumstances that have to be addressed so that the harmful effects of these technologies do not disproportionately affect low-income populations.

Potential policy recommendations could include granting access to leisure activities that compete in terms of opportunity cost with smartphone usage, such as reducing the cost of offline or online activities which could have better welfare outcomes, for example, free access or transport subsidies for outdoor activities, greater economic incentives for the use of online education platforms, or even increasing the cost of access to potentially harmful online leisure activities through ads or preventive health warnings.

It is important to acknowledge that the empirical setting of this project restricts the applicability of the results to other contexts, such as developing countries, where the relationship between wages and smartphone leisure consumption could differ. Despite this, the Korean dataset offers a distinctive opportunity to explore disaggregated characteristics that drive the current consumption of digital media, such as format features embedded in digital platforms. Obtaining such detailed information is key to designing efficient policies that maximize population welfare.

The societal consequences of the allocation of time gradient among leisure activities remain potentially ambiguous; therefore, further research is needed that allows a clearer assessment of these distributional effects.

6. APPENDIX A

6.1 Individual's optimization problem

The individual chooses how much time T_i to devote to each activity to maximize her utility $U(Z_A, Z_B, Z_o)$, subject to the full income constraint. As the costs of using a smartphone are mainly dependent on the time investment, the production function of the individual for smartphone-related products can be written as $Z_i = f_i(T_i)$. Then the individual maximizes $U(f_A(T_A), f_B(T_B), g(x_o, T_o))$, where $g(x_o, T_o)$ is the production function for non-smartphone commodities. Then the maximization problem will be

$$\max_{T_A, T_B, T_o, x_o} U[f_A(T_A), f_B(T_B), g(x_o, T_o)] \quad \text{s.t. } wT_A + wT_B + p_o x_o + wT_o = wT \tag{A.1}$$

To obtain the optimal allocation of time chosen by the individual, the Lagrangian method is used as follows:

$$\mathcal{L} = U(f_A(T_A), f_B(T_B), g(x_o, T_o)) - \lambda\left[wT_A + wT_B + p_o x_o + wT_o - wT\right]$$

By taking the derivative of $\mathcal{L}$ with respect to T_i and afterwards setting it to zero, the optimal time allocation for the smartphone-related commodities is obtained:

$$\frac{\partial U}{\partial Z_i} f_i'(T_i) = \lambda w \tag{A.2}$$

By taking the derivative of $\mathcal{L}$ with respect to T_o and afterwards setting it to zero, for the case of non-smartphone commodities the optimal allocation is

$$\frac{\partial U}{\partial Z_o} \frac{\partial g}{\partial T_o} = \lambda w \tag{A.3}$$

Lastly, by taking the derivative of $\mathcal{L}$ with respect to x_o and afterwards setting it to zero, for the case of non-smartphone commodities, the optimal allocation of goods spending is

$$\frac{\partial U}{\partial Z_o} \frac{\partial g}{\partial x_o} = \lambda p_o \tag{A.4}$$

6.2 Optimal time allocation with specific functional form

The utility function of the individual is defined in Eq (4) as

$$U = Z_A^{\gamma_A} + Z_B^{\gamma_B} + u(Z_o) \tag{A.5}$$

where $\gamma_i \in (0, 1)$. The production functions for commodities A and B are defined as

$$Z_i = T_i, \quad Z_o = x_o^{\theta} T_o^{1-\theta} \tag{A.6}$$

The resource constraint is the full income defined as

$$wT_A + wT_B + p_o x_o + wT_o = wT$$

Then the maximization problem is the following:

$$\max_{T_A, T_B, T_o, x_o} \ U = Z_A^{\gamma_A} + Z_B^{\gamma_B} + u(Z_o) \quad \text{s.t. } wT_A + wT_B + p_o x_o + wT_o = wT$$

To obtain the optimal allocation of time, the Lagrangian method for optimization is used as follows:

$$\mathcal{L} = Z_A^{\gamma_A} + Z_B^{\gamma_B} + u(Z_o) - \lambda \left[wT_A + wT_B + p_o x_o + wT_o - wT \right]$$

Plugging the production functions into the previous expression gives

$$\mathcal{L} = T_A^{\gamma_A} + T_B^{\gamma_B} + u(x_o^{\theta} T_o^{1-\theta}) - \lambda \left[wT_A + wT_B + p_o x_o + wT_o - wT \right]$$

Taking the derivative of $\mathcal{L}$ with respect to T_A gives

$$\frac{\partial \mathcal{L}}{\partial T_A} = \gamma_A T_A^{\gamma_A - 1} - \lambda w = 0$$

Solving for the optimal T_A^* gives

$$T_A^* = \left(\frac{\gamma_A}{\lambda w} \right)^{\frac{1}{1-\gamma_A}} \tag{A.7}$$

By symmetry, the optimal allocation of time for commodity B is given by the expression

$$T_B^* = \left(\frac{\gamma_B}{\lambda w}\right)^{\frac{1}{1-\gamma_B}} \tag{A.8}$$

6.3 Wage elasticity of the optimal time allocation

From the optimal expressions for the allocation of time of commodities A and B, it is possible to obtain the elasticity of the optimal time allocation with respect to a change in wage, by first taking logs as follows:

$$\ln(T_A) = \ln\left(\left(\frac{\gamma_A}{\lambda w}\right)^{\frac{1}{1-\gamma_A}}\right)$$

$$\ln(T_A) = \frac{1}{1-\gamma_A}(\ln\gamma_A - \ln\lambda - \ln w)$$

$$\ln(T_A) = \frac{\ln\gamma_A - \ln\lambda}{1-\gamma_A} - \frac{1}{1-\gamma_A}(\ln w)$$

Defining $v \equiv \ln w$, the expression becomes

$$\ln(T_A) = \frac{\ln\gamma_A - \ln\lambda}{1-\gamma_A} - \frac{1}{1-\gamma_A}v$$

Taking the derivative with respect to v at a given λ (as discussed in Section 3.3) gives the following result:

$$\frac{\partial \ln T_A}{\partial v} = -\frac{1}{1-\gamma_A} = \eta_A \tag{A.9}$$

By symmetry:

$$\frac{\partial \ln T_B}{\partial v} = -\frac{1}{1-\gamma_B} = \eta_B \tag{A.10}$$

7. APPENDIX B

Table 5: Share of smartphone usage time in leisure and wage rate: full coefficient estimates

	(1)	(2)	(3)	(4)
Log wage	-2.411***	-1.790***	-2.068***	-1.503***
	(0.417)	(0.425)	(0.428)	(0.437)
HH income 4–6M won			0.213	0.302
			(0.287)	(0.285)
HH income 6–8M won			-0.914***	-0.787**
			(0.336)	(0.335)
HH income 8–10M won			-0.888*	-0.722
			(0.498)	(0.497)
HH income 10M+ won			0.416	0.456
			(0.927)	(0.920)
Female	-1.493***	-1.322***	-1.367***	-1.210***
	(0.164)	(0.170)	(0.167)	(0.172)
Small/medium city	0.639***	0.585***	0.586**	0.538**
	(0.227)	(0.227)	(0.228)	(0.228)
Town/rural area	0.346	0.200	0.285	0.147
	(0.282)	(0.282)	(0.282)	(0.282)
Occ: Professional & Office worker		1.613**		1.590**
		(0.654)		(0.654)
Occ: Service & Sales worker		2.686***		2.624***
		(0.662)		(0.661)
Occ: Skilled agric./forestry/fishery		7.852***		7.723***
		(1.302)		(1.301)
Occ: Skilled trades		2.902***		2.845***
		(0.716)		(0.716)
Occ: Plant/machine operator		4.029***		4.004***
		(0.822)		(0.821)
Occ: Elementary worker		5.991***		5.944***
		(0.937)		(0.936)
Year FE	Yes	Yes	Yes	Yes
Age, Educ & hh size	Yes	Yes	Yes	Yes
Observations	24,791	24,791	24,791	24,791
R^2	0.015	0.021	0.017	0.022

Notes: Full coefficient estimates for the specifications in Table 2. Survey-weighted OLS; standard errors in parentheses, clustered on household. Column (1) is the baseline estimation, (2) controls for occupation, (3) controls for household income, (4) controls for occupation and household income. Sample: workers aged 19–59 earning above the statutory minimum wage, KSOS 2023–2024 pooled. Household income reference category: 2–4M won. Citysize reference category: Large city. Occupation reference category: Manager * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Share of short-form content within online video and wage (H2): full coefficient estimates

	(1)	(2)	(3)	(4)
Log hourly wage	-0.116***	-0.110**	-0.125***	-0.118***
	(0.042)	(0.043)	(0.044)	(0.045)
HH income 4–6M won			0.008	0.006
			(0.029)	(0.029)
HH income 6–8M won			0.058*	0.057*
			(0.034)	(0.034)
HH income 8–10M won			0.035	0.033
			(0.050)	(0.050)
HH income 10M+ won			-0.086	-0.086
			(0.082)	(0.083)
Female	-0.006	-0.010	-0.010	-0.014
	(0.016)	(0.017)	(0.017)	(0.017)
Small/medium city	-0.053**	-0.053**	-0.052**	-0.052**
	(0.022)	(0.022)	(0.022)	(0.022)
Town/rural area	0.071**	0.074***	0.074***	0.076***
	(0.028)	(0.028)	(0.028)	(0.028)
Occ: Professional & Office worker		-0.030		-0.030
		(0.076)		(0.076)
Occ: Service & Sales worker		0.001		0.004
		(0.078)		(0.078)
Occ: Skilled agric./forestry/fishery		-0.252**		-0.243**
		(0.123)		(0.123)
Occ: Skilled trades		0.014		0.017
		(0.081)		(0.081)
Occ: Plant/machine operator		-0.095		-0.093
		(0.092)		(0.092)
Occ: Elementary worker		-0.041		-0.037
		(0.098)		(0.098)
Year FE	Yes	Yes	Yes	Yes
Age, Educ & hh size	Yes	Yes	Yes	Yes
Observations	19,648	19,648	19,648	19,648

Notes: Full coefficient estimates for the specifications in Table 3. Survey-weighted ordered probit of the short-form share of video time (four ordered categories); standard errors in parentheses, clustered on household. Cutpoint estimates omitted. Column (1) is the baseline estimation, (2) controls for occupation, (3) controls for household income, (4) controls for occupation and household income. Sample: video users, workers aged 19–59 earning above the statutory minimum wage, KSOS 2023–2024 pooled. Household income reference category: 2–4M won. Citysize reference category: Large city. Occupation reference category: Manager. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Leisure misalignment and wage (H3): full coefficient estimates

	(1)	(2)	(3)	(4)
Log hourly wage	-8.501***	-7.829***	-7.945***	-7.366***
	(1.295)	(1.322)	(1.332)	(1.359)
HH income 4–6M won			-2.208**	-2.163**
			(0.877)	(0.876)
HH income 6–8M won			-3.504***	-3.394***
			(1.033)	(1.032)
HH income 8–10M won			-4.440***	-4.299***
			(1.468)	(1.469)
HH income 10M+ won			5.499**	5.586**
			(2.559)	(2.561)
Female	-4.585***	-4.312***	-4.309***	-4.065***
	(0.568)	(0.592)	(0.580)	(0.603)
Small/medium city	0.620	0.556	0.537	0.484
	(0.673)	(0.673)	(0.675)	(0.675)
Town/rural area	0.504	0.385	0.398	0.299
	(0.865)	(0.863)	(0.866)	(0.864)
Occ: Professional & Office worker		1.204		1.179
		(2.221)		(2.192)
Occ: Service & Sales worker		2.835		2.702
		(2.259)		(2.230)
Occ: Skilled agric./forestry/fishery		2.317		1.745
		(3.475)		(3.462)
Occ: Skilled trades		5.409**		5.267**
		(2.395)		(2.366)
Occ: Plant/machine operator		1.714		1.481
		(2.597)		(2.573)
Occ: Elementary worker		5.312*		5.005*
		(3.005)		(2.990)
Year FE	Yes	Yes	Yes	Yes
Age, Educ & hh size	Yes	Yes	Yes	Yes
Observations	24,791	24,791	24,791	24,791
R^2	0.024	0.025	0.026	0.027

Notes: Full coefficient estimates for the specifications in Table 4. Survey-weighted LPM; outcome coded 0/100. Standard errors in parentheses, clustered on household. Column (1) is the baseline estimation, (2) controls for occupation, (3) controls for household income, (4) controls for occupation and household income. Sample: workers aged 19–59 earning above the statutory minimum wage, KSOS 2023–2024 pooled. Household income reference category: 2–4M won. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Use of AI tools. During the preparation of this thesis, the author used Claude (Anthropic) to check grammar and language in author-written text, to assist with LaTeX formatting and Stata code, and to verify the consistency of arguments. All content, analysis, and conclusions are the author's own, and the author reviewed and takes full responsibility for the final text.

References

Aguiar, M., Bils, M., Charles, K. K., and Hurst, E. (2021). Leisure luxuries and the labor supply of young men. *Journal of Political Economy*, 129(2):337–382.

Aguiar, M. and Hurst, E. (2007). Measuring trends in leisure: The allocation of time over five decades. *The quarterly journal of economics*, 122(3):969–1006.

Allcott, H., Braghieri, L., Eichmeyer, S., and Gentzkow, M. (2020). The Welfare Effects of Social Media. *American Economic Review*, 110(3):629–676.

Allcott, H., Gentzkow, M., and Song, L. (2022). Digital Addiction. *American Economic Review*, 112(7):2424–2463.

Bang, M. and Sieg, H. (2025). Estimating a time allocation and information acquisition model using revealed and stated preference data.

Becker, G. S. (1965). A theory of the allocation of time. *The economic journal*, 75(299):493–517.

Boppart, T. and Ngai, L. R. (2021). Rising inequality and trends in leisure. *Journal of Economic Growth*, 26(2):153–185.

Braghieri, L., Levy, R., and Makarin, A. (2022). Social media and mental health. *American Economic Review*, 112(11):3660–3693.

Bursztyn, L., Handel, B., Jiménez-Durán, R., and Roth, C. (2025). When Product Markets Become Collective Traps: The Case of Social Media. *American Economic Review*, 115(12):4105–4136.

Goldfarb, A. and Prince, J. (2008). Internet adoption and usage patterns are different: Implications for the digital divide. *Information economics and policy*, 20(1):2–15.

Goodman, J., de Frahan, L. H., Holz, J. E., List, J. A., MacMenamin, N., McKay, E. C., Mogstad, M., Sadoff, S., and Sider, H. (2026). Consumer demand and market competition with time-intensive goods. Technical report, National Bureau of Economic Research.

Gronau, R. (1977). Leisure, home production, and work–the theory of the allocation of time revisited. *Journal of political economy*, 85(6):1099–1123.

Jo, S., Baek, I. C., Fava, M., Mischoulon, D., Hong, J. P., Kim, H., Park, M. J., Kim, E. J., and Jeon, H. J. (2021). Association of smartphone overuse with depression, anxiety, and other addictive behaviors: A nationwide community sample of korean adults. *Psychiatry Research*, 304:114133.

Juster, F. T. and Stafford, F. P. (1991). The allocation of time: Empirical findings, behavioral models, and problems of measurement. *Journal of Economic literature*, 29(2):471–522.

Ministry of Employment and Labor (2025). Survey on labor force at establishments: Wages and working hours by industry and establishment size. https://stathtml.moel.go.kr/statHtml/statHtml.do?orgId=118&tblId=DT_118N_MON051. Statistics Approval No. 118002. Series: total working hours, all industries, all establishment sizes (1 or more employees), annual averages. Retrieved from KOSIS, table DT_118N_MON051.

Ministry of Science and ICT and National Information Society Agency (2024). The survey on smartphone overdependence 2024. Research Report NIA VIII-RBE-C-24021, National Information Society Agency, Daegu, Republic of Korea. In Korean, translation using Claude AI.

New York State Assembly (2025). Bill a5346: An act requiring warning labels on addictive social media platforms. 2025–2026 Regular Sessions, State of New York. Signed into law December 2025.

Park, S. (2025). Wealth, digital overuse, and the changing landscape of digital inequality1. *Computers in Human Behavior*, page 108805.

Ramey, V. A. and Francis, N. (2009). A century of work and leisure. *American Economic Journal: Macroeconomics*, 1(2):189–224.