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Addictive Consumption, Imperfect Substitutes and Self Control: A Model and an Application to Slot Machines

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Addictive Consumption, Imperfect Substitutes and Self Control: A Model and an Application to Slot Machines*

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Abstract

We propose a model of addictive consumption to study the demand for imperfect substitutes involving substances like alcohol, nicotine and opioids, as well as behavioral addictions like gambling and digital addiction. We study a 2017 Italian policy aimed at reducing gambling by limiting the number of available slot machines. Despite the reduction in slot machines, the policy produced an unintended 25% increase in net expenditure, particularly among low-wealth and low-educated individuals who also engage in other addictive behaviors. This result can be rationalized as the consequence of changes in self-control costs due to social contagion effects.

Keywords: Addiction; Gambling; Horizontal differentiation; Self-control; Slot machines, Temptation.

JEL codes: I18, L43, L83.

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Non-technical summary

Addictive behaviors, including substance use disorders and behavioral addictions, pose significant challenges to policymakers due to their adverse effects on physical and mental health, interpersonal relationships, economic stability, and quality of life. Governments worldwide have implemented strategies such as taxation, prohibition, educational programs, and restrictions on access to mitigate these harms. These interventions often rely on the economic principle that increasing the cost of consumption reduces demand. However, the outcomes can deviate from expectations when such policies inadvertently alter self-control and temptation costs.

This paper examines the consumption of addictive goods that are imperfect substitutes, combining theoretical modeling and empirical analysis. It integrates concepts from horizontal differentiation, rational addiction, and temptation costs to predict how addiction levels, availability of alternatives, and self-control constraints influence behavior. The theoretical framework addresses a broad range of addictive goods, including substances like nicotine, alcohol, and opioids, as well as behavioral addictions such as gambling and gaming disorders. Although behavioral addictions are less damaging to physical health than substance use disorders, they can significantly impair functioning across personal and professional domains.

The empirical application focuses on gambling addiction, specifically assessing the effects of a 2017 Italian policy aimed at reducing gambling opportunities by limiting the availability of slot machines. Using municipality-level administrative data and household expenditure surveys, the study evaluates the policy's impact through a difference-in-differences approach. The findings show that the number of slot machines declined by 21% and gambling venues by 11%. However, contrary to the policy's intent, slot machine expenditures increased by 25%, driven largely by low-income and less-educated individuals. These unintended consequences indicate that the policy may have exacerbated harm for the very groups it sought to protect.

Under standard economic assumptions, reduced access should discourage gambling by increasing transportation and opportunity costs. However, the findings suggest that reduced access also led to increased waiting times, which amplified cravings and temptation costs, especially among more addicted individuals. This dynamic likely increased gambling intensity, underscoring the importance of psychological factors in driving addictive behaviors

1 Introduction

Substance use disorders and behavioral addictions raise policy concerns due to their impact on individual physical and mental health, personal relationships, economic and financial stability, and overall quality of life. To address these concerns, policymakers have adopted a range of strategies, including prohibition and taxation of addictive substances, education programs, age limits, and time curfews (see, e.g., Evans et al., 1999; Adda and Cornaglia, 2006; Carpenter and Dobkin, 2009; Anger et al., 2011; Cawley and Ruhm, 2012; Hansen, 2015; Ahammer et al., 2022; Moore and Morris, 2024). The rationale underlying these forms of regulation is that consumption, even when addictive, is expected to decrease when its cost increases (Becker and Murphy, 1988). However, when the policy intervention also affects self-control and temptation costs, this prediction may not hold.

In this paper, we propose a theoretical and empirical investigation into the consumption of goods that are imperfect substitutes, addictive, and induce self-control costs. Building on the Hotelling (1929)'s model of horizontal differentiation, the Becker and Murphy (1988)'s theory of rational addiction, and the Gul and Pesendorfer (2001)'s model of temptation and self-control, we derive predictions about the extensive and intensive margins of addictive consumption as functions of the level of addiction, characteristics and availability of different addictive options, temptation costs, and access costs. The theoretical model provides a conceptual framework to understand consumption related to addictive substances such as, e.g., nicotine (Pesko and Warman, 2022), alcohol (Calcott, 2019) and opioids (Agrawal et al., 2023), and for behavioral addictions such as gambling and gaming disorders (WHO, 2022).[1]

As an empirical application, we focus on gambling addiction. Specifically, we estimate the effects of a 2017 policy in Italy that mandated a large reduction in the number of available slot machines. Using novel Italian administrative data on various types of gambling activities at the municipality level and a representative survey data on household expenditure, we estimate the effects of the policy with a standard difference-in-differences approach.

We find that in treated municipalities the number of slot machines decreases by 21%, and the number of venues hosting them decreases by 11%. However, the policy leads to unintended consequences, with net slot machine expenditure rising by 25% (30.20 EUR). This increase is driven by higher spending among players with low wealth and low education who also engage

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[1] Despite being non-substance-related, and thus generally less harmful to health, behavioral addictions can also yield adverse consequences, impairing an individual's ability to function across various life domains (Alavi et al., 2012; WHO, 2018, 2024). The ICD11 –the WHO (2022)'s latest International Classification of Diseases– describes gambling and gaming as disorders due to addictive behaviors that develop as a result of repetitive, rewarding activities. Other disorders, such as shopping disorder, exercise addiction (Berczik et al., 2012), and digital addictions related to internet use, including smartphone addiction (Allcott et al., 2022), are not included in the ICD-11. See Petry (2015) for a comprehensive overview.

in other addictive behaviors. Since slot machine players are predominantly from disadvantaged backgrounds (Mastrobattista et al., 2019; Resce et al., 2019), our results imply that the policy has harmed the very population it aimed to protect.

The theoretical model allows to gain insights on the possible mechanisms driving this finding. In the absence of self-control and temptation costs, the reduction in slot machines should increase the transportation costs and reduce willingness to play because of, e.g., increased congestion and longer waiting times. This would unambiguously reduce the extensive and intensive margin of slot machines play. The observed evidence suggests that, on the contrary, temptation costs do play a role because waiting times can also increase cravings for playing, and the more so in more addicted individuals. When these cravings and the associated temptation costs are large enough, the intensive margin of playing and, thus total expenditure on slot machines, can eventually increase.

Theoretically, our paper bridges three distinct streams of literature: addiction, horizontal product differentiation and self-control. The literature on addiction is typically focused on individual choices related to an addictive good that features habit-formation and self-control problems. The former is based on the assumption that current preferences depend on past consumption experiences (Pollak, 1970), an idea that is typically formalized as accumulation of an addiction stock which creates tolerance and reinforcement (Becker and Murphy, 1988). The latter has been studied as the consequence of regret (Orphanides and Zervos, 1995), time-inconsistent behavior (Strotz, 1955; Laibson, 1997; Gruber and Köszegi, 2001; Piccoli and Tiezzi, 2021), costly temptation (Gul and Pesendorfer, 2001, 2007), projection bias (Loewenstein et al., 2003), dual-self models (Thaler and Shefrin, 1981; Loewenstein and O'Donoghue, 2004; Ozdenoren et al., 2012), environmental cues (Bernheim and Rangel, 2004), or a combinations of these factors (Allcott et al., 2022). Most existing contributions, however, focus on a single addictive good.[2] In this paper we extend the analysis to allow for imperfect substitutes and horizontal product differentiation à la Hotelling (1929). This allows to take into account that people are heterogeneous, and they can satisfy their needs through goods that are imperfect substitutes, including the option of abstaining if the addictive alternatives are not good enough.

Empirically, we contribute to understanding the effects of a policy aimed at regulating addictive behavior by restricting the availability to consumption opportunities. Specifically, we add to the economics literature on gambling behavior. By providing the first causal analysis of a policy aimed at reducing gambling access, our results complement those of Badji et al. (2023) and Baker et al. (2024), who analyze the effects of the opposite type of regulation—greater

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[2] For exceptions see, e.g., Dockner and Feichtinger (1993); Bask and Melkersson (2004); Cawley and Dragone (2024).

gambling accessibility. Additionally, we contribute to empirical studies on gambling addiction and the substitutability between different types of gambling (Kearney, 2005; Guryan and Kearney, 2010). Finally, by emphasizing the possible roles of temptation and social contagion in gambling choices, we contribute to understanding behavioral drivers of gambling (Stetzka and Winter, 2023), such as the "lucky store" effect (Guryan and Kearney, 2008), the impact of unmet liquidity needs and financial constraints on gambling behavior (Herskowitz, 2021), and the role of media exposure (De Paola and Scoppa, 2014).

The paper is organized as follows. In the next Section we present a model of addictive consumption with imperfect substitutes and self-control costs. In Section 3 we describe the empirical application of the model to the case of the gambling industry in Italy. Section 4 describes the empirical strategy and Section 5 reports the empirical results. Section 6 concludes.

2 Becker and Murphy meet Hotelling, Gul and Pesendorfer

2.1 A model of addictive consumption with imperfect substitutes and self-control costs

Consider a scenario where addictive consumption can occur at two venues v, denoted as A and B and located at the extremes of a $[0,1]$ segment. Individuals are distributed along the $[0,1]$ segment and pay a marginal transportation cost $\tau_v \geq 0$ to reach venue $v \in \{A, B\}$ and consume. Once in a venue, individuals allocate their budget m between s units of addictive consumption and a composite numeraire z. The cost of each addictive unit consumed at venue v is p_v.

In each period t, individuals first choose whether to reach a venue, then they choose the optimal amount of addictive consumption. The former choice informs about the extensive margin of addictive consumption, while the latter one describes the intensive margin. Addictive consumption contributes to building an individual level of addiction $a \geq 0$. Addiction evolves over time depending on past and current consumption, according to

$$a\left(t+1\right) = \gamma\left(s\left(t\right) + a\left(t\right)\right), \tag{1}$$

where parameter $\gamma \in [0,1)$ and $a\left(0\right) = a_0$. After playing, individuals return to their initial location ("home"), the addiction level changes and a new period begins.

Consumption of the composite good yields utility $\mathcal{Z}\left(z\right)$, with $\mathcal{Z}_z > 0, \mathcal{Z}_{zz} \leq 0$. If an individual attends a venue v, consuming s at venue v (denoted as s_v) yields, for a given level of addiction a, the following utility:

$$\mathcal{U}\left(s_v; a\right) \tag{2}$$

The utility function (2) is strictly increasing in addictive consumption ($\mathcal{U}_s > 0$). Consistent with Becker and Murphy (1988) and Becker et al. (1991), we assume that given levels of playing are less satisfying when past consumption has been greater ($\mathcal{U}_a < 0$) and that the more a person has played in the past, the more they like playing today ($\mathcal{U}_{sa} > 0$). These two assumptions describe tolerance and reinforcement, which are typical properties of addictions.[3]

Utility from addictive consumption depends on the characteristics of the specific venue. These characteristics can literally describe features of the venue where addictive consumption occurs, such as the possible presence of amenities, the quality of the service, the presence of other consumers, but they can also be interpreted more broadly as features of the two available consumption goods. With the latter interpretation s_A and s_B describe imperfect substitutes for addictive consumption for which consumers have different tastes, conditional on consuming. This is the case of, e.g., vaping as an imperfect substitute for smoking, beer for wine, or heroin for other opioids.

Addictive consumption typically features temptation and self-control costs. Specifically, we assume that addicted individuals are tempted to spend all available budget m on addictive consumption, disregarding the composite good z. In the spirit of Gul and Pesendorfer (2001, 2004), individuals can partially overrule such temptation, but at a cost. Specifically, an individual consuming s_v pays a temptation cost that depends on the distance between the tempting choice of spending all budget on the addictive good and the actual choice. For concreteness, we consider the following cost function (Allcott et al., 2022; Cawley and Dragone, 2024):

$$\mathcal{C}\left(s_v; a, \sigma_v\right) \equiv a \cdot \sigma_v \cdot \left(m - s_v\right) \geq 0 \tag{3}$$

Expression (3) depends on a to account for the possibility that the temptation cost is higher when addiction is higher, and nil in case of no addiction, Parameter $\sigma_v \geq 0$ describes the marginal temptation cost at venue v, and it can depend on factors such as previous exertion of self-control (Muraven and Baumeister, 2000; Loewenstein and O'Donoghue, 2004), cognitive load (Shiv and Fedorikhin, 1999), as well as environmental cues (Loewenstein, 1996, 2000; Bernheim and Rangel, 2004), waiting times (Houser et al., 2018, 2021), social contagion and peer-pressure (Lundborg, 2006; Clark and Lohéac, 2007).

Taking into account the temptation costs, the individual objective function is:

$$\begin{aligned} U\left(s_v, z; a, \sigma_v\right) &\equiv \mathcal{U}\left(s_v; a\right) + \mathcal{Z}\left(z\right) - \mathcal{C}\left(s_v; a, \sigma_v\right) \\ &= \mathcal{U}\left(s_v; a\right) + \mathcal{Z}\left(z\right) + a\sigma_v\left(s_v - m\right) \end{aligned} \tag{4}$$

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[3] The utility function is also assumed to be strictly concave. Note that partial derivatives of the utility function are denoted with subscripts, as in, e.g., $U_{sa} \equiv \frac{\partial^2 U(\cdot)}{\partial s \partial a}$.

It can easily be verified that the objective function (4) is increasing in consumption ($U_s > 0$), features reinforcement and tolerance ($U_{sa} > 0$, $U_a < 0$), and that it decreases when the temptation parameter is higher ($U_\sigma \leq 0$).

Individuals that do not attend either venue spend all budget on the composite good and obtain the reservation utility $U(0) \equiv U(0, m; a, \sigma_0)$, which negatively depends on addiction a and the temptation parameter σ_0.

2.2 Solving the model

The problem is solved by backward induction. In the second stage of each period t, and conditional on being at venue $v \in \{A, B\}$, an individual with addiction stock a optimally chooses addictive consumption s and the amount of consumption of the composite good z that solve:[4]

$$\max_{s_v, z} U(s_v, z; a, \sigma_v) \tag{5}$$

$$\text{s.t. } m = p_v s_v + z \tag{6}$$

The optimal amount of addictive consumption (s_v^*, z_v^*) exhausts the available budget and, assuming an interior solution, it satisfies the familiar condition where the marginal rate of substitution between s and z equals the relative price:

$$(s_v^*, z_v^*): \quad \frac{U_s(s_v^*, z_v^*)}{U_z(s_v^*, z_v^*)} = p_v \tag{7}$$

The participation choice in the first stage depends on the individual location i along the unit line, and on the individual addiction level a. The former affects the transportation cost to reach the venues, the latter affects the utility from consumption and the marginal incentives to consume. An individual chooses to reach a specific venue, or the outside option of no addictive consumption, by comparing the reservation value $U(0)$ and the maximized utility of consuming at either venue, i.e.:

$$\begin{aligned} \mathcal{V}(i, a, A) &\equiv U(s_A^*, z_A^*; a, \sigma_A) - \tau_A \cdot i, & (8) \\ \mathcal{V}(i, a, B) &\equiv U(s_B^*, z_B^*; a, \sigma_B) - \tau_B \cdot (1 - i) & (9) \end{aligned}$$

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[4] Unlike rational addiction models, which assume individuals account for how current choices impact future addiction, here we assume that individuals are myopic. Readers interested in forward-looking addiction models without horizontal product differentiation can refer to Becker and Murphy (1988), Chaloupka (1991), and Dragone and Raggi (2021) for time-consistent behavior, and to Piccoli and Tiezzi (2021) and Allcott et al. (2022) for models with time-inconsistent agents.

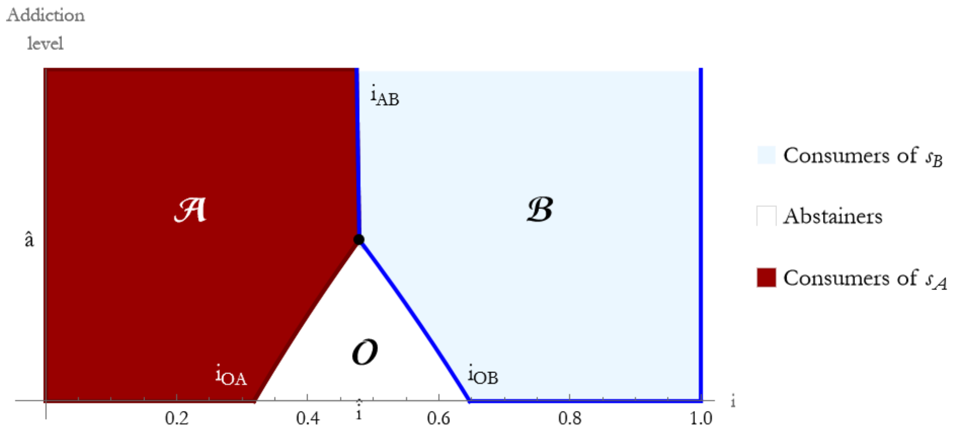

Figure 1: Coverage of the market depending on individual location and level of addiction. For a given level of addiction a, individuals on the left of i_{OA} or i_{AB} consume at venue A; individuals on the right of i_{OB} or i_{AB} consume at venue B. The market is fully covered for addiction levels above $\hat{a}$, and partially covered otherwise. Individuals' addiction increases over time, until people reach the venue-specific stationary addiction levels (not drawn).

Consider Figure 1. For a given level of addiction a, individual at location i_{AB} is indifferent between venue A and B, while i_{OA} and i_{OB} are the locations of individuals indifferent between abstaining and consuming at venue A or B, respectively. These three indifferent consumers determine the extensive margins of abstension and of consumption at venue A and B. They coincide at $(\hat{\imath}, \hat{a})$, which denotes the individual location and level of addiction that make a person indifferent to consuming at either venue and abstaining from addictive consumption. For some density function $\phi(i,a)$ of individual locations and levels of addiction, the share of the population that consumes at either A or B and the share of abstainers are:

$$\mathcal{N}_A = \iint_{\mathcal{A}} \phi(i,a)\,\text{dida}; \qquad \mathcal{N}_B = \iint_{\mathcal{B}} \phi(i,a)\,\text{dida}; \qquad \mathcal{N}_O = \iint_{\mathcal{O}} \phi(i,a)\,\text{dida}; \tag{10}$$

where $\mathcal{A} = \{(i,a) : i \leq \min\{i_{OA}(a), i_{AB}(a)\}\}$ and $\mathcal{B} = \{(i,a) : i \geq \max\{i_{OB}(a), i_{AB}(a)\}\}$ denote the sets of consumers, and $\mathcal{O} = \{(i,a) : i \in [i_{OA}(a), i_{OB}(a)], a \leq \hat{a}\}$ denotes the set of abstainers.

Individuals that abstain have low levels of addiction ($a \leq \hat{a}$) and are relatively far from either venue. Individuals that are closer to either venue go there and consume s_v^*. When the level of addiction is large enough ($a \geq \hat{a}$), individuals always consume at some venue because the utility of consuming some addictive good, net of the transportation cost to pay for reaching the venue, is larger than the outside option of abstaining.

2.3 Comparative statics

In each period t, individuals make their participation and consumption choices based on the current level of addiction and their location. As shown in Appendix A.2, addictive consumption is predicted to feature adjacent complementarity, i.e., positive correlation between current consumption and the addiction level. This outcome is commonly associated with habit formation and addictive consumption (Becker and Murphy, 1988; Becker et al., 1991). It implies that individuals with higher levels of addiction are less likely to abstain from addictive consumption (see Figure 1) and tend to consume more than those with lower addiction. This prediction will be tested in the empirical application (Section 5.3).

In the following, we focus on venue A and consider three comparative statics exercises: an increase in the transportation cost τ_A, an increase in the marginal temptation cost σ_A, and a reduction in the enjoyability of consumption at A.

Denote with $E_A \equiv p_A \bar{s}_A \mathcal{N}_A$ and with $E_B \equiv p_B \bar{s}_B \mathcal{N}_B$ the expenditure on addictive consumption at venue A and B, respectively, where $\bar{s}_v$ is the venue-specific average amount of addictive consumption and $\mathcal{N}_v$ is the number of consumers at venue v. The following Proposition holds:[5]

Proposition 1. *In a model of addictive consumption with imperfect substitutes, everything else equal:*

- *After an increase in transportation cost τ_A:*
  - *The number of consumers at A decreases, while the number of consumers at B increases.*
  - *Individual consumption at either venue is unaffected.*
  - *Expenditure E_A decreases, while expenditure E_B increases.*
- *After an increase in the marginal temptation cost σ_A:*
  - *The number of consumers at A decreases, while the number of consumers at B increases.*
  - *Individuals at A consume more, conditional on consuming. Individual consumption at B is unaffected.*

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[5] All proofs are in Appendix A.2, under the assumption that $(\hat{\imath}, \hat{a})$ is positive and feasible. The addiction stock increases over time until addictive consumption exhausts all available income (i.e. $s_v^* = m/p_v$), or it reaches the stationary venue-specific level, $s_v^{ss} = (1-\gamma)a_v^{ss}/\gamma$; see Equation (1). We assume that the initial level of addiction of the whole population is lower than that steady state level of addiction a_v^{ss}.

- *Expenditure E_A increases if and only if the increase in consumption at the intensive margin offsets the decrease in the number of consumers at A. Expenditure E_B increases.*

To understand the intuition behind the above Proposition, note that both transportation and temptation costs affect utility levels, which drive choices at the extensive margins. When either τ_A or σ_A increases, individuals who are not highly addicted (those along the i_{A0} locus, see Figure 1) quit consuming, while more addicted individuals (those along the i_{AB} locus) switch venues.

Temptation costs also affect marginal utility, which determines the intensive margin of consumption once a venue is reached. As temptation increases, the number of consumers at venue A decreases, but those who reach it consume more. Consequently, the effect on expenditure at venue A is theoretically ambiguous. In contrast, since more consumers reach venue B, expenditure E_B unambiguously increases.[6]

We now consider how consumption, as well as the number of consumers and abstainers, depends on the features of consumption options. This is relevant not only for the literal interpretation of consumption venues (e.g., drinking wine at a restaurant versus at home) but also for product innovation or regulation targeting specific consumption options. Consider, for example, the introduction of bans on flavored e-cigarettes in the context of substitution between vaping and smoking, or the reduction in the number of slot machines at venue A, as we examine empirically in the next section.

Everything else equal, reductions in the desirability of addictive consumption s_A, induce some previous consumers at venue A to abstain, while some other consumers (those with higher addiction levels) switch venue and consume s_B. Specifically, for individuals who were previously consuming at venue A, one of the following scenarios occurs:

1. Consumers of s_A continue consuming at venue A if they are relatively close to it; once at the venue they consume less;

2. Consumers of s_A switch and begin consuming s_B if their level of addiction is relatively high and they are relatively close to venue B; if $s^*_B > s^*_A$, these consumers also increase their consumption level;

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[6] In the Proposition, we consider the case where temptation costs change at only one venue. However, one could also consider a generalized increase in marginal temptation costs. In this case, all individuals, especially abstainers, would experience a reduction in utility. This is because higher temptation costs make abstaining less attractive relative to consuming, inducing some abstainers to start consuming at either venue. As expected, once at a venue, individuals consume more due to the higher marginal utility of addictive consumption. Consequently, a general increase in marginal temptation costs raises net expenditure at both venues.

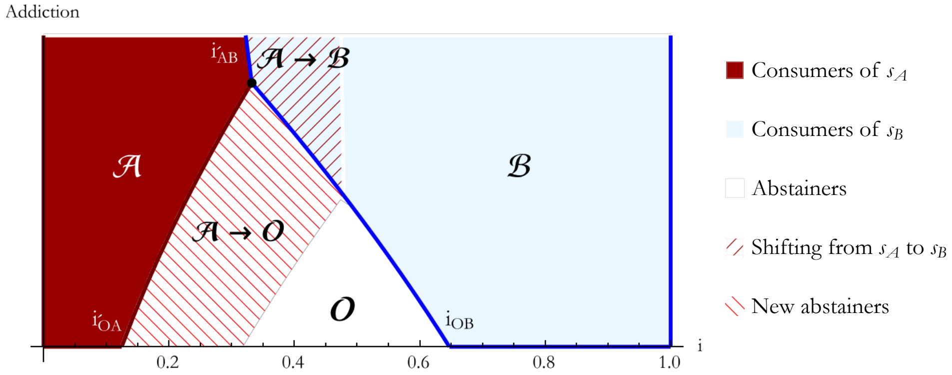

Figure 2: When addictive consumption becomes less enjoyable at A, some consumers quit, while others switch from A to B. Expenditure on the addictive good decreases at venue A and increases at venue B.

3. Consumers at A cease consuming if venue B is too distant, if their addiction level is low, or if addictive consumption at venue A is no longer available.

Figure 2 illustrates the previous observations when the features of addictive consumption at venue A become worse. Overall, individuals relatively close to venue A will continue consuming at venue A, although they consume less because s_A is now less enjoyable. Previous consumers of s_A that were not highly addicted quit consuming, while consumers with higher addiction levels shift to venue B. Consumption at venue B is not affected. Hence, the following holds:

Proposition 2. *Everything else equal, if the enjoyability of consumption at venue A is reduced, expenditure E_A decreases, while expenditure E_B increases.*

3 An empirical application to slot machine play

3.1 Gambling in Italy and the 2017 slot machine bill

Slot machine play, and gambling more generally, are behavioral addictions that exhibit characteristics similar to substance addictions, even though no substance is consumed. Since the various gambling options available to a player are imperfect substitutes, the theoretical model presented in Section 2 can be applied. As an empirical application, we assess the impact on slot machine play of a 2017 bill which reduced the number of slot machines in Italy.

Focusing on gambling is compelling because, in many countries, the prevalence of gambling disorders has been steadily increasing (WHO, 2024).[7] Italy is an interesting case to study gambling addiction. After the UK, Italy has the second largest gambling sector in Europe.

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[7] Each year, an estimated 350 million people worldwide experience gambling problems, with a prevalence rate ranging from 0.1% to 5.8%.

Total revenues from gambling have steadily increased in the past years, going from EUR 88.2 billion in 2015 to EUR 110.5 billion in 2019. This corresponds to more than 5% of Italian GDP, an amount of resources comparable to the total education expenditure (7.8%) and total health expenditure (8.7%, OECD 2018).

According to the Ministry of Health, 1.3 million Italians in 2019 were diagnosed with pathological gambling. A survey conducted in 2017 by the the Italian National Institute of Health (*Istituto Superiore di Sanità*) documents that one in three adults has gambled at least once in the previous 12 months. Among them, almost 6% are classified as medium-to-high-risk gamblers. Using Italian data, Resce et al. (2019) show the existence of a socio-economic gradient in gambling, as wealthier individuals tend to prefer traditional lotteries, while poorer players prefer betting and new generation games. The latter category, which includes slot machines, is also the major contributor to the recent increase in gambling disorders. Accordingly, the health and social costs of gambling may disproportionally affect the most vulnerable parts of the population.

In Italy, gambling is a state monopoly. The country's regulatory body, the Italian Agency for Customs and Monopolies (*Agenzia delle Dogane e Monopoli*, ADM) oversees all aspects of the Italian gambling industry, from licensing to enforcement. ADM operates a strict licensing regime for all forms of gambling and monitors operators to ensure they comply with the existing regulations, aimed at preventing gambling disorder and protecting consumers. There are different forms of legal gambling: lotteries, scratch cards, sports bets, bingo, online bets, and slot machines.[8]

Most slot machines in Italy are *Newslots*. They feature fast gameplay, with each bet capped at one euro and a maximum win of EUR 100. The minimum payout is legally set at approximately 70%, and there is no jackpot. These machines are commonly found in tobacco shops, bars, betting venues, and bingo halls.[9] The legislation regulating the features of slot machines and the venues that host them (e.g., minimum payout, taxation, number and location, distance from schools, etc.) applies nationwide. As with all other forms of gambling, operators must obtain licenses from the ADM. Each license is linked to a single device, and each device

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[8] Lottery tickets and scratch cards are typically purchased in tobacco shops. Their prices range from one to several tens of EUR, and they often feature substantial jackpots. Sports bets, including those on horse races, can be placed in tobacco shops or betting venues. Bingo halls are usually located in cities or large towns. Online betting is only permitted on licensed web platforms. Additionally, there are four legally operating casinos in Italy, while gambling houses are illegal. The minimum legal age for gambling is 18 years.

[9] Newslots are also called Amusement with Prizes (AWP). Another type of slot machine that is less widespread and less accessible is *Videolotteries* (VLT). VLT offer a wider variety of games, including poker, blackjack, and roulette. The minimum payout is around 84%, users can bet up to 10 EUR in a single round; the maximum amount they can win is $5,000$ EUR. There is also a number of jackpots, which can reach $500,000$ EUR. VLT are typically found in dedicated venues which must be clearly delimited and are subject to stricter control.

can legally operate only if associated to a valid license.

In 2017, the Italian government introduced a bill aimed at addressing pathological gambling and gambling addiction. The bill mandated a large reduction in the number of slot machines across the country, with the goal of reducing their availability and increasing the cost of gambling for potential players. As mentioned in the introduction, this approach is common to many policies aimed at preventing harmful addictive consumption, such as smoking bans, tobacco restrictions, and minimum drinking age laws.

The 2017 bill required a reduction in the number of Newslots by at least 15% by December 31, 2017, and by at least 34.9% by April 30, 2018, based on the stock of slot machines available as of December 31, 2016. This meant that by the end of 2017, no more than 345,000 Newslots could remain active, and by the end of April 2018, no more than 265,000.[10]

In case of non-compliance, ADM would intervene by revoking licenses within a month. Notably, the bill explicitly states that, when revoking licenses, priority should be given to slots in areas with a higher number of devices. Additionally, it specifies that the cuts should target devices with the lowest average net daily revenue over the past 12 months, relative to the regional average.[11] These provisions in the 2017 bill are exploited in the next sections to empirically identify the effects of the policy.

As shown in Figure 3, compliance with the law was high, as the total number of active slot machines in Italy decreased, in accordance with the 2017 bill. Interestingly, total net expenditures by gamblers and total winnings remained stable over the period 2014-2019. While

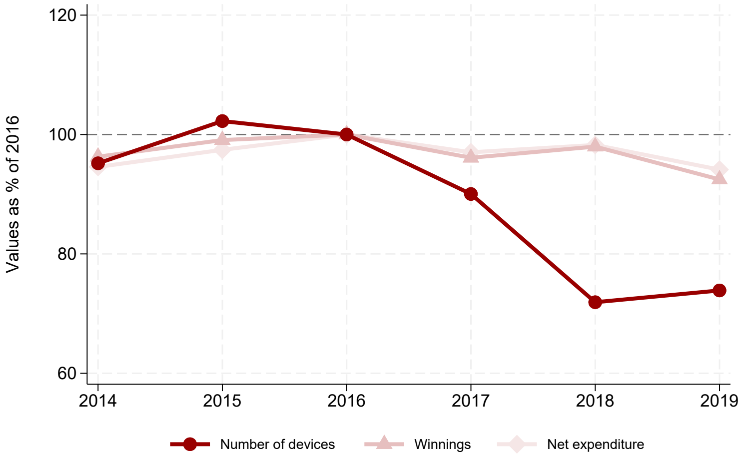

Figure 3: Number of slot machines, winnings and net expenditure in slot machines. Country-level totals by year as percentage of the 2016 values.

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[10] Decree of April 24, 2017, article 6bis, converted in Law on June 21, 2017.

[11] Decree of July 25, 2017, by the Minister of Economy and Finance, which supervises ADM.

this finding is suggestive, it does not allow for causal conclusions about the effectiveness of the 2017 bill. This analysis will be conducted in Sections 4 and 5.

3.2 Data sources

We use two main datasets: administrative data on gambling at municipality level and survey data on expenditure at the household level. For additional insights on the empirical results, we use the ADM geolocalized data on the universe of tobacco shops in 2016 and the Italian Census 2011 data on socio-demographic characteristics.

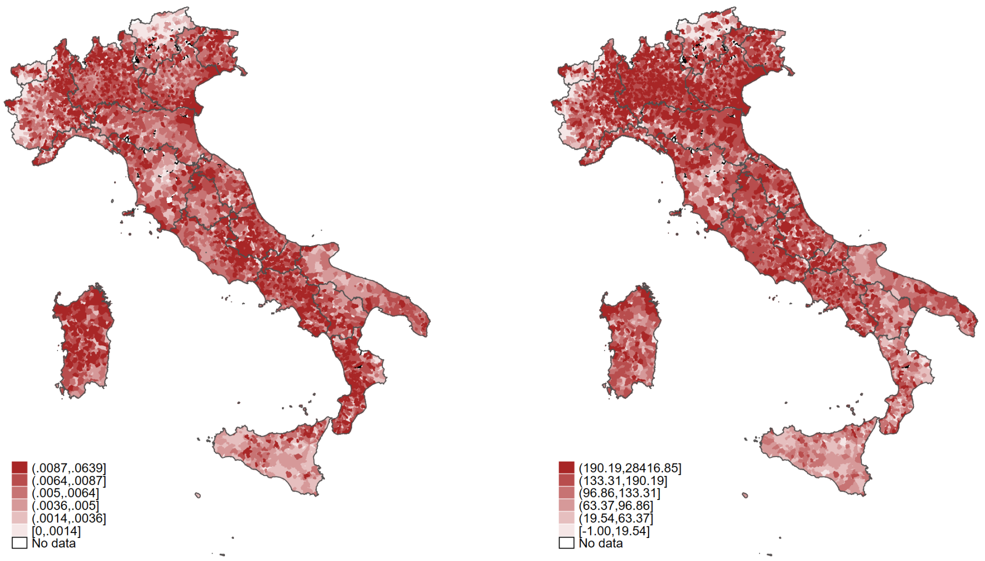
Gambling data

The gambling data are sourced from ADM. They span from 2015 to 2019, they cover $7,877$ Italian municipalities, and they contain the universe of legal gambling activities in Italy. ADM reports municipality-level yearly data on the counts of slot machines (both Newslots and Videolotteries), the counts of licensed venues where slot machines are installed, and the total expenditure net of winnings on various forms of gambling.

Table 1 presents the main summary statistics on the 2015 per capita net expenditure at the municipality level, categorized by gambling type: slot machines, sports bets, lotteries, bingo, scratch cards, and online betting. Slot machines account for the highest per capita expenditure, averaging EUR 121.35. This figure is largely driven by expenditure on Newslots, which alone accounts for EUR 101.83. Expenditure on other types of gambling is substantially lower. For instance, lotteries, which constitute the second-highest category, collect an expenditure that is approximately half of that spent on slot machines. Online betting collects only EUR 0.88 on average in 2015. It is noteworthy that, although this figure nearly doubles to EUR 1.42 by

	Mean	Std. dev.	Min	Max
Slot Machines	121.35	345.64	-1.00	28,416.85
— Newslots	101.83	218.18	-1.00	17,992.04
— VLT	19.51	140.43	0.00	10,424.82
Lotteries	60.77	213.05	-4,359.54	17,614.33
Scratch cards	7.01	41.86	-1,022.57	3,404.31
Sport bets	4.09	30.49	-22.65	2,575.94
Bingo	1.24	15.89	-70.48	625.04
Online	0.88	6.20	-1.26	491.62

Table 1: Per capita net expenditure in 2015, by type of gambling. Municipality-level per capita expenditure, net of winnings, in the year 2015. Sample: $7,877$ municipalities.



(a) Newslots per capita

(b) Newslots net expenditure per capita

Figure 4: Newslots: per capita number and net expenditure in 2015. Geographical distribution of the per capita number of Newslots (panel a) and the per capita net expenditure on Newslots (panel b) by municipality in 2015. Black lines indicate regional borders (20 NUTS-2 areas).

2019, its overall importance in the Italian market during this period remains relatively small.

The geographical distribution of per capita Newslots is positively correlated with per capita net expenditure, as shown in Figure 4 for 2015.[12] In line with the 35% reduction mandated by the 2017 bill, between 2016 and 2018 the number of Newslots decreases by about one third in each region. This is accompanied by a decrease in the number of venues (see Figure B.1 in Appendix B).[13] The number of Videolotteries and their corresponding venues, which are not subject to the policy, remains substantially constant over time or slightly increased.

Household expenditure data

To examine the heterogeneous effects of addiction levels and socio-economic status on gambling expenditure, we use the Italian Household Expenditure Survey (HES). Published by the Italian National Institute of Statistics (ISTAT), the survey is representative of the Italian population and covers a broad range of household expenses, including gambling and alcohol consumption, as well as demographic characteristics of household members and self-reported economic conditions. We analyze data from the 2014 to 2019 survey waves, with an overall sample of over 100,000 households. The data includes total expenditure, and specific spending details on

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[12] The pairwise correlation is equal to 0.25 and is statistically significant at any conventional level.

[13] Piedmont and Valle d'Aosta are an exception as a consequence of more stringent local policies. As shown in the robustness checks section, this does not drive the empirical results.

gambling and on alcoholic beverages, such as beer, cider, wine, liquors, and spirits. It covers regional information, household composition (number of members), and detailed characteristics of the household head, including gender, age, nationality, education level, employment status, occupation, economic sector, and type of employment contract.

On average, total household monthly expenditure is around EUR 2,500. Households who report no expenditure on gambling amount to 87% of the sample. Figure B.2 shows the distribution of expenditure on gambling for the remaining 13%. For this subsample, average reported expenditure on gambling is EUR 23.77.

4 Empirical strategy

4.1 Conceptual framework

We empirically assess the causal effects of the 2017 bill using a standard difference-in-differences approach. The predictions from the theoretical model presented in Section 2 provide a natural framework for interpreting the empirical estimates. In fact, slot machine play can be entertaining (Conlisk, 1993; Burger et al., 2020), although it may lead to negative consequences, such as adverse effects on mental health, including depression, anxiety, and stress (Muggleton et al., 2021; Wardle and McManus, 2021; Badji et al., 2023), as well as loss of money and financial hardship. Furthermore, slot machines are designed to create addiction (Schüll, 2012), particularly due to visual and sensory features that encourage reinforcement through repeat play (Harrigan et al., 2010; James et al., 2016).

Denoting the level of gambling addiction as a, and the amount of slot machine play–the number of spins– as s, the requirements for the utility function used in the Section 2 are satisfied ($U_s > 0$, $U_a < 0$, and $U_{sa} > 0$). Moreover, playing slot machines requires reaching the physical venue (v) where they are located, at a transportation cost (τ_v).[14] Once at the venue, individuals choose how much to play (s_v). The net expected cost of playing is $p \equiv P - \mathbb{E}(w) > 0$, where P is the cost per play (by law, it is equal across venues) and $\mathbb{E}(w)$ is the expected monetary win.[15]

Denote venue A as a treated unit, and venue B as the control unit. Empirically, we aim at

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[14] Slot machines are imperfect substitutes because they are located in different venues. In this sense, the horizontal differentiation component of the model is literally understood in terms of location. However, transportation costs can also be interpreted as access or stigma costs for being a player. We will consider this alternative interpretation when discussing the empirical results in Section 5.

[15] Taking literally the notion of playing, our approach is complementary to the approach based on risk-loving preferences over monetary outcomes, which explains why people choose uncertain prospects even when the net expected gain is negative. See Friedman and Savage (1948); Hartley and Farrell (2002); Levitt (2004) for an alternative approach focused on the role of uncertainty in gambling choices. For an approach aimed at describing optimal stopping time for playing, based on cumulative earnings, see Lien and Zheng (2015).

estimating the following difference-in-differences (DiD) estimator:

$$\beta = \big(E'_A - E_A\big) - \big(E'_B - E_B\big) = \Delta E_A - \Delta E_B \tag{11}$$

where E'_v denotes net expenditure at venue v after the implementation of the policy, and ΔE_A and ΔE_B are the differences in net expenditure at venue A and B, respectively.

Using the terminology of the theoretical model, we conjecture that the reduction in the number of available slot machines produces different effects. First, a reduction in the number of available slot machines is likely to increase the transportation cost τ_A to reach the treated venue A. Second, the policy may reduce the utility derived from gambling at A, due to factors such as congestion or longer waiting times, which may make slot machine play at A less enjoyable. Both mechanisms imply that the expected effect of the bill is to reduce the extensive and intensive margins of slot machine play at A (hence $\Delta E_A < 0$) and to increase the number of players at B (hence $\Delta E_B > 0$). This is consistent with Badji et al. (2023), who show that people residing in close proximity to gambling venues are more likely to gamble and less likely to be happy.

Third, it is possible that the bill influences the marginal temptation cost σ_A of playing at A, due to, e.g., longer waiting times that increase the desire to consume (Loewenstein, 1987; Houser et al., 2018, 2021) or the cost of exerting self-control (Muraven and Baumeister, 2000; Vohs and Faber, 2007; Hagger et al., 2010; Baumeister et al., 2018), or possible social contagion effects induced by higher concentration of players in the same venue (Rockloff and Dyer, 2007; Rockloff et al., 2011, 2012, 2017; Hopfgartner et al., 2021). Since the model predicts that greater temptation leads to higher consumption (but also less consumers) at A, its effect on net expenditure can oppose those produced by increased transportation costs and reduced utility.[16]

The sign of the empirical estimate of β can suggest which of the mechanisms above dominates. In the absence of changes in the temptation parameter σ_A, an increase in transportation costs and a reduction in the utility from playing is predicted to unambiguously decrease expenditure at A, while expenditure at B should increase (see Propositions 1 and 2). In such a case, the difference-in-difference estimate β is predicted to be negative. If, however, the policy also produces an increase in the temptation parameter σ_A, or a reduction in the stigma cost associated to being a player, net expenditure at venue A may increase (hence $\Delta E_A > 0$). If

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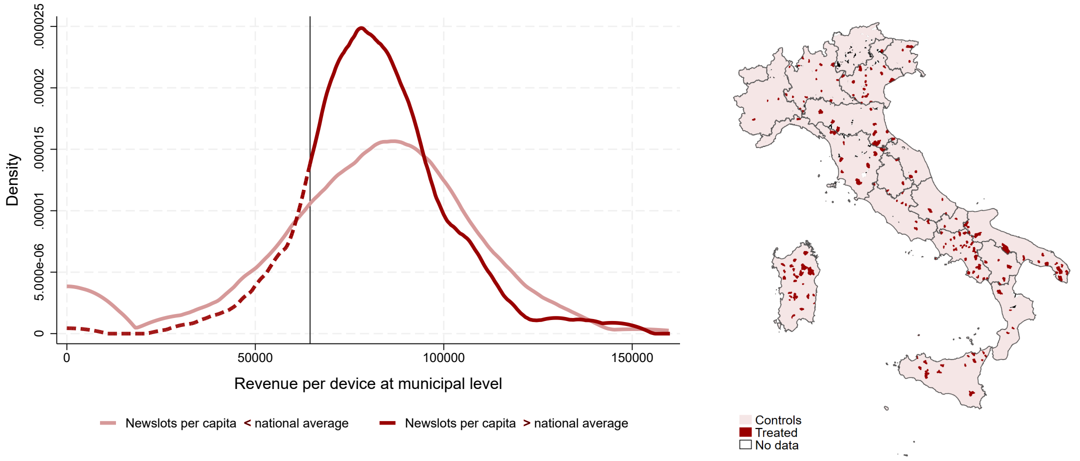
[16] In principle, longer waiting times and increased crowding can reduce the utility of playing, but they may also raise temptation costs. Furthermore, a higher concentration of players in fewer venues could reduce the perceived stigma associated with being a player, which might be interpreted as a reduction in "transportation costs" (if τ_A is understood in a non-literal sense), leading to more players at venue A. We do not take an a-priori stance on which of these potential channels dominates.

such effect is large enough, β is positive (see Equation 11).

4.2 Treated units

The 2017 bill required Newslots to be reduced in areas where they were more abundant and least profitable. Hence, we classify municipalities as *treated* units (the empirical counterparts of venue A in the model) if two criteria are satisfied: (i) the number of slot machines per capita at the municipality level is above the national average as of December 2016, and (ii) total revenue per device at municipal level is below the 15th percentile of the regional distribution.[17]

Panel (a) of Figure 5 illustrates the treatment assignment, using the Emilia-Romagna region as an example. Municipalities are first categorized based on whether the *per capita number* of Newslots in the municipality exceeds or falls below the national average. This corresponds to criterion (i) and is graphically represented by the red and pink curves in panel (a). Within each group, we identify municipalities where the average *revenue per device* in 2016 is below the 15th percentile This corresponds to criterion (ii) and by the municipalities to the left of the vertical line in panel (a) of Figure 5. Therefore, the treated municipalities are those that have a higher-than-average number of Newslots per capita (red curve) and lower-than-average



(a) Municipalities by revenue per device, Emilia Romagna

(b) Treated municipalities, Italy

Figure 5: Assignment of treated and control units. Panel (a) shows the distributions of municipalities based on the revenue per device in the Emilia-Romagna region in 2016. The pink and red curves correspond to the municipalities with a number of Newslots per capita below and above the national average, respectively. The vertical line indicates the 15th percentile of the regional distribution of the revenue per device. The dashed red curve denotes the treated units. Panel (b) shows the geographical distribution of the treated municipalities (221, in red). Black lines indicate regional borders (20 NUTS-2 areas).

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[17] The 15% threshold is motivated by the 15% reduction in slot machines mandated in 2017. The empirical results are robust to using different thresholds (see Appendix C).

revenues per device (left of the vertical line). These treated units are indicated by the dashed red curve. This procedure is repeated for each of the 20 Italian regions. Panel (b) displays the geographical distribution of the treated municipalities (221, 3% of the sample) across the 107 provinces and the 20 regions of Italy.

Figure B.3 illustrates the time variation in the per capita number of Newslots and the per capita net expenditure on total slot machines across treated and control municipalities. Panel (a) shows the compliance of the treated municipalities with the 2017 bill. Before 2017, trends are parallel across treated and control units; afterwards, the gap narrows. Panel (b) displays the evolution of per capita net expenditure. Expenditure increases over time in treated units, while it remains substantially constant in control municipalities.

4.3 Empirical model

We estimate the following empirical model:

$$Y_{mpt} = \alpha + \beta C_m \times \mathbb{1}(t \geq 2017) + \gamma_{mp} + \delta_{tp} + \epsilon_{mpt} \tag{12}$$

where Y_{mpt} is the outcome of interest for municipality m in province p and year t. Specifically, we consider the per capita number of Newslots, the per capita expenditure on slot machines, the per capita number of venues hosting Newslots, the per capita number of Videolotteries (i.e. slot machines not affected by the cut), and the expenditure on other types of gambling (scratch cards, lotteries, sports bets, and online bets).

The coefficient of interest is β, as it captures the causal effect of reducing the number of slot machines (C_m) on the outcome. In the theoretical model, this corresponds to Equation 11. To account for time-varying heterogeneities at sub-regional level, the empirical model includes municipality fixed effects (γ_{mp}) and a set of year-province dummy variables (δ_{tp}). Regressions are population-weighted and standard errors are clustered at municipality level.

To test for the possible existence of differentials between treatment and control groups in the pre-policy period, and to rule out that the reduction in Newslots is endogenously related to pre-treatment differentials in the outcomes, we consider the following event-study specification:

$$Y_{mpt} = \alpha + \sum_{j=2015}^{2019} \beta_j C_m \times \mathbb{1}[t = j] + \gamma_{mp} + \delta_{tp} + \epsilon_{mpt} \tag{13}$$

with year 2016 as the baseline. We also use this specification to examine potential heterogeneous effects based on the distance to tobacco shops, which serves as a proxy for the transportation costs discussed in Proposition 1.

To further support the causal interpretation of our results, we run additional tests as robustness checks. First, we perform sensitivity analyses on the definitions of treated and control groups. Second, we re-estimate the model considering different sub-samples. Third, we conduct several falsification exercises, including exercises focusing on unaffected outcomes and treatment randomization. The results are reported in Appendix C.

Finally, we use household-level data from the Household Expenditure Survey (HES) to investigate the possible correlation between gambling and risky health behaviors, and to understand what parts of the population are most affected by the policy. This analysis is policy-relevant because the literature on risky health behaviors has consistently shown that individuals who engage in one risky behavior, such as drinking, are more likely to engage in others, such as smoking, substance use, and gambling (Cawley and Ruhm, 2012). Moreover, Resce et al. (2019) note that in Italy, slot machines are predominantly used by individuals of lower socio-economic status, raising concerns about income-related inequalities in gambling, particularly among the most vulnerable populations. We estimate the following regression with Pseudo-Poisson Maximum Likelihood (PPML):

$$W_{hrp} = \exp\left(\vartheta + \phi T_{hr} \times \mathbb{1}(p \geq 2017) \times A_{hrp} + \psi_p + \zeta_r + X_{hrp}\eta\right) + \nu_{hp} \tag{14}$$

where W_{hrp} is the monthly household expenditure of household h in region r and period p (month of the year in 2014m1-2019m12). We consider reported expenditure on gambling and total expenditure.

Since the HES dataset only provides geographical information at the regional level, without specifying municipalities, we must adapt the identification strategy to the regional scale. Households are defined as treated ($T_{hr} = 1$) if they reside in a region that is relatively more exposed to the reduction in Newslots in 2017 —that is, in a region where the share of the population living in treated municipalities is above the median of the distribution. Variable A_{irp} identifies households who are in the top quartile of the distribution of expenditure in alcohol (beer, cider, wine, liquors and spirits). This proxies for individuals with high levels of addiction to alcohol and, possibly, of addiction in general. With this interpretation, the coefficient ϕ captures the causal effect of the reduction in Newslots on monthly expenditure for households with higher addiction levels.

The empirical model in Equation 14 includes period (ψ_p) and region fixed effects (ζ_r) to capture heterogeneities over time and across regions. X_{hrp} describes a set of household characteristics: number of components, household head's gender, age, nationality, education, employment status, occupation, economic sector and type of contract.[18]

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[18] The categories for employment status are: employed, unemployed, homemaker/student, retired, or other;

5 Empirical results

5.1 Effects of the policy: Administrative data

Table 2 displays our main results, estimated using Equation 12. As shown in column 1, compliance with the bill was high, as the number of Newslots per capita in treated municipalities decreased by 21% after 2017. Column 2 of Table 2 shows that also the number of venues hosting Newslots declined, by approximately 11%. The number of Newslots per venue decreased by a similar amount (column 3).

The corresponding event-study analyses are illustrated in Figure 6. Panel (a) shows that the bill reduced the per capita number of Newslots by 0.0005 in 2017 and by to 0.0015 in 2018 and 2019. Given the 2015 average of 0.0054, this means that the reduction in the per capita number of Newslot devices reached 10% by the end of 2017 and 31% by the end of 2019. Panel (b) and (c) show that the reduction in the per capita number of venues was 4% in 2017 and 17% in 2019, while the number of Newslots per venue decreases by 7% in 2017 and by 14% in 2018 and 2019. Together, these results suggest that the policy likely increased transportation costs for players and led to higher crowding in the remaining venues.

Contrary to the goal of the policy, per capita expenditure on slot machines significantly increases by 25% (EUR 30.20) in treated municipalities compared to control units. The results are shown in column 4 of Table 2. The corresponding event-study analysis, shown in panel (d) of

	(1) Per capita Newslots	(2) Per capita venues	(3) Newslots per venue	(4) Per capita expenditure
Treat × Post	-0.0012***	-0.0002**	-0.4088***	30.1966***
	(0.0003)	(0.0001)	(0.1052)	(9.3459)
Observations	39,385	39,385	39,385	39,385
Municipalities	7,877	7,877	7,877	7,877
Mean outcome in 2015	0.0054	0.0015	3.6800	121.3451
Elasticity	-21.42	-10.69	-11.11	24.88
Municipality FE	✓	✓	✓	✓
Province × Year	✓	✓	✓	✓

Table 2: Effect on Newslots, venues and expenditure. The outcomes are the number of Newslots per capita (column 1), the number of venues hosting Newslots (column 2), the number of Newslots per venue (column 3) and the per capita net expenditure on slot machines (column 4). Elasticity is calculated and then multiplied by 100. The variable *Treat* is defined as in Section 4; *Post* represents the period after 2016. Population-weighted regressions are estimated based on Equation 12, with standard errors clustered at the municipality level.
* p<.10 ** p<.05 *** p<.01.

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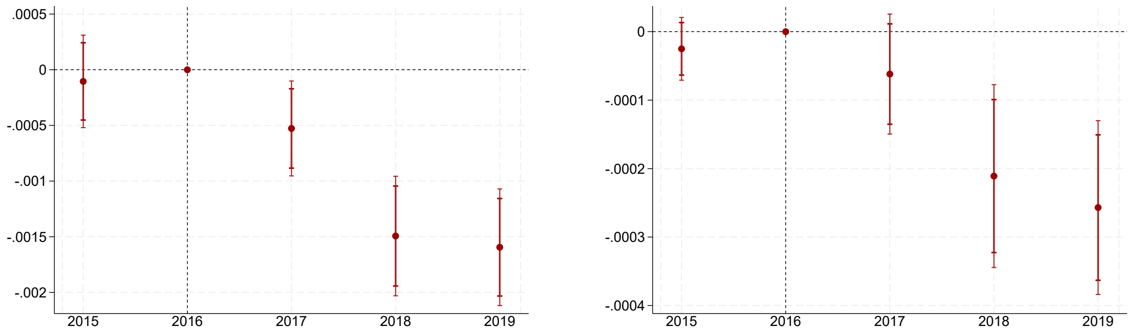
for occupation: executive/manager, administrative staff, manual workers, business owners/independent professionals, or self-employed; for the economic sector: agriculture, manufacturing, or services; and for the type of contract: full-time or part-time.

(a) Per capita number of Newslot devices **(b)** Per capita number of Newslot venues



(c) Number of Newslots per venue **(d)** Per capita expenditure on slot machines

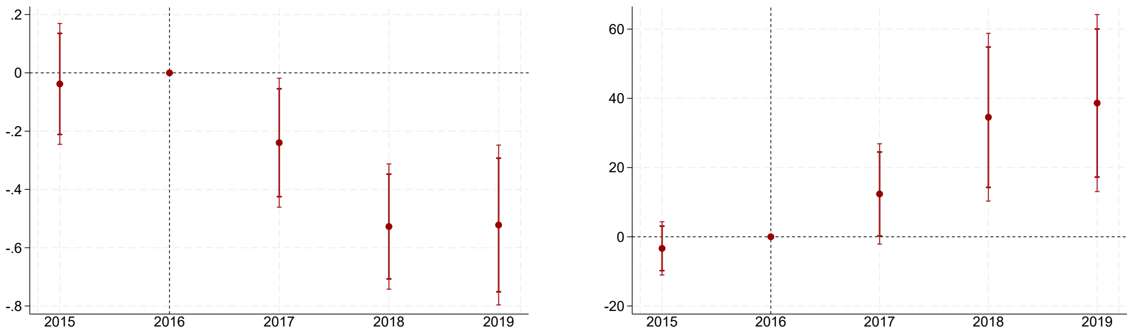


Figure 6: Event-study: Effect on Newslots, expenditure, and crowding. Coefficients and corresponding 90% and 95% confidence intervals. Panel (a) shows the per capita number of Newslot devices, (b) shows per capita expenditure on slot machines, (c) shows the per capita number of venues hosting Newslots, and (d) shows the number of Newslots per venue. Regressions are population-weighted and include municipality and year-province fixed effects, with 2016 as the baseline year. Standard errors are clustered at the municipality level.

Figure 6, displays a net expenditure increase of 10% in the first year, of 28% in 2018, and of 32% in 2019. These findings contradict the intended objective of the bill but they can be explained within our theoretical model as a consequence of increased temptation. In the absence of temptation costs, reducing the number of slot machines would be expected to decrease both the intensive and extensive margins of slot machine play due to higher transportation costs and reduced enjoyment. However, if the bill increases the cost of temptation, for example, through longer waiting times, crowding, or social contagion effects in treated municipalities, the opposite effect may occur (see Proposition 1).

It should be noted that, since ADM did not release separate data for 2016, the per capita net expenditure on slot machines shown in column 4 of Table 2 combines expenditure on both Newslots and Videolotteries. However, for the other years, separate expenditure data are available, enabling us to re-run the analysis while distinguishing between Newslots and VLTs, except for 2016. This allows us to assess the direct impact of the policy on Newslots, as well as any spillover effects on Videolotteries, which were not directly affected by the policy.

The results are shown in Table B.1 in the Appendix. Consistent with the previous findings, total expenditure on slot machines (Newslots and VLTs combined) significantly increases. As shown in column 3, the increase is primarily driven by increased spending on Newslots (EUR 22.27, corresponding to 70% of the overall increase). Notably, while the policy does not affect the number of Videolotteries (column 4), it also leads to an increase in expenditure on this type of device (EUR 9.72, column 5). This spillover effect is an additional unintended consequence of the bill.

In Appendix C we show that the results presented above are robust to additional checks using (*i*) different definitions of treated and control groups, (*ii*) different sub-samples, and (*iii*) falsification exercises.

5.2 Closer venues, more gambling

The previous Section has shown that, although the policy effectively reduced the number of slot machines and venues, it also produced unintended effects, with a 25% increase in slot machine expenditures. These results are not consistent with higher transportation costs or a decrease in the enjoyability of slot machine play in the treated municipalities. As stated in Propositions 1 and 2, these drivers should instead lead to a reduction in the number of players and in the amount of play and, consequently, a reduction in slot machine expenditure.

Expenditure in the treated municipalities could increase if the reduction in the number of slot machines and venues affects temptation costs. This may be the case if players concentrate in the remaining venues, potentially producing social contagion effects, peer pressure, and competition among players. More crowded venues may also reduce the stigma associated with gambling, making slot machine play more appealing.[19] If these factors increase the temptation to play, and possibly the number of players, then expenditure in the treated units can increase after the policy. Notably, this effect would be more pronounced in places where the transportation costs are lower and among more addicted players (Proposition 1).

To investigate the role of transportation costs, we create a measure of proximity to tobacco shops at the municipal level—since Newslots are often located in these venues—using data from the 2011 Census tracts and the 2016 list of tobacco shop addresses published by ADM. We compute the minimum distance between the centroid of each census tract and the nearest

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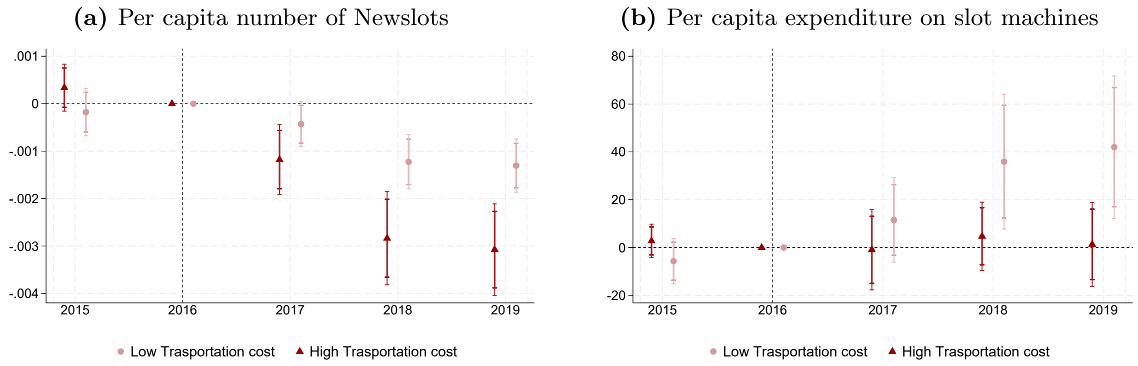
[19] The reduction in the stigma associated with being a slot machine player, due to an increase in the number of people playing slot machines in the same venue, can be formally described as a decrease in τ_A. As shown in Proposition 1, this would increase the extensive margin of slot machine play in the treated units.


(a) Per capita number of Newslots

(b) Per capita expenditure on slot machines

Figure 7: Effect by distance from tobacco shops. Coefficients and corresponding 90% and 95% confidence intervals. Outcomes are the per capita number of Newslot devices (panel a) and the per capita expenditure on slot machines (panel b). Distance from tobacco shops is the municipality-level median minimum distance between each census tract and the closest tobacco shop. A municipality is classified as having high transportation costs if the distance is above the upper tercile of the distribution and low transportation costs otherwise. The population-weighted regressions include municipality and year-province fixed effects. The baseline year is 2016. Standard errors are clustered at the municipality level.

tobacco shop. We then determine the median distance for each municipality. Municipalities are classified as having *low transportation costs* if their assigned distance falls within the lowest tercile of the national distribution, and as having high transportation costs if it falls within the highest tercile.

The results are illustrated in Figure 7. Panel (a) shows that the reduction in the number of devices is similar across the three categories of transportation costs. Panel (b) shows that the increase in slot machine expenditure is driven by municipalities with lower transportation costs. This is consistent with the theoretical predictions, as the reduction in the number of players is smaller when the increase in the transportation cost is smaller.[20]

5.3 Alcohol consumption and socioeconomic status gradient

Risky health behaviors and lifestyles are typically more frequent among the most vulnerable segments of the population (see, e.g., Cawley and Ruhm, 2012; Ahammer et al., 2022). To investigate the existence of a possible socioeconomic status (SES) gradient in gambling behavior,

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[20] To ensure our measure of distance to tobacco shops is not capturing other characteristics at the municipality level, in Table B.2 we run several regressions in a “horse-race” fashion, where we flag municipalities at the top tercile of the distribution of population density, the proportion of elderly individuals, the proportion of young individuals with degrees, the unemployment rate, the percentage of individuals not engaged in education, employment, or training (NEET), wealth (measured by housing prices and the proportion of households experiencing financial hardship), and social capital (measured as the share of the population paying for a TV licence). In all cases, the effects are separately identified, hence we confidently exclude that the distance to tobacco shops is capturing other kinds of geographical variations.

Panel A: Dep. variable	Gambling expenditure			Total expenditure
	(1)	(2)	(3)	(4)
Post × Treat	-0.3459***		-0.4247***	-0.0154**
	(0.0425)		(0.0545)	(0.0077)
Post × **Alcohol**		0.0997**	-0.0116	0.0088
		(0.0424)	(0.0623)	(0.01)
Post × Treat × **Alcohol**			0.1697**	0.0148
			(0.0857)	(0.0144)
Observations	100,221	100,221	100,221	100,221

Panel B: Dep. variable	Gambling expenditure			
	Current Wealth		Education	
	Low	High	Low	High
	(5)	(6)	(7)	(8)
Post × Treat	-0.5792***	-0.4348***	-0.3463***	-0.4306***
	(0.1016)	(0.0658)	(0.1337)	(0.0598)
Post × **Alcohol**	-0.0491	0.017	0.0702	-0.0237
	(0.1111)	(0.0769)	(0.176)	(0.0668)
Post × Treat × **Alcohol**	0.3401**	0.1559	0.4281*	0.1263
	(0.161)	(0.1031)	(0.2329)	(0.0925)
Observations	32,652	67,569	22,336	77,885

Table 3: Slot machine play and alcohol abuse. Poisson Pseudo Maximum Likelihood (PPML) regressions with robust standard errors estimated on Equation 14. *Total expenditure* excludes expenditure on gambling. Variable *Treat* equals one for households in regions where the share of the population living in treated municipalities is above the median; *Alcohol* equals one for households in the top quartile of the distribution in expenditure in alcohol beverages (i.e. beer, cider, wine, liquors and spirits). The coefficients associated to Alcohol and Treat × Alcohol are not shown. *Low current wealth* equals one if the respondent reckons their current wealth is insufficient (32% of the sample). *Low education* equals one if the respondent has no formal qualifications or only elementary school education (23% of the sample). All regressions include region and month-year fixed effects and control for number of components, household head's gender, age, nationality, education, employment status, occupation, economic sector and type of contract. * p<.10 ** p<.05 *** p<.01.

we use the HES data and examine heterogeneous effects based on addiction levels. Since we lack direct measures of gambling addiction, we proxy it by whether the household reports relatively high expenditure on alcohol (specifically, if it falls in the top quartile of the distribution). This approach is based on the evidence that alcohol consumption is typically associated with other risky behaviors, and that alcohol abuse is positively correlated to pathological gambling (Mastrobattista et al., 2019; Resce et al., 2019). As an additional heterogeneity analysis, we also consider the role of education and household wealth as proxies for household SES.

Table 3 presents the results of the heterogeneity analysis, estimated using Equation 14. On average, expenditure on gambling for households exposed to the 2017 bill decreases by approximately 29% (column 1).[21] This suggests that the representative household significantly reduces expenditure on gambling when access to gambling becomes more costly.

As shown in column 2, however, households with relatively high alcohol consumption levels increase gambling expenditure by 11% after 2017. Column 3 shows that this increase is driven by households with high alcohol consumption living in the treated areas, i.e. those most exposed to the cut in Newslots after the 2017 bill. Our results do not seem to be due to an overall increase in household expenditure, as the coefficient of the triple interaction reported in column 4 is economically negligible (about 1%) and not statistically significant.

In panel B of Table 3 (columns 5-8) we explore heterogeneities across households based on their reported current wealth status and their education. The estimated coefficients show that gambling expenditure increases among households that are economically constrained and with low education (columns 5 and 7). The magnitude of the increase in gambling expenditure is statistically significant and substantial (41% and 53%, respectively). Overall, these results indicate that responses to the 2017 bill vary with socioeconomic status, and they suggest the existence of a SES gradient in gambling.

6 Discussion and conclusions

In this paper, we study consumption choices involving addictive goods that are imperfect substitutes and imply self-control costs. We propose a theoretical model that builds on the Hotelling (1929)'s model of horizontal differentiation, the Becker and Murphy (1988)'s theory of rational addiction, and the Gul and Pesendorfer (2001)'s model of temptation and self-control to understand how transportation costs, temptation costs, and product features influence the intensive and extensive margin of addictive consumption. The theoretical model can be applied to various behaviors associated with addictive consumption, including both substance use (e.g., smoking, drinking, or opioid use) and non-substance behavioral addictions (such as gambling and gaming).

Empirically, we focus on gambling addiction and investigate the effects of a 2017 Italian policy mandating a one-third reduction in the number of slot machines. The policy aimed at reducing slot machine play by increasing the costs associated with accessing these devices, including higher transportation costs, increased congestion, and longer waiting times. Our empirical results show that, while the policy effectively reduced the number of slot machines and venues, it had unintended consequences, as slot machine expenditure increased by 25%.

The observed results cannot be explained by higher transportation costs or by slot machine

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[21] With the PPML estimator we obtain semi-elasticities. Elasticities are computed with $e^{\beta} - 1$ (Santos Silva and Tenreyro, 2006).

play becoming less enjoyable. The empirical findings can be rationalized as the consequence of changes in temptation costs. The reduction in the number of available slot machines and venues has led to a concentration of players in the remaining venues. This crowding may have produced social contagion effects, increased peer pressure and competition among players, and diminished the perceived stigma associated with slot machine play. These social factors likely contribute to higher temptation to gamble. Consequently, although the overall number of players has decreased, expenditure by those who continue to play is higher.

Increased expenditure is more likely when transportation costs are lower, as the reduction in the number of players would be small, and among individuals with higher levels of addiction. In line with this prediction, we find that the observed increase in slot machine expenditure is driven by municipalities with lower transportation costs. Additionally, this increase is more pronounced among individuals who consume alcohol, have lower educational attainment, and come from lower socioeconomic backgrounds.

These findings align with the profile of typical Italian slot machine players, who are often from disadvantaged backgrounds and engage in other risky health behaviors. By increasing slot machine expenditure among the most vulnerable individuals, the policy's unintended and undesirable effects have impacted the very population it was designed to protect.

By limiting the number of slot machines while retaining the most profitable ones, legislators may have inadvertently increased crowding and temptation at remaining sites. Rather than broadly reducing the overall availability of slot machines, policymakers could focus on targeted strategies that address the behavioral drivers of addictive consumption. Examples of such interventions include placing machines in lower-temptation areas and restricting access in venues frequently visited by at-risk groups, as it is the case of policies that require, for example, a minimum distance between slot machines and betting venues, and sensitive sites such as schools, youth clubs, and sports facilities.

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A Appendix: Proofs of the theoretical model

A.1 Solving the model

The model is solved by backward induction. Once at a venue $v \in \{A, B\}$, the individual problem to solve is

$$\max_{s_v, z} U\left(s_v, z; a, \sigma_v\right) \tag{15}$$

$$\text{s.t. } m = p_v s_v + z \tag{16}$$

This is a standard consumer problem. The solution (s_v^*, z_v^*) at either venue satisfies:

$$\frac{U_s\left(s_v^*, z_v^*\right)}{U_z\left(s_v^*, z_v^*\right)} = p_v \tag{17}$$

and the budget constraint. In the following, assume that $0 < s_A^* < s_B^*$ for any given level of addiction. To simplify the notation, we use $U\left(s_v^*\right)$ as a shorthand for $U\left(s_v^*, z_v^*; a, \sigma_v\right)$, whenever it does not create confusion.

At the participation stage, the choice depends on the comparison between the indirect utility levels that an individual at location i with addition stock a obtains when consuming at either venue, or abstaining altogheter. Depending on the individual level of addiction a, the threshold locations that denote the indifferent player between A and B are

$$i_{AB}\left(a\right) = \frac{\tau_B + U\left(s_A^*\right) - U_B\left(s_B^*\right)}{\tau_A + \tau_B} \tag{18}$$

The individuals indifferent between abstaining and consuming at venue v are

$$i_{OA}\left(a\right) = \frac{U\left(s_A^*\right) - U\left(0\right)}{\tau_A}; \qquad i_{OB}\left(a\right) = 1 - \frac{U\left(s_B^*\right) - U\left(0\right)}{\tau_B} \tag{19}$$

To justify the slope of the three loci for the indifferent consumers drawn in Figure 1, note that the threshold positions depend on the addiction level as follows:

$$\frac{\partial i_{AB}}{\partial a} = \frac{1}{\tau_A + \tau_B}\left(U_a\left(s_A^*\right) - U_a\left(s_B^*\right)\right) < 0, \tag{20}$$

$$\frac{\partial i_{OA}}{\partial a} = \frac{1}{\tau_A}\left(U_a\left(s_A^*\right) - U_a\left(0\right)\right) > 0, \tag{21}$$

$$\frac{\partial i_{OB}}{\partial a} = \frac{1}{\tau_B}\left(U_a\left(0\right) - U_a\left(s_B^*\right)\right) < 0. \tag{22}$$

Recall we assumed $s_A^* < s_B^*$ and $U_{sa} > 0$ for all a, hence $0 > U_a\left(s_B^*\right) > U_a\left(s_A^*\right) > U_a(0)$, Let a^A denote the intersection point of i_{AB} with the vertical axis (it can be a finite value or infinity), and $a_v^{ss} = s_v^{ss} \cdot \gamma/(1-\gamma)$ the steady state value of addiction at a venue v. Given the budget constraint, the maximum feasible consumption is $s^m = m/p$ for either v, which is associated to the addiction level $a^m = s^m \cdot \gamma/(1-\gamma)$.

In equations 23 and 24, we consider the case in which the value of the addiction stock is bounded between 0 and a^m. This occurs when the budget constraint binds before reaching the (unconstrained) steady state, i.e. $s_v^{ss} > s^m$ for either v. Formally, we assume $a^m > a^A > \hat{a} > 0$. If the intersection point $(\hat{\imath}, \hat{a})$ is in the interior of the first quadrant, then the population is divided into consumers of s_A, of s_B, or abstainers, as shown in Figure 1. For given distribution function $\phi\,(i,a)$ of individual positions and levels of addiction in the population at time t, the shares of addictive consumers at either venue are:

$$\mathcal{N}_A = \iint_{\mathcal{A}} \phi\,(i,a)\,\mathrm{d}a\mathrm{d}i = \int_0^{i_{OA}} \int_0^{\hat{a}} \phi\,(i,a)\,\mathrm{d}a\mathrm{d}i + \int_0^{i_{AB}} \int_{\hat{a}}^{a^A} \phi\,(i,a)\,\mathrm{d}a\mathrm{d}i \tag{23}$$

$$\mathcal{N}_B = \iint_{\mathcal{B}} \phi\,(i,a)\,\mathrm{d}a\mathrm{d}i = \int_{i_{OB}}^{1} \int_0^{\hat{a}} \phi\,(i,a)\,\mathrm{d}a\mathrm{d}i + \int_{i_{AB}}^{1} \int_{\hat{a}}^{a^A} \phi\,(i,a)\,\mathrm{d}a\mathrm{d}i + \int_0^{1} \int_{a^A}^{a^m} \phi\,(i,a)\,\mathrm{d}a\mathrm{d}i \tag{24}$$

A.2 Comparative statics

Intensive margin of consumption. We now assess the effect of changes in the individual level of addiction, in marginal transportation costs, and in the marginal temptation costs reported in Proposition 1. By applying the implicit function theorem, the following holds:

$$\frac{\partial s_v^*}{\partial a} = -\frac{U_{sa}\left(s_v^*\right)}{U_{ss}\left(s_v^*\right)} > 0 \tag{25}$$

$$\frac{\partial s_A^*}{\partial \tau_A} = \frac{\partial s_B^*}{\partial \tau_A} = 0 \tag{26}$$

$$\frac{\partial s_A^*}{\partial \sigma_A} = -\frac{U_{s\sigma_A}\left(s_A^*\right)}{U_{ss}\left(s_A^*\right)} > 0; \qquad \frac{\partial s_B^*}{\partial \sigma_A} = 0 \tag{27}$$

Note that the effect of a change in the marginal temptation cost at venue A is higher for more addicted individuals if (omitting the arguments)

$$\frac{\partial}{\partial a}\left(\frac{\partial s_A^*}{\partial \sigma_A}\right) = \frac{1}{U_{ss}^2}\left(U_{s\sigma}U_{ssa} - U_{sa\sigma}U_{ss}\right) = \frac{1}{\mathcal{U}_{ss}^2}\left(a\mathcal{U}_{ssa} - \mathcal{U}_{ss}\right) > 0 \tag{28}$$

where the last equality follows from (4). In the linear-quadratic specification typically used in the rational addiction literature (see, e.g. Becker and Murphy, 1988), expression (28) always holds because $\mathcal{U}_{ssa} = 0$.

To study the effects of a policy x that reduces the enjoyability of addictive consumption at A, we assume that x reduces the utility and the marginal utility of addictive consumption at A, but not at B, i.e. $U_x\left(s_A^*\right), U_{sx}\left(s_A^*\right) < 0$, $U_x\left(s_B^*\right) = 0$. Then the introduction of the policy reduces consumption at A, while consumption at B is unaffected:

$$\frac{\partial s_A^*}{\partial x} = -\frac{U_{sx}\left(s_A^*\right)}{U_{ss}\left(s_A^*\right)} < 0; \qquad \frac{\partial s_B^*}{\partial x} = 0 \tag{29}$$

This explains the claim on the change at the intensive margin of Proposition 2.

Suppose $\sigma_A = \sigma_B = \sigma_0 = \sigma$. A change in all marginal costs of temptation σ implies more play at either venue:

$$\frac{\partial s_A^*}{\partial \sigma} = -\frac{U_{s\sigma}\left(s_A^*\right)}{U_{ss}\left(s_A^*\right)} > 0; \qquad \frac{\partial s_B^*}{\partial \sigma} = -\frac{U_{s\sigma}\left(s_B^*\right)}{U_{ss}\left(s_A^*\right)} > 0 \tag{30}$$

Extensive margin of consumption. Based on the expressions (23) and (24), we focus on changes at the extensive margins. Considering the share of consumers of s_A, we are interested in the following expression:

$$\frac{\partial \mathcal{N}_A}{\partial y} = \underbrace{\int_0^{\hat{a}} \left(\phi\left(i_{OA}\left(a\right), a\right) \frac{\partial i_{OA}}{\partial y}\right) \mathrm{d}a\mathrm{d}i}_{n_{OA}^y} + \underbrace{\int_{\hat{a}}^{m} \left(\phi\left(i_{AB}\left(a\right), a\right) \frac{\partial i_{AB}}{\partial y}\right) \mathrm{d}a\mathrm{d}i}_{n_{AB}^y} \tag{31}$$

Terms n_{OA}^y and n_{AB}^y describe the change in the mass of consumers along the OA and the AB margins, respectively, as a consequence of a change in y. Their sign depends on the sign of $\frac{\partial i_{OA}}{\partial y}$ and of $\frac{\partial i_{AB}}{\partial y}$, hence a movement to the left of either extensive margin of corresponds to a decrease in the share of consumers at A (see Figure 2 for an example).

Analogously, to study changes in the share of consumers of s_B, we consider

$$\frac{\partial \mathcal{N}_B}{\partial y} = -\underbrace{\int_{\hat{a}}^{\hat{a}} \left(\phi\left(i_{AB}\left(a\right), a\right) \frac{\partial i_{AB}}{\partial y}\right) \mathrm{d}a\mathrm{d}i}_{n_{AB}^y} - \underbrace{\int_0^{\hat{a}} \left(\phi\left(i_{OB}\left(a\right), a\right) \frac{\partial i_{OB}}{\partial y}\right) \mathrm{d}a\mathrm{d}i}_{n_{OB}^y} \tag{32}$$

Consider an increase in the marginal transportation cost to reach A. Since

$$\frac{\partial i_{0A}}{\partial \tau_A} = -\frac{i_{OA}}{\tau_A} < 0; \qquad \frac{\partial i_{AB}}{\partial \tau_A} = -\frac{i_{AB}}{\tau_A + \tau_B} < 0; \qquad \frac{\partial i_{OB}}{\partial \tau_A} = 0 \tag{33}$$

we conclude that $\mathcal{N}_A$ decreases, while $\mathcal{N}_B$ and $\mathcal{N}_O$ increase. Considering that no effect is produced at the intensive margin of consumption, we conclude that an increase in the marginal transportation cost to reach A reduces expenditure at A and increases expenditure at B.

An increase in the marginal temptation cost σ_A produces analog results on the shares of consumers and abstainers, as

$$\frac{\partial i_{0A}}{\partial \sigma_A} = \frac{U_{\sigma_A}\left(s_A^*\right)}{\tau_A} < 0; \qquad \frac{\partial i_{AB}}{\partial \sigma_A} = \frac{U_{\sigma_A}\left(s_A^*\right)}{\tau_A + \tau_B} < 0; \qquad \frac{\partial i_{OB}}{\partial \sigma_A} = 0 \tag{34}$$

However, as shown before, consumption at A increases, while it remains unaffected at B. Hence, expenditure at B unambiguously increases. The change in expenditure at A, instead, increases only if the increase at the intensive margin (30) more than offsets the decrease at the extensive margin (34).

Suppose $\sigma_A = \sigma_B = \sigma_0 = \sigma$. A change in all marginal costs of temptation σ, has a different effect on the extensive margin, as

$$\frac{\partial i_{0A}}{\partial \sigma} = \frac{U_\sigma\left(s_A^*\right) - U_\sigma(0)}{\tau_A} > 0; \qquad \frac{\partial i_{AB}}{\partial \sigma} = \frac{U_\sigma\left(s_A^*\right) - U_\sigma\left(s_B^*\right)}{\tau_A + \tau_B} < 0; \qquad \frac{\partial i_{OB}}{\partial \sigma} = \frac{U_\sigma(0) - U_\sigma\left(s_B^*\right)}{\tau_B} < 0 \tag{35}$$

Hence $\mathcal{N}_B$ and E_B increase, while the share of abstainers $\mathcal{N}_O$ decreases.

Changing the enjoyability of the good implies

$$\frac{\partial i_{0A}}{\partial x} = \frac{U_x\left(s_A^*\right)}{\tau_A} < 0; \qquad \frac{\partial i_{AB}}{\partial x} = \frac{U_x\left(s_A^*\right)}{\tau_A + \tau_B} < 0; \qquad \frac{\partial i_{OB}}{\partial x} = 0 \tag{36}$$

Hence $\mathcal{N}_A$ decreases, while $\mathcal{N}_B$ and $\mathcal{N}_O$ increase when x reduces the enjoyability of the good. This implies that E_A decreases, while E_B increases.

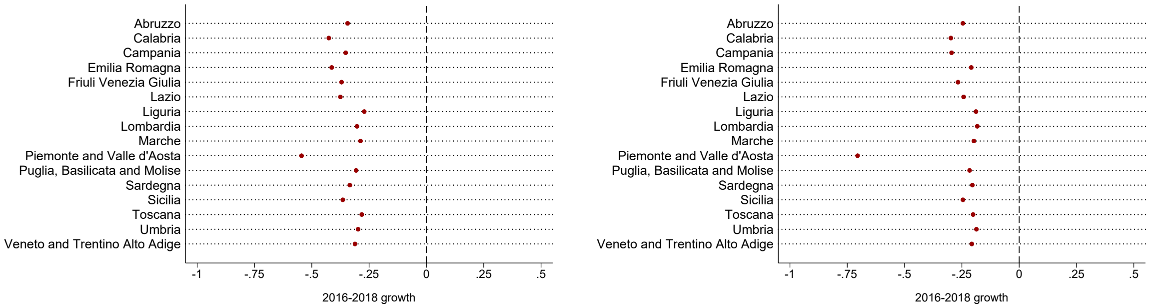
B Appendix: Additional tables and figures

	(1) Total expenditure	(2) Newslots Number	(3) Expenditure	(4) VLT Number	(5) Expenditure
Treat × Post	31.8748***	-0.0011***	22.2686***	0.0000	9.7216**
	(8.8048)	(0.0003)	(6.5536)	(0.0001)	(3.8582)
Observations	31,508	31,508	31,508	31,508	31,508
Municipalities	7,877	7,877	7,877	7,877	7,877
Mean outcome in 2015	121.3451	0.0054	101.8331	0.0004	19.5118
Elasticity	26.27	-20.45	21.87	3.69	49.82
Municipality FE	✓	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓	✓

Table B.1: Effect on expenditure by type of slot machine. The outcomes are total per capita expenditure on slot machines (column 1), the number of Newslots per capita (column 2), total per capita expenditure on Newslots (column 3), the number of Videolotteries per capita (column 4), and total per capita expenditure on Videolotteries (column 5). Elasticity is calculated and then multiplied by 100. The variable *Treat* is defined as in Section 4, and *Post* represents the period after 2016. The results are from population-weighted regressions based on Equation 12, with standard errors clustered at the municipality level. Due to data availability, year 2016 is excluded.
* p<.10 ** p<.05 *** p<.01.

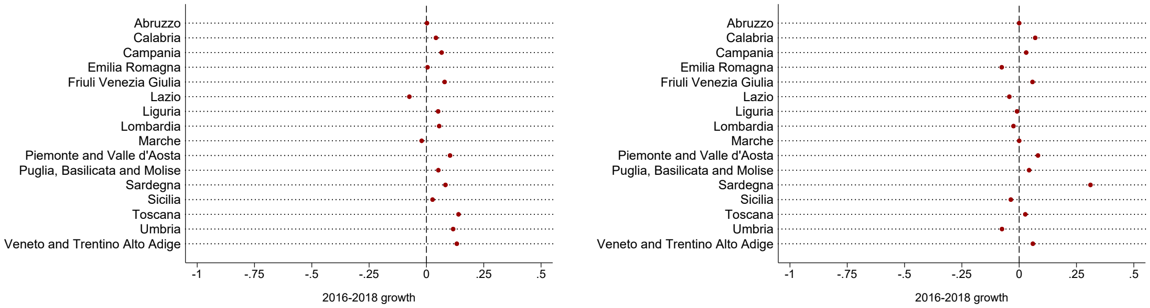
Exposure	Pop Density (1)	Old-age index (2)	Young with degree (3)	Unemployed (4)	NEET (5)	House Prices (6)	Households in Hardship (7)	TV licence (8)
Post × Treat	-0.9108	-2.9035	1.4838	4.3630	4.9784	-0.3034	7.9286	-2.9296
	(7.0163)	(9.2809)	(7.2502)	(11.7332)	(11.4910)	(6.9603)	(10.6709)	(7.1924)
Post × Treat × *Closest to tobacco shops*	40.9709**	35.1430***	35.3691***	35.4921***	35.6363***	36.8134***	37.4609***	35.5365***
	(17.2764)	(11.9893)	(12.4428)	(13.0867)	(12.9459)	(13.2401)	(12.6242)	(13.5418)
Post × Treat × **High Exposure**	-12.6905	5.8661	-18.3797	-11.4608	-12.7358	-12.7674	-19.5852	1.2742
	(18.8739)	(14.3348)	(14.6918)	(17.1686)	(16.8888)	(15.9090)	(16.5958)	(16.3616)
Observations	39,205	39,205	39,205	39,205	39,205	39,205	39,205	39,205
Municipalities	7,841	7,841	7,841	7,841	7,841	7,841	7,841	7,841
Municipality FE	✓	✓	✓	✓	✓	✓	✓	✓
Province X Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Table B.2: Effect by distance from tobacco shops, robustness checks. The variable *Closest to tobacco shops* is a dummy equal to one when the median minimum distance between each census tract and the closest tobacco shop belong to the bottom terciles of the distance distribution. The variable *High Exposure* is a dummy equal to one when the municipalities belong to the top tercile of the distribution of: population density (column 1), over-65 to under-14 ratio (column 2), the share of 30-34yo with a degree (column 3), unemployment rate (column 4), NEET rate (column 5), housing prices (column 6), share of households in economic hardship (column 7), and the share of people paying public TV services (column 8). 36 municipalities are unmatched thus dropped. Coefficients associated to Post × *Closest to tobacco shops* and Post × *High Exposure* are not shown. Population-weighted regressions. Standard errors are clustered at the municipality level.
* p<.10 ** p<.05 *** p<.01.



(a) Newslots

(b) Venues hosting Newslots



(c) VLT devices

(d) Venues hosting VLT devices

Figure B.1: Percentage change in the number of Newslots, VLTs, and venues from 2016 to 2018. The 20 Italian regions are aggregated into 15 regional areas, as reported in the ADM annual reports. Source: ADM annual reports.

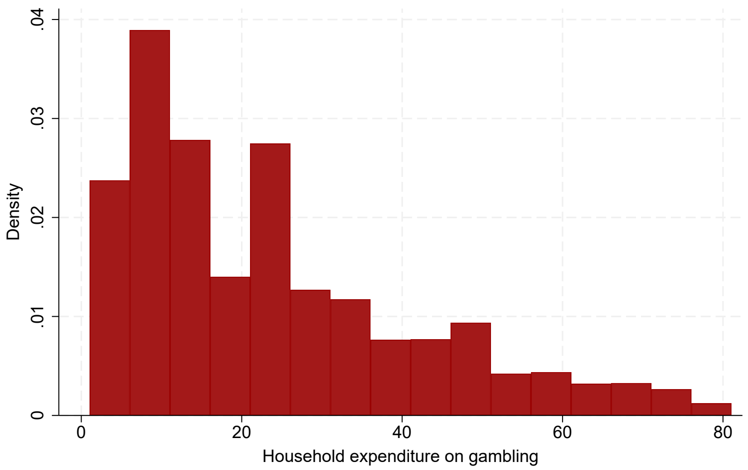


Figure B.2: Household expenditure on gambling Sample of households with positive expenditure on gambling (13% of the total sample) during the period 2014–2019. Expenditure is in EUR/month.

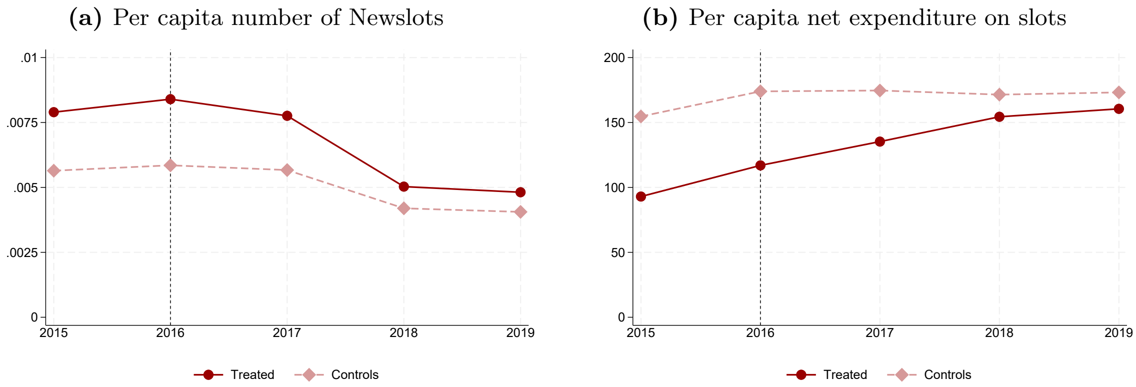


Figure B.3: Trends, raw averages. Municipality-level averages of the per capita count of Newslots (panel a) and per capita net expenditure on slot machines (panel b), by group. Red circles refer to treated units, pink diamonds to controls units.

C Appendix: Robustness checks

In this Appendix we describe three main robustness checks. First, in Table C.1 we assess the robustness of the main results by: (*i*) adding observables such as population and income per capita (columns 1–3), (*ii*) using the Poisson pseudo-log-likelihood (PPML) model (columns 4–6), which accounts for dependent variables with zeros, different patterns of heteroskedasticity, and is robust to outcome measurement errors (Santos Silva and Tenreyro, 2006), and (*iii*) implementing the inverse hyperbolic transformation (columns 7–9).

Second, we vary the threshold that defines the treatment group by considering different ranges of the revenue per device in the pre-intervention period (namely, from up to the 10th percentile to up to the 20th percentile, rather than the 15th percentile). This is equivalent to moving horizontally the vertical line shown in panel (a) of Figure 5. The results of this exercise, presented in Figure C.1, are consistent with our main findings.

Then, we restrict the sample to all municipalities where the average revenue per device in 2015 is below the median (Figure C.2), and to those that have a larger pre-2017 availability of Newslots per capita (Figure C.3). This is to ensure a relatively homogeneous comparison across treated and control units: in the former case we exclude the municipalities that host the most profitable Newslots, in the latter we consider only municipalities with the largest availability of Newslots per capita (i.e., only those lying on the red line in panel (a) of Figure 5). Next, we consider potential geographical heterogeneities and compare treated municipalities that experienced a reduction in the number of slot machines against the sub-sample of their non-treated neighboring municipalities (Figure C.4). We also exclude regions one-by-one from the analysis (Figure C.5), to make sure that results are not driven by specific regions. All these additional checks support the robustness of our results.

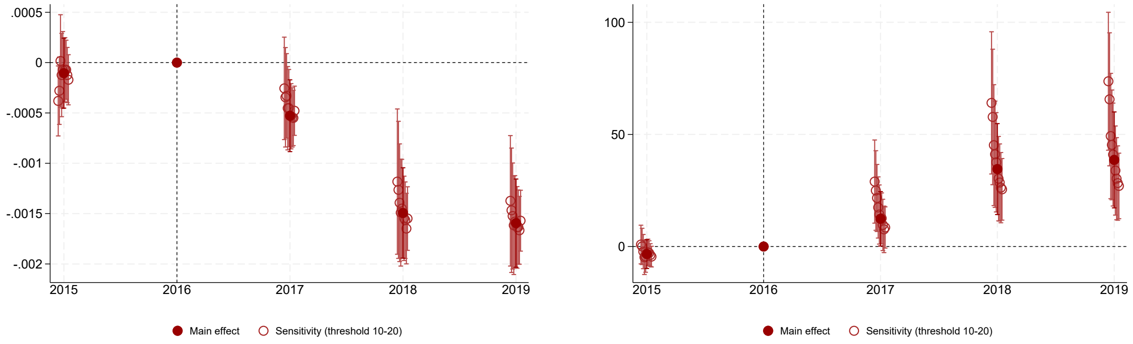
The withdrawal of the licenses concerned only Newslots, and not Videolotteries. Figure C.6 shows that the number of Videolotteries is not affected by the policy. Hence, there is no evidence that Newslots were replaced by Videolotteries (see also Table B.1). This can be interpreted as a placebo test to assess the causal validity of our main findings.

In line with Kearney (2005), we also do not find evidence of substitution effects in expenditure towards other forms of gambling, namely, scratch cards, online bets, instant lotteries, and sports bets (Figure C.7).

Finally, we address the potential influence of spurious correlations or seasonal trends with an additional falsification exercise, where we randomize the treatment across units belonging to the control group. As shown in Figure C.8, the coefficients are small, consistently centered around zero and and not statistically significant.

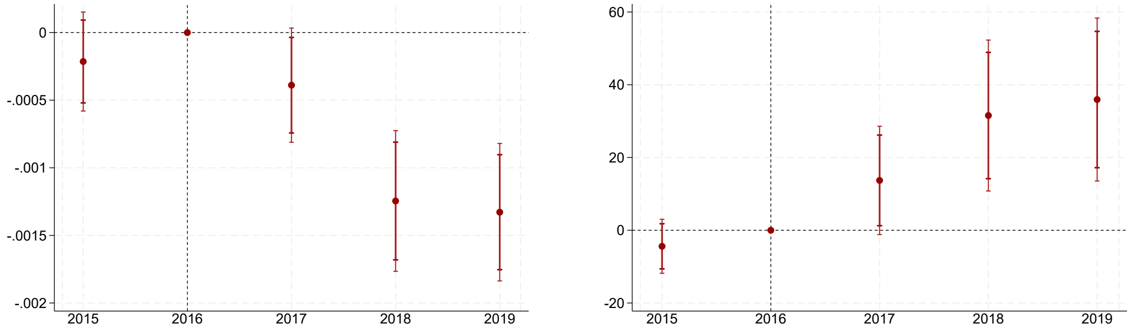
	With controls			PPML			Inv Hyperbolic		
	(1) Per capita Newslots	(2) Per capita venues	(3) Per capita expenditure	(4) Per capita Newslots	(5) Per capita venues	(6) Per capita expenditure	(7) Per capita Newslots	(8) Per capita venues	(9) Per capita expenditure
Treat × Post	-0.0012***	-0.0002***	27.2977***	-0.2792***	-0.1753***	0.1246**	-0.0012***	-0.0002**	0.9529**
	(0.0003)	(0.0001)	(8.0437)	(0.0375)	(0.0371)	(0.0497)	(0.0003)	(0.0001)	(0.4116)
Observations	39385	39385	39385	34185	34185	35090	39385	39385	39385
Municipalities	7877	7877	7877	6837	6837	7018	7877	7877	7877
Mean outcome in 2016	0.0055	0.0015	132.3056	0.0063	0.0017	148.3829	0.0055	0.0015	132.3056
Municipality FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Province × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table C.1: Robustness checks. Population-weighted regressions. Standard errors are clustered at the municipality level. * p<.10 ** p<.05 *** p<.01.


(a) Per capita number of Newslots

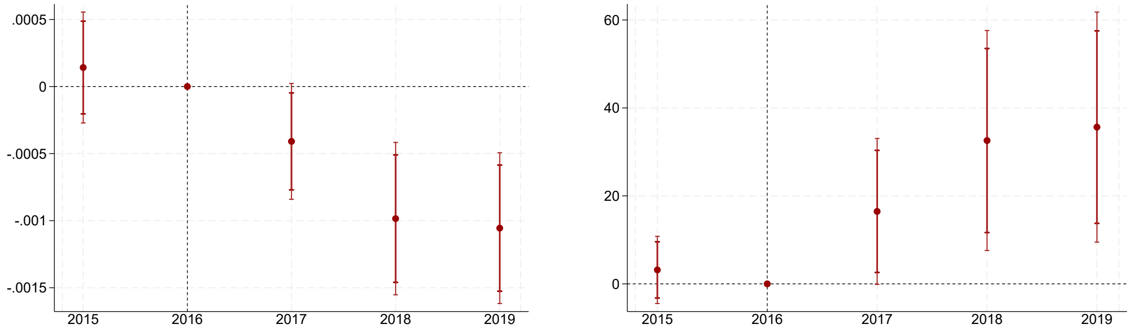
(b) Per capita net expenditure on slots

Figure C.1: Sensitivity on the 15% threshold. Coefficients and corresponding 90% and 95% confidence intervals. Full dots refer to the lowest revenue per device defined at the 15th percentile of the distribution, hollow dots to alternative thresholds set at any level in between the 10th and 20th percentiles (15th excluded). Outcomes are the per capita number of Newslot devices (panel a) and the per capita net expenditure on slot machines (panel b). Population-weighted regressions which include municipality and year-province fixed effects. The baseline year is 2016. Standard errors are clustered at the municipality level.


(a) Per capita number of Newslots

(b) Per capita net expenditure on slots

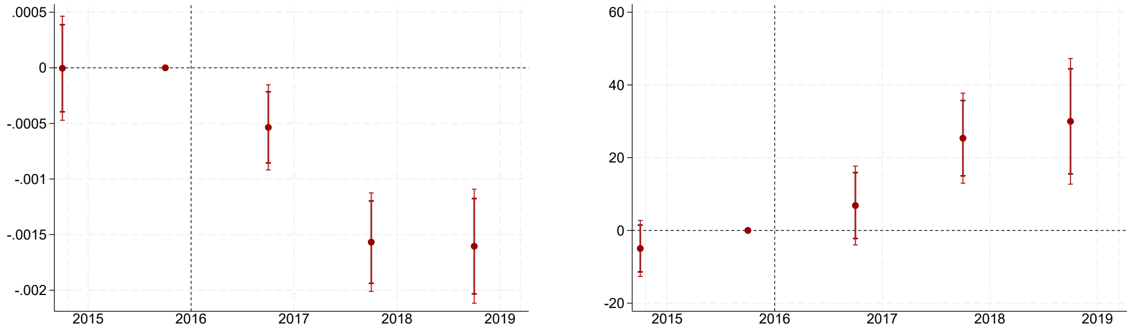
Figure C.2: Sub-sample of municipalities with below-median revenue per device only. Coefficients and corresponding 90% and 95% confidence intervals. Outcomes are the per capita number of Newslot devices (panel a) and the per capita net expenditure on slot machines (panel b). Population-weighted regressions which include municipality and year-province fixed effects. The baseline year is 2016. Standard errors are clustered at the municipality level.



(a) Per capita number of Newslots

(b) Per capita net expenditure on slots

Figure C.3: Sub-sample of municipalities with Newslots per capita above the national average only. Coefficients and corresponding 90% and 95% confidence intervals. Outcomes are the per capita number of Newslot devices (panel a) and the per capita net expenditure on slot machines (panel b). Population-weighted regressions which include municipality and year-province fixed effects. The baseline year is 2016. Standard errors are clustered at the municipality level.



(a) Per capita number of Newslots

(b) Per capita net expenditure on slots

Figure C.4: Sub-sample of treated municipalities and their adjacents only. Coefficients and corresponding 90% and 95% confidence intervals. Outcomes are the per capita number of Newslot devices (panel a) and the per capita net expenditure on slot machines (panel b). Population-weighted regressions which include municipality and year-province fixed effects. The baseline year is 2016. Standard errors are clustered at the municipality level.

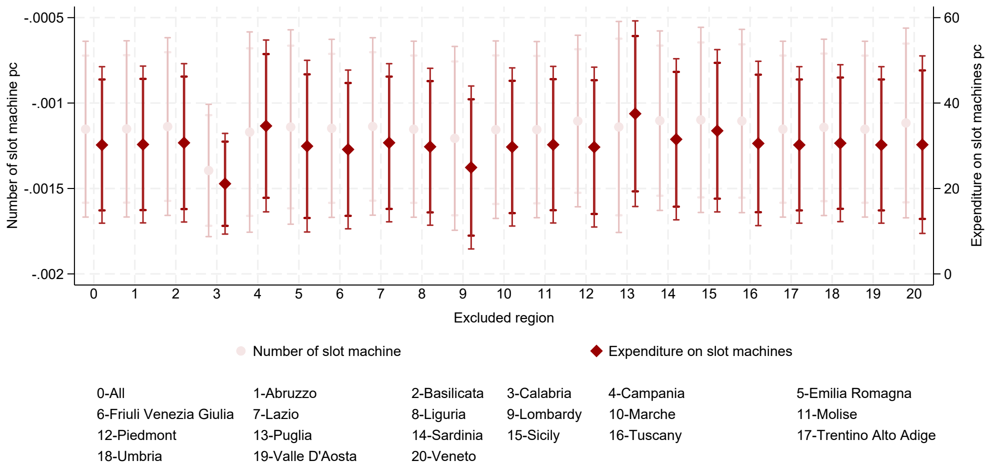


Figure C.5: Dropping regions from the sample, one-by-one. Coefficients and corresponding 90% and 95% confidence intervals. Outcomes are the per capita number of Newslot devices (pink circles) and the per capita net expenditure on slot machines (red diamonds). Population-weighted regressions which include municipality and year-province fixed effects. The baseline year is 2016. Standard errors are clustered at the municipality level.

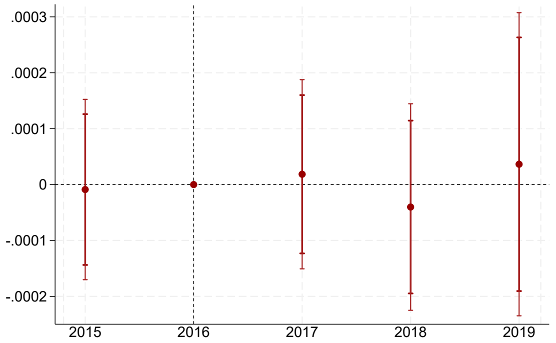
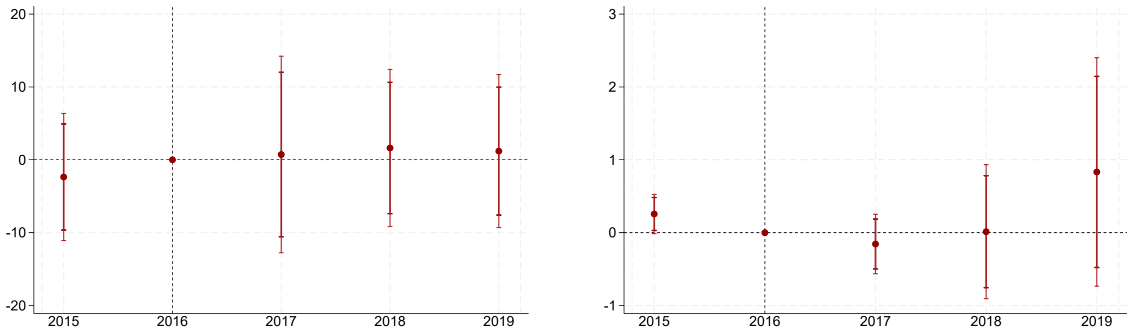
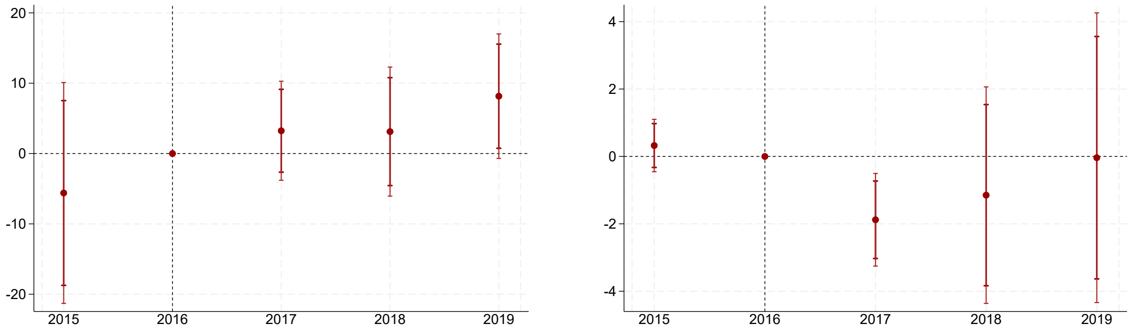


Figure C.6: Effect on the per capita number of Videolotteries. Coefficients and corresponding 90% and 95% confidence intervals. Outcome is the per capita number of VLT devices. Population-weighted regression includes municipality and year-province fixed effects. The baseline year is 2016. Standard errors are clustered at the municipality level.



(a) Expenditure on scratch cards

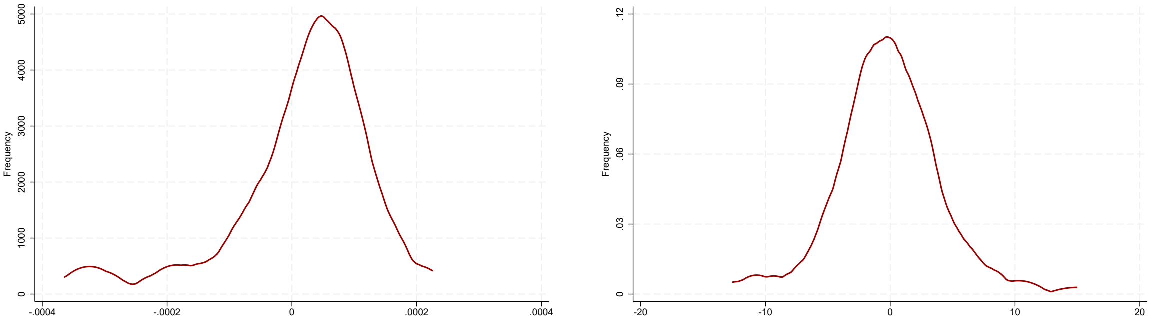
(b) Expenditure on online bets



(c) Expenditure on instant lotteries

(d) Expenditure on sport bets

Figure C.7: Effect on per capita expenditure on alternative forms of gambling. Coefficients and corresponding 90% and 95% confidence intervals. Outcomes are the per capita net expenditure on: scratch cards (panel a), online bets (panel b), lotteries (panel c), and sport bets (panel d). Population-weighted regressions which include municipality and year-province fixed effects. The baseline year is 2016. Standard errors are clustered at the municipality level.



(a) Per capita number of Newslots

(b) Per capita net expenditure on slots

Figure C.8: Treatment randomization. Distribution of average coefficients where the treatment is fully randomized. Standard errors are estimated using 100 bootstrap replications clustered at the municipality level. Outcomes are the per capita number of Newslot devices (panel a) and the per capita net expenditure on slot machines (panel b). Baseline coefficients are out of scale: -0.0012 in panel (a) and 30.1966 in panel (b).