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Supplying Slot Machines to the Poor

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Abstract

As gambling becomes increasingly accessible both in the U.S. and worldwide, governments face an important policy question: how should they exploit the industry's growth to raise tax revenues while protecting individuals from the detrimental effects of gambling? Using data on slot machines from the largest per-capita gambling market in the world, Australia, we estimate a structural oligopoly model to: (1) quantify firms' incentives to make gambling accessible among socio-economically disadvantaged groups; and (2) evaluate the effect of government policy (gambling taxes, supply caps and venue smoking bans) on the distribution of slot machine supply, tax revenue and problem gambling prevalence.

JEL classification: H71, L13, L83, L88, I31

Keywords: Oligopoly, taxes, smoking ban, supply caps, slot machines, problem gambling, structural estimation

1 Introduction

In 2013, the global gambling industry generated \$440 billion (USD) in net earnings (The Economist, 2014). This exceeded global expenditures on broadband Internet (\$421 billion), and every other form of digital entertainment (McKinsey, 2014). The size of the industry reflects substantial growth in recent years that is expected to continue with the expansion of sports and online betting worldwide.¹ For governments, this raises questions over how to regulate public access to gambling. While gambling expenditures are a lucrative source of tax revenue, there is a recognized need to protect the public, particularly the socio-economically disadvantaged, from the detrimental effects of gambling.²

While these policy issues are becoming increasingly pervasive, there is little existing evidence to inform them. In this paper, we provide an empirical analysis that sheds new light on the need for and effects of government regulation in gambling markets. We study an industry that allows us to quantify firms' incentives to make gambling accessible to the poor, and evaluate policies aimed at raising tax revenue while mitigating gambling access among disadvantaged groups.

Our data come from the largest per-capita gambling market in the world: Australia (The Economist, 2014). Specifically, we focus on slot machine gambling in the state of Victoria during the 1990's and 2000's.³ For a number of reasons, this setting is well-suited for our study. First, panel data at the market-level on slot machine counts and net gambling revenues are available.⁴ Second, just two companies are licensed by the state to supply slot

¹Industry reports from PricewaterhouseCoopers (2010) and KPMG (2010) provide relevant overviews of industry growth. The former estimates a near 10% annual growth rate in net earnings globally since 2006, excluding the Great Recession period (2008-09), with growth being particularly strong in Asia. The latter estimates a 42% growth in online gaming revenues from \$21.2 billion in 2008 to \$30 billion in 2012. Sports betting is already legal in large markets like the United Kingdom and Australia. In the U.S., it is currently legal in 4 states: Nevada, Oregon, Delaware and Montana. NBA Commissioner David Silver continues to be a public advocate for legalization in all states; see "Legalize and Regulate Sports Betting", *The New York Times* (November 14, 2014).

²See "Gaming the Poor" in the *The New York Times* (June 21, 2014) for recent press coverage on the issue of targeting gambling access, specifically casinos, in poorer regions of the United States.

³Slot machines are the largest source of revenue in gambling industries (The Economist, 2014). In Victoria, they generate 60% of gambling revenue (Productivity Commission, 2010).

⁴Net gambling revenues equal the gross amount of bets made at a slot machines less the

machines, and they are largely unrestricted in making their supply decisions across local markets in the first half of our sample period. Third, in the second half of our sample, the state government implements policies to curb the spread of slot machines. The regulatory instruments used – taxes, supply-caps and smoking bans – are familiar and may be of interest to other jurisdictions looking to regulate gambling access.

Exploiting these features of the context and data, we develop and estimate a structural econometric model to quantify firms’ incentives to supply slot machines to different types of markets, and to evaluate the equilibrium effects of the policies. We take a structural approach for two reasons. First, given our focus on supply-side incentives and related policy effects, we require estimates of firms’ costs. While cost data are unavailable, we can use the available data and model to infer firms’ costs from the first order conditions that govern their slot machine supply choices. Second, the policies are enacted state-wide or in selected markets. This makes it difficult to find comparable markets without a given policy to construct a counterfactual for reduced-form policy evaluation. With our structural model, we can construct a counterfactual by simulating firms’ decisions in the absence of a given policy.

Getting into specifics, our model assumes firms compete as duopolists who make slot machine quantity choices within local markets anticipating their rival’s choice. In describing the context and data in Section 2, we argue this is an appropriate model for the industry for various reasons. In sum, the firms supply similar types of machines in similar venues and have similar market shares. Moreover, the “price” of slot machine gambling, which corresponds to its winning odds, is likely not a strategic variable because it is regulated.

Section 3 develops the model. We first describe a per-machine gambling revenue function. We assume machines are strategic substitutes, or that per-machine revenue falls with the number of slot machines in a market. We later show empirically that this is indeed the case. The revenue function also depends on demographics and accounts for unobserved market- and year-specific shocks. The specification thus allows for the possibility that, controlling for market size and other factors, poorer markets are larger gambling markets. In other words, total player losses.

bling markets from the firms' perspective. The section goes on to specify the model's cost and profit functions, characterize the Nash Equilibrium, and show how we incorporate the government's policies in the model.

In Section 4 we describe our empirical strategy. In estimating the per-machine revenue function, we account for the fact firms condition on per-machine revenue in choosing how many slot machines to supply in a market. To deal with this simultaneity, we instrument for machine quantities in the revenue function with a slot machine supply shifter: the number of gambling venues (hotels, pubs and clubs) in a market. The exclusion restriction is justified given that venues' revenues mainly come from food and accommodation and not slot machines.⁵

Using the estimated revenue function and the model, we infer the firms' marginal costs and estimate the marginal cost function in a second step. There are two key issues in doing so. We must adapt the traditional approach from IO to inferring marginal costs from firms' first order conditions to account for the effect of binding slot machine supply caps. Moreover, we use IVs to identify how marginal costs vary with the number of machines in a market. For identification, we exploit variation in slot machine counts created by the government's smoking ban which directly affected demand for gambling access but not firms' costs. The estimation results reveal a convex cost function. This aligns with intuition: it becomes increasingly costly to supply slot machines in a market as gambling venues approach their capacity constraints.

Section 5 presents our empirical results. The revenue function estimates show the firms have strong incentives to supply slot machines to disadvantaged markets. Controlling for market size and other demographics, the revenue function estimates imply that if we move from the 25th to the 75th percentile in the distribution of socio-economic disadvantage across markets (as measured by a commonly-used government index), there is a corresponding \$57,000 increase in annual per-machine gambling revenue. This difference, which compares to a sample average of per-machine annual revenues of \$87,000, is large.

Using the model, we run counterfactual simulations to evaluate the effect of the gambling taxes, venue smoking ban and market-level caps on slot ma-

⁵We also discuss auxiliary empirical results that show venue entry decisions are not a function of per-machine revenues across markets and over time.

chine supply, gambling revenues, state tax revenues and problem gambling prevalence.⁶ Among our various findings, two stand out. First, the gambling venue smoking ban has a substantial effect on per-machine revenues, reducing them by \$12,000 annually, or by about 12%. This results in a \$190 million fall in fiscal tax revenues from gambling, which is 15% of the state's gambling tax revenues. We further find the smoking ban has the unintended effect of exacerbating firms' incentives to supply machines to disadvantaged markets; the ban prevented rich people but not poor people from gambling at slot machines.

The second result of note is that the government eventually targeted the right markets with its supply caps to slow the spread of gambling in disadvantaged areas. In doing so, it limited market-level problem gambling prevalence by 4% on average, which compares to corresponding average effects of 2% and 3% from taxes on slot machine installations and the smoking ban. We see this as being a relatively successful policy when compared to a predicted 13% reduction in problem gambling under a hypothetical tagging policy that completely eliminates the relationship between socio-economic disadvantage and per-capita slot machine density. The tagging policy we consider specifies a flat tax on each slot machine that is an increasing function of socio-economic disadvantage.

Related literature

Despite the size and continued growth of the gambling industry, there is surprisingly little economic research on the industry from the field outside of government and industry reports.^{7,8} A handful of papers have studied casinos, documenting their effect on local crime (Grinols and Mustard, 2006), employment and wages in Native American tribes (Evans and Topoleski, 2002; Evans and Kim, 2008) and in Canada (Humphreys and Marchand, 2013). Research on state lotteries has examined the welfare effects of state-run lottos

⁶For the latter outcome, we use auxiliary data provided to us from the state government for our study. Regression estimates show for every ten additional slot machines in a market problem gambling prevalence rises by 1.2%.

⁷This may reflect a lack of data availability. Through our work, we found government agencies to be hesitant to provide disaggregated data on gambling behavior and related outcomes.

⁸The substantial economics literature on decision-making under risk and uncertainty is clearly relevant for understanding the gambling industry. See Perez and Humphreys (2013) for an overview of how insights from theory and lab experiments relate to research from the field.

(Farrell and Walker, 1999), implications of lottery design on revenue generation (Walker and Young, 2001), the demand for lottery tickets (Farrell et. al 2000; Kearney, 2005; Kearney and Guryan, 2008) and lottery addiction (Kearney and Guryan, 2010).

We build on this prior work by extending the domain of study to slot machines, which is the largest sector of the industry. Our focus on supply-side incentives in making gambling accessible to different consumer groups, and the policy issues these incentives create, represent a significant departure from previous research.⁹ Moreover, our structural approach for the purpose of policy evaluation contrasts with the cited reduced-form studies. Indeed, our paper relates to literature in empirical IO as it represents a novel application of methods typically used to study market power in traditional industries like sugar (Genesove and Mullin, 1998) and electricity (Wolfram, 1999; Kim and Knittel, 2003).

2 Industry background and data

The context for our study is the gambling industry of Victoria, Australia from 1996-2010.¹⁰ Slot machine gambling is a major part of the industry, generating \$2.5 billion in net player losses each year, or 60% of the state's annual gambling revenue. In a typical year, one in five of the state's 4.2 million citizens gamble at a slot machine. Gamblers spend \$3,100 annually at slot machines, or 5.3% of average after-tax income in the state. Problem gamblers on average spend considerably more at \$21,000 per year.¹¹

⁹Given that one of these policy remedies in our context is a smoking ban, our work also relates to research on smoking bans. For instance, see Evans, Farrelly and Montgomery (1999). See also Cawley and Ruhm (2011) for an overview of the broader literature on the economics of risky behaviors and policies aimed at reducing their detrimental effects.

¹⁰This section's discussion of the industry is based on remarkably detailed government reports from Productivity Commission (1999) and (2010). The discussion of problem gambling heavily draws from these reports and State Government of Victoria (2009) and Victorian Responsible Gambling Foundation (2014).

¹¹Neal, Delfabbro and O'Neill (2004) provide a national definition of problem gambling: "Problem gambling is characterized by difficulties in limiting money and/or time spent on gambling which leads to adverse consequences for the gambler, others or for the community."

2.1 Market structure and gambling revenue

During our sample period, electronic slot machines are supplied by a state wide duopoly. Two private firms, Tattersalls (Tatts) and Tabcorp (Tab), have exclusive licenses from the government to manage the supply of slot machines in the state. They compete without the threat of entry.

To supply slot machines at a particular gambling venue (hotels, pubs, clubs), the venues enter exclusive contracts with Tatts or Tab that determine the number of slot machines at a given venue. Tatts and Tab have significant bargaining power in negotiating these contracts. They effectively determine the number of machines at each venue, and are free to reallocate slot machines across venues year-to-year subject to venue capacity constraints.

The total gambling revenue a slot machine generates heavily depends on its “payout rate.” Tatts and Tab face a minimum payout rate of 87 percent that is set by the government. This implies that gamblers can expect to win \$0.87 for every \$1 bet at a slot machine. There is variation in payout rates across machines, however most have (non-disclosed) payout rates of 90 percent (Productivity Commission, 1999).¹²

A venue’s slot machine revenues are split among three groups: the firm (Tatts/Tab), the venue, and the state. The government determines the revenue splits; the firms and venues do not engage in bilateral negotiations to divide gambling revenues. From 1992 to 1999, 37.5% of revenue goes to state taxes, 33% goes to the firms, and 29.5% goes to venues. From 2000 onwards, these shares respectively are 41% , 33% and 26%.¹³

2.2 Product homogeneity and local demand

Two other aspects of the industry are important for our analysis. First, Tatts and Tab exhibit little product differentiation. State-wide standards strictly

¹²In addition to payout rates, the minimum/maximum bets and number of bets that can be made with each “pull of the arm” directly affect per-machine gambling revenues. The regulated maximum bet is \$5, and most machines offer smaller bets of 1, 2, or 5 cents as these are the preferred bets of most gamblers (Productivity Commission, 1999). Gamblers can also increase their wagers by betting on multiple “lines” per pull of the arm. Depending on machine configuration, this can involve 10 or more lines. Other regulations that affect per-machine revenue include a minimum spin rate of 2.14 second per spin and a maximum of 28 spins per minute.

¹³Appendix B.1 discusses supporting government documents and detailed calculations behind these revenue shares.

apply to machine design and operation which standardizes machines.¹⁴ In addition, Tatts and Tab source their machines from the same primary upstream supplier (Aristocrat Technologies) which further limits machine-level product differentiation between the firms. Finally, neither Tatts nor Tab dominate the market. They have 50/50 market shares (Productivity Commission, 1999), suggesting that differences in firm-level branding, costs, or venues where they supplied machines, are minimal.

Second, demand for slot machines is highly localized for recreational and problem gamblers. Empirical evidence from the Productivity Commission (1999) reveals that the vast majority of gamblers play at venues less than five kilometers from their homes. This is important for market definition: it suggests that Tatts and Tab compete for market share by supplying slot machines within locally-defined regions. Accordingly, we assume that Local Government Areas (LGAs) represent local markets for slot machines.¹⁵ Importantly, our market definition coincides with the definition used by the state government in implementing public policies that affect slot machine supply.

2.3 Government policy

Slot machines generate a large amount of tax revenue, on the order of \$1 billion per year. This represents 60% of gambling-related tax revenue collected by the state, or 13% of fiscal tax revenue overall. These revenues largely come from the shares of gambling revenue that go directly to the state. In addition, in 2001 the government imposes an annual per-machine tax levy of \$333.33. This increases to \$1533.33 in 2002, then to \$3033.33 in 2006, and finally to \$4333.33 in 2008. From the firms' perspective, the levy increases the marginal cost of supplying a slot machine to a venue each year.

Two other policies affect the supply and demand for slot machine gambling in our sample period. First, the government imposes a smoking ban in September 2002 that makes smoking illegal in all gambling venues. The policy's main goal is to mitigate smoking-related health risk from gambling.

¹⁴Indeed, the government claims these standards help reduce machine development and maintenance costs (Productivity Commission, 1999).

¹⁵As their name suggest, LGAs are incorporated areas of Australia that have their own local governing bodies. On average an LGA spans 2,876 square kilometers and has 70,000 people. They include rural parts of the state, isolated towns and villages, and regions within the sprawling metropolitan area of Melbourne that correspond to historical municipalities.

Moreover, the ban also makes gambling less attractive to smokers and can thus indirectly reduce gambling prevalence. This potentially comes at a fiscal cost, however, as lower slot machine demand implies smaller tax revenues.

Second, the government imposes slot machine supply caps in 13 of the state's 79 LGAs. These caps are effectively introduced to five LGAs in 2001 and eight additional LGAs in 2006. All of these markets are identified as socioeconomically vulnerable areas by the government, which makes slot machine supply restrictions desirable.¹⁶ Beyond these LGA-specific caps, the government has a state-wide cap on aggregate slot machine supply of 27,500 machines.¹⁷

2.4 Data

We use data from the Victorian Commission for Gambling and Liquor Regulation (VCGLR). Specifically, the VCGLR publishes annual data on the number of slot machines, venues and net slot machine revenue for all LGAs in the state. Unfortunately, we were not permitted access to data broken down by Tatts and Tab and individual venues because they were deemed highly sensitive. This does not, however, prevent us from estimating our structural oligopoly model for the industry. Indeed, the modeling strategy we pursue below leverages techniques from empirical IO that explicitly account for these types of data limitations.

We also incorporate demographic variables into our model to account for LGA-specific factors that affect the firms' revenues and costs. These data come from Australian Bureau of Statistics's (ABS) 1996, 2001, 2006 and 2011 censuses. The specific demographics used are listed in Table 1. In addition, we use the ABS's Socio-Economic Indexes for Areas (SEIFA), specifically the Index of Relative Socio-Economic Disadvantage. SEIFAs characterize the socio-economic conditions within an LGA. They are derived from census data, ranking LGAs based on households' income, education attainment, unem-

¹⁶In Appendix B.2 we present government documents that describe these caps and provide details on the definitions of capped markets.

¹⁷While this cap is never been binding in our sample period, it is important for our policy analysis. There are some additional supply-side regulations of note. Tatts and Tab can respectively operate a maximum of 13,750 slot machines state-wide, and a maximum of 105 machines at a given venue. In addition, 20% of the total supply of slot machines must be located outside of the metropolis of Melbourne. Historically these constraints have not been binding either.

ployment and homes without vehicles. They are also available for census years.¹⁸

2.4.1 Sample selection

The working sample has 1002 LGA-year observations. It spans 68 of the state's 79 LGAs, covering the 1996-2010 period. We omit the Melbourne LGA because of the large influence of the state's casino, and the Queenscliff LGA due to its exceptional reliance on tourism. The sample restrictions also omit remote LGAs that do not have slot machines. The panel is unbalanced as there are two LGAs that have 0 machines at the start of the sample but later have machines, and two other LGAs with data available only from 1999 onwards.

The sample period corresponds to years where Tatts and Tab were duopolists who strategically supplied slot machines as described above. The industry underwent major regulatory reforms in 2012 that broke-up the duopoly. Specifically, the government let Tatts' and Tab's historical licenses for acquiring, distributing, operating slot machines across venues expire. From this point onward, licenses for these slot machine distribution rights have been sold to individual venues. Our focus on the pre-2011 period facilitates our modeling strategy for investigating firms' incentives to supply slot machines to socio-economically disadvantaged populations, and in evaluating policies aimed at preventing firms from doing so. Moreover, we also use the model to construct novel measures of market power. These are potentially useful for current policy since the 2012 reforms were partly motivated by the belief that Tatts and Tab earned supernormal profits in supplying slot machines (Victorian Auditor-General Office, 2011).¹⁹

2.5 Descriptive statistics

Table 1 provides summary statistics for our gambling and demographic data. A typical LGA has a population of 72,000 people with eight gambling venues and 44 slot machines per venue. On average, a machine generates \$87,000 in revenues each year to be split among the firms, venue, and state

¹⁸We use linear interpolation to calculate demographic variables and SEIFAs between census years.

¹⁹If the proprietary venue-level data on slot machine demand are made available, our model could be extended to evaluate these recent reforms in market design.

government.

Figure 1 plots the total number of slot machines in the industry and average per-machine revenue across LGAs. The figure highlights two important patterns. First, the industry is still growing between 1996 and 1999. From the peak in machine counts in 2001, we see a downward trend as the industry matures, and as the government implements the tax levies on slot machines, the 2002 smoking ban, and the 2001/2006 supply caps. Second, we similarly see rapid growth in per-machine revenue until 2002. The raw data show that average per-machine revenue experiences a 12.5% fall from \$120,000 per-machine in 2002 to \$105,000, highlighting the effect of the smoking ban on revenues.

Figure 2 helps motivate our structural modeling strategy and policy analysis. Panels (A)-(D) in the figure highlight a negative relationship between the number of slot machines per capita and an LGA's SEIFA for 1996, 2001, 2006 and 2010. That is, more socio-economic disadvantaged markets have more slot machines per-capita. Figure 3 further shows this relationship is statistically significant in each sample year, though its magnitude weakens over time.

Panels (B)-(D) in Figure 2 also highlight where the government targeted its supply caps in 2001 and 2006. Urban LGAs in the northwest part of the scatter plot were targeted; this is consistent with the government attempting to restrict high slot machine supply in socio-economically disadvantaged markets. These policy changes are thus potentially responsible for the weakening in the relationship between slot machine supply and socio-economic disadvantage in Figure 3.

3 Model

This section develops a structural econometric model to identify firms' incentives to supply slot machines to disadvantaged LGAs, and to evaluate the effects of the various government policies. Our model falls within the class of structural oligopoly models pioneered by Bresnahan (1982). Specifically, we assume Tatts and Tab engage in quantity competition and strategically choose how many slot machines to supply in each LGA, each year. We develop this model in three parts. First we define a per-machine revenue function that predicts how much gambling revenue a machine generates in each

LGA and year. We then describe the firms' cost structure. Finally we characterize the Nash Equilibrium and show how we incorporate the tax levies, smoking ban and supply caps in the model.

3.1 Revenue function

The revenue generated by a slot machine in market m and year t is denoted by r_{mt} and is governed by the following function

$$r_{mt} = \alpha Q_{mt} + \mathbf{X}_{mt}\beta + \mu_m + \xi_t + \epsilon_{it}, \quad (1)$$

where $Q_{mt} = \sum_{i=1}^{N_{mt}} q_{imt}$ is the total number of slot machines, N_{mt} is the number of firms, q_{imt} is the quantity of slot machines for firm i . The vector $\mathbf{X}_{mt}$ contains characteristics that affect slot machine revenue. These include the demographic variables listed in Table 1 except for mortgages. The vector also includes a dummy variable that equals one in years where the state-wide gambling venue smoking ban is in place; this accounts for the effect of the smoking ban on gambling revenues. The function's parameters are α and β . We assume $\alpha < 0$, or that per-machine revenue falls as more machines are supplied to a market (e.g., machines are strategic substitutes); we will confirm this empirically below.²⁰

The error includes market and year fixed effects μ_m and ξ_t and an idiosyncratic revenue shock ϵ_{it} that is observed by the firms but not the econometrician. Below, we examine how a market's fixed effect estimate correlates with its SEIFA to evaluate how socio-economic disadvantage predicts differences in per-machine revenues across markets.

There are two simplifications of note with the revenue model. First, we assume both firms use equation (1) in making their supply decisions. This simplification is mainly due to the data limitation that information on slot machine counts and gambling revenue at the firm-level are unavailable. We believe this assumption is reasonable, however, given the minimal degree of differentiation in the industry between the firms and their machines.

Second, the model is reduced-form in the sense that per-machine revenue is fundamentally driven by: (1) the likelihood an individual chooses to

²⁰This is akin to assuming a downward sloping demand curve. The total revenue from slot machine gambling in a market does not increase proportionally with the number of machines in a market if the marginal gambler increasingly derives less utility from gambling.

gamble at a slot machine; and (2) the amount(s) gamblers wager.²¹ We do not model this primitive demand behavior because micro-data on these decisions do not exist. This does not, however, preclude us from evaluating firms' incentives to supplying machines to disadvantaged markets, nor from evaluating the effect of government policy on the distribution of slot machines across the state.²²

3.2 Costs

We denote firm i 's marginal cost of installing an additional slot machine by c_{imt} and assume the following marginal cost function specification

$$c_{imt} = q_{imt}\gamma + \mathbf{W}_{mt}\psi + \phi_m + \eta_t + \omega_{mt}, \quad (2)$$

where $\mathbf{W}_{mt}$ is a vector of characteristics that affect marginal costs. This includes the following variables from Table 1: population, mortgage rate, income, employment, and the share of population not in the labor force. It also includes the number of gambling venues in an LGA, which we take as exogenous.²³ All else equal, it should be easier/less costly for Tatts and Tab to supply more machines in markets with more venues where venue capacity is less limited. The cost parameters are γ and ψ , ϕ_m and η_t are market and year fixed effects, and ω_{mt} is a marginal cost shock observed by firms but not the econometrician. We expect $\gamma > 0$, which would imply a convex cost function. As firms supply additional slot machines, the total capacity of a LGA's venues is approached, making it increasingly difficult to install additional machines.

Recall from the discussion Section 2 that firms enter exclusive contracts with individual venues when supplying slot machines and are free to allocate machines across venues. The marginal cost function in (2) is thus an approximation that aggregates over these contracts. In the absence of firm-venue specific data on slot machine counts and costs, we are unable to incorporate this venue contracting/entry problem in the structural model. We can,

²¹The payout rate can also generate variation in per-machine revenue. However, as discussed above, it is regulated and tends to be similar across all machines.

²²This reduced-form approach to revenues does, however, prevent us from measuring policy effects on consumer welfare. Developing a micro-founded gambling demand model is beyond the scope of this paper and is left for future research.

²³This requires that hotels and private clubs do not condition on unobserved cost shocks in making their entry decisions. We defend this assumption in discussing identification below.

however, use our data and model to identify the implied marginal costs that rationalize the observed revenues and slot machine quantities at the market-level. We describe this identification strategy below. Importantly, it does not require any assumptions about the shape of underlying cost function, nor how market-level marginal costs relate to individual firm-venue contracts.

Moreover, our counterfactual policy simulations below only require market-level marginal cost estimates. This is because we abstract from the venue contracting/entry problem, and instead use a strategic slot machine quantity game to approximate firms' slot machine supply decisions. This modeling choice is not solely based on data limitations: incorporating strategic venue contracting/entry decisions would introduce multiple equilibria in the model and would create related problems for model identification and estimation, and for counterfactual policy simulations.²⁴ Even if firm-venue contracting data were available, incorporating these features of the industry would likely still involve approximations such as equilibrium selection assumptions. A priori, it is not clear that such an approximation would provide better predictions of firms' supply responses to policy than predictions based on our simpler quantity game.²⁵

Combining revenues and costs, firm i 's after-tax profit is computed as

$$\pi_{imt} = ((1 - \tau)r_{mt} - c_{imt})q_{imt}, \quad (3)$$

where $(1 - \tau)$ corresponds to the share of slot machine gambling revenue received by Tatts or Tab, as regulated by the state government. Recall from Section 2 that $(1 - \tau) = 0.33$ for all sample years (e.g., firms receive 33% of gambling revenues).

3.3 Aggregation and equilibrium

We assume that in each year firms simultaneously choose how many slot machines to supply in each LGA, anticipating their rivals' choice. These decisions are strategic because machines are strategic substitutes. We also as-

²⁴See Berry and Tamer (2006) for discussion of numerical challenges with discrete simultaneous entry games, and the problems that multiple equilibria create for model identification and estimation and policy simulations.

²⁵Our modeling simplifications also introduce limitations for the measurement of costs and welfare effects. We cannot identify firms' fixed costs of operation at venues, nor their sunk entry costs to entering new venues.

sume markets are isolated: the firms make their quantity choices in each LGA in isolation from all other LGAs. As discussed above, the highly localized nature of slot machine demand justifies this assumption in theory, and for the government in implementing policy in practice.²⁶

Given our assumptions regarding conduct and market definition, in LGA-years not subject to the government's supply caps the Nash Equilibrium vector of quantities, $\mathbf{q}_{mt}^* = [q_{1mt}^*, \dots, q_{N_{mt}mt}^*]'$, correspond to those that solve the following first order equations

$$\frac{\partial \pi_{imt}}{\partial q_{imt}} = (1 - \tau)r_{mt} + (1 - \tau)q_{imt}^* \frac{\partial r_{mt}(\mathbf{q}_{mt}^*)}{\partial q_{imt}} - c_{imt} = 0; \quad i = 1, \dots, N_{mt}. \quad (4)$$

Adding up the first order equations across firms and dividing through by the number of firms $N_{mt} \in \{1, 2\}$, we can aggregate up to a market supply equation

$$(1 - \tau)r_{mt} + (1 - \tau) \frac{Q_{mt}^*}{N_{mt}} \frac{\partial r_{mt}(\mathbf{q}_{mt}^*)}{\partial q_{imt}} - c_{mt} = 0, \quad (5)$$

where $c_{mt} = (1/N_{mt}) \sum_{i=1}^{N_{mt}} c_{imt}$ is the average or “representative” marginal cost of the firms. Alternatively, c_{mt} can be interpreted as the common marginal costs of the firms if we assume firms face (approximately) similar market-level marginal costs. Again, this latter interpretation of c_{mt} is reasonable given the lack of differentiation across the firms.²⁷

For markets where the government imposes a cap on aggregated slot machine supply, $\bar{Q}_{mt}$, the market supply equation in (5) does not necessarily hold. Letting λ_{mt} be the Lagrange Multiplier for the quantity cap constraint, the market supply equation for capped markets is characterized as follows

$$(1 - \tau)r_{mt} + (1 - \tau) \frac{Q_{mt}^*}{N_{mt}} \frac{\partial r_{mt}(\mathbf{q}_{mt}^*)}{\partial q_{imt}} - c_{mt} - \lambda_{mt} = 0. \quad (6)$$

4 Identification and estimation

This section describes how we estimate and identify the model's parameters. We first discuss estimation of the revenue function. Then we describe

²⁶There is virtually no firm-level entry/exit within LGAs over time, so we abstract from modeling endogenous entry/exit and take the number of competitors in an LGA as given.

²⁷We also assume with the market supply equation that firms are competing and not colluding. Given the industry is tightly monitored this assumption is likely reasonable.

how we recover firms' marginal costs and estimation of the marginal cost function while accounting for the effect of government-imposed supply caps.

4.1 Revenue function

We estimate the revenue function in (1) by two-stage least squares; bootstrap standard errors are clustered at the market-level to account for persistent revenue shocks. OLS estimates will exhibit simultaneity bias if Tatts and Tab supply more slot machines in markets where machines earn higher revenues. In this case an OLS estimate of α will be biased upward. Given we expect $\alpha < 0$, this would imply the magnitude of the OLS estimate would be too small. That is, we would underestimate the degree of strategic substitutability between the firms.

To identify the revenue model, we instrument for Q_{mt} with the total number of registered slot machine venues in a LGA and year. This instrument is analogous to cost shifters commonly used in IO studies to identify demand in the presence of supply-side simultaneity. The fact that it is easier to supply more machines in LGAs with more venues gives the instrument its strength. The exclusion restriction is also reasonable: controlling for market demographics and fixed effects for years and markets, the number of venues only affects per-machine revenue in (1) through its indirect effect on the number of slot machines in a market. That is, households derive gambling utility from the machines and not the total number of venues in a market.

In addition, our identification strategy also assumes venues do not condition on per-machine slot machine revenue in making venue entry/exit decisions. This is justified on two grounds: (1) many venues are historic hotels, pubs and clubs that were established well-before electronic slot machines emerged in the 1990's; and (2) compared to accommodation, food and liquor sales, slot machine revenue accounts for a minor share of total venue revenue (Australian Bureau of Statistics (2005)). Further, we have run auxiliary regressions to see if the number of gambling venues in a market is higher in markets with higher per-machine revenue. We find no evidence of such a relationship empirically.

A final issue in identifying the revenue function is how to deal with the government's supply caps. As we discuss below, we indeed find that they are binding in some markets. This weakens our instrument since the number of

venues in a market generates no exogenous variation in the number of slot machines in market-years where supply caps bind. To deal with this issue we take a conservative approach and estimate equation (1) using data for LGA-years where there are no supply caps. Importantly, our panel is sufficiently long such that we can estimate the model using the entire cross-section of markets while accounting for market fixed effects. We have at least five years of data before the policy is introduced which allows us to do so.

4.2 Marginal cost function

With the revenue function estimates in hand, we estimate the marginal cost function in a second step. We first invert the market supply equation in (5) to recover marginal costs. Specifically, we use the following calculation to do so

$$\hat{c}_{mt} = (1 - \tau)r_{mt} + (1 - \tau)\frac{Q_{mt}}{N_{mt}}\hat{\alpha}, \quad (7)$$

where recall $(1 - \tau) = 0.33$ is the firms' share of gambling revenues, as determined by the state government, Q_{mt} and N_{mt} is the number of slot machines and firms and $\hat{\alpha}$ is the first-step estimate of α from the revenue equation. We compute $\hat{c}_{mt}$ in this way for all LGA-years that are *not* subject to the government's supply caps.

Given our homogeneous firms assumption, we can then replace c_{imt} with $\hat{c}_{mt}$ in equation (2) and estimate the marginal cost function (or equivalently, the market supply equation) by two-stage least squares.²⁸ To account for the endogeneity of q_{mt} to unobserved cost shocks, we use the following excluded demand shifters from Table 1: age, Australian born, indigenous status, employment in manufacturing, blue collar occupation, and university educated. In addition, we use the smoking ban dummy as an instrument. While the ban affected the demand for slot machines gambling, it had no direct effect on costs. For inference we report cluster bootstrap standard errors that account for persistence in market-level cost shocks and first-stage estimation error in $\hat{\alpha}$.²⁹

As with the revenue equation, we estimate the supply equation based on LGA-years without supply caps. We again account for market and year fixed

²⁸Under the assumption of homogeneous revenue functions and marginal costs across the two firms $q_{imt} = q_{mt} \equiv \frac{Q_{mt}}{N_{mt}} \forall i$, so we replace q_{imt} with $q_{mt} = Q_{mt}/N_{mt}$ in estimation.

²⁹Appendix C describes all of our bootstrap routines.

effects. Identification is thus based on all markets, though in estimation we only use years before the caps policy in markets that eventually have supply caps.

4.2.1 Recovering marginal costs in markets with supply caps

One of our main reasons for using a structural model is to evaluate policies such as the LGA-level supply caps. For this we need to obtain marginal costs for LGA-years that are subject to supply caps. These are obtained in three steps:

1. Using the marginal cost function parameter estimates $\hat{\gamma}$ and $\hat{\psi}$, compute the structural cost shocks for all LGA-years *not* subject to supply caps,

$$\hat{\omega}_{mt} = \hat{c}_{mt} - \frac{Q_{mt}}{N_{mt}}\hat{\gamma} - \mathbf{W}_{mt}\hat{\psi} - \hat{\phi}_m - \hat{\eta}_t$$

2. Specify and estimate an AR(1) process for the cost shocks

$$\hat{\omega}_{mt} = \rho_0 + \rho_1\hat{\omega}_{mt-1} + v_{mt}, \quad (8)$$

where v_{mt} is an i.i.d shock. We have experimented with the number of lags and find an AR(1) model captures the persistence in ω_t .³⁰ We estimate ρ_0 and ρ_1 by OLS based on LGA-years without supply caps and obtain $\hat{\rho}_0 = -0.104$ (s.e = 0.066) and $\hat{\rho}_1 = 0.545$ (s.e = 0.046).

3. Consider a market which is not subject to supply caps for periods $t = 1, \dots, T$ and but is for periods $t = T+1, T+2, \dots$. We predict $\hat{c}_{mT+1}$ using the estimated marginal cost function and a one-step ahead forecast for $\hat{\omega}_{mT+1}$

$$\hat{c}_{mT+1} = \frac{Q_{mT}}{N_{mT}}\hat{\gamma} + \mathbf{W}_{mT}\hat{\psi} + \hat{\phi}_m + \hat{\eta}_t + \underbrace{\hat{\rho}_0 + \hat{\rho}_1\hat{\omega}_{mT}}_{\hat{\omega}_{mT+1}}.$$

We similarly use two-step ahead forecasts of $\hat{\omega}_{mT+2}$ to predict $\hat{c}_{mT+2}$, three-step ahead forecasts for $T+3$, and so on.

³⁰By clustering our standard errors in estimating equation (2) we account for this persistence. In fact, we allow for an arbitrary form of persistence in estimating the supply equation. Here, we specify a particular form solely for generating marginal cost predictions for capped markets.

5 Findings

This section presents our findings. We first discuss empirical results from our revenue and marginal cost function estimates. Using the estimated model, we then conduct a series of counterfactual simulations to evaluate the effect of government policies on market outcomes.

5.1 Parameter estimates

5.1.1 Revenue function

Table 2 presents the revenue function estimates. Contrasting the OLS estimates across columns (1)-(3), we see that after controlling for year and LGA fixed effects we obtain a statistically significant effect of slot machine supply on per-machine revenue of $\hat{\alpha} = 0.072$. This strategic effect implies per-machine revenue falls by \$720 annually for every 10 machines that are supplied to a market.

The IV estimates in columns (4)-(6) highlight non-negligible bias in the OLS results. The direction of bias is as expected. If the firms supply more machines to markets with higher per-machine revenue, then this supply-side effect generates positive correlation between the revenues and slot machine counts that dampens the magnitude of the α estimate. After correcting for this endogeneity, we find that 10 additional machines reduces per-machine revenues by about \$1000 annually. Relative to sample means of 386 machines and \$87,000 annually, a 2.5% increase in slot machine supply reduces per-machine revenue by about 1.1%.

The IV estimates also highlight the effect of the gambling venue smoking ban on machine revenues. First, a comparison of columns (4) and (5) reveals that we obtain similar parameter estimates and model fit if we control for secular trends in per-machine revenue with year fixed effects or if we use a quadratic trend and dummy variable for the smoking ban period. The column (5) estimates imply that the smoking ban reduced per-machine revenue by \$14,560 annually. Quantitatively this effect is large since it is 17% of average per-machine revenue.

The column (6) specification allows the smoking ban effect to differ by markets with different socio-economic conditions, as measured by the SEIFA. There is indeed a heterogeneous effect: the smoking ban reduced slot ma-

chine revenues by a larger amount in LGAs with better socio-economic conditions. In other words, the policy was relatively less effective in deterring slot machine gambling in poorer areas. This suggests that the ban potentially had the unintended consequence of making worse-off LGAs even more attractive to the firms for supplying slot machines relative to better-off LGAs.

Finally, the IV estimates in Table 2 reveal that demographics related to income, education and employment largely do not predict variation in per-machine revenue *within* LGAs.³¹ Figure 4 shows, however, that differences in socio-economic status (as measured by the SEIFA) predicts variation in per-machine revenue *across* LGAs. The figure presents a scatter plot of the estimated LGA fixed effects $\hat{\mu}_m$'s from equation (1) and the average SEIFA for a market from the 1996, 2001, 2006 and 2011 censuses. The plot shows that more disadvantaged markets yield higher per-machine revenues, and that relationship is particularly pronounced among urban markets.³²

Quantitatively, the differences in gambling revenues across markets of varying socio-economic conditions are economically significant. For instance, if we compare the fixed effect estimates for markets whose SEIFA correspond to the 25th and 75th quantiles of the distribution SEIFAs across markets, we obtain fixed effect estimates of $\hat{\mu}_{m,25} = 111.62$ and $\hat{\mu}_{m,75} = 54.29$. These estimates imply that the relatively more disadvantaged market yields \$57,000 more annually in per-machine gambling revenue. This difference is large: it is 65% of the average of per-machine revenue across LGAs of \$87,000.

5.1.2 Marginal costs

Before discussing the marginal cost function estimates, it is useful to summarize the marginal costs that we inferred from the model. On average across all LGAs and years, the annual cost of supplying a machine in a market is \$22,290 (s.d.=\$6,730). Using the per-machine revenue data, we can get a sense of the margins Tatts and Tab earned from their slot machines. On average, a machine generates \$64,570 (s.d.=\$20,860) of total profit annually and has a

³¹The exception is locations where people tend to work in blue-collar occupation jobs tend to yield less slot machine gambling revenue per machine.

³²An LGA is classified as "urban" if it is within the Greater Melbourne Area as defined by the Australian Bureau of Statistics. Melbourne is a sprawling metropolis of 4.4 million people that covers 3850 square miles. The urban LGAs in the Great Melbourne Area are thus removed from the city center. In total, there are 30 urban markets and 38 rural markets in our sample.

profit margin of 74% (s.d.=5.80%).³³

The marginal cost function estimates are reported in Table 3. They also highlight the importance of accounting for endogeneity in estimation, in this case between slot machine supply and unobserved cost shocks. The IV estimates reveal that costs are convex in total slot machine supply, which is consistent with venues becoming capacity constrained as machine counts rise within an LGA. Also consistent with this intuition, the estimates also show how the implied marginal cost of supplying a machine falls with the number of gambling venues in an LGA.

5.2 Policy evaluation

Using the estimated model, we now evaluate the equilibrium effect of the tax levy, smoking ban and the LGA supply caps. Our preferred specifications for our counterfactual simulations are the column (6) and (5) estimates from Tables 2 and 3 for the revenue and marginal cost functions.

The main outcome of interest are per-capita slot machine counts, and how they vary across markets of different levels of socio-economic disadvantage. In addition, we also estimate the effects of policy on state tax revenues and problem gambling prevalence. To study the latter, the state government provided us with supplemental data on problem gambling from 2010-2012 (LGA-level data are not available prior to 2010). Specifically, we were provided counts of the number of individuals who sought problem gambling counseling in each LGA and year. Constructing measures of problem gambling prevalence is a difficult problem and this is the best direct measure available at the market level.³⁴

With the problem gambling data we estimate the following regression equa-

³³These figures correspond to the total profits earned by a slot machine. Recalling that Tatts and Tab receive 33% of slot machine gambling revenues yet pay the entire marginal cost, they realize an average annual per-machine profit of \$6,660.

³⁴As government officials have discussed with us, the measure highlights a small fraction of total problem gamblers as many deal with their problems without seeking help. Best estimates from the Victorian Responsible Gambling Foundation suggest that only 10-15% of problem gamblers actively seek help. See Victorian Responsible Gambling Foundation (2014) for an extensive discussion of the many difficulties in measuring overall problem gambling prevalence.

tion by OLS

$$\log(\text{ProblemGambling}_{mt}) = 0.012Q_{mt} + \mathbf{Z}_{mt}\hat{\delta} + \hat{u}_{mt}, \quad (9)$$

(0.007)

f where $\mathbf{Z}_{mt}$ contains the demographic controls from Table 1. We also control for year fixed effects and report cluster bootstrap standard errors. The coefficient estimate on the number of slot machines implies that ten more machines are associated with a 1.2% rise in problem gambling prevalence. Below, we use this estimate to translate changes in slot machine counts Q_{mt} due to policy into changes in problem gambling prevalence.³⁵

5.2.1 Tax levy

Our first set of simulations compares the model's prediction with and without the tax levies. Recall these are ad-valorem per-machine taxes with magnitudes of \$333.33 (2001), \$1533.33 (2002-2005), \$3033.33 (2006-2007) and \$4333.33 (2008-2010). To predict counterfactual outcomes, we set all of these taxes to \$0 while imposing the other LGA-level policies (smoking ban and supply caps), and re-solve for the Nash Equilibrium quantities, as per the constrained optimization problem characterized by equations (5) and (6).

Our simulations also account for the state-wide cap of 27,500 slot machines. If a given simulation predicts a supply of $27,500 + x$ machines, then we iteratively remove the x least profitable machines across the state until we reach a constrained supply of 27,500 machines. While the state-wide cap has never been reached historically, we believe it is reasonable to assume Tatts and Tab would remove their least profitable machines to respect the cap if it were binding.³⁶

Figure 5 presents the effects of the tax levies on per-capita slot machine supply, per-machine gambling revenue, and the slot machine density - SEIFA relationship across LGAs.³⁷ Panel (i) shows that the smaller levies from 2001-

³⁵Table A.5 in the Appendix reports the values for $\hat{\delta}$ and robustness checks where we instrument for Q_{mt} using the number of gambling venues in an LGA. The results are similar. If anything, they suggest an even larger effect of slot machine supply on problem gambling.

³⁶We impose the state-wide cap in this way for all of our counterfactual simulations.

³⁷For clarity, we plot predictions with and without the tax levies/smoking ban/supply caps/tagging policies in Figures 5-8. Cluster bootstrap confidence intervals for these predictions are reported in Table A.3 in the Appendix. Cluster bootstrap confidence intervals for the effect of these policies on state gambling taxes and problem gambling prevalence are reported in the Appendix in Table A.4. Appendix C describes the bootstrap procedures.

2005 reduce slot machine supply by roughly 700 machines per year, or by about 2-3%. The larger levies from 2006-2010 causes these figures double to around 1400 machines annually. Panel (ii) further shows per-machine revenues fall in the absence of tax levies. This is due to strategic substitutability among machines: without the tax levies machine counts rise, which puts downward pressure on per-machine revenue.

Panel (iii) of the figure shows that the tax levies indirectly weaken the slot machine density - SEIFA relationship. This happens because of the convexity of the cost function: the flat per-machine tax implied by the levies has a relatively larger effect on marginal costs, and hence machine supply, in socioeconomically disadvantaged markets where machine supply and marginal costs are relatively higher before the levies are imposed. The corresponding relatively larger reduction in supply in these LGAs thus dampens the magnitude of the machine density - SEIFA relationship when the tax levies are imposed.

Table 4 reports the effect of the tax levies and the other policies on gambling tax revenues and problem gambling prevalence. As the tax levies increase over time, annual tax revenues increase. They jump from \$37.67 million in 2001 to \$85.45 million to 2010, or from about 3% to 7.5% of the state's total revenue base. In addition, the table shows that the rise in tax levies helps reduce average problem gambling prevalence across LGAs by 1.11% in 2002 and 2.83% by 2010.³⁸

5.2.2 Gambling venue smoking ban

To evaluate the effect of the gambling venue smoking ban, we set the coefficients estimates on the smoking ban dummy and the smoking ban dummy - SEIFA interaction from Table 2 to 0 and simulate equilibrium outcomes while imposing the tax levies, LGA-level supply caps and the state-wide machine cap. Panels (i) and (ii) in Figure 6 show that the corresponding effect of removing the smoking ban is large: in the absence of the ban the state-wide machine cap is binding from 2003 onwards and per-machine gambling revenues is on average about \$12,000 higher per year. The latter figure corre-

³⁸To calculate the change in problem gambling prevalence within an LGA, we first compute the predicted change in slot machine supply with and without the tax levies. Denote this change as $\Delta\hat{Q}_{mt}$. Then, using the 0.012 coefficient estimate from equation (9), we predict the percentage change in problem gambling within the LGA to be $1.2 \times \Delta\hat{Q}_{mt}$. Table 4 reports the average value of this predicted change across LGAs and years for the various policies.

sponds to a 12% fall in annual gambling revenue between 2003 and 2010 due to the smoking ban.

The effect of the smoking ban on the machine density - SEIFA relationship requires a more nuanced interpretation that highlights the value of using a structural model that accounts for interactions between the state's policies on equilibrium outcomes. Recall that the column (6) estimates from Table 2 revealed that the smoking ban had a larger negative effect on per-machine revenue in markets with better socio-economic conditions. This suggests that the ban had the consequence of making worse-off LGAs relatively more attractive locations for supplying slot machines which, all else equal, would serve to strengthen the machine density - SEIFA relationship. Panel (iii) of Figure 6 shows the ban has this unintended effect from 2003-2006.

What happened after 2006? Recall that in this year the second wave of LGA-level supply caps is implemented. As we will see, these caps constrained slot machine supply. Through the lens of our model, this loosens the aggregate supply constraint implied by the state-wide slot machine cap under the non-smoking ban counterfactual.³⁹ As an indirect result of the 2006 LGA-level supply caps, under the no smoking ban counterfactual the firms start reducing slot machine supply among less profitable markets. It turns out that these markets tend to have smaller populations and lower SEIFAs. This indirect effect of the 2006 LGA supply caps ultimately weakens the per-capita slot machine count - SEIFA relationship in panel (iii) of Figure 6 under the no smoking ban scenario.

In terms of tax revenue, Table 4 shows the smoking ban has the largest impact of all the state's policies. The model predicts that as a result of the ban, the government forgoes \$190 million annually or about 15% of its overall gambling tax revenues. The table also shows how the tax levies help offset this reduction in gambling-related tax revenue, though the government still realizes a large net fiscal cost from imposing the smoking ban. The table further shows the smoking ban reduced problem gambling by 3% on average across LGAs.

³⁹That is, it reduces the Lagrange Multiplier that corresponds to the state-wide cap. This can be seen in Panel (i) of Figure 6: starting in 2006, the dashed grey line (machine counts without the state-wide cap) converges toward the solid grey line (machine counts with the state-wide cap).

5.2.3 Supply caps

The impact of the supply caps is depicted in Figure 7. To generate counterfactual predictions, we remove the 2001 and 2006 LGA-level supply caps and assume firms are unconstrained in supplying machines in all markets. We again assume the other policies are active in simulating equilibrium outcomes. Panels (i) and (ii) of Figure 7 show that the caps had small effects on aggregate slot machine supply and per-machine gambling revenue. Panel (iii) shows the policy weakened the machine density - SEIFA relationship. That is, consistent with the government's main objective, the caps were effective in mitigating the supply of slot machines in socio-economically disadvantaged markets.

Table 4 shows that relative to the tax levies and smoking ban, the supply caps had a relatively minor effect on gambling tax revenues. They did, however, have a relatively larger effect in reducing problem gambling prevalence, roughly by 4% on average. This reflects the government's targeting of socio-economically disadvantaged areas where problem gambling would have been acute.

5.3 Tagging

To finish our analysis, we consider another potential policy instrument: tagging. Here, we consider a tax that is a function of an LGA's observed SEIFA, which is correlated with unobserved/difficult to measure local factors such as problem gambling, indebtedness, crime, or adverse mental and physical health effects. Like the tax levy, this policy involves a flat tax on each slot machine supplied in a given LGA and year. It differs, however, in that the tax is specified as a decreasing function of an LGA's SEIFA. That is, the tax makes it more costly for firms to supply machines to socio-economically disadvantaged areas where gambling-related problems of indebtedness, crime, or adverse mental and physical health outcomes are potentially more severe.

More specifically, we implement a per-machine tax that is a negative linear function of a market's SEIFA: $t_{mt} = \kappa \times (1100 - SEIFA_{mt})$ where $\kappa < 0$, and 1100 corresponds to the upper bound of the SEIFA variable in the sample. As with the counterfactuals above, we maintain the tax levies, smoking ban, 2001/2006 supply caps and state-wide cap in evaluating the effect of this tax. We choose κ such that the predicted machine density - SEIFA relation-

ship from Figure 3 becomes statistically insignificant at the 90% level in all years. While the government could choose from a variety of functional forms or values of κ , this set-up provides a simple policy that would eliminate (in a statistical sense) the machine density - SEIFA relationship. In this way, the tagging simulation results provide a relevant benchmark for evaluating the government's historical policies in mitigating the oversupply of slot machines in disadvantaged LGAs.

In implementing the policy, we allow κ to differ for urban and rural markets. This is motivated by our finding from Figure 4, namely that firms' incentives to supply slot machines to relatively disadvantaged areas are particularly strong among urban areas. In practice, we find values of $\kappa = 0.272$ and $\kappa = 0.046$ eliminates the per-capita machine supply - SEIFA relationship among the urban and rural markets. To provide a sense of the magnitude of the taxes implied by this policy, the resulting values of t_{mt} for urban markets whose SEIFA are at the 10th and 90th quantiles of the SEIFA distribution in 2006 are $t_{m,2006}^{10} = \$37,386$ and $t_{m,2006}^{90} = \$10,036$ per machine.

Panels (i) and (ii) of Figure 8 depicts the large effect tagging would have on slot machine supply and gambling revenues. Panel (iii) simply shows the degree to which the machine density - SEIFA relationship would have to be weakened to become statistically insignificant. Its magnitude is roughly half what is observed in the baseline scenario without tagging.

Table 4 shows that our tagging policy would ultimately increase gambling tax revenues. The increase is similar in magnitude to the decrease in revenues implied by the smoking ban. The table also shows that the tagging policy would have a large effect on problem gambling prevalence. On average, there would be a 12% reduction in problem gambling across LGAs. We think this estimate sheds favorable light on the corresponding 4% reduction in problem gambling achieved by the state's LGA-level supply caps. By targeting the caps at a handful of LGAs, the government was able to achieve a reduction in problem gambling that is one-third of the reduction under a heavy-handed tagging policy that eliminates the machine density - SEIFA relationship.

6 Conclusion

Using data from slot machines, we have provided the first empirical evidence on firms' incentives to supply gambling access to socio-economically

disadvantaged markets. We have also evaluated a series of actual government policies that helped raise tax revenues, while regulating gambling access, particularly in poor areas. In this way, our paper informs broader policy debates about the motivations and policy options for regulating gambling industries in a world where gambling is becoming increasingly accessible and popular.

We have also taken a first step in developing an oligopoly model for the slot machine industry. We believe that the techniques we employed from IO are useful for thinking about supply-side issues in the gambling industries more broadly since they tend to be concentrated. There is, however, much room for improvement with our model if better data are made available.

Going forward, we are continuing to work with the Victorian state government to gain access to (currently proprietary) disaggregated data at the gambling venue level. Such information could be used to enrich the demand-side of the model to study how policy affects consumer welfare. Moreover, these data could be used to evaluate the major reforms in 2011 that substantially shifted the balance of power between the suppliers of slot machines (Tatts/Tab) and the gambling venues. Indeed, these reforms represent an interesting natural experiment in market design in a business-to-business market (see, Grennan, 2013) that has potentially important welfare implications, especially for disadvantaged areas.

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Tables

Table 1: Summary Statistics

	Mean	Std. Dev.	Min	Max
Gambling variables				
Number of slot machines	386.5	333.73	5	1393
Number of gambling venues	7.73	5.46	1	28
Slot machines per venue	43.93	16.03	5	87.17
Annual revenue per slot machine	86857.91	24645.66	32149.94	171340.7
Demographic variables				
Population	72065.08	55638.77	5918	261282
Median annual household income	52053.62	12842.42	26187.32	94939.02
Median monthly mortgage payment	1213.26	366.9	643.5	2368.83
SEIFA	1004.9	45.75	876.85	1133.77
Percentage of Population ...				
18 ≤ Age ≤ 30	16.3	4.4	8.4	32.5
31 ≤ Age ≤ 40	14.43	2.55	9.09	24.15
41 ≤ Age ≤ 50	14.46	1.06	10.97	18.21
51 ≤ Age ≤ 64	15.82	3.21	7.87	23.9
Age ≥ 65	14.32	4.14	4.49	25.61
Australian born	80.99	12.08	40.44	95.34
Indigenous	0.81	0.75	0.09	4.58
Employed in production industry	29.31	8.85	10.7	56.6
Blue collar occupation	32.21	8.14	9.19	50.57
With university degree	10.82	7.2	3.2	39.45
Employed	58.73	5.53	42.12	73.74
Not in labor force	37.16	4.96	22.91	52.18

Notes: Unit of observation is a Local Government Area-year. In total there are $N = 1002$ observations and 68 Local Government Areas. Summary statistics for demographic variables are based on the 1996, 2001, 2006 and 2011 census years. All dollar amounts are in real terms (2010=100). See the text for details on sample selection.

Table 2: Slot Machine Revenue Function Estimates

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Number of slot machines	0.001 (0.013)	-0.015 (0.014)	-0.072*** (0.017)	-0.100*** (0.026)	-0.104*** (0.025)	-0.100*** (0.024)
Population	0.192 (0.129)	0.293** (0.130)	0.601*** (0.188)	0.683*** (0.203)	0.704*** (0.201)	0.717*** (0.201)
18 ≤ Age ≤ 30	2.068* (1.098)	1.359 (1.026)	2.962** (1.494)	3.108** (1.472)	2.945** (1.461)	2.741* (1.461)
31 ≤ Age ≤ 40	2.397* (1.409)	1.760 (1.459)	2.747 (2.572)	3.230 (2.597)	3.225 (2.567)	2.566 (2.580)
41 ≤ Age ≤ 50	-0.007 (2.401)	-1.610 (2.342)	-1.807 (2.216)	-1.856 (2.257)	-1.909 (2.181)	-2.368 (2.243)
51 ≤ Age ≤ 64	1.635 (1.296)	1.045 (1.263)	0.972 (1.892)	1.067 (1.897)	1.045 (1.882)	1.088 (1.863)
Age ≥ 65	-1.778 (1.192)	-1.383 (1.176)	2.286 (1.954)	2.656 (2.067)	2.559 (2.038)	2.254 (2.067)
Australian born	-0.471 (0.291)	-0.634** (0.278)	0.499 (1.193)	0.594 (1.204)	0.656 (1.182)	0.937 (1.187)
Indigenous	-0.663 (2.754)	-2.534 (2.273)	-4.721 (7.670)	-4.729 (7.690)	-4.942 (7.739)	-6.513 (7.568)
Employed in manufacturing	-0.319 (0.327)	-0.295 (0.321)	1.041 (0.848)	1.099 (0.850)	1.094 (0.819)	1.271 (0.813)
Blue collar occupation	-0.240 (0.395)	-1.010* (0.527)	-3.050*** (0.918)	-3.254*** (0.939)	-3.191*** (0.800)	-3.007*** (0.784)
With university degree	-2.184*** (0.799)	-3.045*** (0.895)	-2.667* (1.381)	-2.810** (1.398)	-2.761** (1.366)	-1.670 (1.488)
Employed	8.104*** (2.124)	2.023 (2.107)	2.797 (2.340)	2.401 (2.457)	2.410 (2.433)	1.167 (2.345)
Not in labor force	10.671*** (2.732)	3.823 (2.645)	4.382 (2.891)	4.000 (3.040)	3.956 (2.975)	2.832 (2.846)
Median annual income	0.042*** (0.015)	0.037*** (0.015)	0.031 (0.023)	0.027 (0.024)	0.022 (0.018)	0.023 (0.018)
Smoking ban active					-14.564*** (1.223)	50.286* (27.867)
Time trend					14.726*** (1.803)	14.873*** (1.769)
Time trend squared					-0.519*** (0.053)	-0.539*** (0.052)
Smoking ban active × SEIFA						-0.064*** (0.027)
Constant	-829.139*** (224.270)	-139.522 (233.036)	-370.869* (219.335)	-349.206 (224.084)	-399.482* (221.878)	-306.360 (214.238)
Year Fixed Effects		✓	✓	✓		
LGA Fixed Effects			✓	✓	✓	✓
R-Squared	0.669	0.767	0.912	0.911	0.908	0.909
Observations	920	920	920	920	920	920

Notes: See Table A.1 in the appendix for the first stage results for the IV estimates. Bootstrap standard errors that account for clustering at the Local Government Area level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Marginal cost function estimates

	OLS				IV
	(1)	(2)	(3)	(4)	(5)
Number of slot machines	0.001 (0.014)	-0.004 (0.014)	-0.057*** (0.015)	-0.042*** (0.012)	0.215*** (0.083)
Number of gambling venues	-0.722*** (0.294)	-0.822*** (0.276)	-0.471* (0.283)	-0.474 (0.314)	-4.449*** (1.249)
Population	0.078* (0.042)	0.103*** (0.042)	0.196*** (0.047)	0.251*** (0.070)	0.029 (0.106)
Median mortgage rate	-0.919*** (0.283)	-0.529 (0.326)	0.265 (0.489)	-1.438*** (0.389)	-1.876*** (0.470)
Median annual income	0.021*** (0.006)	0.014*** (0.006)	-0.003 (0.006)	0.014*** (0.006)	0.025*** (0.008)
Employed	-0.164 (0.322)	-1.378*** (0.479)	1.700*** (0.610)	1.426** (0.643)	0.821 (0.822)
Not in labor force	-0.076 (0.350)	-1.354*** (0.520)	2.134*** (0.678)	1.735*** (0.708)	0.949 (0.894)
Time trend				2.120*** (0.426)	0.206 (0.787)
Time trend squared				-0.092*** (0.016)	-0.012 (0.029)
Constant	26.044 (31.022)	141.328*** (46.761)	-164.751*** (61.102)	-138.218** (62.666)	-62.687 (78.844)
Year Fixed Effects		✓	✓		
LGA Fixed Effects			✓	✓	✓
R-Squared	0.365	0.518	0.836	0.778	0.491
Observations	920	920	920	920	920

Notes: See Table A.2 in the appendix for the first stage results for the IV estimates. Bootstrap standard errors that account for clustering at the Local Government Area level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Policy Effects on State Gambling Revenues and Problem Gambling Prevalence

Year	Total Gambling Tax Revenue	Tax Levies			Smoking Ban			Supply Caps			Tagging		
		Δ Tax Revenue	% Δ Problem Gamblers	% Δ Problem Gamblers	Δ Tax Revenue	% Δ Problem Gamblers	Δ Tax Revenue	% Δ Problem Gamblers	Δ Tax Revenue	% Δ Problem Gamblers	Δ Tax Revenue	% Δ Problem Gamblers	
2001	1216.70	5.86	-0.24				-0.08	-0.22			242.47	-13.55	
2002	1312.19	24.85	-1.11				-0.81	-1.94			228.42	-13.79	
2003	1168.10	27.46	-1.15		-183.43	-3.21	-0.77	-2.71			248.71	-13.35	
2004	1123.83	28.23	-1.14		-184.88	-3.32	-1.13	-4.21			251.73	-13.08	
2005	1143.23	27.53	-1.16		-186.11	-3.37	-0.95	-4.37			249.94	-13.5	
2006	1186.92	63.88	-2.22		-187.34	-3.34	0.04	-4.16			246.29	-13.7	
2007	1188.23	66.13	-1.92		-193.42	-3.14	-6.33	-4.06			254.99	-13.06	
2008	1201.72	84.51	-2.66		-196.77	-3.21	-9.18	-4.68			251.03	-12.76	
2009	1223.10	83.49	-2.69		-196.79	-3.23	-12.45	-5.64			261.86	-13.29	
2010	1147.79	85.45	-2.83		-195.42	-3.33	-4.01	-0.89			167.26	-8.12	

Notes: Tax revenue amounts are in real terms (2010=100) and terms of millions of dollars. In each panel, we compare a scenario without a policy (counterfactual) to one with a policy (baseline). The exception is the Tagging column which compares a scenario without the policy (baseline) to one with the policy (counterfactual).

Figures

Figure 2: Per-Capita Slot Machine Supply and LGA Socio-Economic Status

Figure 3: Per-Capita Slot Machine Supply – LGA Socio-Economic Status Relationship

Figure 4: Revenue Function LGA Fixed Effects and Socio-Economic Status

Figure 5: Counterfactual Policy Analysis: Per-Machine Tax Levies

Figure 6: Counterfactual Policy Analysis: Smoking Ban

(i) State-wide Slot Machine Supply

(ii) Annual Per-Machine Gambling Revenue

(iii) Per-Capita Slot Machine Supply - SEIFA Relationship

Figure 7: Counterfactual Policy Analysis: LGA-level Supply Caps

(i) State-wide Slot Machine Supply

(ii) Annual Per-Machine Gambling Revenue

(iii) Per-Capita Slot Machine Supply - SEIFA Relationship

Figure 8: Counterfactual Policy Analysis: Tagging

(i) State-wide Slot Machine Supply

(ii) Annual Per-Machine Gambling Revenue

(iii) Per-Capita Slot Machine Supply - SEIFA Relationship

Appendix

A Supplemental tables

Table A.1: First Stage Regression Estimates for Slot Machine Revenue Function

	(1)	(2)	(3)
Number of gambling venues	28.956*** (4.467)	29.919*** (4.385)	29.869*** (4.398)
Population	2.416*** (0.491)	2.419*** (0.497)	2.410*** (0.498)
18 ≤ Age ≤ 30	-3.447 (7.168)	-2.182 (7.151)	-2.104 (7.239)
31 ≤ Age ≤ 40	-1.869 (8.901)	-0.712 (8.920)	-0.471 (9.052)
41 ≤ Age ≤ 50	-15.846* (8.348)	-15.088* (8.053)	-14.896* (8.210)
51 ≤ Age ≤ 64	-5.640 (4.785)	-5.439 (4.838)	-5.445 (4.864)
Age ≥ 65	3.794 (6.145)	6.220 (6.121)	6.321 (6.237)
Australian born	6.932** (3.284)	6.719** (3.338)	6.605** (3.353)
Indigenous	-9.047 (17.531)	-5.502 (17.690)	-4.920 (17.704)
Employed in manufacturing	2.298 (1.913)	1.736 (2.016)	1.669 (2.004)
Blue collar occupation	-5.126* (2.904)	-5.016** (2.277)	-5.075** (2.259)
With university degree	-2.388 (3.691)	-2.857 (3.393)	-3.250 (3.447)
Employed	-3.145 (8.466)	-3.156 (8.712)	-2.697 (8.669)
Not in labor force	-4.084 (9.937)	-4.039 (10.062)	-3.622 (9.943)
Median annual income	-0.084 (0.074)	-0.022 (0.063)	-0.022 (0.063)
Smoking ban active		-2.610 (3.657)	-26.244 (74.986)
Time trend		19.475*** (5.307)	19.388*** (5.306)
Time trend squared		-0.640*** (0.176)	-0.632*** (0.177)
Smoking ban active × SEIFA			0.023 (0.074)
Constant	179.349 (826.189)	26.421 (832.643)	-7.568 (839.191)
Year Fixed Effects	✓		
LGA Fixed Effects	✓	✓	✓
R-Squared	0.994	0.994	0.994
Observations	920	920	920
F-Statistic	42.157***	47.563***	47.429***

Notes: Columns (1)-(3) respectively correspond to the first stage regressions for the IV regressions in columns (4)-(6) of Table 2 in the paper. Bootstrap standard errors that account for clustering at the Local Government Area level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.2: First Stage Regression Estimates for Marginal Cost Function

	(1)
Smoking ban active	-3.565* (1.855)
18 ≤ Age ≤ 30	-1.172 (3.639)
31 ≤ Age ≤ 40	-0.461 (4.406)
41 ≤ Age ≤ 50	-7.722* (3.982)
51 ≤ Age ≤ 64	-2.638 (2.409)
Age ≥ 65	2.938 (2.994)
Australian born	3.131* (1.744)
Indigenous	-2.708 (8.730)
Employed in manufacturing	0.698 (1.008)
Blue collar occupation	-2.522** (1.160)
With university degree	-2.147 (1.922)
Number of gambling venues	14.852*** (2.202)
Population	1.103*** (0.250)
Median monthly mortgage payment	2.941 (1.926)
Median annual income	-0.029 (0.032)
Employed	-0.768 (4.347)
Not in labor force	-1.278 (5.043)
Time trend	10.818*** (2.746)
Time trend squared	-0.388*** (0.101)
Constant	-37.634 (409.172)
Year Fixed Effects	
LGA Fixed Effects	✓
R-Squared	0.994
Observations	920
F-Statistic	4.002***

Notes: Column (1) corresponds to the first stage regressions for the IV regressions in column (5) of Table 3 in the paper. Bootstrap standard errors that account for clustering at the Local Government Area level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.3: Counterfactual Policy Simulations with Confidence Intervals

Year	Baseline			Tax Levy			Smoking Ban			Supply Caps			Tagging		
	Slot Machines	Revenue per Machine	Slot Machines	Revenue per Machine	Slot Machines	Revenue per Machine	Slot Machines	Revenue per Machine	Slot Machines	Revenue per Machine	Slot Machines	Revenue per Machine	Slot Machines	Revenue per Machine	Slot Machines
2001	26510	111865.2	26639 (26383.5, 26852)	111783.8 (111471.8, 112406.8)	26512 (26512, 26512)	111981.6 (111970.1, 111989.8)	26512 (26512, 26512)	111981.6 (111970.1, 111989.8)	26524 (26265.2, 27429.5)	111964.9 (109895.4, 112607.7)	21161 (20931.5, 21278)	111964.9 (109895.4, 112607.7)	21161 (20931.5, 21278)	123119.5 (119661.5, 128301.5)	21161 (20931.5, 21278)
2002	26468	117880.2	27076 (26681.5, 27500)	116982.1 (115943.6, 117796.8)	26476 (26476, 26476)	117894.7 (117873.4, 117909.5)	26476 (26476, 26476)	117894.7 (117873.4, 117909.5)	26553 (26170, 28017)	117749.9 (114593.4, 118689.1)	21033 (20831.2, 21257)	117749.9 (114593.4, 118689.1)	21033 (20831.2, 21257)	129232.1 (125697.2, 134415.5)	21033 (20831.2, 21257)
2003	26340	104802	26898 (26478.5, 27500)	103911.4 (102791.2, 104768.3)	27500 (27447.5, 27500)	117025.7 (114158.6, 118698.7)	27500 (27447.5, 27500)	117025.7 (114158.6, 118698.7)	26400 (25978, 27937.5)	104652.3 (101283.6, 105680.4)	21062 (20758, 21271.5)	104652.3 (101283.6, 105680.4)	21062 (20758, 21271.5)	115823.4 (112465.1, 120965)	21062 (20758, 21271.5)
2004	26218	100764.7	26772 (26380, 27500)	99843.57 (98706.81, 100632.4)	27500 (27312.5, 27500)	112832.5 (109972.3, 114523.9)	27500 (27312.5, 27500)	112832.5 (109972.3, 114523.9)	26323 (25888.5, 27959)	100472 (96942.66, 101505.2)	21089 (20753, 21345.5)	100472 (96942.66, 101505.2)	21089 (20753, 21345.5)	111535.6 (108274.4, 116676.6)	21089 (20753, 21345.5)
2005	26230	102359.6	26769 (26435, 27500)	101389.3 (100219.9, 102075.1)	27500 (27362.5, 27500)	114324.3 (111446.9, 115973.8)	27500 (27362.5, 27500)	114324.3 (111446.9, 115973.8)	26304 (25956, 27625.5)	102020.9 (98792.64, 102939.1)	20910 (20867.5, 21296)	102020.9 (98792.64, 102939.1)	20910 (20867.5, 21296)	113437 (109502.7, 118165.2)	20910 (20867.5, 21296)
2006	26286	102171	27370 (26921.5, 27500)	100356.6 (98628.6, 101127.5)	27500 (27382, 27500)	114159.5 (111271.6, 115786.1)	27500 (27382, 27500)	114159.5 (111271.6, 115786.1)	26293 (25975.5, 27618)	101872.7 (98642.06, 102818.6)	21011 (20949, 21362)	101872.7 (98642.06, 102818.6)	21011 (20949, 21362)	113441.5 (109546.8, 118328.9)	21011 (20949, 21362)
2007	26398	102197.2	27061 (26504.5, 27500)	101155.6 (99707.85, 102529)	27500 (26984.5, 27500)	114837.2 (112234.1, 116898.2)	27500 (26984.5, 27500)	114837.2 (112234.1, 116898.2)	26465 (25826, 28975.5)	101843.6 (96007.54, 103756.7)	21155 (20084.5, 21548)	101843.6 (96007.54, 103756.7)	21155 (20084.5, 21548)	113464.8 (10329.8, 119366.8)	21155 (20084.5, 21548)
2008	25964	102361.7	27363 (26670.5, 27500)	100200.9 (98269.94, 101783.4)	27500 (26773.5, 27500)	114414.1 (111650.1, 116651.9)	27500 (26773.5, 27500)	114414.1 (111650.1, 116651.9)	26426 (25595.5, 29837)	101367.7 (93750.5, 103743.8)	21169 (19388.5, 21621)	101367.7 (93750.5, 103743.8)	21169 (19388.5, 21621)	112877.2 (110175, 119065.7)	21169 (19388.5, 21621)
2009	26001	104294.5	27395 (26808.5, 27500)	102096.4 (100123.5, 103194)	27500 (26862, 27500)	116285.3 (113500, 118269.5)	27500 (26862, 27500)	116285.3 (113500, 118269.5)	26557 (25772.5, 30013.5)	103076.4 (96002.5, 104964.2)	21058 (18921, 21753.5)	103076.4 (96002.5, 104964.2)	21058 (18921, 21753.5)	115233.2 (112487, 122002.2)	21058 (18921, 21753.5)
2010	25889	97935.27	27308 (26661.5, 27500)	95680.83 (93548.77, 96922.59)	27471 (26682, 27500)	109866.9 (106980.3, 111830.2)	27471 (26682, 27500)	109866.9 (106980.3, 111830.2)	25898 (25342, 28193.5)	97813.98 (92838.97, 99318.47)	22546 (22274, 22752.5)	97813.98 (92838.97, 99318.47)	22546 (22274, 22752.5)	104678.9 (102546.7, 107950.4)	22546 (22274, 22752.5)

Notes: 95% bootstrap confidence intervals that account for clustering at the Local Government Area level are reported in parentheses. In each panel, we compare a scenario without a policy (counterfactual) to one with a policy (baseline). The exception is the Tagging column which compares a scenario without the policy (baseline) to one with the policy (counterfactual).

Table A.4: Policy Effects on State Gambling Revenues and Problem Gambling Prevalence with Confidence Intervals

Year	Tax Levy			Smoking Ban			Supply Caps			Tagging		
	Total Tax	Δ Tax	% Δ Problem	Δ Tax	% Δ Problem	Δ Tax	Δ Tax	% Δ Problem	Δ Tax	% Δ Problem	Δ Tax	% Δ Problem
	Revenue	Revenue	Gamblers	Revenue	Gamblers	Revenue	Revenue	Gamblers	Revenue	Gamblers	Revenue	Gamblers
2001	1216.70	5.86 (0.24,7.48)	-0.24 (-0.87,0.5)				-0.08 (-4.39,9.39)	-0.22 (-34.57,9.06)	242.47 (23.45,390.38)	-13.55 (-29.73,1.99)		
2002	1312.19	24.85 (10.25,32.08)	-1.11 (-3.5,0.37)				-0.81 (-7.37,26.13)	-1.94 (-55.89,11.83)	228.42 (9.77,365.75)	-13.79 (-30.14,2.01)		
2003	1168.10	27.46 (12.21,32.82)	-1.15 (-3.68,0.4)	-183.43 (-204.02,-154.76)	-3.21 (-8.8,0.54)		-0.77 (-5.09,32.29)	-2.71 (-60.67,12.12)	248.71 (37.92,371.87)	-13.35 (-29.27,1.99)		
2004	1123.83	28.23 (12.35,33.64)	-1.14 (-3.7,0.39)	-184.88 (-204.84,-155.64)	-3.32 (-9.06,0.56)		-1.13 (-5.7,35.2)	-4.21 (-66.44,11.35)	251.73 (44.49,365.87)	-13.08 (-28.82,1.95)		
2005	1143.23	27.53 (10.88,32.95)	-1.16 (-3.79,0.33)	-186.11 (-205.02,-156.26)	-3.37 (-9.19,0.57)		-0.95 (-4.36,30.41)	-4.37 (-60.62,9.67)	249.94 (27.87,380.04)	-13.5 (-28.16,1.93)		
2006	1186.92	63.88 (56.08,75.49)	-2.22 (-6.39,0.46)	-187.34 (-206.68,-157.61)	-3.34 (-9.15,0.56)		0.04 (-3.27,30.92)	-4.16 (-60.71,9.92)	246.29 (22.7,378.04)	-13.7 (-28.69,1.99)		
2007	1188.23	66.13 (54.17,71.2)	-1.92 (-5.61,0.53)	-193.42 (-214.32,-164.95)	-3.14 (-8.4,0.7)		-6.33 (-14.92,54.5)	-4.06 (-39.92,4.93)	254.99 (32.98,371.29)	-13.06 (-29.59,2.06)		
2008	1201.72	84.51 (75.33,96.81)	-2.66 (-7.44,0.66)	-196.77 (-217.66,-163.19)	-3.21 (-8.7,0.69)		-9.18 (-25.36,68.95)	-4.68 (-50.53,7.07)	251.03 (33.49,352.91)	-12.76 (-30.1,2.07)		
2009	1223.10	83.49 (75.75,98.84)	-2.69 (-7.55,0.64)	-196.79 (-216.7,-162.17)	-3.23 (-8.83,0.73)		-12.45 (-31.48,60.54)	-5.64 (-50.29,4.4)	261.86 (40.14,366.78)	-13.29 (-32.68,2.17)		
2010	1147.79	85.45 (75.9,100.46)	-2.83 (-8.1,0.7)	-195.42 (-215.82,-158.96)	-3.33 (-9.28,0.73)		-4.01 (-28.16,11.93)	-0.89 (-29.02,6.52)	167.26 (38.68,247.65)	-8.12 (-17.89,1.21)		

Notes: Dollar amounts are in real terms (2010=100) and terms of millions of dollars. Bootstrap 90% level confidence intervals that account for clustering at the Local Government Area level are reported in parentheses.

Table A.5: Problem Gambling Regression Estimates

	OLS			IV	
	(1)	(2)	(3)	(4)	(5)
Number of slot machines	0.012* (0.007)	0.012* (0.007)	0.037 (0.070)	0.010 (0.015)	0.022 (0.610)
Population	0.112** (0.054)	0.111** (0.053)	1.008*** (0.354)	0.121 (0.087)	0.985 (0.883)
18 ≤ Age ≤ 30	1.311* (0.791)	1.328* (0.797)	-4.717 (9.223)	1.358 (0.866)	-5.288 (11.530)
31 ≤ Age ≤ 40	-0.200 (1.088)	-0.150 (1.103)	15.934 (14.510)	-0.093 (1.157)	16.859 (20.495)
41 ≤ Age ≤ 50	0.261 (1.799)	0.374 (1.863)	-5.596 (16.418)	0.386 (1.913)	-4.901 (18.237)
51 ≤ Age ≤ 64	-0.105 (0.835)	-0.133 (0.842)	0.608 (10.512)	-0.099 (0.892)	0.912 (13.701)
Age ≥ 65	-0.188 (0.852)	-0.150 (0.865)	7.324 (8.621)	-0.123 (0.896)	7.257 (9.030)
Australian born	0.342 (0.245)	0.353 (0.250)	-4.436 (8.303)	0.332 (0.277)	-4.831 (8.943)
Indigenous	3.235** (1.423)	3.158** (1.429)	-11.630 (32.339)	3.145** (1.453)	-13.879 (34.451)
Employed in manufacturing	-0.853*** (0.299)	-0.845*** (0.300)	-6.920** (3.348)	-0.877*** (0.335)	-7.061* (3.739)
Blue collar occupation	0.518 (0.549)	0.491 (0.555)	7.973 (6.881)	0.458 (0.581)	8.225 (7.468)
With university degree	-0.147 (0.716)	-0.178 (0.725)	-2.042 (8.968)	-0.258 (0.843)	-3.013 (11.467)
Employed	6.201* (3.643)	6.024 (3.668)	-15.684 (12.763)	6.197 (3.889)	-16.598 (17.095)
Not in labor force	6.694* (3.702)	6.535* (3.729)	-19.697 (18.602)	6.699* (3.956)	-20.725 (20.983)
Median annual income	0.007 (0.012)	0.007 (0.012)	-0.020 (0.117)	0.007 (0.012)	-0.012 (0.190)
Constant	-646.132* (346.680)	-632.845* (348.401)	1817.744 (1885.740)	-644.893* (368.521)	1927.290 (2099.633)
Year Fixed Effects		✓	✓	✓	✓
LGA Fixed Effects			✓		✓
R-Squared	0.7602	0.7601	0.9035	0.7599	0.9034
Observations	158	158	158	158	158

Notes: See Table A.1 in the appendix for the first stage results for the IV estimates. Bootstrap standard errors that account for clustering at the Local Government Area level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Public policy details

B.1 Tax revenue calculations

This appendix describes how we calculate slot machine tax revenues year-to-year. The main references for these calculations are:

- Victorian state government reports from 1996 to 2010
url: <http://www.dtf.vic.gov.au/State-Budget/Previous-budgets>
- Victorian Commission for Gambling and Liquor Regulation Annual reports, Appendix 15: Distribution of Player Loss from Gaming Machines
url: <http://www.vcglr.vic.gov.au/utility/about+us/about+the+vcglr/annual+reports>
- 2002 report from the Interchurch Gambling Taskforce: “Breaking a Nasty Habit? Gaming Policy and Politics in the State of Victoria,” by D. Hayward and B. Kliger

From these documents we have gleaned the following details regarding taxes on slot machine revenues:

- Before 2001, the state government received a 33.33% share of annually slot machine revenue (net player losses) from each gambling venue
- From 2001 onwards, the state government share of slot machine revenue was reduced to 24.24%. However, a 9.09% goods and services tax was applied to machine revenue. This implies that the state government continued to receive a 33.33% share of slot machine revenue.
- There is an 8.33% tax on slot machine revenue from hotels called the Community Support Fund (CSF). This is applied in all sample years.
- From 2000 onwards Tatts has an additional 7% tax on slot machine revenue that corresponds to the Tatts license fee.

Recall from the text that: (1) Tatts and Tab have roughly 50/50 market shares; and (2) that slot machine counts are roughly split between hotels and clubs. Assuming that the companies have equal numbers of slot machines across hotels and clubs, and that hotels and clubs generate the same amounts of slot machine revenue, we estimate the aggregate share of slot machine revenues captured by the state through taxes to be:

- Before 2000: $0.5 \times (0.5 \times 33.33\% + 0.5 \times (33.33 + 8.33)) + 0.5 \times (0.5 \times 33.33\% + 0.5 \times (33.33 + 8.33)) = \mathbf{37.5\%}$
- After 2000: $0.5 \times (0.5 \times 33.33\% + 0.5 \times (33.33 + 8.33)) + 0.5 \times (0.5 \times (33.33\% + 7\%) + 0.5 \times (33.33 + 8.33 + 7\%)) = \mathbf{41\%}$

Further recall from the text that the state government imposed a per-machine tax levy of \$333.33 in 2001, \$1533.33 in 2002, \$3333.33 in 2006 and \$4333.33 in 2008 (and onwards). The collective tax revenue calculations can thus be summarized in the following table:

Table B.6: Slot Machine Tax Revenue Calculations

Period	Total state tax revenue
1996-1999	$0.375 \times \text{Total Machine Revenue}$
2000	$0.410 \times \text{Total Machine Revenue}$
2001	$0.410 \times \text{Total Machine Revenue} + 333.33 \times \text{Total Number of Machines}$
2002-2005	$0.410 \times \text{Total Machine Revenue} + 1533.33 \times \text{Total Number of Machines}$
2006-2007	$0.410 \times \text{Total Machine Revenue} + 3333.33 \times \text{Total Number of Machines}$
2008-2010	$0.410 \times \text{Total Machine Revenue} + 4333.33 \times \text{Total Number of Machines}$

B.2 Capped market definitions

This appendix provides details on the slot machine supply caps. We have two main references that provide in-depth details of the policy and its implementation:

- 2001 caps: 2005 report from the South Australian Centre for Economic Studies: “Study of the Impact of Caps on Electronic Gaming Machines,” 255 pages.
- 2006 caps: 2003 Gambling Regulation Act (version no. 038, section 3.4), State Government of Victoria.

These documents report the caps for all the regulated regions in each year and provide details of their calculation. In implementing the caps, the government required there be no more than ten slot machines per thousand people in a market. If a market slot machine density was below this level at the time a cap was imposed, then the cap was set to this density.

2001 caps

Supply caps were first introduced in April 2001 in five LGAs: Greater Dandenong Plus, Maribyrnong Plus, Darebin Plus, Latrobe, Bass Coast Shire. The latter two markets correspond precisely to LGAs. The prior three “Plus” markets are based on LGAs but include contiguous postcodes (postal areas that are smaller than LGAs) that were considered leakage areas; Greater Dandenong, Maribyrnong and Darebin are LGAs/markets in our sample. For these regions, we compute the effective supply cap for LGA m in year t as follows:

$$\bar{Q}_{mt} = \left(\frac{Q_{m,2000}}{Q_{m+plus,2000}} \right) \bar{Q}_{m+plus,t} \quad (10)$$

where $Q_{m+plus,2000}$ and $\bar{Q}_{m+plus,t}$ correspond to the total number of slot machines and the reported supply cap for LGA m “Plus” market.⁴⁰ The effective caps for LGAs are scaled down by the relative number of slot machines in the LGA and the LGA “Plus” region. The implicit assumption is that the caps had a uniform effect across LGA m and its leaked regions. The LGA-level slot machine counts help rationalize this assumption and our effective cap calculation: our effective caps track closely

⁴⁰We motivate our use of effective caps at the LGA-level rather than redefining the three “Plus” markets to include the leaked postcodes in a moment.

with slot machine counts at the LGA level that are unchanged following the implementation of the 2001 caps. This indicates that the caps are indeed binding at the LGA-level for LGAs that are included within the larger “Plus” markets.

We made two exceptions in using effective caps as defined in equation (10). First, for the years 2004-2006 in Greater Dandenong, the raw data indicates that 1078 slot machines is a binding supply cap which is slightly below our effective supply cap of 1080. We therefore use 1078 as the supply cap in these LGA-years. Second, for Darebin the raw data indicates that 986 machines is the binding supply cap in the market from 2001 onwards as slot machine counts are fixed at this level for this period. We therefore impose a supply cap of 986 and not our effective cap estimate of 1006.

2006 caps

When the 2006 supply caps were implemented the three “Plus” regions were re-defined to simply being LGAs (e.g., our market definition). Caps from the 2001 policy thus continued to be implemented for Greater Dandenong, Maribyrnong, Darebin, Latrobe and Bass Coast Shire. Accordingly, we use effective caps for the previously defined “Plus” regions from 2001-2005, with the noted exceptions for Greater Dandenong and Darebin, and then use the caps defined by the 2003 Gambling Regulation Act from 2006 onwards. This redefining of the capped areas in 2006 to the LGA-level is what motivates our use of LGA-level effective caps from 2001-2005 for the “Plus” markets.

15 additional LGAs were capped in 2006: Ballarat, Banyule, Brimbank, Casey, Greater Geelong + Borough of Queenscliff, Greater Shepparton, Hobsons Bay, Hume, Melbourne, Monash, Moonee Valley, Moreland, Warrnambool, Whittlesea, Yarra Ranges. Six of the caps (Ballarat, Greater Shepparton, Hobsons Bay, Moonee Valley, Warrnambool) apply to the entire LGA. For these markets, we apply these caps directly.

For the other nine LGAs, the caps only apply to smaller postcodes within an LGA. Given our LGA market definition, such partial caps are potentially not binding at the larger LGA-level as firms could freely supply machines to other parts of the LGA. To check on the importance of a cap at the LGA-level, we use population data from the 2006 Census to determine the proportion of the LGA population that is covered by the partial cap in these nine LGAs. In Brimbank and Whittlesea the partial cap covers more than 90% of the LGA's population so we define these partial caps as applying at the entire LGA-level. The remaining partial caps apply to less than 50% of the population within the LGA and are thus treated as non-binding.

In sum, we have 13 LGAs where the supply caps potentially bind from 2006 onwards: 5 from the 2001 caps and 8 new LGAs from the 2006 caps. Table B.7 lists the caps we use in estimating and identifying the model and in conducting counterfactual policy simulations:

Table B.7: Slot Machine Supply Caps

	Bass Coast	Greater Dandenong		Latrobe	Maribyrnong	Ballarat	Brimbank	Greater Geelong		Greater Shepparton	Hobsons Bay	Moonee Valley	Warrnambool	Whittlesea
		Darebin												
1996-2000	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2001	261	986	1191	663	804	-	-	-	-	-	-	-	-	-
2002	253	986	1170	650	785	-	-	-	-	-	-	-	-	-
2003	237	986	1128	626	747	-	-	-	-	-	-	-	-	-
2004	220	986	1078	602	709	-	-	-	-	-	-	-	-	-
2005	220	986	1078	602	709	-	-	-	-	-	-	-	-	-
2006	220	986	1078	602	709	-	-	-	-	-	-	-	-	-
2007	216	986	989	522	511	663	953	1371	329	579	746	234	621	621
2008	216	986	989	522	511	663	953	1371	329	579	746	234	621	621
2009	216	986	989	522	511	663	953	1371	329	579	746	234	621	621
2010	216	986	989	522	511	663	953	1371	329	579	746	234	621	621

C Bootstrap routines

Throughout the paper we report cluster bootstrap standard errors. This appendix describes their calculation explicitly. We refer the interested reader to Cameron, Gelbach and Miller (2008, *Review of Economics and Statistics*) for an excellent discussion of these methods.

C.1 Revenue function

Let $\mathcal{D} \equiv \{(\mathbf{r}_1, \mathbf{Q}_1, \mathbf{X}_1), \dots, (\mathbf{r}_M, \mathbf{Q}_M, \mathbf{X}_M)\}$ be the original dataset of per-machine gambling revenue, number of slot machines and revenue function shifters. The subscript $m = 1, \dots, M$ corresponds to the clusters (LGAs) in the data, where $\mathbf{r}_m = (r_{m,1996}, \dots, r_{m,2010})'$ stacks the yearly observations for cluster m (and similarly for $\mathbf{Q}_m$ and $\mathbf{X}_m$).

The standard errors in Table 2 are computed as follows:

- R1. Construct bootstrap sample b , $\mathcal{D}_b$ by re-sampling with replacement from the M mutually exclusive clusters in $\mathcal{D}$. $\mathcal{D}_b$ in total contains $M_b = M$ clusters and does not necessarily have the same number of LGA-years as $\mathcal{D}$.
- R2. Estimate the revenue function in equation (2) by 2SLS with $\mathcal{D}_b$. Denote the corresponding bootstrap parameter estimates $(\hat{\alpha}_b^*, \hat{\beta}_b^*)$.
- R3. Repeat steps 1. and 2. $b = 1, \dots, B$ times using the same bootstrap samples from R1. In practice we use $B = 1000$ bootstrap samples.⁴¹ This yields a bootstrap distribution of parameter estimates that account for clustering at the LGA level, $\{(\hat{\alpha}_1^*, \hat{\beta}_1^*), \dots, (\hat{\alpha}_B^*, \hat{\beta}_B^*)\}$
- R4. Compute the bootstrap standard error for element k of $\hat{\beta}$ (and similarly for $\hat{\alpha}$) as:

$$se(\hat{\beta}_k) = \left(\frac{1}{B-1} \sum_{b=1}^B (\hat{\beta}_{b,k}^* - \tilde{\beta}_{b,k}^*) \right)^{1/2}$$

$$\text{where } \tilde{\beta}_{b,k}^* = (1/B) \sum_{b=1}^B \hat{\beta}_{b,k}^*$$

C.2 Marginal cost function

Let $\mathcal{C} \equiv \{(\hat{\mathbf{c}}_1, \mathbf{q}_1, \mathbf{W}_1), \dots, (\hat{\mathbf{c}}_M, \mathbf{q}_M, \mathbf{W}_M)\}$ be the original dataset of inferred marginal costs, per-firm slot machine counts and marginal cost function shifters. Again, the subscript $m = 1, \dots, M$ corresponds to the clusters (LGAs), where $\hat{\mathbf{c}}_1 = (\hat{\mathbf{c}}_{m,1996}, \dots, \hat{\mathbf{c}}_{m,2010})'$ stacks the yearly observations for cluster m (and similarly for $\mathbf{q}_m$ and $\mathbf{W}_m$). There are two points of further note. First recall that $q_{mt} = Q_{mt}/N_{mt}$ under the homogeneous firms assumption. Second the market-years included in $\mathcal{C}$ correspond to those where the government has not imposed supply caps.

The standard errors in Table 3 are computed as follows:

- C1. Using the b^{th} bootstrap sample $\mathcal{D}_b$ from step R1 and the corresponding bootstrap estimates $(\hat{\alpha}_b^*, \hat{\beta}_b^*)$, construct a bootstrap sample of inverted marginal

⁴¹The standard errors, confidence intervals and corresponding inferences reported throughout the paper are virtually unchanged if we use $B = 5000$.

costs as per equation (6) using market-years without supply caps only. Denote these costs $\{\hat{\mathbf{c}}_{1,b}, \dots, \hat{\mathbf{c}}_{M,b}\}$. With these construct bootstrap sample $\mathcal{C}_b$.

- C2. Estimate the marginal cost in equation (3) by 2SLS with $\mathcal{C}_b$. Denote the corresponding bootstrap parameter estimates $(\hat{\gamma}_b^*, \hat{\psi}_b^*)$.
- C3. Repeat steps 1. and 2. $b = 1, \dots, B$ times. This yields a bootstrap distribution of parameter estimates that account for clustering at the LGA level, $\{(\hat{\gamma}_1^*, \hat{\psi}_1^*), \dots, (\hat{\gamma}_B^*, \hat{\psi}_B^*)\}$
- C4. Compute the bootstrap standard error for element k of $\hat{\psi}$ (and similarly for $\hat{\gamma}$) as:

$$\text{se}(\hat{\psi}_k) = \left(\frac{1}{B-1} \sum_{b=1}^B (\hat{\psi}_{b,k}^* - \tilde{\psi}_{b,k}^*) \right)^{1/2}$$

where $\tilde{\psi}_{b,k}^* = (1/B) \sum_{b=1}^B \hat{\psi}_{b,k}^*$

Recovering marginal costs in capped markets

To compute bootstrap standard errors for our counterfactual policy simulations (discussed in Section C.3), we need to recover marginal costs for all LGA-years in each bootstrap sample, including those for capped markets. To do so, we follow the procedure described in the text in Section 3.2:

- C1a. Using bootstrap sample b and corresponding demand and cost estimates $\hat{\theta}_b^* = (\hat{\alpha}_b^*, \hat{\beta}_b^*, \hat{\gamma}_b^*, \hat{\psi}_b^*)'$, recover the structural cost shocks $\hat{\omega}_{mt,b}^*$ for uncapped LGA-years directly from equation (2).
- C2a. With the recovered $\hat{\omega}_{mt,b}^*$ values for uncapped LGA-years, estimate an AR(1) process for cost shocks as per equation (8). This yields bootstrap estimate b $\hat{\rho}_{0,b}^*$ and $\hat{\rho}_{1,b}^*$ from equation (8).
- C3a. Using the $\hat{\omega}_{mt,b}^*$ values for uncapped LGA-years and $\hat{\rho}_{0,b}^*$ and $\hat{\rho}_{1,b}^*$, construct one-step ahead forecasts within LGAs to recover the unobserved marginal costs for LGA-years affected by supply caps in bootstrap sample b exactly as described in the text in Section 3.2
- C4a. Repeat steps C1a. to C3a. to obtain $\hat{\omega}_{mt,b}^*$ values for capped LGA-years in all bootstrap samples $b = 1, \dots, B$.

We further note that this procedure yields bootstrap distributions for $\hat{\rho}_0$ and $\hat{\rho}_1$: $\{\hat{\rho}_{0,1}^*, \dots, \hat{\rho}_{0,B}^*\}$ and $\{\hat{\rho}_{1,1}^*, \dots, \hat{\rho}_{1,B}^*\}$. With these we compute bootstrap standard errors as follows:

$$\text{se}(\hat{\rho}_0) = \left(\frac{1}{B-1} \sum_{b=1}^B (\hat{\rho}_{0,b}^* - \tilde{\rho}_{0,b}^*) \right)^{1/2}$$

where $\tilde{\rho}_{0,b}^* = (1/B) \sum_{b=1}^B \hat{\rho}_{0,b}^*$. An analogous calculation is used for $\text{se}(\hat{\rho}_1)$. These are the standard errors reported just under equation (8) in the text.

C.3 Policy evaluation

In the Appendix we also report percentile bootstrap standard errors for all predicted policy effects in the paper. To recover the bootstrap distribution of policy effects for a given counterfactual, we simulate market-level slot machine counts, government revenues and problem gambling prevalence (as described in the text) for each parameter draw $\hat{\theta}_b^*, \hat{\rho}_{0,b}^*, \hat{\rho}_{01b}^*$ and corresponding vector of revenue and cost shocks across all LGAs and years, $\hat{\epsilon}_b^*(\hat{\theta}_b^*, \hat{\rho}_{0,b}^*, \hat{\rho}_{01b}^*)$ and $\hat{\omega}_b^*(\hat{\theta}_b^*, \hat{\rho}_{0,b}^*, \hat{\rho}_{01b}^*)$