# An Empirical Model of Price Competition with Predatory Strategies and Network Effects, with an Application to the Mexican Wireless Telecommunications Market

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**Abstract**

We present an oligopolistic model of price competition where one player has an additional non-price "predatory strategy" that can shift consumer preferences away from its competitors. This strategy is treated as an unobserved market-level random variable which is optimally chosen in equilibrium, along with prices, in a noncooperative game. We also include a "network effect" whereby consumer preferences depend on their beliefs about the proportion of consumers that will choose each one of the competing players. Ours is a special case of a BLP-style demand model with a market-level, firm-specific unobserved shock in consumers' utility that is explicitly modeled as a function of the unobserved predatory strategy. We apply our model to the Mexican wireless telecommunications industry where three carriers serve the market and where the dominant player (América Móvil or 'AMX') has had a market share consistently above 60% in spite of reforms enacted in 2013 to promote competition. Our example is suitable since AMX has engaged in documented practices that fit our description of predatory strategies. Our results suggest that, while the network effect has lost significance over time to explain AMX's market share, the predatory-strategy effect has increased in magnitude. This finding has important policy implications.
***JEL Codes****: C3, C51, C57, D12, L10.*

## 1 Introduction

We present an oligopolistic model of price competition where one of the competing firms has at its disposal an additional non-price strategy that can shift consumers' preferences away from its competitors and towards itself. We call this a *predatory strategy* and it

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is meant to summarize all the non-price practices that this player can undertake which have the aforementioned ability of pulling consumers away from its competitors. These practices are not necessarily anticompetitive in nature, although our empirical example will deal with an industry (the Mexican wireless phone market) where the dominant firm, América Móvil (AMX), has engaged in documented anticompetitive behavior consistent with the characterization of predatory strategy in our model. The model will also include a *network effect* whereby each consumer's preferences depend on her expectations about the proportion of consumers who will select each firm.

Our baseline model is motivated by the real-world features of our empirical example: the Mexican wireless telecommunications industry. Accordingly, the first feature of our model is that it will involve three competing firms: a dominant firm with the ability of using a predatory strategy, and two other firms whose only strategy is price. The second main feature is that we will assume that the researcher only has market-level data (not individual consumer data). The predatory strategy will be treated as an unobserved market-level random variable which is chosen optimally, along with prices, as the equilibrium of a noncooperative game. Our model will enable us to separate the network effect from the predatory effect in order to explain market shares. This is a policy-relevant question in our empirical example and potentially in many other real-world applications. Even though the features of our baseline model are tailored to fit our application, we discuss several extensions, such as having more players and alternative specifications for consumer preferences.

In the context of models of consumer behavior, ours can be seen as a special case of BLP demand models (Berry, Levinsohn, and Pakes (1995)) with an unobserved, firm-specific, market-level shock in consumers' utility functions which is modeled explicitly as a function of the unobserved predatory strategy. To our knowledge, this is the first BLP-type demand model of price competition that also includes a non-price predatory strategy and a network effect. The paper proceeds as follows. Section 2 describes our baseline model. Section 3 describes the type of data we assume and the observable implications from our model. Extensions of the baseline model are discussed in Section 4. Our empirical example is presented in Section 5 and Section 6 concludes

# 2 Model

## 2.1 Players' strategies

We have three players[1]: $j \in \{1, 2, 3\}$, who provide a differentiated good or service. They compete against each other in order to attract consumers in market $t$. Based on the features

[1] We will choose the term "player" and "firm" interchangeably.

of our empirical example, our setup is one where the same three firms compete against each other repeatedly in a collection of markets $t = 1, \dots, T$, and these are the only firms consumers can select to receive the good or service in question. Also motivated by our empirical example we will focus on a situation where we have data at the *market level* (not at the individual consumer level). Extensions to more than 3 players as well as the case where consumer-level data is available will be discussed in Section 4.

#### 2.1.1 Prices

The three firms choose prices in market $t$, labeled as $p_{1t}$, $p_{2t}$ and $p_{3t}$.

#### 2.1.2 Predatory strategy of player 1

In addition to the price $p_{1t}$, player 1 also has a *predatory strategy*, labeled as $a_t$ which can *shift* the preferences of consumers and "separate" them from players 2 and 3 (in a way to be described below) and towards player 1. We think about $a_t$ as an aggregate measure of the non-price predatory practices undertaken by player 1 and we assume $a_t \in [0, \infty)$, with $a_t = 0$ representing the case where there are no predatory efforts exerted by player 1 in market $t$. Empirical examples of non-price predatory strategies and tactics are described in Gundlach (1990). Among the ones mentioned there which can fit the description of "predatory strategy" in our model (see equation (2.1) below) are the following: predatory advertising (disparaging advertising or promotional activities beyond those required to maintain brand recognition), market channel exclusionary covenants (contractual terms with suppliers or outlets that preclude them from dealing with rivals), market channel integration (using ownership of essential inputs, infrastructure or sales/distribution networks to strategically shift consumers away from its rivals), among others. Predatory practices do not necessarily involve anticompetitive behavior. However, some of the documented predatory strategies of the dominant player (AMX) in our empirical example include documented anticompetitive practices which we will describe in Section 5.

### 2.2 Consumers

Inspired by the features of our empirical example, we will focus on a situation where we have data at the *market level* (not at the individual consumer level), and this will inform our assumptions and modeling choices for our baseline model[2]. Our first assumption is that we have a population of $\mathcal{N}_t$ *symmetric* consumers in market $t$. The $i^{th}$ consumer in market

[2] Section 4 will discuss several extensions.

$t$ has random utilities given as follows,

$$\begin{aligned} V_{i1t} &= \Delta_1 - \beta_1 \cdot p_{1t} + \sigma_1 \cdot a_t + \lambda_t \cdot \pi^e_{i1t} + \xi_{i1t}, \quad \text{(utility of choosing firm 1)} \\ V_{i2t} &= \Delta_2 - \beta_2 \cdot p_{2t} - \sigma_2 \cdot a_t + \lambda_t \cdot \pi^e_{i2t} + \xi_{i2t}, \quad \text{(utility of choosing firm 2)} \\ V_{i3t} &= \Delta_3 - \beta_3 \cdot p_{3t} - \sigma_3 \cdot a_t + \lambda_t \cdot \pi^e_{i3t} + \xi_{i3t}, \quad \text{(utility of choosing firm 3)} \end{aligned} \tag{2.1}$$

Where $\pi^e_{ijt}$ denotes consumer $i$'s subjective expectation (beliefs) for the proportion of consumers in market $t$ that will choose firm $j$. Since we assume that these three firms are the only alternatives for consumers[3], beliefs must satisfy $\pi^e_{i1t} + \pi^e_{i2t} + \pi^e_{i3t} = 1$, and we can rewrite $V_{i3t}$ as

$$V_{i3t} = \Delta_3 - \beta_3 \cdot p_{3t} - \sigma_3 \cdot a_t + \lambda_t \cdot (1 - \pi^e_{i1t} - \pi^e_{i2t}) + \xi_{i3t}.$$

$\xi_{ijt}$ is a privately observed, idiosyncratic random utility shock, unobserved by firms or by the econometrician, while $\Delta_j$, $\beta_j$, $\sigma_2$, $\sigma_3$ and $\lambda_t$ are unknown parameters. Note that $\lambda_t$ is explicitly allowed to change across markets. We will treat it as an unobserved market-level random coefficient. Note from (2.1) that preferences depend on the following:

- Prices.
- The expected proportion of the market that will choose each firm. This represents what we will call the network effect.
- The predatory strategy of firm 1.
- A random utility component which represents consumers' idiosyncratic preferences for each of the three firms.

The parameter $\beta_j$ measures the direct effect of price $p_{jt}$ on the utility of choosing firm $j$, while $\lambda_t$ measures the network effect in market $t$. The parameters $\sigma_1$, $\sigma_2$ and $\sigma_3$ measure the effect of the predatory strategy $a_t$ on consumers' preferences. If we assumed that the network effect is positive, the expected signs for the preference parameters in (2.1) would be

$$\beta_j \geq 0, \quad \sigma_1 \geq 0, \quad \sigma_2 \geq 0, \quad \sigma_3 \geq 0, \quad \lambda_t \geq 0$$

If $\sigma_1 = \sigma_2 = \sigma_3 = 0$, the predatory actions of firm 1 have no effect on consumer preferences. Allowing for $\sigma_2 \neq \sigma_3$ allows for different effects of firm 1's predatory strategy on each of its competitors.

The effect of $a_t$ on preferences described in (2.1) fully captures the impact of what we call the "predatory strategy" of player 1 in this paper. Mathematically, it provides player

[3] The model can be straightforwardly extended to include an outside option in the usual way.

1 the ability of shifting consumer preferences, away from players 2 and 3, and towards herself. Beyond this, our model is not specific about what exactly constitutes the extent of the predatory practices. However, we will enumerate a list of documented practices in our empirical example and we will explain there why the type of shift in preferences described in (2.1) is a reasonable approximation.

Advertising is perhaps the main example of non-price predatory strategies studied previously in oligopolistic models. In this literature a distinction has been made between predatory advertising and cooperative advertising. The difference lies in the type of externalities generated by it. While cooperative advertising results in positive externalities that expand the market for all firms, predatory advertising produces negative externalities that merely redistribute market shares (see Chen, Roayaei, and Seldon (1993)). The latter is the type of effect described in (2.1). To our knowledge, this paper presents the first empirically-oriented model of consumer choice that models explicitly price competition alongside a predatory strategy.

**Assumption 1** *The random utility shocks* $(\xi_{i1t}, \xi_{i2t}, \xi_{i3t})$ *are independent of beliefs* $\pi^e_{ijt}$*, market prices* $p_{jt}$ *and the predatory strategy* $a_t$*. These utility shocks are iid with a Type I Extreme Value distribution and their realization is only privately observed by each consumer.*

Let $p_t \equiv (p_{1t}, p_{2t}, p_{3t})$. Take any given pair $\pi_1, \pi_2 \in [0,1]^2$ such that $\pi_1 + \pi_2 \leq 1$ and let $\pi \equiv (\pi_1, \pi_2)$. Define,

$$
\begin{aligned}
G_{1t}(p_t, a_t, \pi) &= \frac{e^{\Delta_1 - \beta_1 \cdot p_{1t} + \sigma_1 \cdot a_t + \lambda_t \cdot \pi_1}}{e^{\Delta_1 - \beta_1 \cdot p_{1t} + \sigma_1 \cdot a_t + \lambda_t \cdot \pi_1} + e^{\Delta_2 - \beta_2 \cdot p_{2t} - \sigma_2 \cdot a_t + \lambda_t \cdot \pi_2} + e^{\Delta_3 - \beta_3 \cdot p_{3t} - \sigma_3 \cdot a_t + \lambda_t \cdot (1 - \pi_1 - \pi_2)}},\\
G_{2t}(p_t, a_t, \pi) &= \frac{e^{\Delta_2 - \beta_2 \cdot p_{2t} - \sigma_2 \cdot a_t + \lambda \cdot \pi_2}}{e^{\Delta_1 - \beta_1 \cdot p_{1t} + \sigma_1 \cdot a_t + \lambda_t \cdot \pi_1} + e^{\Delta_2 - \beta_2 \cdot p_{2t} - \sigma_2 \cdot a_t + \lambda_t \cdot \pi_2} + e^{\Delta_3 - \beta_3 \cdot p_{3t} - \sigma_3 \cdot a_t + \lambda_t \cdot (1 - \pi_1 - \pi_2)}},\\
G_{3t}(p_t, a_t, \pi) &= 1 - G_{1t}(p_t, a_t, \pi) - G_{2t}(p_t, a_t, \pi).
\end{aligned}
\tag{2.2}
$$

Let $\pi^e_{it} \equiv (\pi^e_{i1t}, \pi^e_{i2t})$. From Assumption 1 we have,

$$
Pr\left[\text{Consumer } i \text{ chooses firm } j \text{ in market } t | p_t, a_t, \pi^e_{it}\right] = G_{jt}(p_t, a_t, \pi^e_{it})
$$

Conditional on payoff parameters, beliefs, prices and on the predatory strategy, ours is a characteristics-based demand model with Logit choice probabilities (see McFadden (1974) and Nevo (2011, Section 3.3.2)).

### 2.2.1 Reparameterization

Define $\gamma_2 \equiv \sigma_1 + \sigma_2$, $\gamma_3 \equiv \sigma_1 + \sigma_3$, $\delta_2 \equiv \Delta_2 - \Delta_1$ and $\delta_3 \equiv \Delta_3 - \Delta_1$. Group

$$\theta \equiv (\delta_2, \delta_3, \beta_1, \beta_2, \beta_3, \gamma_2, \gamma_3) \in \mathbb{R}^7. \tag{2.3}$$

The probabilities in (2.2) can be written as

$$G_1(p_t, a_t, \pi|\theta, \lambda_t) \equiv \frac{e^{-\beta_1 \cdot p_{1t} + \lambda_t \cdot \pi_1}}{e^{-\beta_1 \cdot p_{1t} + \lambda_t \cdot \pi_1} + e^{\delta_2 - \beta_2 \cdot p_{2t} - \gamma_2 \cdot a_t + \lambda_t \cdot \pi_2} + e^{\delta_3 - \beta_3 \cdot p_{3t} - \gamma_3 \cdot a_t + \lambda_t \cdot (1 - \pi_1 - \pi_2)}},$$

$$G_2(p_t, a_t, \pi|\theta, \lambda_t) = \frac{e^{\delta_2 - \beta_2 \cdot p_{2t} - \gamma_2 \cdot a_t + \lambda_t \cdot \pi_2}}{e^{-\beta_1 \cdot p_{1t} + \lambda_t \cdot \pi_1} + e^{\delta_2 - \beta_2 \cdot p_{2t} - \gamma_2 \cdot a_t + \lambda_t \cdot \pi_2} + e^{\delta_3 - \beta_3 \cdot p_{3t} - \gamma_3 \cdot a_t + \lambda_t \cdot (1 - \pi_1 - \pi_2)}},$$

$$G_3(p_t, a_t, \pi|\theta, \lambda_t) = 1 - G_1(p_t, a_t, \pi|\theta, \lambda_t) - G_2(p_t, a_t, \pi|\theta, \lambda_t) \tag{2.4}$$

Note that

$$Pr\left[\text{Consumer } i \text{ chooses firm } j \text{ in market } t | p_t, a_t, \pi^e_{it}\right] = G_j(p_t, a_t, \pi^e_{it}|\theta, \lambda_t).$$

The model is therefore observationally equivalent to one where random utility functions are given by

$$\begin{aligned} V_{i1t} &= -\beta_1 \cdot p_{1t} + \lambda_t \cdot \pi^e_{i1t} + \xi_{i1t}, \\ V_{i2t} &= \delta_2 - \beta_2 \cdot p_{2t} - \gamma_2 \cdot a_t + \lambda_t \cdot \pi^e_{i2t} + \xi_{i2t}, \\ V_{i3t} &= \delta_3 - \beta_3 \cdot p_{3t} - \gamma_3 \cdot a_t + \lambda_t \cdot (1 - \pi^e_{i1t} - \pi^e_{i2t}) + \xi_{i3t}. \end{aligned} \tag{2.5}$$

We assume individual consumer beliefs are unobserved in the data. In order to recover them, we will impose the assumption that every consumer holds *equilibrium beliefs* as described next.

### 2.2.2 Equilibrium beliefs

**Assumption 2** *For a given $\theta$ and a given $(p, a, \lambda)$, we refer to equilibrium beliefs as any pair $\pi_1, \pi_2 \in [0,1]^2$ with $\pi_1 + \pi_2 \leq 1$ that solve the system*

$$\begin{aligned} \pi_1 - G_1(p, a, \pi|\theta, \lambda) &= 0 \\ \pi_2 - G_2(p, a, \pi|\theta, \lambda) &= 0 \end{aligned} \tag{2.6}$$

*We assume that, given the prices and predatory strategies chosen by the firms, consumers hold equilibrium beliefs and, if the equilibrium system* (2.6) *has multiple solutions, consumers* *use the same, degenerate equilibrium selection rule to choose one solution w.p.1. That is, their equilibrium selection rule does not randomize across existing solutions. Note that this implies that consumers' beliefs correspond to firms' true ex-post market shares.*

Existence of a solution to (2.6) follows from Brouwer's fixed-point theorem (de la Fuente (2000, Chapter 5, Theorem 3.2)). Sufficient conditions for uniqueness can be characterized in terms of properties of the principal minors of the Jacobian of (2.6) with respect to $\pi$, as in Gale and Nikaido (1965).

**Assumption 2 and the existence of a representative consumer**

Under Assumption 2 we have $\pi_{it} = \pi_t$ for all $i = 1, \ldots \mathcal{N}_t$, where $\pi_t$ satisfy (2.6). Therefore every consumer's choice probabilities correspond to those of a *representative consumer* whose choices are summarized as,

$$Pr\left[\text{Representative consumer chooses firm } j \text{ in market } t | p_t, a_t, \pi_{it}^e\right] = G_j(p_t, a_t, \pi_t | \theta, \lambda_t).$$

The model of consumer behavior we have assumed so far is a special case of the class of demand models in the "product characteristics space" described in Nevo (2011, Section 3.3.2). By treating both the network-effect coefficient $\lambda_t$ and the predatory strategy $a_t$ as unobserved market-level random variables, ours will be a special case of the family of BLP demand models (Berry, Levinsohn, and Pakes (1995)) which use random coefficients and introduce unobserved product-specific characteristics in consumers' random utility functions. What is special about our model is that it adds structure to these product-specific (in our case, firm-specific) characteristics by *modeling them as functions of the unobserved predatory strategy* $a_t$. Like BLP models, we will use equilibrium conditions to recover the unobserved $a_t$ and $\lambda_t$. We describe firms' optimal choice of prices and of the predatory strategy next.

## 2.3 Firms' expected payoffs

Now we will describe firms' choice of prices and of the predatory strategy. In order to do this we need to characterize their expected payoffs, which requires specifying our assumptions about firms' costs, the sequence of moves, and the information possessed by firms when they choose their strategies.

### 2.3.1 Costs of providing service

We assume that each firm $j$ has a constant cost-per-consumer of providing the good or service in market $t$ and we denote it as $c_{jt}$. For each consumer in the market, firm $j$

incurs this cost if and only if it provides the good or service to the consumer. Thus the revenue-per-consumer for firm $j$ is $p_{jt} - c_{jt}$. We assume that the realization of $(c_{1t}, c_{2t}, c_{3t})$ is common knowledge among the firms prior to making their choices.

#### 2.3.2 Predatory strategy costs

Firm 1 has a cost associated with the predatory strategy. We assume that this cost is only a function of the level chosen for $a_t$ and is independent of the number of consumers in the market that select firm 1. We denote this cost as $c_a(a_t)$ and, for simplicity, we assume that the cost function $c_a(\cdot)$ is the same across all markets, but this could be relaxed. The cost function $c_a(\cdot)$ is assumed to be common knowledge among the three firms.

#### 2.3.3 Firms' information about consumers

Next we specify the information firms are assumed to possess about consumer behavior.

**Assumption 3** *Firms are unable to observe the characteristics of each consumer in the market prior to choosing their strategies. We assume that the following information is common knowledge among firms in each market $t$,*

- *The distribution of the idiosyncratic utility shocks $\xi_{ijt}$ as described in Assumption 1.*
- *The true value of the utility parameters $\theta$ and the realization of the network-effect coefficient $\lambda_t$.*
- *The fact that consumers' beliefs satisfy the equilibrium conditions in* (2.6)*.*
- *The number of consumers $\mathcal{N}_t$.*

#### 2.3.4 Sequence of choices and firms' expected payoffs

Firms first choose their strategies (prices and the predatory strategy) *simultaneously* and, once these are set, consumers make their choices. Letting

$$Y_{ijt} = \mathbb{1}\{\text{ consumer } i \text{ selects firm } j \text{ in market } t\},$$

firms' ex-post payoffs are

$$u_{1t} = (p_{1t} - c_{1t}) \cdot \sum_{i=1}^{\mathcal{N}_t} Y_{i1t} - c_a(a_t),$$
$$u_{2t} = (p_{2t} - c_{2t}) \cdot \sum_{i=1}^{\mathcal{N}_t} Y_{i2t},$$
$$u_{3t} = (p_{3t} - c_{3t}) \cdot \sum_{i=1}^{\mathcal{N}_t} Y_{i3t}.$$

However, due to the sequence of moves, firms must choose their strategies prior to observing consumers' choices, so they must focus on the ex-ante expected payoffs. Fix $p \equiv (p_1, p_2, p_3)$ and $a$. By Assumption 3, firms' expected payoffs in market $t$ if $p_t = p$ and $a_t = a$ are given by

$$E\left[u_{1t}|p_t = p, a_t = a\right] = \mathcal{N}_t \cdot \left( (p_1 - c_{1t}) \cdot G_1(p, a, \pi^e|\theta, \lambda_t) - \frac{c_a(a)}{\mathcal{N}_t} \right),$$
$$E\left[u_{2t}|p_t = p, a_t = a\right] = \mathcal{N}_t \cdot \Big( (p_2 - c_{2t}) \cdot G_2(p, a, \pi^e|\theta, \lambda_t) \Big),$$
$$E\left[u_{3t}|p_t = p, a_t = a\right] = \mathcal{N}_t \cdot \Big( (p_3 - c_{3t}) \cdot \big[1 - G_1(p, a, \pi^e|\theta, \lambda_t) - G_2(p, a, \pi^e|\theta, \lambda_t)\big] \Big),$$

Where $\pi^e$ are the beliefs of the representative consumer given $p$ and $a$. By Assumption 3, firms recover $\pi^e$ as the solution to the equilibrium system (2.6) for the given $p$ and $a$. From the above expressions, in choosing their optimal strategies firms can focus on maximizing the expected payoff-per-consumer in the market,

$$\begin{aligned} u_1(p, a, \pi^e|\theta, \lambda_t, c_{1t}, c_a, \mathcal{N}_t) &\equiv (p_1 - c_{1t}) \cdot G_1(p, a, \pi^e|\theta, \lambda_t) - \frac{c_a(a)}{\mathcal{N}_t}, \\ u_2(p, a, \pi^e|\theta, \lambda_t, c_{2t}) &\equiv (p_2 - c_{2t}) \cdot G_2(p, a, \pi^e|\theta, \lambda_t), \\ u_3(p, a, \pi^e|\theta, \lambda_t, c_{3t}) &\equiv (p_3 - c_{3t}) \cdot [1 - G_1(p, a, \pi^e|\theta, \lambda_t) - G_2(p, a, \pi^e|\theta, \lambda_t)]\,. \end{aligned} \tag{2.7}$$

## 2.4 Equilibrium strategies

By Assumption 3, firms internalize the fact that the representative consumer's beliefs solve the equilibrium system (2.6). We take advantage of this assumption by expressing the unobserved market-level network effect $\lambda_t$ and the unobserved predatory strategy $a_t$ as implicit functions of prices and market shares by solving (2.6).

### 2.4.1 Network effect, predatory strategy and Assumption 3

We have assumed that the conditions in Assumption 3 are common knowledge among the competing firms and that this is internalized into their optimal strategy choices. Thus, in equilibrium, the network effect $\lambda_t$ and the predatory strategy $a_t$ can be *defined implicitly as functions of prices* $p$ *and market shares* $\pi$ *since they must solve the system given in* (2.6). Accordingly, for a given set of prices and market shares $(p, \pi)$ and given $\theta$, we will denote the solutions in $(\lambda, a)$ to the equilibrium-belief system (2.6) as $\lambda(p, \pi|\theta)$ and $a(p, \pi|\theta)$. For a pre-specified set of market shares $\pi$, plugging in these solutions into firms' expected payoff functions will allow us to characterize the equilibrium of the game purely in terms of prices $p$. This will be helpful when bringing the model to the data, where we will plug-in the observed market shares $\pi_t$ in each market $t$.

Recovering $\lambda$ and $a$ by solving (2.6) is the same principle used in BLP models (Berry, Levinsohn, and Pakes (1995)) to recover unobserved product-specific characteristics in demand models (see Nevo (2011)). In the context of BLP models, ours can be seen as a special case in which these unobserved product characteristics are modeled explicitly as functions of the unobserved predatory strategy. Sufficient conditions for invertibility of (2.6) can be based on properties of the principal minors of its Jacobian (with respect to $\lambda$ and $a$), as described in Gale and Nikaido (1965). They can also be based on the results presented in Berry, Haile, and Gandhi (2013).

### 2.4.2 Best-response prices

Expressing the network effect and the predatory strategy as implicit functions of prices and market shares by solving (2.6) allows us in turn to express expected payoff functions solely as functions of prices for a given set of market shares. For a pre-specified $\pi$ and a given $p$, let us replace $\lambda$ and $a$ with $\lambda(p, \pi|\theta)$ and $a(p, \pi|\theta)$ respectively in the expressions of expected payoff functions (2.7). We obtain,

$$
\begin{aligned}
&u_1(p, \pi|\theta, c_{1t}, c_a, \mathcal{N}_t) = (p_1 - c_{1t}) \cdot G_1(p, a(p, \pi|\theta), \pi|\theta, \lambda(p, \pi|\theta)) - \frac{c_a(a(p, \pi|\theta))}{\mathcal{N}_t}, \\
&u_2(p, \pi|\theta, c_{2t}) = (p_2 - c_{2t}) \cdot G_2(p, a(p, \pi|\theta), \pi|\theta, \lambda(p, \pi|\theta)), \\
&u_3(p, \pi|\theta, c_{3t}) = (p_3 - c_{3t}) \cdot [1 - G_1(p, a(p, \pi|\theta), \pi|\theta, \lambda(p, \pi|\theta)) - G_2(p, a(p, \pi|\theta), \pi|\theta, \lambda(p, \pi|\theta))] .
\end{aligned} \tag{2.8}
$$

This is useful because, for a given set of market shares $\pi$, the equilibrium can be described entirely in terms of prices $p$.

Fix a set of market shares $\pi$. For a given $c_1$, $c_a$ and $\mathcal{N}$, let $BR_1(p_2, p_3, \pi|\theta, c_1, c_a, \mathcal{N})$ denote the best-response price $p_1$ for firm 1 if its opponents choose prices $p_2, p_3$. Similarly, for a given $c_2$ let $BR_2(p_1, p_3, \pi|\theta, c_2)$ denote the best-response price $p_2$ for firm 2 if its opponents choose prices $p_1, p_3$. Finally, for a given $c_3$ let $BR_3(p_1, p_2, \pi|\theta, c_3)$ denote the best-response price $p_3$ for firm 3 if its opponents choose prices $p_1, p_2$. We have

$$\begin{aligned} BR_1(p_2, p_3, \pi|\theta, c_1, c_a, \mathcal{N}) &= \underset{p_1 \geq 0}{argmax}\Big\{u_1(p, \pi|\theta, c_1, c_a, \mathcal{N})\Big\}, \\ BR_2(p_1, p_3, \pi|\theta, c_2) &= \underset{p_2 \geq 0}{argmax}\Big\{u_2(p, \pi|\theta, c_2)\Big\}, \\ BR_3(p_1, p_2, \pi|\theta, c_3) &= \underset{p_3 \geq 0}{argmax}\Big\{u_3(p, \pi|\theta, c_3)\Big\}. \end{aligned} \tag{2.9}$$

# 3 Data and observable implications

We assume to observe $t = 1, \ldots, T$ realizations of this game, each one called a "market". For the $t^{th}$ realization of the game, the researcher observes prices $p_t \equiv (p_{1t}, p_{2t}, p_{3t})$, a measure of service costs $c_t \equiv (c_{1t}, c_{2t}, c_{3t})$ and market shares $\pi_t \equiv (\pi_{1t}, \pi_{2t})$ (with $\pi_{3t} = 1 - \pi_{1t} - \pi_{2t}$). With regard to $\mathcal{N}_t$ (the size of the market) we assume that either of the following is true,

(a) $\mathcal{N}_t$ is known for all $t$, or

(b) $\mathcal{N}_t/\mathcal{N}_{t^*}$ is known for all $t$ and some $t^*$.

Case (b) will correspond to our empirical example.

## 3.1 Treating observed prices as best-response equilibrium prices given the observed market shares

Suppose the prices observed $p_t$ correspond to an equilibrium of the game given the observed market shares $\pi_t$ and costs $c_t \equiv (c_{1t}, c_{2t}, c_{3t})$. Then the following must be true. For a given price vector $p \equiv (p_1, p_2, p_3)$ take the best-responses

$$\begin{aligned} BR_1(p_2, p_3, \pi_t|\theta, c_{1t}, c_a, \mathcal{N}_t) &= \underset{p_1 \geq 0}{argmax}\Big\{(p_1 - c_{1t}) \cdot G_1\big(p, a(p, \pi_t|\theta), \pi_t|\theta, \lambda(p, \pi_t|\theta)\big) - \frac{c_a\left(a(p, \pi_t|\theta)\right)}{\mathcal{N}_t}\Big\}, \\ BR_2(p_1, p_3, \pi_t|\theta, c_{2t}) &= \underset{p_2 \geq 0}{argmax}\Big\{(p_2 - c_{2t}) \cdot G_2(p, a(p, \pi_t|\theta), \pi_t|\theta, \lambda(p, \pi_t|\theta))\Big\}, \\ BR_3(p_1, p_2, \pi_t|\theta, c_{3t}) &= \underset{p_3 \geq 0}{argmax}\Big\{(p_3 - c_{3t}) \cdot G_3(p, a(p, \pi_t|\theta), \pi_t|\theta, \lambda(p, \pi_t|\theta))\Big\}. \end{aligned} \tag{3.1}$$

If we assume that the prices observed constitute an equilibrium of the game, then

$$\begin{aligned} p_{1t} &= BR_1(p_{2t}, p_{3t}, \pi_t|\theta, c_{1t}, c_a, \mathcal{N}_t), \\ p_{2t} &= BR_2(p_{1t}, p_{3t}, \pi_t|\theta, c_{2t}), \\ p_{3t} &= BR_3(p_{1t}, p_{2t}, \pi_t|\theta, c_{3t}). \end{aligned} \tag{3.2}$$

The restrictions in (3.6) would summarize the observable implications of our model and they would be the basis for inference. In order to proceed we must make more precise assumptions about the predatory-strategy cost function $c_a$.

### 3.2 A specification for the cost function of the predatory strategy, $c_a$

Using (3.6) to infer $\theta$ requires assumptions about $c_a$, the cost function for the predatory strategy $a$. As an illustration suppose we assume a power cost function of the form,

$$c_a(a) = \zeta_a \cdot a^r.$$

We assume $\zeta_a > 0$ to be a parameter that is constant across all markets $t = 1, \ldots, T$ and $r > 0$ is a pre-specified power. Consistent with our assumptions about what the researcher observes about $\mathcal{N}_t$, let $t^*$ be a market for which $\mathcal{N}_t/\mathcal{N}_{t^*} \equiv \eta_t$ is known for all $t$. Define

$$\kappa_a \equiv \frac{\zeta_a}{\mathcal{N}_{t^*}}, \quad \text{and let} \quad \widetilde{a} \equiv {\kappa_a}^{1/r} \cdot a.$$

Then, the cost-per-consumer of the predatory strategy $a$ is

$$\frac{c_a(a)}{\mathcal{N}_t} = \frac{1}{\eta_t} \cdot \widetilde{a}^r$$

The parameter $\kappa_a$ cannot be separately identified from the random utility coefficients $\gamma_2$ and $\gamma_3$ which measure the sensitivity of consumers' preferences to the predatory strategy $a$ (see Equation (2.5)). To see why, let $\widetilde{\gamma}_2 \equiv \gamma_2/{\kappa_a}^{1/r}$ and $\widetilde{\gamma}_3 \equiv \gamma_3/{\kappa_a}^{1/r}$. Then we could re-express the entire model in terms of $\widetilde{a}_t \equiv {\kappa_a}^{1/r} \cdot a_t$. The random utility functions in (2.5) can be expressed as

$$\begin{aligned}
V_{i1t} &= -\beta_1 \cdot p_{1t} + \lambda \cdot \pi^e_{i1t} + \xi_{i1t}, \\
V_{i2t} &= \delta_2 - \beta_2 \cdot p_{2t} - \widetilde{\gamma}_2 \cdot \widetilde{a}_t + \lambda_t \cdot \pi^e_{i2t} + \xi_{i2t}, \\
V_{i3t} &= \delta_3 - \beta_3 \cdot p_{3t} - \widetilde{\gamma}_3 \cdot \widetilde{a}_t + \lambda_t \cdot (1 - \pi^e_{i1t} - \pi^e_{i2t}) + \xi_{i3t}.
\end{aligned}$$

Accordingly, the choice probabilities of the representative consumer would be computed from here replacing $(\gamma_2, \gamma_3)$ with $(\widetilde{\gamma}_2, \widetilde{\gamma}_3)$ and $a$ with $\widetilde{a}$. Finally, firms' expected payoffs-per-consumer in market $t$ can be expressed as

$$\begin{aligned}
u_1(p, \widetilde{a}, \pi^e | \theta, \lambda, c_1, \eta_t) &= (p_1 - c_1) \cdot G_1(p, \widetilde{a}, \pi^e | \theta, \lambda) - \frac{1}{\eta_t} \cdot \widetilde{a}^r, \\
u_2(p, \widetilde{a}, \pi^e | \theta, \lambda, c_2) &= (p_2 - c_2) \cdot G_2(p, \widetilde{a}, \pi^e | \theta, \lambda), \\
u_3(p, \widetilde{a}, \pi^e | \theta, \lambda, c_3) &= (p_3 - c_3) \cdot \left[1 - G_1(p, \widetilde{a}, \pi^e | \theta, \lambda) - G_2(p, \widetilde{a}, \pi^e | \theta, \lambda)\right].
\end{aligned}$$

Thus, any cost function of the form $c_a(a) = \zeta_a \cdot a^r$ is observationally equivalent to a model where the cost-per-consumer for the predatory strategy is

$$\frac{1}{\eta_t} \cdot a^r \tag{3.3}$$

and where the predatory-strategy sensitivity parameters in (2.5) are measured relative to ${\kappa_a}^{1/r} \equiv \zeta_a / {\mathcal{N}_{t^*}}^{1/r}$. As a result, we shall assume the cost-per-consumer expression (3.3) and our interpretation for the magnitude of the parameters $\gamma_2, \gamma_3$ will be relative to ${\kappa_a}^{1/r}$. As a result, under this specification for predatory-strategy costs, our expected payoff-per-consumer functions in market $t$ described in (2.7) become,

$$\begin{aligned} u_1(p, a, \pi^e|\theta, \lambda_t, c_{1t}, \eta_t) &\equiv (p_1 - c_{1t}) \cdot G_1(p, a, \pi^e|\theta, \lambda_t) - \frac{1}{\eta_t} \cdot a^r, \\ u_2(p, a, \pi^e|\theta, \lambda_t, c_{2t}) &\equiv (p_2 - c_{2t}) \cdot G_2(p, a, \pi^e|\theta, \lambda_t), \\ u_3(p, a, \pi^e|\theta, \lambda_t, c_{3t}) &\equiv (p_3 - c_{3t}) \cdot \left[1 - G_1(p, a, \pi^e|\theta, \lambda_t) - G_2(p, a, \pi^e|\theta, \lambda_t)\right]. \end{aligned} \tag{3.4}$$

### 3.3 Observable implications for $\theta$

Using the power function specification for predatory-strategy costs described in Section 3.2 and the resulting expression for expected payoff-per-consumer functions in (3.4), the best-response functions described in (3.1) become,

$$\begin{aligned} BR_1(p_2, p_3, \pi_t|\theta, c_{1t}, \eta_t) &= \underset{p_1 \geq 0}{argmax}\Big\{(p_1 - c_{1t}) \cdot G_1\big(p, a(p, \pi_t|\theta), \pi_t\big|\theta, \lambda(p, \pi_t|\theta)\big) - \frac{1}{\eta_t} \cdot a(p, \pi_t|\theta)^r\Big\}, \\ BR_2(p_1, p_3, \pi_t|\theta, c_{2t}) &= \underset{p_2 \geq 0}{argmax}\Big\{(p_2 - c_{2t}) \cdot G_2(p, a(p, \pi_t|\theta), \pi_t|\theta, \lambda(p, \pi_t|\theta))\Big\}, \\ BR_3(p_1, p_2, \pi_t|\theta, c_{3t}) &= \underset{p_3 \geq 0}{argmax}\Big\{(p_3 - c_{3t}) \cdot G_3(p, a(p, \pi_t|\theta), \pi_t|\theta, \lambda(p, \pi_t|\theta))\Big\}. \end{aligned} \tag{3.5}$$

If we assume that the prices observed constitute an equilibrium of the game, then

$$\begin{aligned} p_{1t} &= BR_1(p_{2t}, p_{3t}, \pi_t|\theta, c_{1t}, \eta_t), \\ p_{2t} &= BR_2(p_{1t}, p_{3t}, \pi_t|\theta, c_{2t}), \\ p_{3t} &= BR_3(p_{1t}, p_{2t}, \pi_t|\theta, c_{3t}). \end{aligned} \tag{3.6}$$

The equilibrium relationship between prices and best-response functions described in (3.6) summarizes the observable implications of the model and would therefore lay the inferential foundation for $\theta$. A generic moment-based approach can be described as follows. Group

$$BR(p_t, \pi_t|\theta, c_t, \eta_t) \equiv \big(BR_1(p_{2t}, p_{3t}, \pi_t|\theta, c_{1t}, \eta_t),\ BR_2(p_{1t}, p_{3t}, \pi_t|\theta, c_{2t}),\ BR_3(p_{1t}, p_{2t}, \pi_t|\theta, c_{3t})\big)'.$$

Let $z_t$ denote additional observable variables (if any) other than $(p_t, c_t, \pi_t, \eta_t)$ and let $x_t \equiv (p_t, c_t, \pi_t, \eta_t, z_t)$. Take a function

$$\rho(p_t - BR(p_t, \pi_t|\theta, c_t, \eta_t); x_t) \quad \text{such that} \quad E\left[\rho(0; x_t)\right] = 0.$$

For example,

$$\rho(p_t - BR(p_t, \pi_t|\theta, c_t, \eta_t); x_t) = \Sigma(x_t)\left(p_t - BR(p_t, \pi_t|\theta, c_t, \eta_t)\right),$$

where $\underbrace{\Sigma(x_t)}_{d\times 3}$ is a prespecified collection of "instrument functions". Let

$$M(\theta) = E\left[\rho(p_t - BR(p_t, \pi_t|\theta, c_t, \eta_t); x_t)\right],$$

where the expectation is taken over the observable characteristics $x_t \equiv (p_t, c_t, \pi_t, \eta_t, z_t)$. Our assumptions imply that, for any such $\rho$, we must have

$$M(\theta) = 0. \tag{3.7}$$

Estimation and inference (e.g, the construction of a confidence set) for $\theta$ can be based on (3.7) employing conventional moment-based econometric methods (see Newey and McFadden (1994)). Alternatively, a more powerful approach based on conditional moment restrictions can be employed (see, e.g, Dominguez and Lobato (2004) and Andrews and Shi (2013)).

# 4 Extensions

Our baseline model is inspired by the features of our eventual empirical example. However, the model can be extended in multiple ways depending on the richness of the data. We outline some of the most important potential extensions here.

## 4.1 A model with $J \geq 4$ competing firms

The most straightforward extension would be to leave player 1 as the only one with a predatory strategy but extend the setting from 3 to $J \geq 4$ total players, $J-1$ of which can be affected by the predatory efforts of player 1. To be precise, suppose we generalize the random utility system (2.5) to

$$
\begin{aligned}
V_{i1t} &= -\beta_1 \cdot p_{1t} + \lambda_t \cdot \pi^e_{i1t} + \xi_{i1t}, \\
V_{i2t} &= \delta_2 - \beta_2 \cdot p_{2t} - \gamma_2 \cdot a_t + \lambda_t \cdot \pi^e_{i2t} + \xi_{i2t}, \\
V_{i3t} &= \delta_3 - \beta_3 \cdot p_{3t} - \gamma_3 \cdot a_t + \lambda_t \cdot \pi^e_{i3t} + \xi_{i3t}, \\
V_{i4t} &= \delta_4 - \beta_4 \cdot p_{4t} - \gamma_4 \cdot a_t + \lambda_t \cdot \pi^e_{i4t} + \xi_{i4t}, \\
\vdots \quad & \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\
V_{iJt} &= \delta_J - \beta_J \cdot p_{Jt} - \gamma_J \cdot a_t + \lambda_t \cdot \left(1 - \sum_{j=1}^{J-1} \pi^e_{ijt}\right) + \xi_{iJt}
\end{aligned}
\tag{4.1}
$$

Generalizing Assumption 1 to this case, $(\xi_{i1t}, \xi_{i2t}, \ldots, \xi_{iJt})$ would be assumed to be iid with a Type I Extreme Value distribution and the choice probability expressions in (2.4) would be straightforwardly extended to $G_1(p_t, a_t, \pi|\theta, \lambda_t)$, $G_2(p_t, a_t, \pi|\theta, \lambda_t)$, …, $G_J(p_t, a_t, \pi|\theta, \lambda_t)$ in this case. If we generalize the equilibrium-beliefs conditions in Assumption 2, the system (2.6) would become

$$
\left.
\begin{aligned}
&\pi_1 - G_1(p, a, \pi|\theta, \lambda) = 0, \\
&\pi_2 - G_2(p, a, \pi|\theta, \lambda) = 0, \\
&\pi_3 - G_3(p, a, \pi|\theta, \lambda) = 0, \\
&\vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\
&\pi_{J-1} - G_{J-1}(p, a, \pi|\theta, \lambda) = 0.
\end{aligned}
\right\} J - 1 \text{ restrictions}
\tag{4.2}
$$

In our 3-player model we used the equilibrium-belief system (4.2) to express $\lambda$ and $a$ as implicit functions of prices $p$ and market shares $\pi$. We can extend this approach as follows. Partition prices as

$$
p \equiv (\underbrace{p_1, p_2, p_3}_{\equiv p^I}, \underbrace{p_4, \ldots, p_J}_{\equiv p^{II}}) \equiv (p^I, p^{II}), \quad \text{where} \quad p^I \equiv (p_1, p_2, p_3), \quad p^{II} \equiv (p_4, \ldots, p_J).
$$

Suppose we assume again the power function specification for the predatory strategy cost function described in Section 3.2. Using (4.2), we can now express $(\lambda, a, p^{II}) \in \mathbb{R}^{J-1}$ as implicit functions of $(p^I, \pi)$. Denoting them as $\lambda(p^I, \pi|\theta)$, $a(p^I, \pi|\theta)$ and $p^{II}(p^I, \pi|\theta)$ and letting

$$
p(p^I, \pi|\theta) \equiv (p^I, p^{II}(p^I, \pi|\theta)),
$$

the equilibrium expected payoff functions of firms 1, 2 and 3 can be expressed as

$$\begin{aligned} u_1(p^I,\pi|\theta,c_1,\eta) &= (p_1-c_1)\cdot G_1(p(p^I,\pi|\theta),a(p^I,\pi|\theta),\pi|\theta,\lambda(p^I,\pi|\theta)) - \frac{a(p^I,\pi|\theta)^r}{\eta}, \\ u_2(p^I,\pi|\theta,c_2) &= (p_2-c_2)\cdot G_2(p(p^I,\pi|\theta),a(p^I,\pi|\theta),\pi|\theta,\lambda(p^I,\pi|\theta)), \\ u_3(p^I,\pi|\theta,c_3) &= (p_3-c_3)\cdot G_3(p(p^I,\pi|\theta),a(p^I,\pi|\theta),\pi|\theta,\lambda(p^I,\pi|\theta)). \end{aligned} \tag{4.3}$$

This is a generalization of (2.8). Best-response prices for firms 1,2 and 3 are given by

$$\begin{aligned} BR_1(p_2,p_3,\pi|\theta,c_1,\eta) &= \underset{p_1\geq 0}{argmax}\Big\{u_1(p^I,\pi|\theta,c_1,\eta)\Big\}, \\ BR_2(p_1,p_3,\pi|\theta,c_2) &= \underset{p_2\geq 0}{argmax}\Big\{u_2(p^I,\pi|\theta,c_2)\Big\}, \\ BR_3(p_1,p_2,\pi|\theta,c_3) &= \underset{p_3\geq 0}{argmax}\Big\{u_3(p^I,\pi|\theta,c_3)\Big\}. \end{aligned} \tag{4.4}$$

This is a generalization of equation (2.9). As it was the case with $J = 3$ and equation (3.6), if we assume that prices observed are equilibrium prices, the implications of the model would be summarized by the conditions

$$\begin{aligned} p_{1t} &= BR_1(p_{2t},p_{3t},\pi_t|\theta,c_{1t},\eta_t), \\ p_{2t} &= BR_2(p_{1t},p_{3t},\pi_t|\theta,c_{2t}), \\ p_{3t} &= BR_3(p_{1t},p_{2t},\pi_t|\theta,c_{3t}). \end{aligned} \tag{4.5}$$

Inference for $\theta$ can then proceed using the arguments outlined in Section 3.3. Note that when $J \geq 4$ we can follow the previous steps with any combination of 3 out of the $J$ competing firms as the elements in $p^I$ (i.e, not necessarily firms 1, 2 and 3). In this sense the model would now be overidentified.

### 4.2 Allowing for firm-specific, market-level random utility coefficients $\boldsymbol{\delta_{jt}}$

Let us remain in the more general $J \geq 4$ player setting. A key feature of BLP demand models is the inclusion of market-level, product-specific unobserved random utility shocks. We can enrich our model in this fashion by allowing the firm-specific utility shocks $\delta_j$ to be market-level, unobserved random variables. Accordingly, let us denote them now as $\delta_{jt}$, for $j = 2, \ldots, J$.

One way to approach this could be as follows. Let us now assume that the network coefficient $\lambda$ is constant across all markets[4]. Group

$$\delta \equiv (\delta_2, \delta_3, \ldots, \delta_J), \quad \Gamma \equiv (\beta_1, \beta_2, \ldots, \beta_J, \gamma_2, \gamma_3, \ldots, \gamma_J, \lambda).$$

Accordingly, for a given $(p, a, \pi, \delta, \Gamma)$ let us express the choice probabilities as $G_j(p, a, \pi|\delta, \Gamma)$. The belief-equilibrium system (4.2) can be expressed as

$$\left.\begin{array}{l} \pi_1 - G_1(p, a, \pi|\delta, \Gamma) = 0, \\ \pi_2 - G_2(p, a, \pi|\delta, \Gamma) = 0, \\ \pi_3 - G_3(p, a, \pi|\delta, \Gamma) = 0, \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ \pi_{J-1} - G_{J-1}(p, a, \pi|\delta, \Gamma) = 0. \end{array}\right\} J-1 \text{ restrictions} \tag{4.6}$$

For a given $(p, a, \pi, \Gamma)$, we can now use the equilibrium-belief system (4.6) to recover $\delta$ as an implicit function of $(p, a, \pi, \Gamma)$. Let us denote it as

$$\delta(p, a, \pi, \Gamma) \in \mathbb{R}^{J-1} \tag{4.7}$$

Conditions for the system (4.6) to be invertible in terms of $\delta$ is the type of problem studied in Berry, Haile, and Gandhi (2013). Again, sufficient conditions can revolve around the principal minor properties of the Jacobian of (4.6) (with respect to $\delta$) described in Gale and Nikaido (1965). Let us maintain the power-function specification for the predatory strategy cost we analyzed above. For a given $(p, a, \pi, \Gamma)$, we can plug in (4.7) in place of $\delta$ and obtain an expression for expected payoff-per-consumer functions in terms of $(p, a, \pi, \Gamma)$ along with the costs $(c_1, c_2, \ldots, c_J)$ and $\eta$

$$\begin{aligned} u_1(p, a, \pi|\Gamma, c_1, \eta) &= (p_1 - c_1) \cdot G_1\big(p, a, \pi\big|\delta(p, a, \pi, \Gamma), \Gamma\big) - \frac{a^r}{\eta}, \\ u_2(p, a, \pi|\Gamma, c_2) &= (p_2 - c_2) \cdot G_2\big(p, a, \pi\big|\delta(p, a, \pi, \Gamma), \Gamma\big), \\ &\vdots \\ u_J(p, a, \pi|\Gamma, c_J) &= (p_J - c_J) \cdot G_J\big(p, a, \pi\big|\delta(p, a, \pi, \Gamma), \Gamma\big). \end{aligned}$$

For a given $(p, \pi, \Gamma, c_1, \eta)$, the optimal choice for the predatory strategy of firm 1 is given by,

$$a^*(p, \pi|\Gamma, c_1, \eta) = \underset{a \geq 0}{argmax} \left\{ u_1(p, a, \pi|\Gamma, c_1, \eta) \right\}.$$

[4] Instead of using this assumption, we could impose a restriction –e.g, symmetry– that reduces the dimensionality of the unknown market-specific coefficients $\delta_{jt}$'s below $J - 1$.

Let us now plug in this expression in place of $a$ in the expected payoff functions described above, so we can express them solely as functions of $(p, \pi, \Gamma, c_1, \ldots, c_J, \eta)$,

$$\begin{aligned} u_1(p, \pi|\Gamma, c_1, \eta) &\equiv u_1\big(p, a^*(p, \pi|\Gamma, c_1, \eta), \pi|\Gamma, c_1, \eta\big), \\ u_2(p, a, \pi|\Gamma, c_2, c_1, \eta) &\equiv u_2(p, a^*(p, \pi|\Gamma, c_1, \eta), \pi|\Gamma, c_2), \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad &\vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ u_J(p, a, \pi|\Gamma, c_J, c_1, \eta) &\equiv u_J(p, a^*(p, \pi|\Gamma, c_1, \eta), \pi|\Gamma, c_J). \end{aligned}$$

Let $p_{-j} \equiv (p_\ell)_{\ell \neq j}$. From the above expressions we can characterize best-response prices for each firm,

$$\begin{aligned} BR_1(p_{-1}, \pi|\Gamma, c_1, \eta) &= \underset{p_1 \geq 0}{argmax} \left\{u_1(p, \pi|\Gamma, c_1, \eta)\right\}, \\ BR_2(p_{-2}, \pi|\Gamma, c_2, c_1, \eta) &= \underset{p_2 \geq 0}{argmax} \left\{u_2(p, a, \pi|\Gamma, c_2, c_1, \eta)\right\}, \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad &\vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ BR_J(p_{-J}, \pi|\Gamma, c_J, c_1, \eta) &= \underset{p_J \geq 0}{argmax} \left\{u_J(p, a, \pi|\Gamma, c_J, c_1, \eta)\right\}. \end{aligned}$$

From here, if we assume that the prices observed in market $t$ are an equilibrium, the implications of the model would be summarized by the conditions

$$\begin{aligned} p_{1t} &= BR_1(p_{-1t}, \pi_t|\Gamma, c_{1t}, \eta_t), \\ p_{2t} &= BR_2(p_{-2t}, \pi_t|\Gamma, c_{2t}, c_{1t}, \eta_t), \\ \vdots \quad &\vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ p_{Jt} &= BR_J(p_{-Jt}, \pi_t|\Gamma, c_{Jt}, c_{1t}, \eta_t). \end{aligned} \tag{4.8}$$

Inference for $\Gamma$ can proceed from here along the lines of Section 3.3.

## 4.3 Introducing consumer-level data

Our baseline model presupposed that we only have market-level data. Adapting it to consumer-level data can be done straightforwardly, as it is the case in BLP-type demand models (see Nevo (2000) and Nevo (2011, Section 3.3.2)). For example, this can allow us to assume random-coefficients at the individual level for consumers' random utility functions which can be parameterized as functions of observable consumer characteristics, plus an unobserved consumer attribute with a known, parametric distribution (see Nevo (2011, Equation (8))). This can allow us, for instance, to assume that both the network effect and the effect of the predatory strategy are consumer-specific. With regard to firms' behavior we would still assume that firms choose prices and the predatory strategy for each market by maximizing their expected payoff-per-consumer at the market level. Firms would solve this problem by averaging choice probabilities across consumers. Finally, if consumer beliefs are unobserved in the data (this would likely be the case in most applications), we can still recover them by assuming that consumers have equilibrium beliefs at the market level. Accordingly, the equilibrium conditions in (4.2) can be extended to this setting, once again, by averaging choice probabilities across consumers.

# 5 An empirical illustration for the wireless telecommunications industry in Mexico

## 5.1 Main players in the industry

Since 2016, the wireless telecommunications market in Mexico has been dominated by three carriers[5]: América Móvil (AMX), Telefónica México (TEF) and AT&T México (AT&T). Together they provide service to approximately 99% of all users in the country. Having started as monopolist[6] Telmex's mobile-phone division in the 1990s, AMX was formally established in 2000. TEF first entered the Mexican market in 2000 and AT&T entered in 2015.

Following the Mexican currency crisis of 1995, AMX's predecessor became the dominant player in the wireless market. Table 1 shows the market shares of these three carriers in 2016, 2017 and 2018. As we can see, AMX's market share was close to two thirds during the time period. This share remained persistently high in spite of a sweeping telecommunications reform which came into effect in 2013 and was aimed at increasing the level of competition.

**Table 1: Market shares in the Mexican wireless telecommunications industry**

| | 2016 | 2017 | 2018 |
|---|---|---|---|
| AMX | 65% | 65% | 63% |
| AT&T | 11% | 13% | 15% |
| TEF | 24% | 22% | 22% |

(†) These figures exclude the combined market share of other providers. This combined market share was 1.1% in 2016, 1.3% in 2017 and 1.3% in 2018.

In what follows, we will label players as follows:

· Player 1: AMX. · Player 2: AT&T. · Player 3: TEF.

[5] AMX and TEF operate under the brands "Telcel" and "Movistar", respectively.

[6] Telmex emjoyed a decades-long monopoly in the fixed-telephone market in Mexico following its privatization in 1990.

### 5.2 2013 telecommunications reform in Mexico

Prior to 2013 the telecommunication industry in Mexico was highly concentrated, with AMX enjoying more than 70% of the market. Lack of competition led to consistently high prices and a stagnant mobile phone penetration. To address this, the Mexican Congress approved a sweeping telecommunications reform in 2013 whose main aim was to promote competition and ensure consumer access to telecommunication services[7]. The reform established a new regulator (the Federal Telecommunications Institute or 'IFT') with the power to declare preponderance of the dominant firm (AMX) and impose asymmetrical rules between AMX and its competitors. Among the most important new regulations, *AMX was required to provide its competitors access to its infrastructure at competitive rates.* While the reform led to the entry of new firms and a decrease in prices, the industry remains highly concentrated in comparison with other countries and AMX's market share remains very high by international standards. As Figure 1 and Table 2 illustrate, an international comparison of the Herfindahl–Hirschman Index[8] (HHI) shows that even five years after the reform, the Mexican wireless telecommunications market remained extraordinarily concentrated relative to other countries in the region, including the United States.

#### 5.2.1 Predatory practices by AMX

Even though the 2013 reform explicitly requires it, AMX has persistently failed to share its infrastructure (cellphone towers, poles, ducts, conduits, and rights-of-way) in a timely and effective manner with its competitors. Critics of the reform have pointed out that the laws enacted lacked the necessary teeth to force AMX to comply. As a result, AMX has been accused multiple times by its competitors of failing to provide timely access to its infrastructure[9] in a timely and effective way. After several years of this conduct, in January 2020 the IFT finally took the unprecedented step of imposing a $70-million dollar fine to AMX for failing to share information about the availability of its telecommunication

[7] See, for example:
- Malkin, Elisabeth (2013-03-11). "Mexican Leaders Propose a Telecom Overhaul", *New York Times.* URL: https://www.nytimes.com/2013/03/12/business/global/mexican-plan-would-rein-in-phone-and-tv-providers.html
- Estevez, Dolia (2013-05-01). "Mexico's Congress Passes Monopoly-Busting Telecom Bill, Threatening Tycoon Carlos Slim's Business Empire", *Forbes.* URL: https://www.forbes.com/sites/doliaestevez/2013/05/01/mexicos-congress-passes-monopoly-busting-telecom-bill-threatening-tycoon-carlos-slims-business-empire/?sh=412beef4b073

[8] Antitrust authorities in the United States generally classify markets into three types: Unconcentrated ($HHI < 1500$), Moderately Concentrated ($1500 < HHI < 2500$), and Highly Concentrated ($HHI > 2500$).

[9] Estevez, Dolia (2017-04-10). "Mexico's Anti-Monopoly Telecom Reform has Done Little to End Tycoon Carlos Slim's Market Dominance", *Forbes.* URL: https://www.forbes.com/sites/doliaestevez/2017/04/10/mexicos-anti-monopoly-telecom-reform-has-done-little-to-end-tycoon-carlos-slims-market-dominance/?sh=5b137496e9fb

Figure 1: A comparison of market concentration levels in the wireless telecommunications industry in Latin America

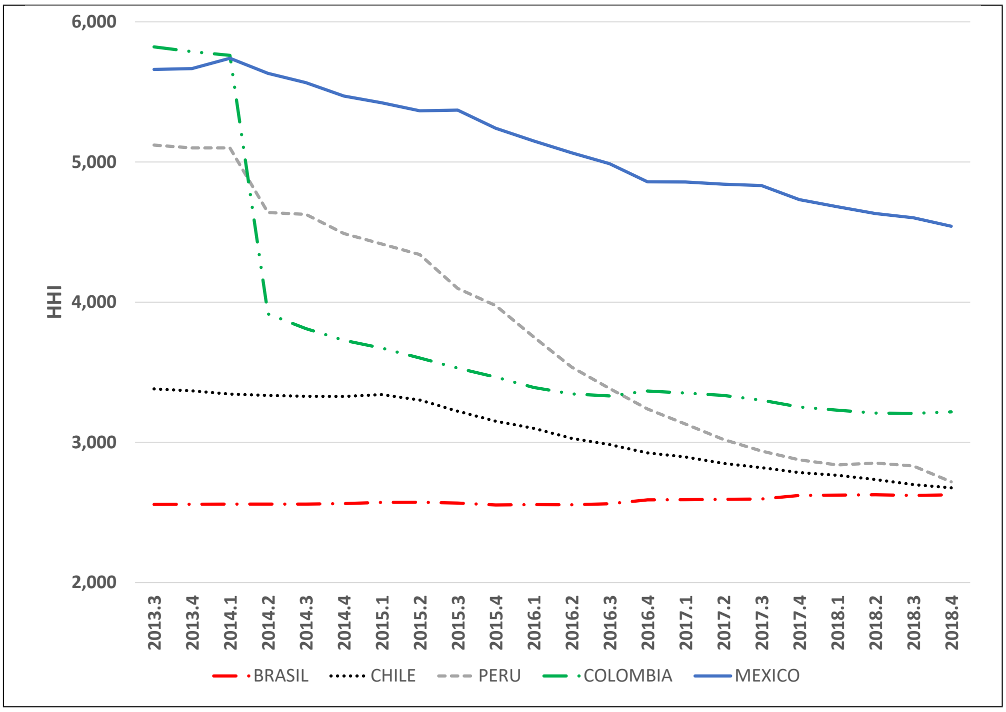


**Table 2: HHI comparison for the wireless telecommunications industry in the Americas**

| | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
|---|---|---|---|---|---|---|---|
| **United States** | 2,873 | 2,966 | 3,027 | 3,138 | 3,111 | 3,101 | 3,106 |
| **Brazil** | 2,562 | 2,559 | 2,559 | 2,564 | 2,554 | 2,591 | 2,621 |
| **Chile** | 3,477 | 3,429 | 3,442 | 3,437 | 3,151 | 2,925 | 2,766 |
| **Colombia** | 5,939 | 5,984 | 5,787 | 3,728 | 3,466 | 3,367 | 3,253 |
| **Peru** | 5,059 | 5,034 | 5,100 | 4,489 | 3,976 | 3,238 | 2,876 |
| **Mexico** | 5,312 | 5,301 | 5,667 | 5,470 | 5,239 | 4,858 | 4,731 |

• Data source for Latin America: Credit Suisse TMT Fact Sheet.
• Data source for the United States: *Annual Report and Analysis of Competitive Market Conditions, 2017* and *Communications Marketplace Report, 2018*. Federal Communications Commission.
• HHI for the United States in 2018 had not been published by the FCC at the time this table was constructed.

infrastructure with competitors[10]

[10]Love, Julia (2020-01-27). "Mexico's America Movil fined by regulator; calls it 'illegal and disproportionate' ", *Reuters*. URL: https://www.reuters.com/article/us-mexico-americamovil/mexicos-america-

AMX's strategic failure to share its infrastructure fits our characterization of a "predatory strategy". By creating data traffic bottlenecks, *it cements the impression among consumers that AMX's service quality and coverage are inherently superior to those of its competitors.* This shifts consumers away from AMX's competitors, which is the way we modeled the effect of the predatory strategy. AMX has also been accused by its rivals of enforcing exclusionary deals with third-party outlets (convenience stores) whereby AMX would offer discounts in pre-paid cellphone cards and other products in exchange for suppressing the sale of AMX's competitors' products. This also has the effect of separating consumers from AMX's competitors and thus fits our definition of a predatory strategy.

While the above constitute examples of anticompetitive practices, AMX also has other predatory advantages with are not necessarily anticompetitive in nature. Foremost among them is AMX's vast advantage in terms of its distribution and sales network (built during the decades when Telmex enjoyed a monopolist position) which the reform does not require AMX to share in any way with its competitors. This makes it easier for consumers to acquire products and services from AMX, shifting them away from its competitors. The cost of maintaining and expanding this sales network as well as the costs associated with engaging in anticompetitive predatory practices (e.g, litigation fees, fines by the IFT, etc.) would constitute the cost of AMX's predatory strategy in our model. Overall we contend that our model, while simple, is a reasonable approximation to the state of the wireless telecommunications industry in the Mexican market, particularly given the scarcity of data available.

#### 5.2.2 An explanation for AMX's persistently high market share: predatory practices or network effect?

Prior to the reform, wireless carriers in Mexico were allowed to discriminate incoming traffic –in terms of pricing and quality of service– depending on which carrier originated this incoming traffic. Since AMX enjoyed the largest market share, this incentivized consumers to choose and remain with AMX. This was known as the "club effect" by the IFT and the discrimination behind it was outlawed by the 2013 reform. The strength of the club effect can be captured, at least partially, by our network-effect coefficient. A crucial policy question is whether AMX's persistently high market share can be explained by this network effect (which stems from consumer behavior and habits[11]) or by the predatory effect (which stems from AMX's direct behavior). By separating both effects, our model allows us to shed light on this important issue.

movil-fined-by-regulator-calls-it-illegal-and-disproportionate-idUSKBN1ZQ2FI

[11] One possibility is that consumers have not internalized that, following the 2013 reform, carriers are no longer allowed to discriminate incoming traffic, and that the incentives of choosing their carrier based on the "club effect" have effectively vanished.

### 5.2.3 Data and measures of price and costs

As is the nature of wireless services, each competing firm offers different plans and options[12]. Data that could allow us to meaningfully compare prices of equivalent wireless plans between carriers over time is not publicly available. Furthermore, consumer-level data is also not available. Our time horizon is also short: AT&T entered the Mexican market in 2015 and it started to effectively compete in 2016, and final data for 2019 has still not been released at the time of elaboration of this paper. As a result, we only have comparable data for the years 2016, 2017 and 2018 and this will be our sample. Lastly, even though quarterly data is available, variation across quarters within each year is minimal; for this reason, our empirical illustration will rely on yearly information for 2016, 2017 and 2018. That is, our data consists of three observations, $t = 2016, 2017, 2018$, and we will treat each year as an independent realization of the game described in the previous section. Our methodology assumes that we observe a measure of prices and costs. These were obtained as follows,

- **A price measure.** As we mentioned above, there is no publicly available, comparable data for specific wireless plans[13]. For this reason we opted to construct an aggregate price measure for each firm using publicly available information. For each firm $\ell$ and year $t$ we defined

$$p_{jt} = \frac{\text{total wireless service revenue for firm } j \text{ in year } t}{\text{total number of active subscribers (active SIM cards) for firm } j \text{ in year } t}$$

  Our measure of price is the service revenue per subscriber for each firm. This is an indicator commonly used in the industry and known as average revenue per user (ARPU). It aggregates across the different plans offered by each firm but we contend that variations of this measure across firms and across years should capture the corresponding variation in price levels. By focusing exclusively on mobile service revenue, our price measure excludes things such as equipment sales and other sources of revenue, thus more credibly capturing only variation in the prices and fees of wireless plans.

- **A measure of the cost of providing service.** Using the same logic we construct a measure of cost-per-consumer of providing service which can be directly comparable

[12] The Mexican wireless telecommunications market is dominated by prepaid plans. In 2018, approximately 83 percent of mobile subscriptions in Mexico were prepaid, whereas 17 percent were postpaid (i.e, paying a monthly rent).

[13] Also importantly, there is no data available of market shares for specific types of plans, only aggregate market shares.

to our price measure. For each firm $j$ and year $t$ we defined

$$c_{jt} = \frac{\text{total cost of service for firm } j \text{ in year } t}{\text{total number of active subscribers (active SIM cards) for firm } j \text{ in year } t}$$

Table 3 compares the price measures for AT&T and TEF relative to AMX in 2016, 2017 and 2018. As we can see there, these *relative prices decreased in all three years.* We can also see that AT&T's price measure was higher than that of AMX while the opposite was true for TEF. This reflects the fact that each one of these carriers specializes in different types of plans. While TEF specializes mostly in cheap, prepaid plans, AT&T is the carrier with the highest proportion of postpaid plans where customers pay a monthly rent, and these plans are the most expensive. AMX has a more balanced mix of prepaid and postpaid plans. Overall, prepaid plans tend to be cheaper and they come with fewer perks and features. Postpaid plans are more expensive but they have benefits such as more reliable data speeds. Having firm-specific coefficients in our random utility specifications allows our model to accommodate this type of product differentiation.

**Table 3: A relative comparison of our price measure**

| | 2016 | 2017 | 2018 |
|---|---|---|---|
| $(p_{2t}/p_{1t})$ | 2.08 | 1.73 | 1.09 |
| $(p_{3t}/p_{1t})$ | 0.64 | 0.56 | 0.45 |

$p_{1t}$ = AMX price measure in year $t$,

$p_{2t}$ = AT&T price measure in year $t$,

$p_{3t}$ = TEF price measure in year $t$.

Table 4 describes our measure of cost of service relative to our measure of price during the time period analyzed. This proportion remained almost constant for AMX during the three years analyzed. For AT&T and TEF, it remained approximately constant in 2016 and 2017 and it jumped in 2018. This followed both firms' aggressive bidding in spectrum auctions (particularly AT&T) in an effort to expand their 4G capabilities and compete with AMX. As the table indicates, AT&T had a smaller profit margin than its two competitors during the period analyzed.

**Table 4: Cost of service as a proportion of price**

| | 2016 | 2017 | 2018 |
|---|---|---|---|
| $(c_{1t}/p_{1t})$ | 0.38 | 0.37 | 0.38 |
| $(c_{2t}/p_{2t})$ | 0.69 | 0.66 | 0.82 |
| $(c_{3t}/p_{3t})$ | 0.37 | 0.39 | 0.46 |

$c_{1t}/p_{1t}$ = AMX in year $t$,
$c_{2t}/p_{2t}$ = AT&T in year $t$,
$c_{3t}/p_{3t}$ = TEF in year $t$.

## 5.3 An empirical implementation of our model

### Parameterization of the utility function

Our representative consumer random utility is parameterized as described in (2.5). That is,

$$V_1 = -\beta_1 \cdot p_1 + \lambda \cdot \pi_1^e + \xi_1, \qquad \text{(utility from selecting AMX)}$$
$$V_2 = \delta_2 - \beta_2 \cdot p_2 - \gamma_2 \cdot a + \lambda \cdot \pi_2^e + \xi_2, \qquad \text{(utility from selecting AT\&T)}$$
$$V_3 = \delta_3 - \beta_3 \cdot p_3 - \gamma_3 \cdot a + \lambda \cdot \pi_3^e + \xi_3, \qquad \text{(utility from selecting TEF)}$$

### Parameterization of the predatory-strategy cost function

We assumed a *quadratic* cost function for AMX's predatory strategy. Regarding the cost-per-consumer for the predatory strategy, we noted first that there was very little change in the size of the cellphone market $\mathcal{N}_t$ during these three years, so we fixed $\eta_t = 1$ for the three periods. Consequently, as discussed in in Section 3.2, we used

$$\frac{a_t^r}{\eta_t} = a_t^2,$$

for the three years observed.

### Unknown parameters and observable implications in our empirical example

The model consist of seven parameters,

$$\theta \equiv (\delta_2, \delta_3, \beta_1, \beta_2, \beta_3, \gamma_2, \gamma_3) \in \mathbb{R}^7.$$

If we assumed that prices observed are best-response equilibrium prices the model would produce nine restrictions, as described in (3.6),

$$\left.\begin{aligned} p_{1t} &= BR_1(p_{2t}, p_{3t}, \pi_t|\theta, c_{1t}, \eta_t) \\ p_{2t} &= BR_2(p_{1t}, p_{3t}, \pi_t|\theta, c_{2t}) \\ p_{3t} &= BR_3(p_{1t}, p_{2t}, \pi_t|\theta, c_{3t}) \end{aligned}\right\} \text{ for } t = 2016, 2017, 2018.$$

with $\eta_t = 1$ for the three years (for the reasons described above) and quadratic specification for AMX's predatory-strategy cost function. Due to the limited nature of our data, we will take a conservative approach and we will characterize and compute a *set of parameter values* $\theta$ such that prices observed are "close" to being an equilibrium of the model given the market shares observed. We describe how we approached this next.

### 5.3.1 Computing a set of parameter values for which the outcomes observed in the data are "close" to being an equilibrium of the model

Our limited data set precludes any econometric analysis based on asymptotic theory. However, the fact that our model produces more restrictions (nine) than the number of parameters (seven) means that identifying parameter values that are consistent with our model (in a well defined sense) and rejecting parameter values that are not, is still a meaningful exercise and we will undertake it as follows. For a given $\theta$ group

$$BR(p_t, \pi_t|\theta, c_t, \eta_t) \equiv (BR_1(p_{2t}, p_{3t}, \pi_t|\theta, c_{1t}, \eta_t),\ BR_2(p_{1t}, p_{3t}, \pi_t|\theta, c_{2t}),\ BR_3(p_{1t}, p_{2t}, \pi_t|\theta, c_{3t}))'.$$

And let

$$\rho(p_t - BR(p_t, \pi_t|\theta, c_t, \eta_t); x_t) = \frac{1}{3}\left(\frac{|p_{1t} - BR_1(p_{2t}, p_{3t}, \pi_t|\theta, c_{1t}, \eta_t)|}{p_{1t}} + \frac{|p_{2t} - BR_2(p_{1t}, p_{3t}, \pi_t|\theta, c_{2t})|}{p_{2t}} + \frac{|p_{3t} - BR_3(p_{1t}, p_{2t}, \pi_t|\theta, c_{3t})|}{p_{3t}}\right). \tag{5.1}$$

This measures the average percentage difference across the three firms between observed prices and best-response equilibrium prices predicted by $\theta$ in year $t$. By construction we have $\rho(0; x_t) = 0$. Let

$$\overline{M}(\theta) = \frac{1}{3}\sum_{t=2016}^{2018} \rho(p_t - BR(p_t, \pi_t|\theta, c_t, \eta_t); x_t).$$

$\overline{M}(\theta)$ measures the average percentage difference between observed prices and best-response equilibrium prices for the three firms across the three years observed. Now let

$$\widetilde{\Theta} = \left\{\theta \in \Theta \colon\ \overline{M}(\theta) < 0.025\right\}. \tag{5.2}$$

The set $\widetilde{\Theta}$ is *the collection of parameter values such that the average percentage difference between observed prices and best-response equilibrium prices is less than 2.5% for our sample.* Computing results based on $\widetilde{\Theta}$ will be the focus of our empirical exercise. Note that any $\theta$ for which prices observed are *exactly* an equilibrium of the game would be contained in $\widetilde{\Theta}$. However, by focusing on a set rather than a point (e.g, the global minimizer of $\overline{M}(\theta)$), we can compute a *range* of possible versions of our model that can provide a reasonable approximation to the outcomes observed in our limited data. From here we can compute a range of values for the various effects (price, network, predatory strategy) in our model. Focusing on $\widetilde{\Theta}$ also helps us avoid having to assume that $\theta$ is point-identified or that there is a unique equilibrium to the game (or that an equilibrium exists at all); we only focus on finding a *set* of parameter values for which the observed outcome is "close" to being an equilibrium of the model, in the sense described in (5.2).

### 5.3.2 Results

We performed a grid search to find parameter values consistent with criterion (5.2). The parameter space was constrained as follows,

$$\beta_j \in [0, 6], \quad \delta_j \in [0, 6], \quad \gamma_j \in [0, 6].$$

Our computation of the best-response prices in (3.6) focused on an interval of ±25% around the prices observed in the data.

#### Utility-function parameters

Table 5 presents the range of values for each of the random utility parameters that were consistent with criterion (5.2). Some of the most interesting findings are the following,

- Even with limited data, our model was able to produce an informative range of parameter values consistent with criterion (5.2).
- The predatory strategy has a nonzero effect on both of AMX's competitors, and there is evidence that this effect is larger for TEF than for AT&T.
- The network effect diminished significantly over time, from 2016 to 2018. This is consistent with the elimination of the club effect. As we explained above, this was

one of the main goals of the 2013 reform.

**Table 5: Range of parameter values consistent with criterion** (5.2)

| **Firm-specific coefficients** | | **Predatory-strategy sensitivity coefficients** | |
|---|---|---|---|
| $\delta_2$ | $\delta_3$ | $\gamma_2$ | $\gamma_3$ |
| $[-0.398, -0.373]$ | $[0.810, 0.868]$ | $[1.561, 1.646]$ | $[2.011, 2.129]$ |

| **Price-sensitivity coefficients** | | |
|---|---|---|
| $\beta_1$ | $\beta_2$ | $\beta_3$ |
| $[2.898, 3.089]$ | $[0.825, 0.870]$ | $[3.329, 3.565]$ |

| **Network-effect coefficient** $\lambda_i$ | | |
|---|---|---|
| 2016 | 2017 | 2018 |
| $[0.893, 1.005]$ | $[0.110, 0.123]$ | $[0.031, 0.049]$ |

**The effect of the predatory strategy**

Perhaps the easiest way to interpret the magnitude of the predatory-strategy effect is by looking at the market share elasticities

$$\frac{\partial G_{jt}}{\partial a_t}\frac{a_t}{G_{jt}}, \quad \text{for } j = 1 \text{ (AMX)}, j = 2 \text{ (AT\&T) and } j = 3 \text{ (TEF)}.$$

Table 6 presents the results for the range of parameter values consistent with criterion (5.2). These correspond to the elasticities computed for all the parameter values that were consistent with said criterion. A summary of the main findings is the following,

- Unlike the network effect, which decreased in magnitude from 2016 to 2018, our results indicate that the predatory-strategy effect increased during this time period.
- While, in 2016, a 10% increase in $a_t$ led, approximately[14], to an increase of 5.7% (percentage change, not percentage points) in AMX's market share, this figure increased

[14]This is the mid-point of the interval.

to approximately 8.4% in 2018.

- Consistent with our results for $(\gamma_2, \gamma_3)$, the predatory impact of AMX is greater on TEF than on AT&T.
- In 2016, a 10% increase in $a_t$ led, approximately, to a decrease of 7.9% and 11.8% (percentage change, not percentage points) in the market shares of AT&T and TEF, respectively. In 2018 these figures became 10.9% and 16.6%, respectively.

**Table 6: Predatory effect**

| **Predatory effect for AMX: Elasticity of AMX's market share, $G_{1t}$ with respect to the predatory strategy $\boldsymbol{a_t}$. Range of values consistent with criterion (5.2).** | | |
|---|---|---|
| 2016 | 2017 | 2018 |
| [0.548, 0.592] | [0.724, 0.758] | [0.824, 0.860] |
| **Predatory effect for AT&T: Elasticity of AT&T's market share, $G_{2t}$ with respect to the predatory strategy $\boldsymbol{a_t}$. Range of values consistent with criterion (5.2).** | | |
| 2016 | 2017 | 2018 |
| [−0.811, −0.765] | [−1.081, −1.014] | [−1.139, −1.054] |
| **Predatory effect for TEF: Elasticity of TEF's market share, $G_{3t}$ with respect to the predatory strategy $\boldsymbol{a_t}$. Range of values consistent with criterion (5.2).** | | |
| 2016 | 2017 | 2018 |
| [−1.234, −1.130] | [−1.620, −1.515] | [−1.704, −1.619] |

**Network effect and the impact of changes in consumers' beliefs**

Our model assumes equilibrium beliefs, but our results can help us study the effect of an out-of-equilibrium change in the beliefs $\pi_t^e$ of the representative consumer. Since well-defined beliefs satisfy $\pi_{1t}^e + \pi_{2t}^e + \pi_{3t}^e = 1$, it must be the case that if $\pi_{jt}^e$ changes exogenously by an amount $\Delta\pi_{jt}^e$, beliefs $\pi_{\ell t}^e$ and $\pi_{kt}^e$ must change by amounts $\Delta\pi_{\ell t}^e$ and $\Delta\pi_{kt}^e$ respectively, such that $\Delta\pi_{1t}^e + \Delta\pi_{2t}^e + \Delta\pi_{3t}^e = 0$. Thus, our exercise must make assumptions about how $\pi_{\ell t}^e$ and $\pi_{kt}^e$ change when $\pi_{jt}^e$ changes exogenously. Let us focus on perhaps the most intuitive scenario and assume the following,

- $\pi_{jt}^e$ (the representative consumer's *expected* market share of firm $j$) changes exogenously by an amount $\Delta\pi_{jt}^e$ such that $0 \leq \pi_{jt}^e + \Delta\pi_{jt}^e \leq 1$.

- The exogenous change in $\pi_{jt}^e$ changes $\pi_{\ell t}^e$ and $\pi_{kt}^e$ (for $\ell, k \neq j$) by equal proportional amounts,
$$\Delta\pi_{\ell t}^e = \Delta\pi_{kt}^e = -\frac{1}{2}\Delta\pi_{jt}^e,$$
as long as $0 \leq \pi_{kt}^e + \Delta\pi_{kt}^e \leq 1$ and $0 \leq \pi_{\ell t}^e + \Delta\pi_{\ell t}^e \leq 1$. That is,
$$\Delta\pi_{jt}^e \geq 0 \implies \begin{cases} \Delta\pi_{kt}^e = \max\left\{-\frac{1}{2}\Delta\pi_{jt}^e \ , \ -\pi_{kt}^e\right\} \\ \Delta\pi_{\ell t}^e = \max\left\{-\frac{1}{2}\Delta\pi_{jt}^e \ , \ -\pi_{\ell t}^e\right\} \end{cases}$$
$$\Delta\pi_{jt}^e \leq 0 \implies \begin{cases} \Delta\pi_{kt}^e = \min\left\{-\frac{1}{2}\Delta\pi_{jt}^e \ , \ 1-\pi_{kt}^e\right\} \\ \Delta\pi_{\ell t}^e = \min\left\{-\frac{1}{2}\Delta\pi_{jt}^e \ , \ 1-\pi_{\ell t}^e\right\} \end{cases}$$

Once again, the easiest way to study the impact of a realignment in beliefs is through market-share elasticities,
$$\frac{\partial G_{mt}}{\partial \pi_{jt}^e}\frac{\pi_{jt}^e}{G_{mt}}.$$
Table 7 presents the results for the range of parameter values consistent with criterion (5.2). The main findings can be summarized as follows,

- Consistent with our findings of a decrease in the magnitude of the network effect $\lambda_t$, market-share elasticities with respect to consumers' expected market shares also decreased from 2016 to 2018. This is the outcome the 2013 telecommunications reform aimed to achieve by eliminating the club effect.

- During the three years analyzed, the market shares of AT&T and TEF were more sensitive to changes in consumers' expected market share of AMX than the other way around. The elasticity of AT&T's and TEF's market shares with respect to consumers' expected market share of AMX was about 8 times larger than AMX's market share elasticity with respect to changes in consumers' expected market shares of either AT&T or TEF. However, the magnitudes of these elasticities decreased steadily.

**Table 7: Network effect. Elasticity of $G_{mt}$ (market share of firm $m$) with respect to $\pi^e_{jt}$ (expected market share of firm $j$). Range of values consistent with criterion (5.2).**

| | **2016** | | |
|---|---|---|---|
| | $G_{1t}$ | $G_{2t}$ | $G_{3t}$ |
| $\pi^e_{1t}$ | $[0.305, 0.343]$ | $[-0.663, -0.566]$ | $[-0.663, -0.566]$ |
| $\pi^e_{2t}$ | $[-0.018, -0.016]$ | $[0.131, 0.148]$ | $[-0.018, -0.016]$ |
| $\pi^e_{3t}$ | $[-0.087, -0.077]$ | $[-0.087, -0.077]$ | $[0.244, 0.275]$ |

| | **2017** | | |
|---|---|---|---|
| | $G_{1t}$ | $G_{2t}$ | $G_{3t}$ |
| $\pi^e_{1t}$ | $[0.037, 0.042]$ | $[-0.078, -0.070]$ | $[-0.078, -0.070]$ |
| $\pi^e_{2t}$ | $[-0.003, -0.002]$ | $[0.019, 0.021]$ | $[-0.003, -0.002]$ |
| $\pi^e_{3t}$ | $[-0.009, -0.008]$ | $[-0.009, -0.008]$ | $[0.028, 0.032]$ |

| | **2018** | | |
|---|---|---|---|
| | $G_{1t}$ | $G_{2t}$ | $G_{3t}$ |
| $\pi^e_{1t}$ | $[0.011, 0.017]$ | $[-0.029, -0.019]$ | $[-0.029, -0.019]$ |
| $\pi^e_{2t}$ | $[-0.001, -0.001]$ | $[0.006, 0.009]$ | $[-0.001, -0.001]$ |
| $\pi^e_{3t}$ | $[-0.004, -0.002]$ | $[-0.004, -0.002]$ | $[0.008, 0.013]$ |

**Price effects**

The final effect we can discuss involves market-share price elasticities,

$$\frac{\partial G_{\ell t}}{\partial p_{jt}} \frac{p_{jt}}{G_{\ell t}}.$$

Since each firm has a different mix of pre-paid and post-paid wireless plans and this reflects in structural differences in price levels across the three firms (as our price measures showed), a direct comparison of own-price elasticities across the three competitors is a little hard to interpret. However, an analysis over time of each firm's own-price elasticity as well as some discussion about cross-price elasticities is insightful. Table 8 presents the results for the range of parameter values consistent with criterion (5.2). Some of the main findings are the following,

- The market share of AMX has become more sensitive to its own price. The elasticity increased consistently over the three-year period studied. This can be interpreted as a beneficial effect of the 2013 reform, which has made it easier for consumers to switch to AMX's competitors.
- However, the magnitude of the own-price elasticity of AT&T and TEF's market shares has decreased over time. This suggests that it has become increasingly difficult for these firms to attract more consumers through competitive price offers.
- On the other hand, the cross-price elasticity of AT&T and TEF's market shares with respect to AMX's price has increased over time, which suggests that consumers have switched out of AMX and into its competitors mostly as a response to AMX's prices rather than as a reaction to AT&T and TEF's decreases in prices (which were continuously observed over the three years studied).
- Consistent with the conjecture that the market has shown a diminished response to pricing policies of AT&T and TEF, our results suggest that AMX's market share has become increasingly less responsive to price changes of its competitors. Overall our results suggest that it has become increasingly difficult for both of the smaller firms to directly attract costumers through lower prices.

**Table 8: Price effect. Elasticity of $G_{jt}$ (market share of firm $j$) with respect to $p^e_{\ell t}$ (price of firm $\ell$). Range of values consistent with criterion (5.2).**

| | **2016** | | |
|---|---|---|---|
| | $G_{1t}$ | $G_{2t}$ | $G_{3t}$ |
| $p_{1t}$ | $[-0.422, -0.395]$ | $[0.735, 0.783]$ | $[0.735, 0.783]$ |
| $p_{2t}$ | $[0.074, 0.077]$ | $[-0.627, -0.594]$ | $[0.074, 0.077]$ |
| $p_{3t}$ | $[0.199, 0.214]$ | $[0.199, 0.214]$ | $[-0.677, -0.633]$ |

| | **2017** | | |
|---|---|---|---|
| | $G_{1t}$ | $G_{2t}$ | $G_{3t}$ |
| $p_{1t}$ | $[-0.444, -0.415]$ | $[0.770, 0.823]$ | $[0.770, 0.823]$ |
| $p_{2t}$ | $[0.076, 0.080]$ | $[-0.538, -0.509]$ | $[0.076, 0.080]$ |
| $p_{3t}$ | $[0.167, 0.180]$ | $[0.167, 0.180]$ | $[-0.640, -0.598]$ |

| | **2018** | | |
|---|---|---|---|
| | $G_{1t}$ | $G_{2t}$ | $G_{3t}$ |
| $p_{1t}$ | $[-0.503, -0.471]$ | $[0.804, 0.857]$ | $[0.804, 0.857]$ |
| $p_{2t}$ | $[0.059, 0.063]$ | $[-0.355, -0.337]$ | $[0.059, 0.063]$ |
| $p_{3t}$ | $[0.147, 0.156]$ | $[0.147, 0.156]$ | $[-0.557, -0.519]$ |

### 5.4 Summary of results

- The magnitude of the network effect decreased consistently during the time period studied. This is consistent with the 2013 reform's stated goal of eliminating the "club effect" in the wireless market.

- In contrast, the magnitude of the predatory-strategy effect increased, and our results consistently suggested that it affected TEF more than AT&T (even though it reduced both firms' market shares).

- An ongoing policy discussion in Mexico revolves around whether AMX's sustained large market share results from: (a) from consumer habits and a lingering network effect whereby users have continued to flock to the carrier with the most customers, or (b) direct predatory actions from AMX. Our results point strongly to the latter, as the network effect has diminished over time while the impact of the predatory effect has increased steadily. This points towards the need to supplement the 2013 reform with more effective oversight of AMX's practices.

- A study of price elasticities suggests that it has become increasingly difficult for AT&T and TEF to attract costumers through pricing strategies. In terms of prices, the market has responded increasingly more to AMX's pricing policies rather than those of its competitors. Our model suggests that AMX has the ability to counteract reductions in competitors' prices through predatory practices that shift consumers away.

#### 5.4.1 Divestment of TEF from the Mexican telecommunications market

In November 2019, TEF announced that it would scale back significantly its operations the Mexican telecommunications market[15]. They described a gradual process that will take place in stages, starting with the sale of fibre assets, the migration of mobile subscribers to AT&T Mexico's network and the return of spectrum concessions to the regulator (IFT). TEF will use AT&T's wireless equipment and will become effectively a mobile virtual network operator[16] (MVNO). The reasons cited by TEF included the predatory practices by AMX that we enumerated previously, combined with the comparatively expensive cost of the spectrum in Mexico. The announced effective exit of TEF from the market is in line with the empirical findings of our model which indicated that AMX's predatory strategies had a

[15] Love, Julia (2020-01-27). "Telefonica teams up with AT&T in Mexico in new bid to take fight to Slim ", *Reuters*. URL: https://www.reuters.com/article/us-mexico-telefonica/telefonica-teams-up-with-att-in-mexico-in-new-bid-to-take-fight-to-slim-idUSKBN1XV2CM

[16] An MVNO is a typically smaller wireless carrier that does not own the wireless network infrastructure over which it provides services to its customers.

significantly greater impact on TEF than on AT&T and it constitutes an ominous sign for the future of the industry.

## 6 Concluding remarks

A number of real-world examples of oligopolistic price competition can be more reasonably modeled by assuming that, in addition to prices, a subset of firms have a non-price "predatory strategy" at their disposal which enables them to shift consumer preferences away from competitors and towards themselves. This paper proposed an example of such a model where we treated the predatory strategy as an unobserved market-level random variable. Ours can be seen as a special case of BLP demand models with the feature that the unobserved, market-level, product-specific characteristics are modeled explicitly as functions of the unobserved predatory strategy. By presenting a theory of optimal choice for prices and the predatory strategy, our model allows us to measure the direct effect of the unobserved predatory strategy. Inspired by our empirical example, our model also included a "network effect" whereby consumers' preferences and choices also depend on their subjective expectations of the proportion of other consumers who will choose the product or service of each firm. We believe this feature can describe a number of interesting real-world applications.

We applied our model to study the Mexican wireless telecommunications industry, which has remained heavily concentrated in spite of a 2013 telecommunications reform that was explicitly aimed at increasing competition. This is an interesting application of our model since the dominant firm (América Móvil or 'AMX') has engaged in documented (and recently sanctioned) practices that fit our model's description of predatory strategies. One of our main questions was whether the persistently high market share of AMX was the result of the network effect (whereby consumers are driven to select the largest carrier) or the predatory-strategy effect (by which AMX's predatory practices directly shift consumer preferences away from its competitors). Using data from 2016-2018, our results indicated that the network effect diminished steadily over time while the predatory effect increased. The recent exit of one of AMX's two main competitors from the Mexican market is a worrisome outcome that is in line with our empirical results.

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