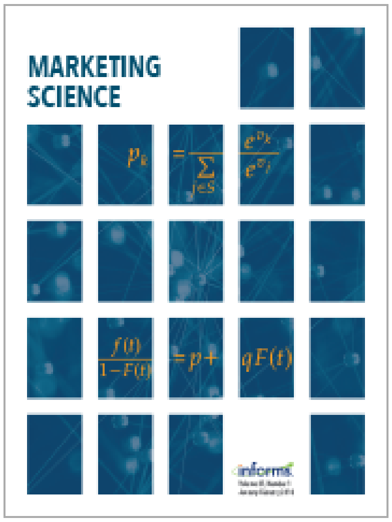

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Licensing and Price Competition in Tied-Goods Markets: An Application to the Single-Serve Coffee System Industry

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Abstract. We develop a structural model of demand and supply for tied goods, which we estimate using aggregate data from the single-serve coffee system industry. We use the parameter estimates to quantify the impact of licensing on equilibrium prices and profits for firms in the industry. In particular, we look at the decision to allow other firms to sell components (coffee pods) that are compatible with a firm's primary good (coffee machines) by licensing the use of its patents. We solve for the counterfactual market equilibrium in which one of the market leaders enters a licensing agreement with one of the competitor brands—with the latter brand only selling compatible coffee pods and not the machines. We show the existence of a range of royalty rates under which firms could potentially reach a beneficial licensing agreement. In addition, we find that the relationship between the licensee's profits and the royalty rate is not always decreasing. Finally, we find that, within the set of royalty rates in which licensing benefits both brands, the licensing agreement is associated with less price dispersion in the aftermarket (coffee pods), and with lower prices of the primary good (coffee machines) relative to the nonlicensing scenario.

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1. Introduction

Many firms follow a "razor–razor-blade" business model that involves providing a "system" of complementary goods. Typically, the primary or initial good is durable and sold relatively inexpensively while the consumable good(s) sold in the aftermarket involve large markups and represent an income stream that may continue for years. The durable good can only be used in combination with, and is unusable without, the complementary (or "tied") consumables. Examples include printers and ink cartridges, instant cameras and film, game consoles and games, and coffee machines and coffee pods.

For the firm offering both durables and consumables, an important business decision is whether to control the compatibility with other companies' products. The firm may choose to make use of the proprietary nature of its system and prevent other manufacturers from selling components in the aftermarket that are compatible with its patented system. Alternatively, the firm may allow other firms to sell components that are compatible with the firm's primary good by licensing the use of its patents. In addition, if the firm chooses to license the use of its patents, there are several possible types of pricing agreements that firms can follow. For example, firms can enter a licensing agreement with independent pricing whereby each firm in the agreement is allowed to set the price of the aftermarket product(s) (e.g., the video game industry) or a licensing agreement with uniform pricing whereby the price of the aftermarket product(s) is the same for both firms and set by the leader—i.e., the developer of the system (e.g., Keurig in the single-serve coffee industry).

From the firm's perspective, the decision to license other firms to manufacture and sell complementary goods involves several considerations. A firm may consider licensing to limit competition in the primary market (by reducing the follower's incentives to enter with its own system). In turn, this may increase the sales of the primary market good (especially if consumers value variety in the aftermarket products), and hence of the installed base, thus leading to more sales in the aftermarket. On the other hand, licensing generates more competition in the aftermarket when compared with a monopoly situation. But, when compared with facing entry from a new system, the effects of licensing on competition and profits are not clear, especially because the licensee is usually expected to pay a royalty fee to the licensor in exchange for using the licensor's patented intellectual property. Therefore, the implications of licensing for pricing and profits can be ambiguous.

Naturally, the decision of whether to license and the associated type of pricing agreement constitute important strategic decisions. Nonetheless, quantifying the effect of licensing decisions on firms' performance is difficult because the market outcomes under the counterfactual scenarios are not observed. In particular, firms could have followed different pricing strategies from the observed ones under a different licensing scenario, which in turn would have led to different sales and profits. However, policy simulations can be used to study the economic consequences of alternative strategic options (as suggested in Bronnenberg et al. 2005 and Franses 2005).

In this paper we develop a tractable structural model of tied goods that is suitable for estimation and allows us to examine market outcomes of alternative licensing strategies through policy simulations. We focus on a particular tied-goods market: the single-serve coffee system industry. A typical single-serve coffee system consists of a coffee machine, which is durable, and coffee pods, which are consumable. Through policy simulations, we use the model to quantify the impact of licensing (and different pricing agreements) on equilibrium outcomes such as prices, profits, and competition in both the primary market (coffee machines) and the aftermarket (coffee pods). Even though the model is applied to the coffee system industry, the tractability and generality of the model makes it suitable for application in other markets as well.

Specifically, we use the model to answer the following questions. Is there a range of royalty rates under which firms could potentially reach a beneficial licensing agreement? Does the answer to this question depend on the type of pricing agreement (uniform or independent pricing)? More generally, what is the impact of licensing on equilibrium prices and profits for the firms in the market? Answering these questions is important for several reasons. First, this analysis constitutes an important diagnostic of firms' chosen strategies, providing the inputs for the market players to readjust their strategies, if possible. Second, measuring the economic impact of licensing on equilibrium outcomes helps us to understand which effects of licensing (change in competition, change in customer base, and increased variety, among others) are more important in practice. In turn, understanding the relative importance of these effects might help the firms' future decision processes regarding their optimal licensing strategies.

Our data cover the single-serve coffee system industry in Portugal for the period between 2007 and 2012. We benefit from the fact that our data set covers the industry almost since its inception, which allows us to study the dynamics related with the evolution of the installed customer base that are common to the introduction of new durable products.

Further, the fact that all firms in our studied market (Portugal) entered with their own systems (and without licensing agreements) allows us to estimate the costs and markups of the different systems. These serve as important inputs in determining the equilibrium prices in the counterfactual analyses. If instead we had data on one system licensed to several competitors, the study of the counterfactual in which several (incompatible) systems enter the market would require a greater set of assumptions because it would be difficult (if not impossible) to predict how many systems would enter both components' markets and at what prices.

The structural model captures the complementarities in demand for coffee machines and coffee pods as well as the forward-looking behavior of consumers in the market for coffee machines (a durable good) that are typical in tied-goods markets. In addition, it allows for heterogeneous consumers who have different levels of consumption of coffee pods. On the supply side, firms make pricing decisions taking into account the profits from both the foremarket (coffee machines) and the aftermarket (coffee pods), and how the pricing decisions in one market affects the other market.

We estimate the model parameters (that characterize consumer preferences and firms' costs) using aggregate sales data. The model estimates imply own- and cross-price elasticities for coffee pods and coffee machines that are reasonable. In addition, the estimates reveal that consumers put a large weight on the utility from coffee pods when choosing a coffee machine system, and that there is substantial heterogeneity in consumers' consumption intensity. Finally, the supply side allow us to recover measures of marginal costs and profit margins that are consistent with values reported by industry sources. The positive profit margins for coffee pods (around 20%) and negative profit margins for coffee machines (estimated to be between –9% and –56%) show that firms in this market lose money on the sales of coffee machines and recover it back from the sales of coffee pods in the aftermarket, a pattern that is common in tied-goods markets.

To investigate the impact of licensing on equilibrium outcomes in this market, we use the model and the parameter estimates to solve for the counterfactual market equilibrium in which one of the incumbents (DeltaQ) enters a licensing agreement with one of its competitors (a store brand), keeping the other competitors with their own systems. In this case, the store brand does not sell a machine and only sells pods compatible with DeltaQ. We then compare the industry's profits and prices, under the counterfactual scenario with different levels of royalties, to what is observed in the data.

Our results show that the overall effect of licensing on equilibrium variables is complex and usually depends on the agreed royalty rate and on the type of licensing agreement. Despite the complexity of the effects, however, our analysis allows us to reach several conclusions about the effect of licensing on equilibrium outcomes in this market.

First, the model allows us to identify a range of royalty rates (between 14.1% and 30.1%) in which both the licensor (DeltaQ) and the licensee (Store Brand) could benefit from entering a licensing agreement with independent pricing. For the licensee, the gains from licensing come mostly from avoiding the losses in the primary good market. For the licensor, the gains come mostly from an increase in demand for its products because consumers value variety in the sense that they benefit from having access to more coffee pod options, some of which are sold at lower prices.

Second, the results show that the relationship between the profits of the licensee and the royalty rate is not always monotonic. In the licensing scenario with independent pricing, the relationship between total profits of the licensee and the royalty rate is positive for royalty rates below 12.7%, and negative for higher royalty rates. The initial, perhaps counterintuitive, positive relationship between total profits of the licensee and the royalty rate the licensee has to pay follows from the fact that a higher royalty rate increases the profits for the licensor in the aftermarket. In turn, this motivates the licensor to further reduce the price of the primary good, which increases the licensor's (and the licensee's) installed customer base. For moderately low royalty rates, this increase in demand has a stronger positive effect on the licensee's profits than the negative effect of the higher royalty rate.

In addition, we show that, even though the licensee always prefers an independent-pricing licensing agreement to a uniform-pricing licensing agreement in the market we study, the relative preference of the licensor depends on the agreed-upon royalty rate. For low levels of the royalty rate, the licensor prefers a uniform-pricing licensing agreement because it avoids price competition. For high levels of the royalty rate, however, the licensor prefers an independent-pricing licensing agreement as it facilitates price discrimination.

Finally, licensing has an unambiguous effect on the equilibrium prices of coffee machines and pods within the relevant equilibrium set in which both firms have an incentive to license (independent-pricing agreement with a royalty rate between 14.1% and 30.1%). In this range, licensing leads to some (but not full) convergence on the coffee pod prices of the two brands, despite the independent pricing agreement. In this licensing agreement, relative to the nonlicensing scenario, the coffee pods of the licensee exhibit lower prices while the coffee pods of the licensor exhibit higher prices. More generally, this result suggests that the independent-pricing licensing agreement leads to less price dispersion in theaftermarket. Further, the results show that the prices of the primary good (coffee machines) in the relevant royalty-rate region are lower in the independent-pricing licensing agreement scenario than in the nonlicensing scenario. In turn, this suggests that the independent-pricing licensing agreement can lead to an increase in the customer base of the two brands because, with lower coffee machines prices, the cost of entry of new customers is lower.

The paper proceeds as follows. Section 2 discusses the related literature. Section 3 describes the data and presents some descriptive evidence about the evolution of the single-serve coffee industry in Portugal. Section 4 presents the model of demand and supply for coffee machines and coffee pods. Section 6 presents the estimation results. Section 7 presents the results from counterfactual market outcomes under alternative licensing strategies. Finally, Section 8 concludes.

2. Related Literature

This paper is related to several streams of literature. First, it is related to the literature on product compatibility, especially in the context of system competition. Previous studies investigate theoretically the welfare and pricing implications of system compatibility when products are consumed simultaneously (e.g., Matutes and Regibeau 1988, Economides 1989, and Farrell et al. 1998) or when there is an aftermarket good (e.g., Shapiro 1994, Borenstein et al. 2000, and Mariñoso 2001). Most of these studies look at the case of established firms (each with its own system) that face the choice of producing components that are compatible with different systems. Different from these studies, we compare a firm's incentives to enter the market with its own (complete) system versus only with aftermarket goods that are compatible with a system that belongs to an incumbent firm. This phenomenon is ubiquitous in several industries, such as, e.g., the video game industry, the e-book reader industry, and the single-serve coffee system industry, which we study here.

In addition, most of the studies on system competition do not consider the option of side payments such as royalty rates that are paid by one firm to another firm that has a patented system in exchange for the rights to sell components compatible with that firm's system (an exception is the theoretical work by Katz and Shapiro 1985). Side payments are a feature of many industries, however. In this paper, we compare licensing agreements with and without side payments and provide empirical evidence that the competitive (pricing) equilibrium changes as a function of such payments.

This paper is also related to the licensing literature. Previous theoretical studies have identified two major incentives for licensing: to reduce competition (Gallini 1984, Rockett 1990) and to increase demand (Shepard 1987, Farrell and Gallini 1988, Sun et al. 2004). Most of these studies, however, only consider the case of a single (non-tied) product. So, our paper extends this literature by studying the implications of licensing in the context of tied products. While licensing in the aftermarket might bring additional competition to the market, it also increases the variety of aftermarket goods, which in turn enhances the demand for the primary good. The overall effect of licensing on firm's profits is therefore, a priori, unclear.

Lastly, this paper contributes to the growing empirical literature on tied products. Previous work has studied the video game console industry (Nair 2007, Dubé et al. 2010, Liu 2010, Lee 2013, Derdenger 2014), the razor and blades industry (Hartmann and Nair 2010), and the e-book readers industry (Li 2015), for example. Our work is the first to study the single-serve coffee system industry. Recently, Kong et al. (2016) and Lin (2017) also look at this industry, but the focus is different from ours. Specifically, they focus on the effects of partner brands on consumer demand.

The empirical literature on tied products has studied the consumer's dynamic choice and stockpiling behavior (Hartmann and Nair 2010) as well as firms' dynamic pricing strategies (Dubé et al. 2010, Liu 2010, Li 2015). Few papers study the aftermarket strategies of the tied goods, however. The only two exceptions are Lee (2013) and Derdenger (2014). Both of these studies investigate the effects of video game titles' exclusiveness: Lee (2013) focuses on the welfare implications of exclusive arrangements, and Derdenger (2014) focuses on the pricing effect of an exclusive strategy for video game consoles. Relative to these last two studies, our work is different in that the type of industry we study involves different considerations with respect to tying. In the video game console industry, tying means that some game titles are only available on certain consoles. There, the main incentive console manufacturers have for tying is to increase the sales of the video game consoles. In our application, as in many other industries with a razor–razor-blade business model, the purpose of tying is to increase market power in the aftermarket. The different goals of the tying strategies in the two markets raise different research questions and require a different modeling approach. Given the nature of the video game industry, neither of the previous papers models the pricing decisions for the aftermarket goods. This decision is important to model in our case because licensing increases competition in the aftermarket, which most likely will have implications for pricing. Further, in our counterfactual analyses we take into account the incentives that both the licensor and the licensee have (or do not have) to enter a licensing agreement, and study the effect of different licensing fees and licensing agreements on equilibrium outcomes.

3. Data

We study the single-serve coffee system industry in Portugal from January 2007 to April 2012. This section describes the evolution of this industry and our data.

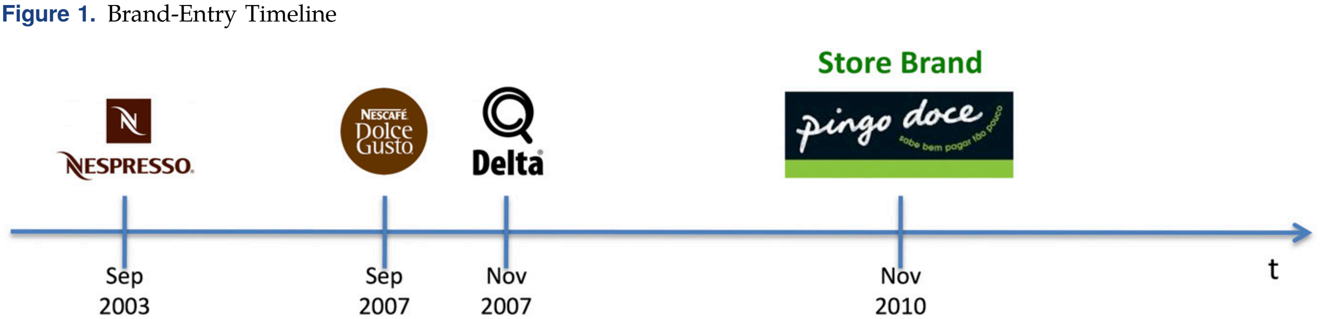
3.1. The Single-Serve Coffee System Industry in Portugal

The single-serve coffee system industry in Portugal has grown rapidly in recent years. The market share in sales value of pod coffee (out of all retail sales of coffee) went from 3% in 2005 to almost 65% in 2013, taking the place of both standard ground coffee and instant coffee (Source: Euromonitor International Passport Statistics).

Figure 1 shows the timeline of entry of the four major players in Portugal: Nespresso, DolceGusto, DeltaQ, and a Store Brand. Nespresso entered the market in late 2003 and was the first entrant. It was followed by DolceGusto and DeltaQ, which entered the market in 2007. In late 2010, one of the major local supermarket chains, Pingo Doce, introduced its own Store Brand.[1] The coffee machines of Nespresso, DeltaQ, and the Store Brand can only be used with espresso coffee pods, but DolceGusto has a multibeverage coffee system that provides other drinks as well, such as hot chocolate and tea.[2] By 2012, the combined market share (in sales value) of these four brands in the market of coffee pods exceeded 93% (Sources: Nielsen Portugal and Euromonitor Passport Statistics).

DeltaQ is a subsidiary of the parent company Delta Cafés. Delta Cafés is a Portuguese company that was founded in 1961. Its main activities are the production, marketing, and distribution of coffee. The Delta brand is one of the most well-known brands in Portugal. Delta

Figure 1. Brand-Entry Timeline



Note. This figure shows the timeline of entry of the four major brands in the single-serve coffee system industry in Portugal.

Cafés is the overall market leader in the coffee market in Portugal with a market share of about 40% in 2010 (Source: Nielsen Portugal). Nespresso and DolceGusto both belong to the Swiss company Nestlé, which has a stronger global presence than DeltaQ. While Nespresso and DolceGusto both belong to the same parent company, they are part of distinct business units that are mostly independently responsible for their marketing strategies.

All of the four major brands entered the market with coffee systems that were incompatible with the other brands' coffee systems. This means that each brand has its own machines and coffee pods. In terms of the market positioning of the different brands, Nespresso focuses on the premium market and sells its coffee exclusively through its own channels (online channel and own brick-and-mortar stores), while both DeltaQ and DolceGusto employ a mass-market strategy with their products being readily available at specialty stores and supermarkets. Consistent with this, Table 1 shows that, in 2011 (the first year in the sample in which all four brands studied are present in the market), the average price of a Nespresso coffee machine was about 40 euros higher than the price of DeltaQ's and DolceGusto's coffee machines. The Store Brand also employs a mass-market strategy, selling its coffee machines and coffee pods through its own channel (where DeltaQ's and DolceGusto's coffee pods are also available).

Table 1 also reports the average coffee pod prices for each brand in 2011. Across all brands, the average coffee pod price is around €0.30. Nespresso has the most expensive pods, and the Store Brand has the least expensive pods. The brands sell different varieties of espresso coffee pods called *blends*. These blends are unique, making it hard (if not impossible) to project each pod variety/blend onto a common set of attributes across blends. While, for products like yogurt or ice cream, brands typically offer the same or similar set of flavors (although one can argue that even there, brands like Ben & Jerry's sell unique ingredient combinations), in our setting each blend of coffee is unique, within and across brands.

The different pod blends can be grouped into two categories based on their prices: a category of more expensive pods (we call these "premium" pods) and a category of cheaper pods (we call these "regular" pods).[3] In 2011, the average price per "premium" coffee pod was €0.41, while the average price per "regular" coffee pod was €0.27 (not tabulated). Pods are typically sold in packs of 10 units.

Although the unit price of the coffee pods is much lower than the prices of the coffee machines, Table 1 shows that the total annual sales of coffee pods are significantly higher than the sales of coffee machines. This is a typical pattern in tied-goods products: the sales of coffee pods satisfy the demand of all consumers who already own a coffee machine, while the sales of coffee machines are made only to new consumers.

3.2. Data Sources

Our main data come from two sources.[4] Country-level data on monthly unit sales and prices for coffee machines are provided by the market research firm GfK, and data on monthly sales units and prices for coffee pods are provided by Nielsen.[5]

We exclude from our analysis coffee machine models that are rarely sold (i.e., that account for less than 2% of their brand's monthly sales units). We also exclude coffee machine models with prices over €250 as these correspond to specialty machines that have different usages from the rest of the models. Dropping these models eliminates a further 3% of the coffee machine sales in our data set. In the aftermarket, we restrict our attention to the sales of espresso coffee pods, as these account for over 96% of the coffee pod sales.

3.3. Descriptive Evidence

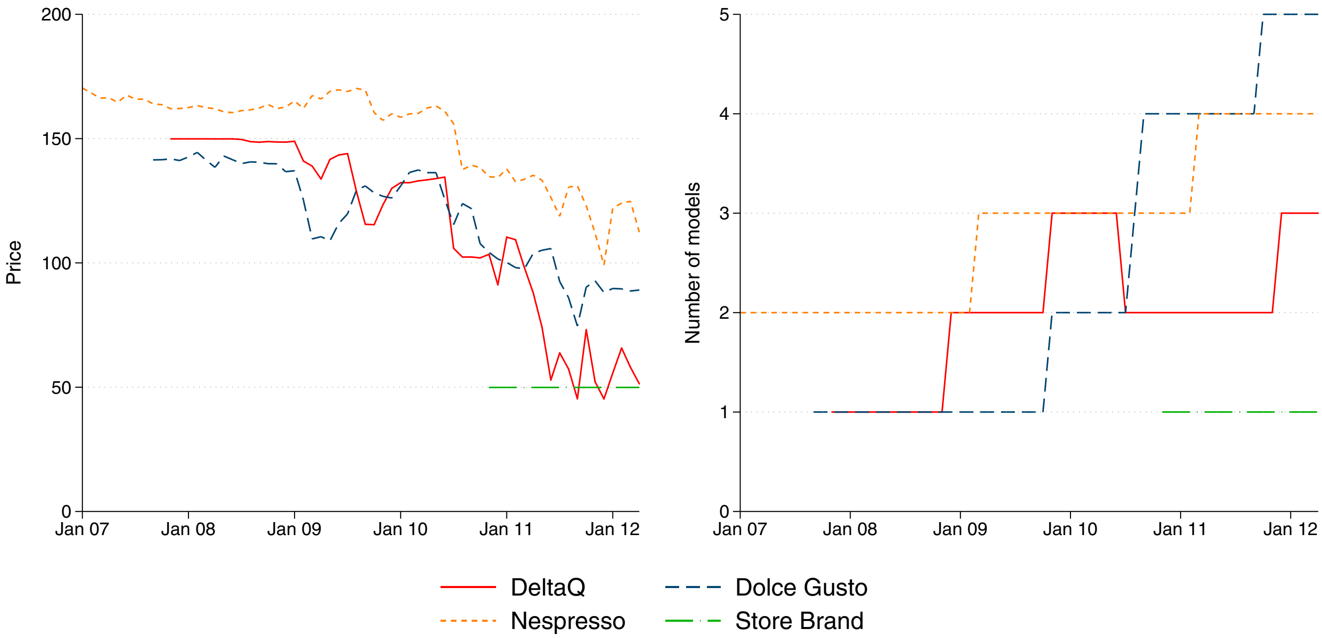
Figure 2 shows the evolution of average coffee machine prices (across models, weighted by their corresponding sales units) and the evolution of the number of coffee machine models available for each brand. Similar to what happens in other durable goods markets, the market for coffee machines experienced a significant price decline over time. At the same time, the number of available coffee machine models has increased. Over time, consumers face more choices of coffee machines at lower prices.[6] This suggests the importance of modeling consumers as forward-looking agents because consumers may anticipate more choices and lower average

Table 1. Average Prices and Revenue from Coffee Systems

	Nespresso	DolceGusto	DeltaQ	Store Brand
Average machine price	116.5	92.2	57.2	49.9
Average pod price	0.36	0.30	0.29	0.21
Revenue from machines (millions)	9.8	9.7	6.8	6.1
Revenue from pods (millions)	N/A	28.8	22.1	9.6

Notes. This table reports the average prices of coffee machines and espresso coffee pods across brands in Portugal in 2011. The total revenue from coffee machines and coffee pods in the same year is also reported. All values are in euros. Machine and pod prices are weighted by sales (except in the case of Nespresso pods, for which we do not observe sales because of data unavailability). All values are calculated based on the data used in the model estimation as described in Section 3.2 with the exception of the average pod price for Nespresso that was obtained from industry sources. N/A, not available.

Figure 2. Coffee Machines' Prices and Number of Models

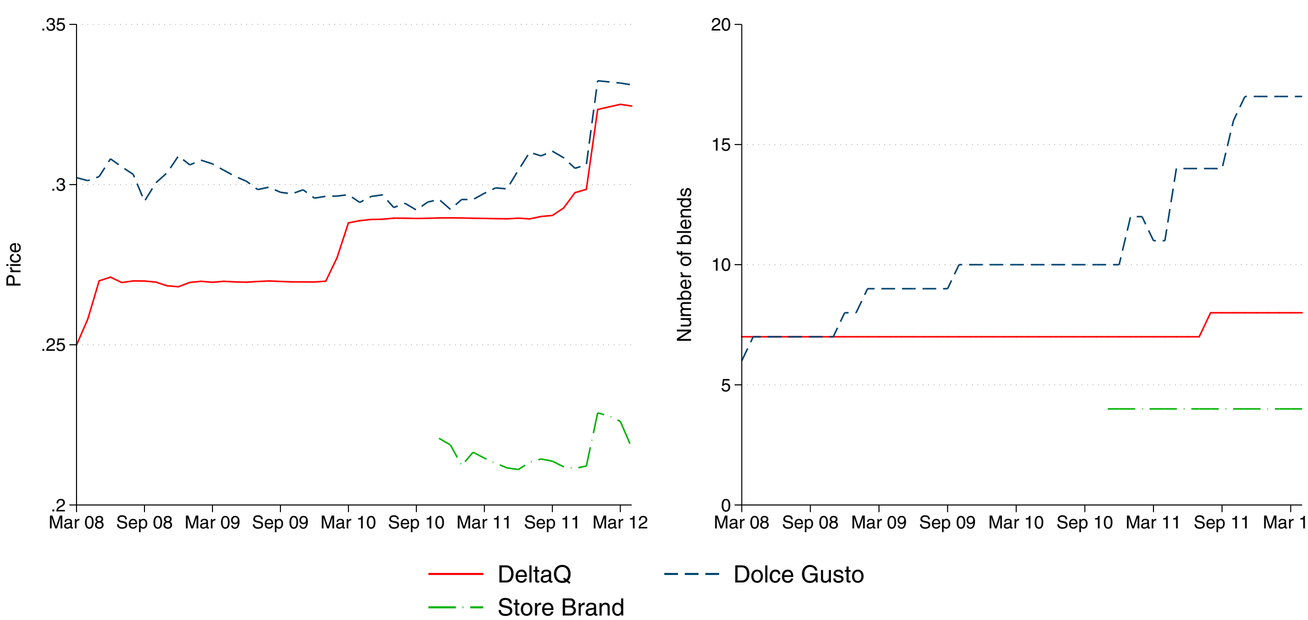


Notes. This figure shows the evolution of the average prices (in euros) and number of models of coffee machines, by brand. Average prices are weighted averages (by sales) of individual coffee machine models' prices.

prices of coffee machines in the future and therefore may choose to wait to purchase a machine.

Figure 3 shows the evolution of average prices (across pod types, premium and regular, weighted by their corresponding sales) and the evolution of the number of coffee pod blends available for each brand. Although the variety of coffee pods available increases over time, coffee pod prices are quite stable. The stable nature of prices is consistent with the tied nature of single-serve coffee systems. Once a consumer purchases a coffee machine, he has to consume the coffee pods of the same brand. This gives the firms some monopoly power in the

Figure 3. Coffee Pods' Prices and Number of Blends



Notes. This figure shows the evolution of the average prices (in euros) and number of pod-blends available, by brand. Average prices are weighted averages (by sales) of individual coffee pod types' (premium and regular) prices.

aftermarket as described in Shapiro (1994). Firms compete in the primary market but exploit consumers in the aftermarket. So, firms have no incentive to run price promotions for coffee pods. The lack of price promotions on the coffee pod side of the market simplifies our analysis because it does not require us to model consumers' stockpiling behavior (as in Erdem et al. 2003). Nevertheless, there is sufficient price variation in regular price changes, as we can see in Figure 3, that allows us to estimate the price sensitivity for coffee pods.

Figure 4 shows the evolution of total sales for coffee machines and average coffee pod sales per machine, respectively. We divide the monthly sales of coffee pods by the installed base of coffee machines to capture the average consumer's demand for coffee pods. The left panel of Figure 4 shows that the market for coffee machines has grown significantly over time and that there is strong seasonality, with sales spiking around the Christmas season. For coffee pods, the right panel of Figure 4 shows that there is strong seasonality similar to the one observed for coffee machines' sales. Further, there seems to be a downward trend in the average consumption of pods. Because market research reports (provided by Nielsen and the International Coffee Organization) are not consistent with a decrease in coffee consumption (across all types of coffee) in Portugal during the period studied, this suggests that consumers with different tastes for coffee pods enter the market at different times (consumers that drink less coffee pods enter later bringing the average consumption down).[7] For this reason, it will be important to account for consumer heterogeneity in the model.

To simplify our analysis, we seasonally adjust our sales data for both coffee machines and coffee pods in a similar manner to Gowrisankaran and Rysman (2012).[8] Specifically, we multiply sales by a separate constant for each month of the year such that (a) the geometric mean of adjusted sales is the same across all months of the year and (b) the adjusted total sales over the sample period is equal to the total sales in the raw data. Figure 4 shows that the sales series become smoother after making this adjustment.[9]

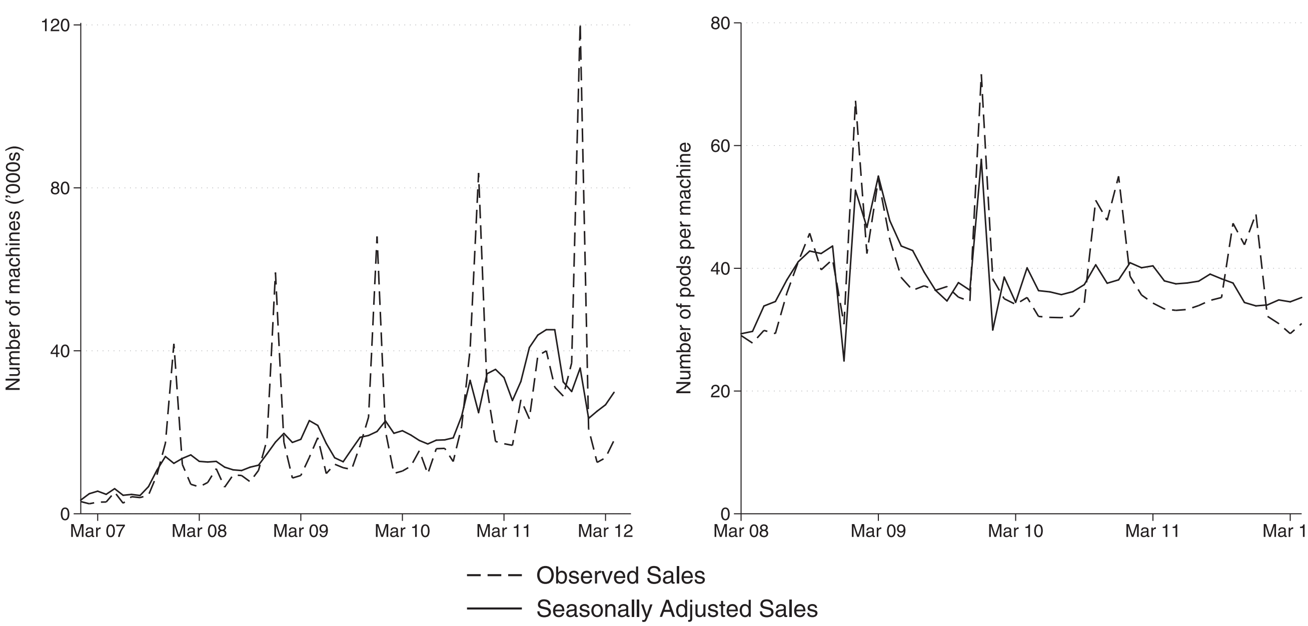
4. Model

In this section we describe the structural econometric model of the single-serve coffee system industry that we estimate. Section 4.1 describes the demand side of the market, and Section 4.2 describes the supply side of the market

4.1. Demand

Consumers are forward-looking when buying coffee machines. That is, consumers take into consideration the evolution of variables such as prices, coffee machine alternatives, and the availability of pods with different coffee blends when making their coffee machine purchase decision, and can therefore potentially delay their purchase. After buying a coffee machine, the consumer

Figure 4. Sales of Coffee Machines and Coffee Pods per Machine



Notes. Left: This graph shows the evolution of the total number of coffee machines sold across the four major brands in the single-serve coffee system industry in Portugal. Right: This graph shows the average number of pods sold by machine over time (using data only for the brands for which we have both machine and pod data). The average number of pods per machine in a given month is obtained by dividing the number of pods sold in that month by the size of the coffee machines' installed base (this average number is calculated using data for the brands for which we observe both machine and pod sales and assuming consumers replace their coffee-machines every three years). Both graphs show the observed sales and the seasonally adjusted sales.

exits the coffee machine market and enters the market for coffee pods; the consumer then chooses which coffee blend(s) to buy.

4.1.1 Demand for Coffee Machines. Each period (month) t, consumers make a discrete choice from J_t available single-serve coffee systems and an outside option. Each system consists of a coffee machine, of brand j, and of coffee pods, each with a different set of coffee-blends. Coffee systems are not compatible with each other which means that only coffee machines and coffee pods of the same brand can be used together. Multi-homing is not allowed; a consumer purchases and uses at most one coffee-pod machine.[10]

We specify a utility function for coffee machines that links the utility from the primary market to that in the aftermarket in a manner similar to Lee (2013) and Derdenger (2014). Consumer i's utility from purchasing a coffee machine of brand j at time t is then given by

$$u_{i,j,t}^{\text{mac}} = \alpha_j + x_{j,t}\alpha^{x,\text{mac}} + \alpha^{p,\text{mac}} p_{j,t}^{\text{mac}} + \psi^{\Upsilon}\Upsilon_{i,j,t} + \xi_{j,t}^{\text{mac}} + \epsilon_{i,j,t}^{\text{mac}}, \tag{1}$$

where the superscript "mac" stands for "machine" (as opposed to "pod"), and α_j is the fixed effect for a coffee machine of brand j, which controls for both observed and unobserved characteristics of the system that do not vary over time. $x_{j,t}$ is a vector of time-varying observable characteristics for the coffee machines of brand j at time t, and $p_{j,t}^{\text{mac}}$ is the price of a machine of brand j at time t. $\Upsilon_{i,j,t}$ captures the expected utility from optimally purchasing coffee pods from brand j and is a function of brand j's pods' prices and variety. We present and discuss the functional form of $\Upsilon_{i,j,t}$ in the next section. ψ^{Υ} is a scale parameter that links the utility from coffee pods to the utility from purchasing a coffee machine. More specifically, the value of ψ^{Υ} measures the importance to the consumer's utility from consuming the coffee pods of a given brand conditional on purchasing a coffee machine of the same brand. $\xi_{j,t}^{\text{mac}}$ captures machine brand-time specific characteristics that are observable to the consumer but not to the econometrician (this error term can be interpreted as unobserved quality). Finally, $\epsilon_{i,j,t}^{\text{mac}}$ is a consumer-brand-time specific component that represents idiosyncratic consumer heterogeneity unobservable to the econometrician and realized by the consumer only at time t. $\epsilon_{i,j,t}^{\text{mac}}$ is assumed to be Type I Extreme Value, and independently and identically distributed across consumers, brands, and time periods.

Note from Equation (1) that we do not directly account for unobserved heterogeneity in the sensitivities to machine characteristics. However, unobserved heterogeneous preferences are captured by the term $\Upsilon_{i,j,t}$, which is a function of the random coefficient γ_i that we define formally in the next section. This term accounts for unobserved heterogeneity in coffee-pod preferences which in turn generates unobserved heterogeneity in the choice of coffee machines. This specification allows us to link utility from pods to machines while allowing for unobserved heterogeneity in the preferences for the system (machine-pod) in a relatively parsimonious way that preserves the computational tractability of the problem. Directly relaxing the assumption of no unobserved heterogeneity in the coffee-machine demand parameters would come at considerable computational cost (especially when conducting counterfactual analyses).[11]

Consumer i's decision problem regarding his coffee-machine purchase is equivalent to an optimal stopping problem as in Rust (1987): the consumer decides whether to buy a machine at time t (and if so, which brand to purchase) or to wait until the next period. A consumer who is in the market for coffee machines (and thus does not currently hold a machine) but does not purchase any machine at time t receives $u_{i,0,t}^{\text{mac}} = \epsilon_{i,0,t}^{\text{mac}}$.

Let Ω_t denote the current industry state. Ω_t contains any variables in the consumer's information set at time t that affect his utility, value from waiting and current and future machine and pod attributes (both observable and unobservable). Ω_t, together with ϵ_t^{mac}, constitute all the demand-side state variables at time t.

For a consumer in the coffee-machine market, the Bellman equation that describes the consumer's value of being in a current state $\Omega_{i,t}$ prior to his realization of ϵ (i.e. the *expected value function* of consumer i) is:

$$V_i(\Omega_{i,t}) = \int \max\left\{\epsilon_{i,0,t}^{\text{mac}} + \beta E[V_i(\Omega_{i,t+1})|\Omega_{i,t}], \max_{j=1\ldots J_t} u_{i,j,t}^{\text{mac}}\right\} g(\epsilon^{\text{mac}})d\epsilon^{\text{mac}}, \tag{2}$$

where β is the discount factor and $E(\cdot)$ denotes the expectation operator, a conditional expectation in this case. The first term within the braces is the utility from waiting and the second term is the utility from purchasing the best coffee machine available in period t. We set β to 0.975, as in Nair (2007) and Derdenger (2014), who also estimate dynamic demand models for durable goods using data that have monthly periodicity.[12] Given that Ω encompasses a large number of state variables it would be computationally burdensome to estimate the demand model using the above equation. We follow Gowrisankaran and Rysman (2012) and assume consumers do not take into account all possible state variables individually when making their decision to purchase a coffee machine. Rather, by their *Inclusive Value Sufficiency* (IVS) assumption, they consider only a consumer-specific logit inclusive-value state variable δ that captures the effects of all the variables in Ω.

The logit inclusive-value term is the ex-ante present discounted lifetime value of buying the preferred coffee machine, as opposed to holding the outside option and is given by:

$$\delta_{i,t}^{\text{mac}} = \int \left\{ \max_{j=1\ldots J_t} u_{i,j,t}^{\text{mac}} \right\} g(\epsilon^{\text{mac}}) d\epsilon^{\text{mac}}. \tag{3}$$

Given the extreme value distribution for ϵ^{mac}, $\delta_{i,t}^{\text{mac}}$ can be written as

$$\delta_{i,t}^{\text{mac}} = \ln\left(\sum_{j=1}^{J_t} \exp\left\{ \alpha_j + x_{j,t}\alpha^{x,\text{mac}} + \alpha^{p,\text{mac}} p_{j,t}^{\text{mac}} + \psi^{\Upsilon}\Upsilon_{i,j,t} + \xi_{j,t}^{\text{mac}} \right\} \right). \tag{4}$$

The IVS assumption, together with the extreme value distribution for ϵ^{mac} and the definition of $\delta_{i,t}^{\text{mac}}$ in (4) allow us to rewrite the Bellman equation in (2) in a simpler form:

$$V_i(\delta_{i,t}^{\text{mac}}) = \ln\left(\exp\left(\beta E_{\delta^{\text{mac}}}[V_i(\delta_{i,t+1}^{\text{mac}}) | \delta_{i,t}^{\text{mac}}] \right) + \exp(\delta_{i,t}^{\text{mac}}) \right). \tag{5}$$

Equation (5) shows that consumers predict future values of δ^{mac} based only on the current δ^{mac}, rather than on the full information set Ω. As in Gowrisankaran and Rysman (2012), we assume that consumers perceive the inclusive value δ^{mac} to evolve according to an AR(1) process. Accordingly, we estimate the parameters θ in the equation

$$\delta_{i,t+1}^{\text{mac}} = \theta_{i,1}^{\text{mac}} + \theta_{i,2}^{\text{mac}}\delta_{i,t}^{\text{mac}} + \phi_{i,t+1}^{\text{mac}}, \tag{6}$$

where $\phi_{i,t}^{\text{mac}}$ is normally distributed with mean zero and standard deviation $\sigma_{\phi_i}^{\text{mac}}$, and is *i.i.d* across consumers and time periods. The consumer-specific parameters $\theta_{i,1}^{\text{mac}}$ and $\theta_{i,2}^{\text{mac}}$ define the evolution of the inclusive-value state variable, and yield a probability distribution for the future states which is conditional on the current state.

The expected value functions $V_i(\delta_{i,t}^{\text{mac}})$ are obtained by solving the Bellman equation in Equation (5), and used to determine the individual consumers' purchase probabilities. Consumer i's probability of purchasing a coffee machine of brand j is then a function of the inclusive value, $\delta_{i,t}^{\text{mac}}$ and is given by

$$Pr_{i,j,t}^{\text{mac}}(\delta_{i,t}^{\text{mac}}) = \frac{\exp\left(\delta_{i,t}^{\text{mac}}\right)}{\exp\left(V_i(\delta_{i,t}^{\text{mac}})\right)} \times \frac{\exp\begin{pmatrix} \alpha_j + x_{j,t}\alpha^{x,\text{mac}} + \alpha^{p,\text{mac}} p_{j,t}^{\text{mac}} \\ +\psi^{\Upsilon}\Upsilon_{i,j,t} + \xi_{j,t}^{\text{mac}} \end{pmatrix}}{\exp\left(\delta_{i,t}^{\text{mac}}\right)}. \tag{7}$$

Once a consumer makes the decision to purchase a coffee machine, the consumer leaves the coffee-machine market and enters the coffee-pod market. In each subsequent period, the customer purchases coffee pods of the same brand as the coffee machine he purchased, until he replaces his coffee machine. Due to the lack of individual level data, we do not observe consumers' replacement behavior. So, we assume that consumers return to the market for coffee machines three years after the purchase of a coffee machine.[13]

4.1.2. Demand for Coffee Pods. Unlike coffee machines, coffee pods are consumable goods that consumers buy on a regular basis. Further, as discussed in Section 3.3, the prices of coffee pods do not change frequently (that is, we rarely observe price promotions), so we expect no stockpiling behavior from consumers. This means that the decision to purchase coffee pods in one period does not affect that decision in other periods. For these reasons, we assume that consumers have a static demand for coffee pods.

Consider a consumer who purchased a coffee machine of brand j and is in the market for coffee pods. Because all coffee systems are incompatible with each other, the consumer only has the option to purchase coffee pods from brand j. Alternatively, the consumer may drink coffee in some other way other than by using his coffee pod machine (outside option).

Each period (month) t, consumers purchase coffee pods according to the potential consumption occasions during that month. The total number of potential consumption occasions in a given month t is given by C.

Let $B_{j,t}$ be the set that includes all coffee pod blends of coffee of brand j that are available at time t. The utility consumer i gets from consuming a pod of blend $k \in B_{j,t}$ in occasion c_t ($c_t = 1, \ldots, C$) in month t is given by

$$u_{i,j,k,c_t}^{\text{pod}} = \gamma_i + \alpha_{j,k} + \alpha^{p,\text{pod}} p_{j,k,t}^{\text{pod}} + \xi_{j,k,t}^{\text{pod}} + \epsilon_{i,j,k,c_t}^{\text{pod}}, \tag{8}$$

where γ_i is a parameter that captures an individual-specific taste for pods that does not change over time or across coffee blends, $\alpha_{j,k}$ is a coffee-blend k (of brand j) fixed effect, and $\alpha^{p,pod}$ is the price coefficient. We let γ_i be consumer specific to allow for the fact that some consumers derive more utility from consuming coffee pods than others. A higher γ_i implies a higher consumption rate of pods and a higher propensity to buy a coffee machine sooner (despite it being more expensive). The parameter γ_i is assumed to be randomly distributed with $\gamma_i = \overline{\gamma_i} + \nu_i\sigma$, where ν_i follows a standard normal distribution. Thus, σ captures the importance of consumer heterogeneity in this market. $\xi_{j,k,t}^{\text{pod}}$ captures the characteristics of coffee pods that are observable to consumers and firms but not observable to the econometrician. Finally, $\epsilon_{i,j,k,c_t}^{\text{pod}}$ is a consumer-brand-blend– and drinking-occasion–specific component that represents idiosyncratic consumer heterogeneity unobservable to the econometrician and realized by the consumer only at occasion c_t. $\epsilon_{i,j,k,c_t}^{\text{pod}}$ is assumed to be Type I Extreme Value, and independently and identically distributed across consumers, brands, pod blends, and consumption occasions. Consumers are thus assumed to make pod purchases each month based on multiple and independent (but conditional on the brand of machine that they own) consumption decisions during that month. In Section 5.1 we discuss our market-size assumptions and their implications for the number of consumption decisions C made by consumers.

Given the distribution for $\epsilon^{\text{pod}}_{i,j,k,c_t}$, the probability of consumer i choosing blend $k \in B_{j,t}$ on occasion c_t is given by

$$Pr^{\text{pod}}_{i,j,k,c_t} = \frac{\exp\left(\gamma_i + \alpha_{j,k} + \alpha^{p,\text{pod}} p^{\text{pod}}_{j,k,t} + \xi^{\text{pod}}_{j,k,t}\right)}{1 + \sum_{k \in B_{j,t}} \exp\left(\gamma_i + \alpha_{j,k} + \alpha^{p,\text{pod}} p^{\text{pod}}_{j,k,t} + \xi^{\text{pod}}_{j,k,t}\right)}. \tag{9}$$

Also, we can write consumers' expected utility from optimally choosing among any coffee pods of brand j or the outside option prior to observing $\epsilon^{\text{pod}}_{i,j,k,c_t}$ (that is, the inclusive value for coffee pods) as

$$\delta^{\text{pod}}_{i,j,c_t} = \ln\left(\sum_{k \in B_{j,t}} \exp\left(\gamma_i + \alpha_{j,k} + \alpha^{p,\text{pod}} p^{\text{pod}}_{j,k,t} + \xi^{\text{pod}}_{j,k,t}\right) + 1\right). \tag{10}$$

Notice that the only term in (8) with c_t subscript is the error term ϵ. Everything else is constant within a month because of the monthly nature of our data. Given this, and the distribution of $\epsilon^{\text{pod}}_{i,j,k,c_t}$, the expected proportion of occasions in month t in which the consumer consumes blend k is[14]

$$Pr^{\text{pod}}_{i,j,k,t} \equiv Pr^{\text{pod}}_{i,j,k,c_t}. \tag{11}$$

We now formalize the connection between the demand for machines and the demand for pods. The term that links the utility from coffee pods to that from machines is given by $\Upsilon_{i,j,t}$ in Equation (1). This term enters the utility function for machines and captures the fact that a consumer considers the purchase of future pods (their variety and prices) when buying a machine. More formally, $\Upsilon_{i,j,t}$ is consumer i's expected discounted utility at time t from optimally choosing coffee pods from brand j until time $t + T^{\text{mac}}$. T^{mac} is the time after which the consumer returns to the machine market and, as discussed before, is assumed to be equal to 36 months. Because we assume that consumers leave the coffee pod market a finite number of periods after purchasing a coffee machine (and at that time reenter the coffee machine and coffee pod markets again), $\Upsilon_{i,j,t}$ can be written as

$$\Upsilon_{i,j,t} = \delta^{\text{pod}}_{i,j,t} + \sum_{l=t+1}^{t+T^{\text{mac}}-1} \beta^{l-t} E\left(\delta^{\text{pod}}_{i,j,l} | \delta^{\text{pod}}_{i,j,t}\right), \tag{12}$$

where the inclusive value $\delta^{\text{pod}}_{i,j,t}$ represents the total expected utility from optimally choosing coffee pods of brand j across all C consumption occasions during period t. If we assume that consumers perceive $\delta^{\text{pod}}_{i,j,t}$ to evolve according to an AR(1) process, then

$$\delta^{\text{pod}}_{i,j,t+1} = \theta^{\text{pod}}_{i,1} + \theta^{\text{pod}}_{i,2} \delta^{\text{pod}}_{i,j,t} + \phi^{\text{pod}}_{i,j,t+1}, \tag{13}$$

where $\phi^{\text{pod}}_{i,j,t}$ is normally distributed with mean zero and standard deviation $\sigma^{\phi,\text{pod}}_{i,j}$, and is *i.i.d.* across consumers, brands and time periods. The individual-specific parameters $\theta^{\text{pod}}_{i,1}$ and $\theta^{\text{pod}}_{i,2}$ define the evolution of the optimal utility from purchasing coffee pods.

4.2. Supply

We now discuss the supply side of the market for coffee machines and coffee pods. We focus our analysis on the firm's optimal pricing decisions. Thus, we abstract away from the firm's other strategic considerations such as the timing of entry, the firm's product composition, and quality choice.

Specifying a supply side is important in our case for two reasons. First, the supply side allows us to obtain the marginal costs and price-cost margins that are required for the counterfactuals we conduct. Second, to analyze the effects of licensing on pricing we need a supply side to be able to solve for the market equilibria under different counterfactual scenarios.

We start by presenting a general formulation of the firm's pricing problem that we later simplify to make the problem computationally tractable. Although we estimate the simplified version of the model, presenting the general formulation first is useful to understand all of the sources of intertemporal pricing considerations in the context of durable and tied goods, as well as to make clear the implicit assumptions regarding the firm's pricing problem in the simplified model.

4.2.1. Firm's Optimization Problem: General Formulation.

Firm j's profits at each period t include both the profits from coffee machines (denoted Π^{mac}) and the profits from coffee pods (denoted Π^{pod}). Because it will be convenient to distinguish between two different sources of pod profits depending on whether they originate from consumers that purchased their machine in a time period previus to t (superscript "old") or from those that purchase their machine in time t (superscript "new"), we write firm j's profit function at time t as

$$\begin{aligned}\Pi_{j,t}(\Delta_t, p_t) = {} & \Pi^{\text{mac}}_{j,t}(\Delta_t, p_t) + \Pi^{\text{pod,old}_t}_{j,t}(\Delta_t, p_t) \\ & + \Pi^{\text{pod,new}_t}_{j,t}(\Delta_t, p_t),\end{aligned} \tag{14}$$

where p_t is a vector that includes the prices of both coffee machines and coffee pods for all brands at time t, and the payoff-relevant state variables, Δ_t, include the set of state variables that affect the demand of machines and pods at time t—namely, the customer installed base, the composition of consumers for each brand's installed base, the age of the customer installed base, and the marginal costs for coffee machines and coffee pods. Note that we omit the fixed costs from the profit function, because these do not affect firms' pricing decisions.

The term $\Pi_{j,t}^{\text{mac}}$ represents the profits from machines of brand j sold at time t, the term $\Pi_{j,t}^{\text{pod,new}_t}$ captures the current pod profits that come from the "new" customers that purchase their machine at time t, and the term $\Pi_{j,t}^{\text{pod,old}_t}$ captures the pod profits that come from "old" customers that have purchased their machine before time t. Each of these terms can be formally defined as follows:[15]

$$\Pi_{j,t}^{\text{mac}} = M_t S_{j,t}\,(p_{j,t}^{\text{mac}} - mc_{j,t}^{\text{mac}}), \tag{15}$$

$$\Pi_{j,l}^{\text{pod,old}_t} = \sum_{k\in B_{j,l}} \left(M_{j,l}^{\text{old}_t} S_{j,k,l}^{\text{old}_t}\right)\left(p_{j,k,l}^{\text{pod}} - mc_{j,k,l}^{\text{pod}}\right), \quad l \geq t, \tag{16}$$

$$\Pi_{j,l}^{\text{pod,new}_t} = \sum_{k\in B_{j,l}} \left(M_{j,l}^{\text{new}_t} S_{j,k,l}^{\text{new}_t}\right)\left(p_{j,k,l}^{\text{pod}} - mc_{j,k,l}^{\text{pod}}\right), \quad l \geq t, \tag{17}$$

where, in Equation (15), M_t is the coffee machines' potential market size at time t, $S_{j,t}$ is the machines' market share of brand j at time t, $p_{j,t}^{\text{mac}}$ is the price of a machine of brand j at time t, and $mc_{j,t}^{\text{mac}}$ is the marginal cost of producing a machine of brand j at time t. In addition, in Equation (16), $M_{j,l}^{\text{old}_t}$ represents the part of the potential market size of brand j's coffee pods that is composed of the set of consumers that purchased brand j's machine prior to time t and that still hold their machine at time l. Similarly, in Equation (17), $M_{j,l}^{\text{new}_t}$ represents the part of the potential market size of brand j's coffee pods that is composed of the set of consumers that purchased brand j's machine at time t and that still hold their machine at time l. Note that $M_{j,l}^{\text{new}_t} \equiv M_t S_{j,t}$ for $t \leq l < t + T^{\text{mac}}$, which implies that $M_{j,l}^{\text{new}_t}$ is constant over the economic life of a machine, and zero after that. Finally, $S_{j,k,l}^{\text{old}_t}$ and $S_{j,k,l}^{\text{new}_t}$ are the market shares at time l of blend k for consumers that purchased their machine prior to or at time t, respectively, and $p_{j,k,l}^{\text{pod}}$ and $mc_{j,k,l}^{\text{pod}}$ are the prices and marginal costs at time l for coffee pods of blend k, respectively.

Let $\sigma \equiv \{p_j(\Delta_t) : j = 1, \ldots, J\}$ be a vector of strategy functions, one for each firm, where p_j is a vector of prices for coffee machines and coffee pod blends for firm j. A Markov perfect equilibrium in this game is a vector of strategy functions σ such that each firm's pricing strategy maximizes the value of the firm for each possible state and taking as given the other firms' strategies. Let $V_j^{\sigma}(\Delta_t)$ represent the expected present value of firm j's current and future profits given that the other firms behave according to their respective strategies in σ and that firm j chooses its current and future prices optimally. By the principle of optimality, the value function V_j^{σ} is then implicitly defined as the solution to the following Bellman equation:

$$V_j^{\sigma}(\Delta_t) = \max_{p_{j,t}} \left\{\Pi_{j,t}^{\sigma}(\Delta_t, p_{j,t}) + \beta E[V_j^{\sigma}(\Delta_{t+1}) | \Delta_t, p_{j,t}]\right\}, \tag{18}$$

where β is the discount factor and $E(\cdot)$ denotes the expectation operator, a conditional expectation in this case.

Let $p_{j,t}^{*}(\Delta_t)$ denote the vector of optimal prices for firm j at state Δ_t. For the sake of notational simplicity, in what follows, we drop the dependency of the optimal prices on Δ_t. Substituting recursively the definition of current profits given in Equation (14) and rearranging terms, the firm's optimal prices can be written as Equation (19) (see Online Appendix A for details).

$$\begin{aligned}
p_{j,t}^{*} = \arg\max \Bigg[& \underbrace{\Pi_{j,t}^{\sigma,\text{mac}}(\Delta_t,p_{j,t}) + \Pi_{j,t}^{\sigma,\text{pod,old}_t}(\Delta_t,p_{j,t}) + \Pi_{j,t}^{\sigma,\text{pod,new}_t}(\Delta_t,p_{j,t})}_{\text{① current profits (at time } t)} \\
& \underbrace{+ \sum_{h=1}^{\infty} \beta^h E\left(\Pi_{j,t+h}^{\sigma,\text{mac}}(\Delta_{t+h}, p_{j,t+h}^{*} | \Delta_t, p_{j,t})\right) + \sum_{h=1}^{\infty} \sum_{l=t}^{t+T^{\text{mac}}-1} \beta^{h+l-t} E\left(\Pi_{j,h+l}^{\sigma,\text{pod,new}_{t+h}}(\Delta_{h+l}, p_{j,h+l}^{*} | \Delta_t, p_{j,t})\right)}_{\text{② future coffee-machine and coffee-pod profits from customers who buy a coffee machine at } t+1 \text{ and later}} \\
& \underbrace{+ \sum_{l=t+1}^{t+T^{\text{mac}}-2} \beta^{l-t} E\left(\Pi_{j,l}^{\sigma,\text{pod,old}_t}(\Delta_l, p_{j,l}^{*} | \Delta_t, p_{j,t})\right)}_{\text{③ future coffee-pod profits from customers who buy a coffee machine prior to } t} \\
& \underbrace{+ \sum_{l=t+1}^{t+T^{\text{mac}}-1} \beta^{l-t} E\left(\Pi_{j,l}^{\sigma,\text{pod,new}_t}(\Delta_l, p_{j,l}^{*} | \Delta_t, p_{j,t})\right)}_{\text{④ future coffee-pod profits from customers who buy a coffee machine at } t} \Bigg].
\end{aligned} \tag{19}$$

This equation makes clear the determinants of the firm's optimal coffee machine and pod prices and the intertemporal trade-offs that the firm faces. In a static framework, firms set prices to maximize the single-period profits given by term ①. In the context of durable and tied goods there are additional forward-looking considerations that firms need to take into account when choosing current prices. First, the sales of machines today affect the future installed base of machines and thus the future sales of coffee pods. This is captured by term ④, which implies that firms set the prices for coffee machines today taking into account not only the sales of coffee machines today, but also the profits that the sale of each additional machine means in terms of future sales of coffee pods. Second, the sales of machines today affect the size and composition of the future potential market size for machines. That is, higher sales of coffee machines today not only reduces the market size tomorrow, but also changes the market composition of different types of consumers. This affects the future profits from coffee machines, $\Pi^{\sigma,\text{mac}}_{j,t+h}$ (with $h > 0$), and the pod profits associated with the sales of coffee machines in the future, $\Pi^{\sigma,\text{pod},\text{new}_{t+h}}_{j,h+l}$ (both of these captured in term ②). In addition, it affects the future pod profits from customers who buy a coffee machine prior to t or at t (i.e., terms ③ and ④, respectively). This second source of intertemporal considerations arises because the potential market size is finite and we have heterogeneous consumer segments.

4.2.2. Firm's Optimization Problem: Simplified Formulation.

The dynamic problem specified in Equation (19) is computationally infeasible due to the very large size of the state space, and the need to solve for equilibrium prices in an oligopoly setting.

We simplify the firm's optimization problem by focusing on the intertemporal pricing considerations in Equation (19) that we believe to be the most important in our context—namely, those that originate from the tied nature of the goods sold by the firm. Specifically, when setting current prices, we assume that the firm looks at the impact of current prices on firm's profits given by the terms ① and ④, and that the effect of current prices on the change in firm's profits given by terms ② and ③ is small.[16] Underlying this specification is the fact that the demand for coffee pods of existing consumers is static,[17] and the assumption that the effect of current prices on the firm's future profits due to the change in the potential market size for machines and in the distribution of consumer types tomorrow (and in subsequent periods) is very small. The impact of these considerations on firms' pricing decisions is likely to be small in our application because the potential market size for coffee machines is very large when compared with the installed base in the period under analysis. In addition, consumers replace coffee machines every 36 months, which further slows down the decrease in the potential market size.[18]

As a robustness check we estimated a two-period repeated game model using a backward solving methodology in the spirit of Chintagunta and Vilcassim (1995) and Che et al. (2007) that incorporates the effects given by terms ② and ③ up to two periods ahead (incorporating more periods ahead makes the problem even more challenging computationally). The marginal costs obtained under this more general specification of the model are comparable to the ones recovered by the more parsimonious version used here.[19]

Consistent with the data, we also assume that firms set the same prices for all pod blends of a given type (regular or premium). Accordingly, we set marginal costs to be the same for pods of the same type and brand. Given this, define the full set of pod blends of brand j, as $B_{j,t} = B^{pr}_{j,t} \bigcup B^{rg}_{j,t}$, in which pr stands for "premium" and rg for "regular." With these assumptions, the dynamic problem in Equation (19) can be written in a simplified form as

$$p^*_{j,t} = \arg\max \Bigg[M_t S_{j,t}\,(p^{\text{mac}}_{j,t} - mc^{\text{mac}}_{j,t}) + \sum_{v\in\{pr,rg\}} M^{\text{old}_t}_{j,t}\, \mathcal{S}^{\text{old}_t}_{j,v,t} \left(p^{\text{pod}}_{j,v,t} - mc^{\text{pod}}_{j,v,t}\right) + \sum_{l=t}^{t+T^{\text{mac}}-1} \beta^{l-t} E\left[\sum_{v\in\{pr,rg\}} M^{\text{new}_t}_{j,l}\, \mathcal{S}^{\text{new}_t}_{j,v,l} \left(p^{\text{pod}}_{j,v,l} - mc^{\text{pod}}_{j,v,l}\right)\right]\Bigg], \tag{20}$$

where $\mathcal{S}^{\text{new}_t}_{j,v,l} = \sum_{k\in\{B^v_{j,t}\}} S^{\text{new}_t}_{j,k,l}$ and $\mathcal{S}^{\text{old}_t}_{j,v,t} = \sum_{k\in\{B^v_{j,t}\}} S^{\text{old}_t}_{j,k,t}$, for $v \in \{pr, rg\}$.

Finally, the implementation of Equation (20) requires the computation of expected future pod profits for consumers that purchase a machine at time t. This would require solving for the firms' game in future periods to obtain equilibrium prices and hence profits. As noted before, solving this game is computationally infeasible. To simplify the problem we approximate firms' future (time $l = t+1\ldots t+T^{\text{mac}}-1$) stream of profits from pods for consumers that purchase a machine at time t, using the current profits for these consumers. Specifically, we assume firms' expected costs for coffee pods to be the same as the current (time t) pod costs, and we take advantage of the fact that, in the data, equilibrium pod prices are fairly stable during a machine's lifetime.[20] Likewise, we use the distribution of new consumers' fitted shares for pod types regular and premium at time t to approximate their expected future shares. The expected future profits from coffee pods for consumers that purchase a machine at time t can then be written as a function of current pod profits as

$$p^*_{j,t} = \arg\max \Bigg[M_t S_{j,t}\,(p^{\text{mac}}_{j,t} - mc^{\text{mac}}_{j,t}) + \sum_{v\in\{pr,rg\}} M^{\text{old}_t}_{j,t}\, \mathcal{S}^{\text{old}_t}_{j,v,t} \left(p^{\text{pod}}_{j,v,t} - mc^{\text{pod}}_{j,v,t}\right) + \frac{1-\beta^{T^{\text{mac}}}}{1-\beta} \sum_{v\in\{pr,rg\}} M^{\text{new}_t}_{j,t}\, \mathcal{S}^{\text{new}_t}_{j,v,t} \left(p^{\text{pod}}_{j,v,t} - mc^{\text{pod}}_{j,v,t}\right)\Bigg]. \tag{21}$$

The first-order conditions for coffee machine prices and coffee pod prices at time t are then given, respectively, by

$$\frac{\partial M_t S_{j,t}}{\partial p^{\text{mac}}_{j,t}}(p^{\text{mac}}_{j,t} - mc^{\text{mac}}_{j,t}) + M_t S_{j,t} + \frac{1-\beta^{T^{\text{mac}}}}{1-\beta}\frac{\partial M^{\text{new}_t}_{j,t}}{\partial p^{\text{mac}}_{j,t}} \sum_{v\in\{pr,rg\}} \mathcal{S}^{\text{new}_t}_{j,v,t}\left(p^{\text{pod}}_{j,v,t} - mc^{\text{pod}}_{j,v,t}\right) = 0, \tag{22}$$

$$\begin{aligned}&\frac{\partial M_t S_{j,t}}{\partial p^{\text{pod}}_{j,v,t}}(p^{\text{mac}}_{j,t} - mc^{\text{mac}}_{j,t}) \\ &+ \sum_{\tilde v\in\{pr,rg\}} \frac{\partial M^{\text{old}_t}_{j,t}\mathcal{S}^{\text{old}_t}_{j,\tilde v,t}}{\partial p^{\text{pod}}_{j,v,t}}\left(p^{\text{pod}}_{j,\tilde v,t} - mc^{\text{pod}}_{j,\tilde v,t}\right) + M^{\text{old}_t}_{j,t}\mathcal{S}^{\text{old}_t}_{j,v,t} \\ &+ \frac{1-\beta^{T^{\text{mac}}}}{1-\beta}\left(\sum_{\tilde v\in\{pr,rg\}} \frac{\partial M^{\text{new}_t}_{j,t}\mathcal{S}^{\text{new}_t}_{j,\tilde v,t}}{\partial p^{\text{pod}}_{j,v,t}}\left(p^{\text{pod}}_{j,\tilde v,t} - mc^{\text{pod}}_{j,\tilde v,t}\right)\right. \\ &\left. + M^{\text{new}_t}_{j,t}\mathcal{S}^{\text{new}_t}_{j,v,t}\right) = 0, \forall v \in \{pr, rg\}.\end{aligned} \tag{23}$$

These first-order conditions reflect that (a) firms set coffee machine prices taking into account not only the sales of coffee machines, but also the profits that the sale of each additional machine means in terms of future sales of coffee pods (the tied-goods nature of our problem); and (b) firms choose coffee pod prices to maximize profits in the coffee pod market while taking into account the impact that coffee pod prices will have on the substitution between pods of the same brand (and the outside option) and also on the sales of coffee machines.

5. Model Estimation and Identification

We estimate the parameters that characterize the demand and the supply side of the model using a two-step sequential approach (as in Nevo 2001, Derdenger 2014, and Sinkinson 2016, among others). More specifically, after obtaining the demand estimates, we recover marginal costs by assuming that the observed prices represent equilibrium outcomes of a Bertrand pricing game. This ensures that the possible misspecification of the pricing model will not contaminate the demand parameter estimates. Section 5.1 describes the estimation procedure, and Section 5.2 discusses the identification of the demand side parameters.

5.1. Estimation Procedure

To recover the demand model's structural parameters, we follow the method proposed by Gowrisankaran and Rysman (2012) to estimate the demand of durable goods with aggregate data, and extended by Lee (2013) and Derdenger (2014) to allow for durable goods that have complementary add-ons. The demand for coffee machines and for coffee pods is estimated jointly for two reasons. First, the utility from purchasing coffee machines depends on coffee pod characteristics such as the pods' coffee blends and prices. Second, the market size for coffee pods, which is a function of the installed base for coffee machines, also depends on the utility from coffee machines.

We estimate the demand side parameters by the generalized method of moments (GMM). Specifically, we minimize the objective function given by

$$F_{\text{GMM}} = [\xi^{\text{mac}}(\boldsymbol{\theta}), \xi^{\text{pod}}(\boldsymbol{\theta})]\boldsymbol{Z}\boldsymbol{W}\boldsymbol{Z}'\begin{bmatrix}\xi^{\text{mac}}(\boldsymbol{\theta})\\ \xi^{\text{pod}}(\boldsymbol{\theta})\end{bmatrix}, \tag{24}$$

where $\boldsymbol{\theta}$ is the vector of structural parameters $(\alpha_j, \alpha^x, \alpha^{p,\text{mac}}, \alpha_{j,k}, \alpha^{p,\text{pod}}, \psi^\Upsilon, \sigma)$, $\boldsymbol{Z}$ is a matrix of instruments orthogonal to the vector of unobservable characteristics $\xi^{\text{mac}}(\boldsymbol{\theta})$ and $\xi^{\text{pod}}(\boldsymbol{\theta})$, and $\boldsymbol{W}$ is the weight matrix.

Firms' pricing decisions may be correlated with unobserved product characteristics included in the ξ's, leading potentially to bias in the price coefficients. To alleviate price endogeneity concerns we use cost shifters as instruments for the prices of both coffee machines and coffee pods. Specifically, and because coffee machines are primarily manufactured in China, we use the Chinese Producer Price Indices (PPIs) for plastic products, aluminum products, measuring and control instruments, and rubber products as instruments for coffee machines. We use three-month lagged PPIs to allow machine manufacturers to respond to cost changes. As in Liu (2010) and Derdenger (2014), we interact the instruments with the brand dummies to get brand-specific instruments. For coffee pods, we use as cost shifters World Bank commodity price data on the global prices for robusta and arabica coffee beans. Again, we use three-month lagged coffee pod cost shifters and interact them with the brand dummies.[21]

To recover $\xi^{\text{mac}}(\boldsymbol{\theta})$ and $\xi^{\text{pod}}(\boldsymbol{\theta})$, we first determine the predicted aggregate market shares for coffee machines and coffee pods. Specifically, we calculate the purchase probability for each consumer type using Equations (7) and (9), and then integrate the purchase probabilities over the distribution of consumer heterogeneity in each time period to obtain the market-level purchase shares. The integration is performed using a Gaussian–Hermite quadrature approach with 15 nodes as in Derdenger (2014). We approximate the integral with a weighted sum of the integrand values evaluated at a finite set of well-specified points called nodes with weights λ (defined below) as in Skrainka and Judd (2011). The predicted market shares are given by equations

$$\widehat{S}_{j,t} = \sum_i \lambda^{\text{mac}}_{i,t}\widehat{Pr}^{\text{mac}}_{i,j,t}\left(\overline{u^{\text{mac}}_{j,t}}, \Upsilon_{i,j,t}, \psi^\Upsilon, \sigma\right), \tag{25}$$

$$\widehat{S}_{j,k,t} = \sum_i \lambda^{\text{pod}}_{i,j,t}\widehat{Pr}^{\text{pod}}_{i,j,k,t}\left(\overline{u^{\text{pod}}_{j,k,t}}, \psi^\Upsilon, \sigma\right), \tag{26}$$

where $\widehat{S}_{j,t}$ and $\widehat{S}_{j,k,t}$ are predicted market shares for coffee machines and coffee pods, respectively, and $\overline{u_{j,t}^{\text{mac}}}$ and $\overline{u_{j,t}^{\text{pod}}}$ are the mean utility levels for machines and pods and are given by $\overline{u_{j,t}^{\text{mac}}} = \alpha_j + \alpha^x x_{j,t} + \alpha^{p,\text{mac}} p_{j,t} + \xi_{j,t}^{\text{mac}}$ and $\overline{u_{j,t}^{\text{pod}}} = \alpha_{j,k} + \alpha^{p,\text{pod}} p_{j,k,t} + \xi_{j,k,t}^{\text{pod}}$. $\lambda_{i,t}^{\text{mac}}$ and $\lambda_{i,j,t}^{\text{pod}}$ are the fraction of consumers of type i that remains in the market for coffee machines at time t and the fraction of consumers of type i that has purchased a coffee machine of brand j up to and at time t, respectively. Once we have the aggregate market shares we use a contraction mapping as in Berry et al. (1995) to back out the mean utilities from coffee machines and coffee pods given by $\overline{u_{j,t}^{\text{mac}}}$ and $\overline{u_{j,k,t}^{\text{pod}}}$, respectively, that equate the predicted aggregate market shares to the observed shares in the data.

The matching of the observed and predicted market shares is done by using the equations

$$S_{j,t} \equiv \frac{Q_{j,t}}{M_t} = \widehat{S}_{j,t}, \tag{27}$$

$$S_{j,k,t} \equiv \frac{Q_{j,k,t}}{M_{j,t}} = \widehat{S}_{j,k,t}, \tag{28}$$

where $S_{j,t}$ and $S_{j,k,t}$ are the observed market shares for coffee machines and coffee pods, respectively. $Q_{j,t}$ and $Q_{j,k,t}$ are the aggregate sales for coffee machine j and coffee pod k at time t, respectively, and M_t and $M_{j,t}$ are the market sizes for machines and pods.

We use the number of households with non-single-serve coffee machines (two millions) as the initial (in January 2007) potential market size for single-serve coffee machines.[22] In addition, we can assume that at the start of the period studied all consumers hold the outside good because a strength of our data set is that it reaches back essentially to the effective start of the industry.[23]

Because consumers leave the coffee machine market for 36 periods (months) after buying a coffee machine and stay in the market for coffee pods during that time, the potential market size for coffee machines evolves according to the law of motion:

$$M_t = M_{t-1}\left(1 - \sum_j \sum_i \lambda_{i,t-1}^{\text{mac}} \widehat{Pr}_{i,j,t-1}\right) + \mathbb{1}_{t>T^{\text{mac}}}\left\{M_{t-T^{\text{mac}}}\left(\sum_j \sum_i \lambda_{i,t-T^{\text{mac}}}^{\text{mac}} \widehat{Pr}_{i,j,t-T^{\text{mac}}}\right)\right\}. \tag{29}$$

The first term in this equation refers to the consumers that are left in the market from the previous period and the second term refers to the consumers that return to the market when their machines reach time T^{mac} (36 months).

The size of the coffee pod market depends not only on the installed base of coffee machines, but also on consumers' drinking habits. Specifically, to calculate the monthly potential market size for coffee pods we multiply the installed base of machines by C, the number of monthly consumption decisions made by an household as described in Section 4.1.2. Thus, the market size for coffee pods evolves according to the following law of motion:

$$M_{j,t} = M_{j,t-1} + Q_{j,t} \times C - \mathbb{1}_{t>T^{\text{mac}}}\{Q_{j,t-T^{\text{mac}}} \times C\}, \tag{30}$$

where $\mathbb{1}_{t>T^{\text{mac}}}$ is an indicator function that takes value 1 if we are in a time period t greater than T^{mac} and 0 otherwise. We assume C to be equal to 180, which can be interpreted as each household (of average size three people) consuming in total six coffee pods per day.[24]

Our estimation procedure is similar to the one used by Derdenger and Kumar (2013), Lee (2013), and Derdenger (2014), and is summarized in Online Appendix C.

5.2. Identification

We now discuss the identification of the main parameters of interest in the demand model. The price coefficients for coffee machines, $\alpha^{p,\text{mac}}$ and for coffee pods, $\alpha^{p,\text{pod}}$ are identified by the variation in prices and sales across brands, the different pod coffee blends and time. The brand fixed effects for coffee machines as well as the coffee blends fixed effects for coffee pods are identified by the mean levels of sales of coffee machines and coffee pods across alternatives.

The variance σ^2 of the consumer-specific taste for coffee pods, γ_i, is identified using both data from coffee machines and from coffee pods. The identification strategy is very similar to Lee (2013) and Derdenger (2014), who have a similar parameter in their studies on video game consoles. The first source of identification comes from the fact that consumers take into account the expected utility from coffee pods ($\Upsilon_{i,j,t}$) when they purchase coffee machines. Because $\Upsilon_{i,j,t}$ is a function of γ_i, consumers with different tastes for coffee pods will have heterogeneous preferences for coffee machines. The variance of γ_i is thus identified by the substitution patterns among single-serve coffee systems that provide different expected coffee pods utilities. Specifically, when the expected coffee pod utility from one coffee system changes, if consumers substitute disproportionately to another coffee system that provides a similar expected pod utility, then this implies there is heterogeneity in taste for coffee pods. If, on the other hand, consumers substitute to other coffee systems proportionally, then there is no consumer heterogeneity. The second source of identification comes from the dynamic nature of the problem. The potential market size for coffee pods is determined by the installed base of coffee machines, which means that the mixture of consumers over time also helps to identify the heterogeneity in preferences. If there is consumer heterogeneity, the model implies that consumers that derive a higher utility from coffee pods are more willing to purchase coffee machines in the beginning of the period, when coffee machine prices are higher, than low valuation consumers.

Finally, the scale parameter ψ^{Υ}, which links the utility from coffee pods to the utility from coffee machines, is identified by the variation in the sales of coffee machines in response to the variation in the expected utility from coffee pods. To illustrate this, note that if consumers demand fewer coffee machines when the expected coffee pod utility decreases (because of the increase in price or the decrease in variety of pods), this implies a positive ψ^{Υ} as consumers view the two products as complements. If, on the other hand, the change in the variety or prices of coffee pods has no impact on the sales of coffee machines, then this implies that ψ^{Υ} is close to zero.

Because of data limitations, we do not observe quantities sold or price data for Nespresso's coffee pods. Even though our main analysis in the following section focuses on the other firms (as we discuss below), we chose not to ignore Nespresso in the estimation of the model's parameters. This way, we hope to better capture the competition in this market and get more realistic model estimates. Thus, because of the lack of Nespresso data, and to be able to include this brand in the estimation, we make an identifying assumption. Specifically, we assume that, for all consumers, as they consider purchasing a coffee machine, the expected utility from coffee pods for Nespresso is the same as that for DolceGusto in each period—that is, $\Upsilon_{i,NP,t} = \Upsilon_{i,DG,t}\ \ \forall_{i,t}$.[25] One limitation of this assumption is that the coffee-blend dummies for Nespresso's coffee pods are not identified. On the positive side, this assumption implies that the expected utility $\Upsilon_{i,j,t}$ is allowed to change in response to competition, which can be important in counterfactual analyses.

6. Estimation Results

Sections 6.1 and 6.2 present the estimates of the demand- and supply-side parameters, respectively.

6.1. Demand-Side Estimates and Model Fit

Table 2 presents the estimates of the demand-side parameters. We first discuss the parameters for the demand of coffee machines. The scale parameter, ψ^{Υ}, is positive and significant. This means that, as expected, consumers take into account the expected utility from coffee pods when buying coffee machines and that the higher the utility from coffee pods, the more attractive the coffee machines become. The price coefficient for coffee machines is also, as expected, significant and negative. We provide a detailed analysis of the implied price elasticities below. Further, the number-of-machine-models parameter is significant, suggesting that consumers prefer brands that have more machine models.

Turning to the analysis of the coffee machine's brand preference parameters, consumers seem to have a preference for Nespresso's and DolceGusto's coffee machines when compared with the other brands. This is reflected in the positive and significant coefficients for the coffee machine brand dummies for Nespresso and DolceGusto (using the Store Brand as the reference brand). Consumers' intrinsic brand preference for DeltaQ's coffee machines is larger but not very different from that of the Store Brand.

For coffee pods, as expected, the price coefficient is negative and significant. Also, the coefficient that measures the degree of heterogeneity in consumers' preferences for coffee pods, σ, is positive and significant. This indicates that there is heterogeneity in consumers' tastes (consumption intensity levels) for coffee pods. We interpret the economic magnitude of this consumer heterogeneity below.

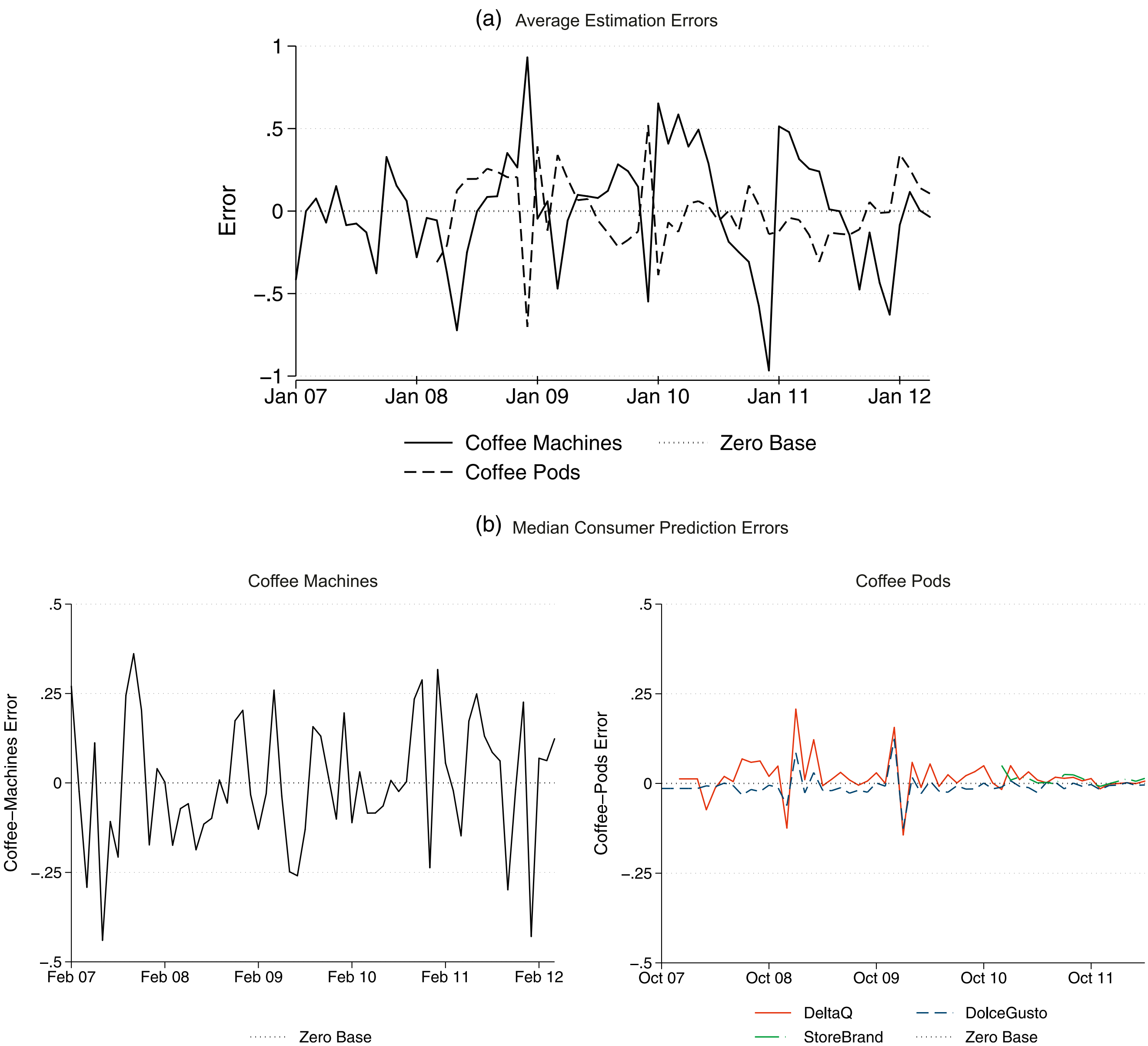
A potential concern in our context is the restrictiveness of the logit error assumption that may imply unrealistic increases in the pod inclusive values and thus in the utility from a given system as new pod blends are introduced over time (see Petrin 2002 and Gowrisankaran and Rysman 2012). Ackerberg and Rysman (2005) recommend addressing this issue by including the log of the number of products as a regressor in the utility function. Finding a coefficient of zero implies that the logit model is well specified, whereas a coefficient of −1 implies "full crowding," so there is no demand expansion from variety. We reestimated the model using the additional variable proposed by Ackerberg and Rysman (2005). As reported in Online Appendix D, we find that other parameters and price elasticities change little and that the coefficient on the log of the number of coffee blends is small and not significantly different from zero, suggesting that the *i.i.d.* logit draws are a reasonable approximation in our context.

Table 2. Demand Estimation Results

Variable	Estimate	Standard error
Coffee machine utility parameters		
Constant	10.787**	2.338
Store Brand	Base	
DeltaQ	0.492*	0.286
DolceGusto	2.313**	0.312
Nespresso	3.225**	0.409
log (Price)	−4.117**	0.509
log (Models)	0.477**	0.170
Scale parameter (ψ^{Υ})	0.011**	0.001
Year fixed effects	Included	
Coffee pod utility parameters		
log (Price)	−4.789**	0.527
Sigma coffee pods (σ)	0.863**	0.030
Blend fixed effects	Included	

Notes. This table reports the estimation results from our structural model of demand. "Models" is a variable with the number of machine models for a given brand and time period. Machine prices correspond to the weighted (by sales) average of machine-model prices for a given brand and time period. Pod prices are at the blend level.
*$p < 0.10$; **$p < 0.05$.

Figure 5. Model Fit



Notes. This figure shows the time series of the error terms that are used to assess the fit of the structural demand model. Panel (a) shows the simple average (across brands) of the unobserved error terms $\xi_{j,t}^{\text{mac}}$ and $\xi_{j,k,t}^{\text{pod}}$ for each month using the estimated demand parameters. Panel (b) shows the difference between $\delta_{i,t+1}^{\text{mac}}$ and $\delta_{i,j,t+1}^{\text{pod}}$ and the period t predictions of each of these values for a consumer with draws in the 50th percentile for the random coefficient γ_i.

6.1.1. Model Fit. Panel (a) of Figure 5 reports the simple average (across brands) of the unobserved error terms $\xi_{j,t}^{\text{mac}}$ and $\xi_{j,k,t}^{\text{pod}}$ for each month using the estimated demand parameters. The figure does not indicate any systematic autocorrelation or heteroscedasticity of the average error over time.[26]

We also find that the restrictions on consumer beliefs given by Equations (6) and (13) fit the evolution of $\delta_{i,t}^{\text{mac}}$ and $\delta_{i,j,t}^{\text{pod}}$ well, with the median (across time) errors comprising less than 3% of the absolute value of $\delta_{i,t}^{\text{mac}}$ and less than 8% (across time and brands) of $\delta_{i,j,t}^{\text{pod}}$ for a consumer with the 50th-percentile value of parameter γ_i. Panel (b) of Figure 5 shows the differences between $\delta_{i,t+1}^{\text{mac}}$ and $\delta_{i,j,t+1}^{\text{pod}}$ and the period t predictions of each of these values for a consumer with draws in the 50th percentile for the random coefficient γ_i. There do not appear to be any significant deviations in the AR(1) processes from our assumed functional forms.[27]

6.2. Supply-Side Estimates

The specification of the supply side of the model together with the demand estimates allows us to infer the

Table 3. Margins and Profit-Cost Margins

	Machines		Pods	
	Margin (euros)	Margin (%)	Margin (euros)	Margin (%)
Nespresso	−11.65	−9.87	N/A	N/A
DolceGusto	−18.39	−20.13	0.63	20.84
DeltaQ	−38.64	−66.99	0.66	21.94
Store Brand	−27.39	−54.89	0.44	20.46

Notes. This table reports average (across time) estimated margins and profit-cost margins. Margin in % is defined as (Price − Marginal Cost)/Price. Coffee pod margins are per package of 10 pods. Average margins are weighted averages (by sales) of individual coffee machine models' and coffee pod types' margins. Calculations are for the sample period from November 2010 to March 2012, when all four brands are present in the market. N/A, not estimated.

marginal costs and profit (price-cost) margins for coffee machines and coffee pods for each of the four brands in the market.

Table 3 shows the average (across time) estimated profit margins for coffee machines for each brand. To make margins comparable across brands we report margins for the sample period after the entry of the Store Brand.

The positive profit margins for coffee pods and negative profit margins for coffee machines show that firms in this market lose money on the sales of coffee machines and recover it back from the sales of coffee pods in the aftermarket, as is common in tied-goods markets.

The estimated machine margins are consistent with statements from industry analysts that say that Nespresso does not make any money on the sales of its machines and that it is the sale of the capsules that determines the profitability of the business.[28] Further, the recovered coffee pod margins are also consistent with industry reports and popular press that mention that the profit margin for espresso coffee pods is estimated to be around 20%–30%.[29]

6.3. Interpretation

To provide an economic interpretation of the parameter estimates and evaluate their plausibility, we compute several metrics implied by the model estimates. Specifically, we compute the implied own- and cross-price elasticities of coffee pods and coffee machines. In addition, we evaluate the responsiveness of the sales of coffee machines to coffee pods' prices. This analysis allow us to assess the complementary nature of coffee machines and coffee pods. Finally, we conduct a break-even analysis to measure the relative importance of the primary good and the aftermarket good for firms' profits, and to show how consumer heterogeneity is related to firm profitability.

Table 4 reports the coffee machine's own- and cross-price elasticities. On average, a 1% increase in the prices of coffee machines for a given brand results in a 4% decrease in the sales of coffee machines for that same brand. The cross-price elasticities of the coffee machines are small and range from 0.05% to 0.09%.[30]

Table 5 reports coffee pods' own-price elasticities (we do not report the brand-cross-price elasticities because each firm is a monopolist in the aftermarket). Consumers seem to be slightly less price sensitive in the market for coffee pods than in the market for coffee machines. The average (in absolute value) own-price elasticity is 3.6% for coffee pods.

To evaluate the responsiveness of the sales of coffee machines to coffee pods prices, we compute pod-machine price elasticities. Specifically, we increase by 1% the price of coffee pods of a certain brand, while holding fixed the prices for the other brands, and calculate how the sales of coffee machines change accordingly. Table 6 summarizes the average pod-machine price elasticities for each brand.

Table 6 shows that the demand for coffee machines is quite responsive to the price increase of coffee pods. For example, a 1% increase in the price of DeltaQ's pods results in a 5.2% decrease in the sales of coffee machines for DeltaQ. This is consistent with the fact that consumers weigh the price of coffee pods when considering the purchase of a single-serve coffee system. Also, the pod-machine elasticities of DeltaQ and the Store Brand are higher than DolceGusto's. This indicates that consumers who purchase DeltaQ's and the Store Brand's coffee systems put more weight on the prices of coffee pods than those that purchase DolceGusto's.

Table 4. Coffee Machine Price Elasticities

	Nespresso	DolceGusto	DeltaQ	Store Brand
Nespresso	−3.971	0.067	0.062	0.079
DolceGusto	0.044	−3.949	0.062	0.079
DeltaQ	0.047	0.072	−3.949	0.087
Store Brand	0.047	0.072	0.067	−3.931

Notes. This table reports the own and cross price elasticities for coffee machines, with cell entry (i, j) implying the percent change in sales of coffee machine for brand j when the price of coffee machine for brand i goes up by 1%. The price change is applied for each period and then averaged across periods. Calculations are for the sample period from November 2010 to March 2012, when all four brands are present in the market.

Table 5. Coffee Pod Price Elasticities

	Own price elasticity
DolceGusto	−3.782
DeltaQ	−3.455
Store Brand	−3.538

Notes. This table reports the own price elasticities for coffee pods, which are calculated by getting the percentage change in the sales of coffee pods of each brand (relative to the outside option) for a 1% increase in price. The price change is applied to all pod blends of a given brand in each period and then averaged across periods. Calculations are for the sample period from November 2010 to March 2012, when all four brands are present in the market.

Turning to the economic analysis of the supply-side parameters, the results in the previous sections show that firms lose money on the sales of coffee machines and recover it back from the sales of coffee pods in the aftermarket. To provide an economic understanding of the relative importance of the primary good and the aftermarket good for the firm, and also of the importance of consumer heterogeneity, we perform a break-even analysis. Specifically, we compute the implied number of months that each brand needs to sell coffee pods to a consumer to recover from the loss of selling a coffee machine, and how this number varies across brands and consumer types (heavy, medium, and light coffee drinkers).

Table 7 reports the results from this analysis. We distinguish between the top-, middle-, and bottom-decile consumers in terms of tastes (consumption intensity) for coffee pods as defined by the distribution of the parameter γ_i, and refer to these consumers as heavy, medium, and light consumers of coffee pods, respectively. The number of months necessary for break-even is calculated for each time period (conditional on the prices and marginal costs of the machines in that period and on the prices and marginal costs of the pods in future periods) and then averaged across time periods. It takes DeltaQ and the Store Brand relatively more time than DolceGusto to recover from the loss of a sale of a coffee machine. This result follows from the fact that these brands price their coffee machines relatively more aggressively (lower prices). More specifically, for DeltaQ and the Store Brand it takes almost 36 months to recover from the loss of selling a coffee machine to a light coffee drinker. If consumers replace their coffee machines after three years, this suggests that these brands are actually losing money on some of the light-drinking consumers. On the other hand, for both DeltaQ and the Store Brand, it takes less than one year to recover from the loss of selling a coffee machine to a heavy drinker. It takes DolceGusto a shorter period of time to recover from the loss associated with the sale of a coffee machine than for DeltaQ or the Store Brand.

Table 6. Sensitivity of Coffee Machine Sales to Coffee Pod Prices

	DolceGusto	DeltaQ	Store Brand
DolceGusto	−3.703	0.144	0.143
DeltaQ	0.094	−5.227	0.108
Store Brand	0.122	0.146	−5.096

Notes. This table reports the own- and cross-pod price elasticities for coffee machines, with cell entry (i, j) implying the percent change in sales of coffee machine for brand j when the price of coffee pods of brand i goes up by 1%. Specifically, we increase by 1% the price of coffee pods of a certain brand while holding the prices for the other brands constant, and calculate how the sales of coffee machines change accordingly. We do this for all time periods (one at a time) and then average the overall effects. Calculations are for the sample period from November 2010 to March 2012, when all four brands are present in the market.

Table 7. Break-Even Analysis

	Consumer type		
	Light	Medium	Heavy
DolceGusto	22.6	11.6	6.2
DeltaQ	36.0	18.7	10.2
Store Brand	35.9	18.9	10.5

Notes. This table reports the number of months that each brand needs to sell coffee pods to a consumer to recover from the loss of selling a coffee machine, and how this number varies across brands and consumer types (heavy, medium, and light coffee drinkers). Heavy, medium, and light drinkers are defined as the top-, middle-, and bottom-decile consumers, respectively, in terms of tastes (consumption intensity) for coffee pods as given by the distribution of the parameter γ_i. The number of months necessary for break-even is calculated for each time period (conditional on the prices and marginal costs of the machines in that period and on the prices and marginal costs of the pods in future periods) and then averaged across time periods. Calculations are for the sample period from November 2010 to March 2012, when all four brands are present in the market.

7. The Impact of Licensing on Equilibrium Outcomes

In this section we use the estimated demand and supply parameters to perform a counterfactual analysis to study the quantitative effects of alternative aftermarket licensing strategies on equilibrium variables (prices and profits). Specifically, we use the model to answer the following questions: Is there a range of royalty rates under which firms could potentially reach a beneficial licensing agreement? Does the answer to this question depend on the type of pricing agreement? More generally, what are the implications of licensing for the equilibrium prices and profits in the market?

We consider two types of licensing agreements in terms of pricing rights:[31] (i) an independent pricing scheme in which the licensor and the licensee set the price of the aftermarket goods independently, and (ii) a uniform pricing scheme in which the licensor sets a uniform price for all of the aftermarket goods compatible with the licensor's system. This last scheme (uniform pricing) is inspired by the fact that, in the U.S. market, Green Mountain's coffee—Keurig's brand—is sold at the same price as several other pods that are compatible with Keurig's machines. For both cases (independent and uniform pricing agreements), we study how the results vary across a reasonable range of royalty rates, defined as the percentage of the coffee pod price that the licensee agrees to pay the licensor for the right to make pods compatible with the licensor's patented system.

For practical purposes, we focus on the case in which one of the incumbents, DeltaQ, enters into a licensing agreement with one of the competitors, the Store Brand. Thus, instead of the Store Brand entering with its own system, as observed in reality, in this counterfactual scenario the Store Brand only enters the coffee pod market.[32] The other two competitors, Nespresso and DolceGusto, maintain their presence in the market with their own systems. The focus on the licensing between DeltaQ and the Store Brand is a natural choice for several reasons.[33] First, DeltaQ is a brand from the parent company Delta Cafés, which is a well-established (market leader) coffee producer in the coffee industry in Portugal, which makes it natural for this brand to enter with its own system. For the Store Brand Pingo Doce, however, the development of an entirely new coffee system (which involves the sale of coffee machines) is not an obvious choice because this is a supermarket chain that does not sell any other appliances. Second, both DeltaQ and the Store Brand target similar consumer segments.[34] Finally, these two firms share the same geographical origin, making the licensing agreement between these two brands more natural.

To facilitate the analysis, we present separately the results for the two alternative licensing agreements in terms of pricing rights (independent and uniform pricing of the coffee pods). Before we examine the results, we explain how we implement the counterfactual analyses.

7.1. Implementation

To compute the new equilibrium outcomes in the counterfactual licensing scenarios, we proceed as follows. Relative to the baseline model presented in Section 4.2, there are two basic changes that affect the profits of both DeltaQ and the Store Brand. First, the licensing agreement implies that the Store Brand makes no profits (or losses) from the sale of coffee machines. Second, DeltaQ receives royalties (paid by the Store Brand) from the sales of the Store Brand's coffee pods.

In addition, when comparing the Store Brand's profits in the nonlicensing scenario and in the licensing scenario, we need to take a stand on the change in possible fixed costs associated with entering the coffee machine business. This is because, in the licensing scenario, the Store Brand does not have to supply coffee machines. To be conservative, we assume that the fixed costs of entering the coffee machine business in the nonlicensing scenario are zero.[35] This is a reasonable assumption in our application because the coffee machines sold by the Store Brand are produced by Flama, a well-established manufacturer of appliances. This means that the Store Brand did not have to adjust its production process in a significant manner (for example, by building a new plant) to enter the coffee machine business. Naturally, it is also possible that Store Brand had to pay a lump sum to enter the production agreement with Flama, which is equivalent to a fixed cost of entering the coffee machine business. In this case, the implicit assumption in our approach of ignoring these costs is that this lump-sum transfer would be approximately similar to an eventual lump-sum payment made to DeltaQ to enter the licensing agreement, and hence has no effect on the comparison of profits (licensing versus nonlicensing) analysis.

In the licensing agreement scenario (denoted below with superscript "L") with independent pricing of coffee pods, and because in this case the Store Brand does not set coffee machine prices, the Store Brand's optimal coffee pod prices for a blend of type v at time t are given by

$$p^{L*}_{SB,v,t} = \arg\max\left[\sum_{v\in\{pr,rg\}} M^{\mathrm{old}_t}_{DQ,t}\mathcal{S}^{\mathrm{old}_t}_{SB,v,t}\left(p^{\mathrm{pod}}_{SB,v,t}\cdot(1-r) - mc^{\mathrm{pod}}_{SB,v,t}\right)\right], \tag{31}$$

in which the subscripts DQ and SB represent DeltaQ and the Store Brand, respectively, and r is the royalty rate. DeltaQ's optimal prices are now given by

$$\begin{aligned} p^{L*}_{DQ,v,t} = \arg\max\Bigg[& M_t S_{DQ,t}\,(p^{\mathrm{mac}}_{DQ,t} - mc^{\mathrm{mac}}_{DQ,t}) \\ & + \sum_{v\in\{pr,rg\}} M^{\mathrm{old}_t}_{DQ,t}\mathcal{S}^{\mathrm{old}_t}_{DQ,v,t}\,(p_{DQ,v,t} - mc_{DQ,v,t}) \\ & + \frac{1-\beta^{T^{\mathrm{mac}}}}{1-\beta}\sum_{v\in\{pr,rg\}} M^{\mathrm{new}_t}_{DQ,t}\mathcal{S}^{\mathrm{new}_t}_{DQ,v,t}\left(p^{\mathrm{pod}}_{DQ,v,t} - mc^{\mathrm{pod}}_{DQ,v,t}\right) \\ & + \sum_{v\in\{pr,rg\}} M^{\mathrm{old}_t}_{DQ,t}\mathcal{S}^{\mathrm{old}_t}_{SB,v,t}\left(p^{\mathrm{pod}}_{SB,v,t}\cdot r - mc_r\right) \\ & + \frac{1-\beta^{T^{\mathrm{mac}}}}{1-\beta}\sum_{v\in\{pr,rg\}} M^{\mathrm{new}_t}_{DQ,t}\mathcal{S}^{\mathrm{new}_t}_{SB,v,t}\left(p^{\mathrm{pod}}_{SB,v,t}\cdot r - mc_r\right)\Bigg], \end{aligned} \tag{32}$$

where the first three terms in the brackets correspond to the same function maximized by DeltaQ in the nonlicensing scenario (see Equation (21)). The licensing scenario adds the last two terms as additional sources of profits for DeltaQ.

Note that here we have introduced the term mc_r, which represents the marginal cost associated with licensing costs that are borne by DeltaQ, such as the costs of monitoring and packaging the licensed coffee pods.[36] We assume mc_r to be of 0.13 euros per package of 10 pods. We compute this value using data from Keurig's 10-K report for 2013 in the U.S. market.[37]

In the licensing agreement with uniform pricing, DeltaQ sets the price for all coffee pods compatible with DeltaQ's system, including the pod brand. This implies that

$$p_{DQ,k,t} = p_{SB,k,t} = p_{DQ,t}, \quad \forall k \in B_{DQ,t} \bigcup B_{SB,t}. \tag{33}$$

We omit the first-order conditions for DeltaQ in the licensing agreement with uniform pricing because they are similar to the ones in the case with independent pricing except for the restriction given by Equation (33).

To calculate each firm's total profits in the licensing scenarios, we proceed by adding up the discounted profits (discounted to November 2010, when the Store Brand entered the market) for coffee pods and coffee machines for each period in the data.[38] In addition, we include the discounted profits (in expectation) from coffee pods that are generated by the installed base of coffee machines in the last period in the data.

To solve for the equilibrium prices in the counterfactual scenarios, we follow the computational steps detailed in Online Appendix E. Note that, because analytical solutions for the first-order conditions for prices are unavailable, we are unable to formally state whether the converged equilibria are unique. Nevertheless, we found that the converged solutions were robust to different initial guesses of the pricing policies within a range that we expect to reasonably see in real-world data.

7.2. Results

To facilitate the discussion of the results, we focus our analysis on the effects of licensing on DeltaQ's and the Store Brand's equilibrium variables (coffee machines' and pods' prices and firms' profits), because these are the firms that are directly involved in the licensing agreement. Figures 6–8 show the main results from this analysis. Figure 6 shows the equilibrium coffee pods' and coffee machines' prices across different royalty rates, in the (observed) nonlicensing scenario and in the two alternative licensing scenarios with different pricing agreements. We report the average prices after the entry of the Store Brand.[39] Figure 7 shows, for each royalty rate, the side-by-side comparison of total profits in the independent- and uniform-pricing scenarios for DeltaQ (panel (a)) and for the Store Brand (panel (b)). Finally, Figure 8 shows the decomposition of equilibrium profits for both DeltaQ and the Store Brand in terms of profits from the sale of the coffee machines and from the sale of coffee pods.[40] We discuss these results in the next sections.

7.2.1. Independent-Pricing Licensing Agreement. We start by comparing the equilibrium variables in the nonlicensing scenario with a licensing scenario in which the two brands set the prices of the coffee pods independently and the royalty rate is set at 0%. We then discuss how the equilibrium outcomes change across different royalty rates.

Effect on Prices. In the licensing scenario with a 0% royalty rate, DeltaQ faces more competition in the aftermarket than in the nonlicensing scenario, because of the entry of the Store Brand's compatible pods. Panel (a) of Figure 6 shows that DeltaQ reacts by setting prices for their own coffee pods that are 3.3% lower in the licensing scenario than in the nonlicensing scenario.

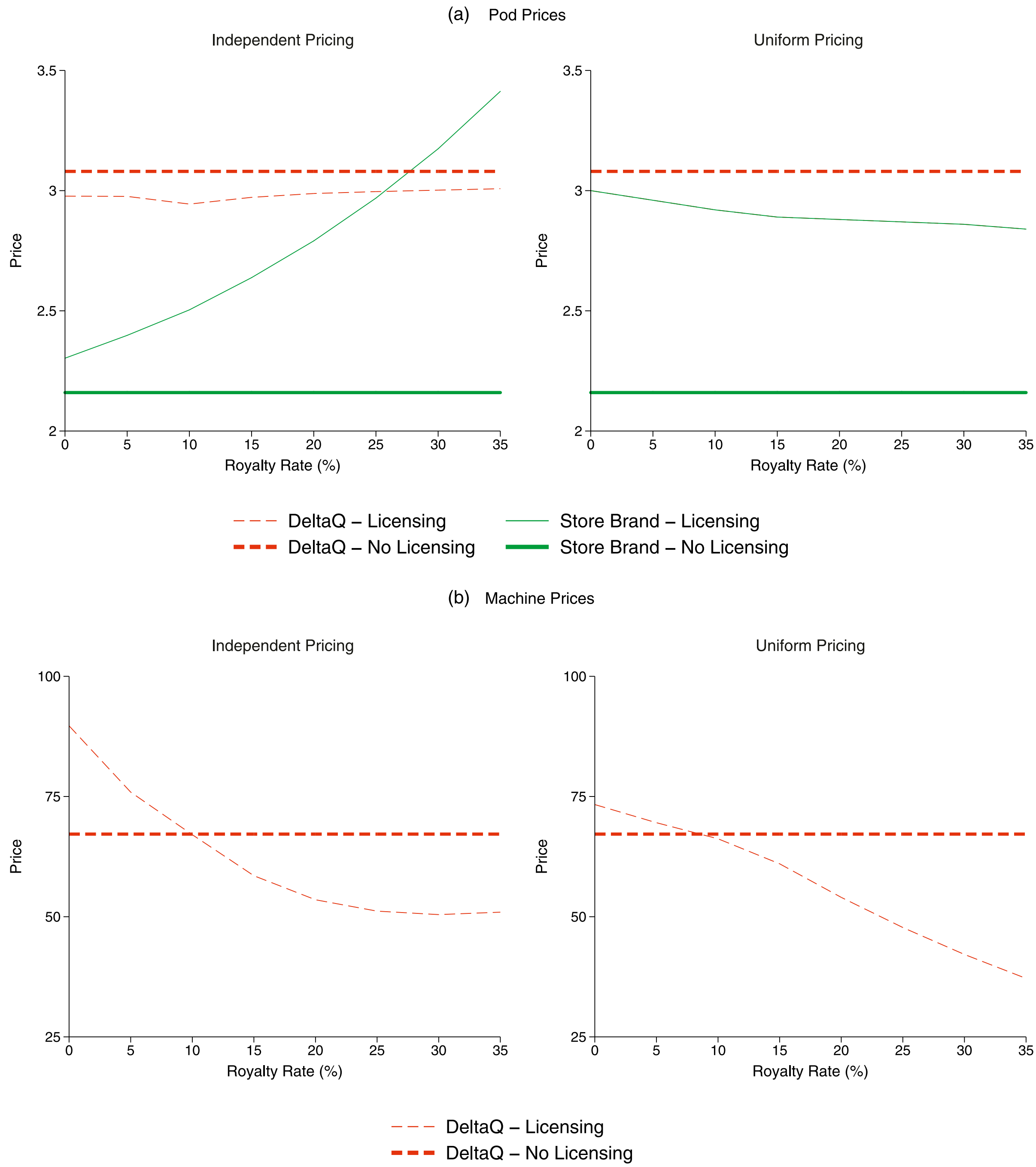
In contrast with the results for DeltaQ, panel (a) of Figure 6 shows that the Store Brand's coffee pods prices are 6.4% higher in the licensing scenario with a 0% royalty rate than in the nonlicensing scenario. This is because, relative to the nonlicensing scenario, the Store Brand no longer internalizes the effect of changes in coffee pods' prices on the sales of coffee machines given that now the Store Brand does not sell coffee machines (that is, licensing reduces the Store Brand's incentive to set lower coffee pod prices to attract more customers to purchase the coffee machine).

In terms of pricing of the coffee machines, panel (b) of Figure 6 shows that, when the licensing rate is 0%, DeltaQ sets a price for its machines that is higher than in the nonlicensing scenario. This is due to the combination of three complementary effects. First, there is less competition in the primary market in the licensing scenario (the Store Brand does not sell machines in the licensing scenario). Second, DeltaQ's system becomes more attractive to consumers relative to the competition (Nespresso and DolceGusto) because DeltaQ's system now has more compatible pods and they are sold at a lower price. Third, because of some business stealing and increased price competition from the Store Brand in the aftermarket, DeltaQ makes fewer profits from coffee pods per machine sold. To compensate for this negative effect, DeltaQ increases the prices of its coffee machines.

How do the previous effects on equilibrium prices vary across different royalty rates? With a positive royalty rate, DeltaQ can make more money in the aftermarket per pod sold. In turn, this effect increases DeltaQ's incentives to lower the prices of its machines to increase the size of the installed base. Panel (b) of Figure 6 shows that, for royalty rates higher than 10%, the price of DeltaQ's machines actually becomes lower than in the nonlicensing case.

Regarding the prices for the coffee pods, panel (a) of Figure 6 shows that DeltaQ's optimal pod prices, in contrast to the coffee machine price, do not vary much across different royalty rates (the licensing price is

Figure 6. Equilibrium Prices in Counterfactual Scenarios



Notes. This figure shows the equilibrium coffee pods' and coffee machines' prices across different royalty rates, in the (observed) nonlicensing scenario and in the two alternative licensing scenarios with different pricing agreements (independent and uniform pricing). Prices are in euros. Pod prices are calculated as simple averages (over time) of the prices in the periods after the entry of the Store Brand. Coffee machine prices are weighted (by monthly sales) averages of the prices in the periods after the entry of the Store Brand. All prices reported are counterfactual prices predicted by the structural model.

always lower than in the nonlicensing scenario). This suggests that DeltaQ has no incentive to engage in price competition with the Store Brand because a price war would lead to both lower margins for DeltaQ's own pods and to lower profits from royalties. The effect of an increase in the royalty rate on the coffee pod prices of the Store Brand is quite different. Here, as the royalty rate increases, the Store Brand has no option other than to increase the prices of the pods to compensate for the decreased profits. This is because the Store Brand does not sell coffee machines in the licensing scenario.

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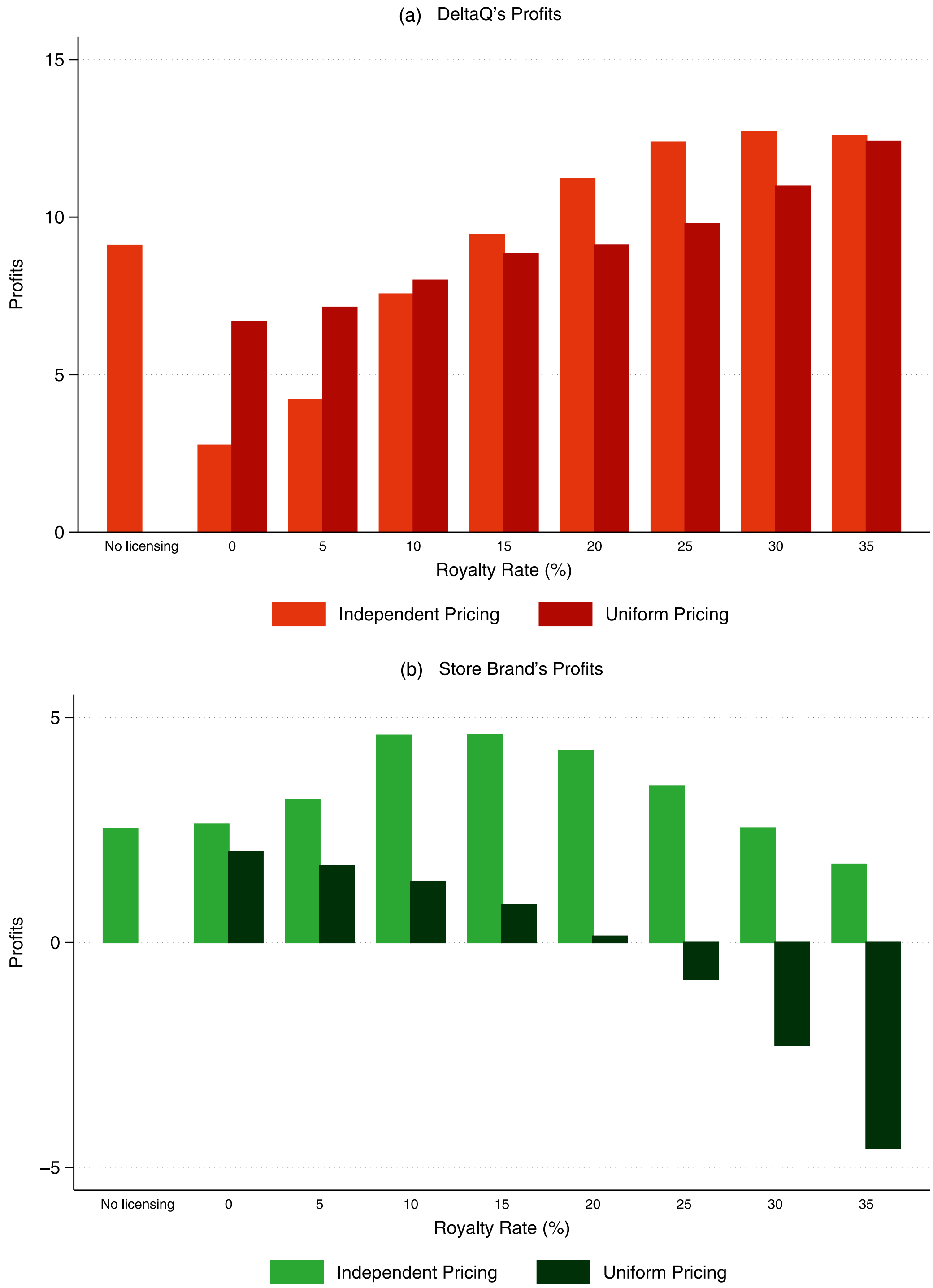
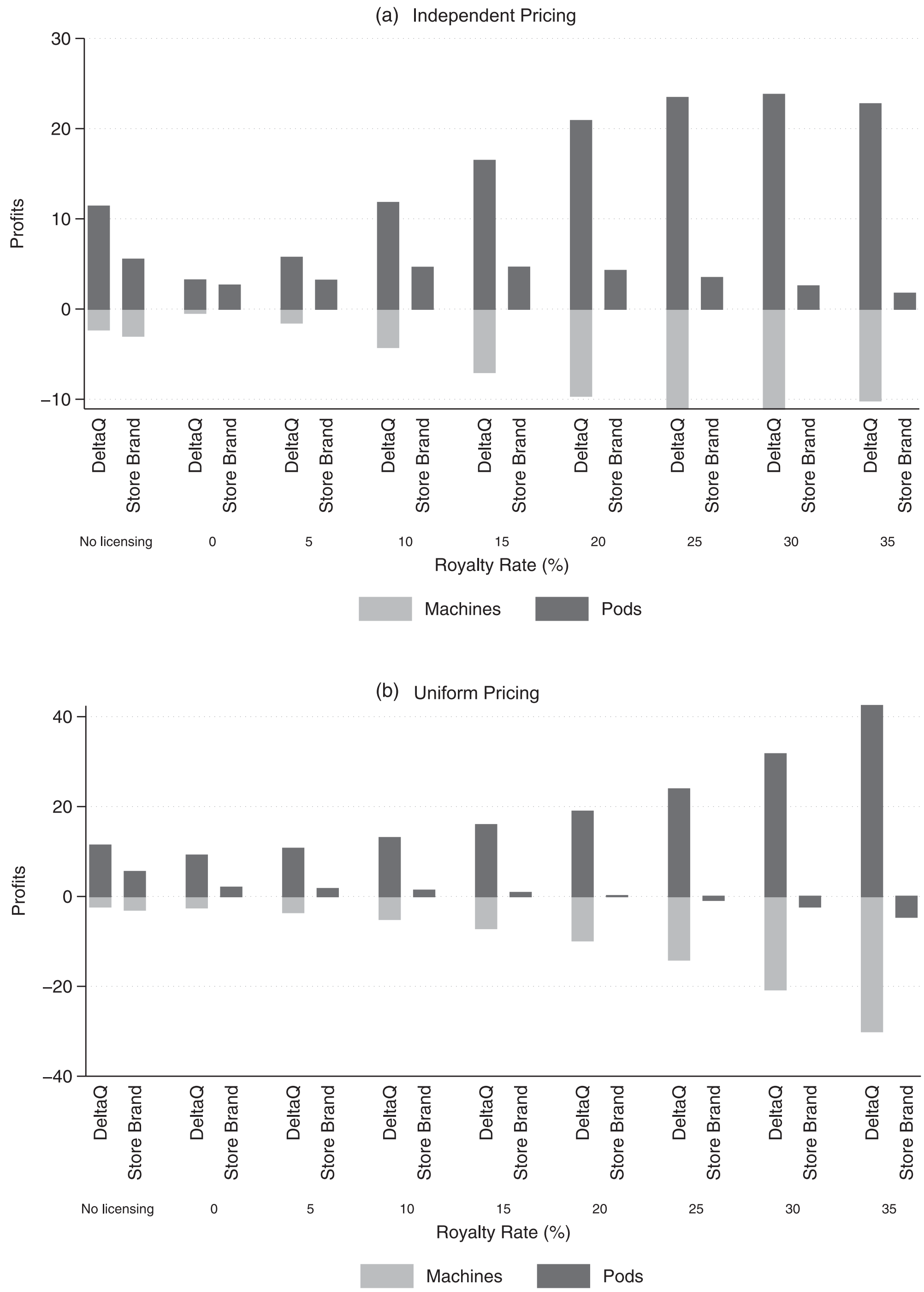
Figure 7. Total Profits in Counterfactual Scenarios



Notes. This figure shows the profits for both DeltaQ and the Store Brand under the nonlicensing scenario and, for each royalty rate, the side-by-side comparison of total profits in the independent-pricing and uniform-pricing licensing scenarios. Counterfactual profits are obtained by using profits predicted by the model for each month after the entry of the Store Brand that are then discounted to November 2010 and added up. Profits are in millions of euros.

Effect on Profits. Turning to the analysis of the effect of licensing on profits, panel (a) of Figure 7 shows that the total profits of DeltaQ are lower in the licensing scenario with a 0% royalty rate than in the nonlicensing scenario, but that the Store Brand's profits are (slightly) higher. According to the profit decomposition reported in Figure 8, the higher profits of the Store Brand are mostly driven by the fact that the Store Brand no longer incurs any losses from the sale of coffee machines. The lower profits for DeltaQ in the

Figure 8. Profit Decomposition in Counterfactual Scenarios



Notes. This figure shows the decomposition of equilibrium profits for both DeltaQ and the Store Brand in terms of profits from the sale of the coffee machines and from the sale of coffee pods. Counterfactual profits are obtained by using profits predicted by the model for each month after the entry of the Store Brand that are then discounted to November 2010 and added up. Profits are in millions of euros.

licensing scenario with a 0% royalty rate (when compared with the nonlicensing scenario) are mostly due to increased competition in the aftermarket (DeltaQ's customers can now buy coffee pods from the Store Brand, which are sold at a lower price), from which the majority of firms' profits in this market originate.

The effects of licensing on profits vary significantly across royalty rates. DeltaQ's and the Store Brand's profits are increasing in the royalty rate up to a certain level (30.4% for DeltaQ and 12.7% for the Store Brand), and then decreasing.

For the Store Brand, the initial, perhaps counterintuitive, positive relationship between total profits and royalty rates for royalty rates below 12.7%, and the subsequent negative relationship, is due to a combination of two opposite effects. On the one hand, an increase in the royalty rate implies that the Store Brand has to pay more to DeltaQ for each coffee pod it sells, which has a negative impact on its profits. On the other hand, a higher royalty rate increases the profits of DeltaQ in the aftermarket. This motivates DeltaQ to further reduce the price of coffee machines (as noted above, DeltaQ's coffee machine prices are decreasing in the royalty rate), which in turn increases its installed customer base, leading to an increase in the demand for the (compatible) coffee pods of the Store Brand. For moderate levels of royalty rates, this increase in demand for the Store Brand's coffee pods is sufficiently strong to compensate for the loss in revenues due to the higher royalty rates that the Store Brand has to pay. For royalty rates above 12.7%, however, the first negative effect on profits starts to dominate and hence the Store Brand's profits become decreasing in the royalty rate.

For DeltaQ, the initial increasing and then decreasing pattern of total profits across royalty rates is due to a combination of several factors. As noted above, the Store Brand reacts to an increase in the royalty rate by increasing the price of its coffee pods, which in turn decreases the quantity demanded (per machine sold) for its coffee pods. For moderate levels of the royalty rate (less than 30.4%), this negative effect on demand is overturned by an increase in the overall demand for the Store Brand's pods due to the increase in the sales of DeltaQ's coffee machines (as discussed before, the equilibrium price of DeltaQ's coffee machines is decreasing in the royalty rate). As such, for moderate levels of the royalty rate, DeltaQ's revenues from royalties increase with the royalty rate. The profits also go up because the additional revenues are initially large enough to compensate for the losses due to the lower prices of DeltaQ's coffee machines (see panel (a) of Figure 8). For royalty rates higher than 30.4%, the negative effect on the quantity demanded of the Store Brand's pods is so high that DeltaQ's profits start to decrease with the royalty rate.

Part of the market expansion of DeltaQ and the Store Brand in the licensing scenario happens at the expense of their competitor's (DolceGusto). In the licensing scenario (both with independent and uniform pricing), DolceGusto sells fewer machines and pods because its system becomes less attractive to consumers when compared with the DeltaQ/Store Brand system.

When compared with a nonlicensing scenario, DeltaQ makes higher profits under the licensing scenario as long as the royalty rate is greater than 14.1%. The Store Brand also makes more profits in the licensing than in the nonlicensing scenario as long as the royalty rate is less than 30.1%. Thus, for a royalty rate between 14.1% and 30.1%, both firms benefit from licensing, suggesting that in this range firms could possibly reach a licensing agreement. This range is consistent with Keurig's royalty rate in the U.S., which we estimate to be around 15%.[41]

7.2.2. Uniform-Pricing Licensing Agreement. In a licensing agreement with uniform pricing, DeltaQ sets the same price for both its coffee pods and the Store Brand's compatible coffee pods.[42] Thus, compared with the independent-pricing licensing agreement, the uniform-pricing strategy avoids excessive price competition between coffee pods from the two brands, but at the same time it limits the firms' ability to charge differentiated prices for products with different qualities. As such, the effect on equilibrium prices and profits is a priori ambiguous.

Effect on Prices. Panel (a) of Figure 6 shows that the prices of the coffee pods of DeltaQ/Store Brand in the licensing scenario are always between the nonlicensing prices of DeltaQ (high price) and the Store Brand (low price). In particular, with a 0% royalty rate, the Store Brand's coffee pod prices are 38.8% higher than the nonlicensing scenario prices. Similarly, with a 0% royalty rate, DeltaQ's coffee pod prices are about 2.4% lower than DeltaQ's prices in the nonlicensing scenario.

Turning to the analysis of the effects of the uniform-pricing licensing agreement on coffee machine's prices, panel (b) of Figure 6 shows that, at a 0% royalty rate, DeltaQ's coffee machine price is 9.1% higher in the licensing case than in the nonlicensing case. This result contrasts with the significantly higher coffee machine price in the licensing scenario with independent pricing relative to the nonlicensing case (in which the price is 33.5% higher). This is because, with a uniform-pricing licensing agreement, the potential loss of margins in the aftermarket due to the increased competition from the Store Brand's coffee pods is smaller. In turn, this means that DeltaQ does not have to increase the price of its coffee machines by much to compensate for the losses in the coffee pod market. The increase in competition in the aftermarket effect is smaller here (when compared with the independent-pricing scenario) because, with uniform pricing, DeltaQ can partially control the intensity of competition in the aftermarket by setting prices for both its own coffee pods and the Store Brand's pods.

The previous effects of licensing on coffee machines' and coffee pods' prices vary across royalty rates. Panel (a) of Figure 6 shows that the DeltaQ/Store Brand's coffee pods equilibrium prices are decreasing in the royalty rate, in contrast with the increasing (for the Store Brand) or flat (for DeltaQ) pattern observed in the independent-pricing licensing agreement. This decreasing pattern observed here is due to the fact that, with uniform pricing, DeltaQ is compensated more in the aftermarket when the royalty rate is higher.

Panel (b) of Figure 6 shows that DeltaQ's coffee machine prices decrease with the royalty rate. This is because the aftermarket profits from DeltaQ increase with the royalty rate when DeltaQ controls the prices of both its coffee pods and the Store Brand's pods (see panel (b) of Figure 8). For positive royalty rates, the coffee machine prices are lower than those in the observed nonlicensing case. This is reasonable because uniform pricing avoids excessive competition in the aftermarket.

Effect on Profits. Turning to the analysis of the effects of the uniform-pricing licensing agreement on profits, Figure 7 shows that the total profits of DeltaQ and the Store Brand are both smaller in the uniform-pricing licensing agreement (with 0% royalty rate) than in the nonlicensing scenario. As the royalty rate increases, however, the profits of DeltaQ also increase. In fact, for royalty rates above 19.9%, the total profits of DeltaQ are higher in the uniform-pricing licensing agreement than in the nonlicensing case. For the Store Brand, the profits are always decreasing in the royalty rate. Thus, the Store Brand is unambiguously worse off in the uniform-pricing licensing agreement case than in the nonlicensing case (and also worse off than with an independent-pricing licensing agreement).

For DeltaQ, the change in profits across royalty rates relative to the nonlicensing case is a combination of two opposite effects. On the one hand, the uniform-pricing licensing agreement allows DeltaQ to set the prices for both its pods and the Store Brand's pods which, relative to the nonlicensing case, has a positive effect on profits (price-control effect). On the other hand, the licensing agreement brings an increase in competition in the aftermarket, which has a negative effect on profits (competition effect). For royalty rates below 19.9%, the second effect (competition) dominates. For royalty rates above 19.9%, however, the first effect (price control) becomes the dominating effect, which explains the higher (relative to the nonlicensing scenario) profits of DeltaQ across this range of royalty rates.

For the Store Brand, the change in profits across royalty rates relative to the nonlicensing case, and the variation of profits across royalty rates, is easier to understand. The lower profits of the Store Brand relative to the nonlicensing scenario are driven by the loss of control of its coffee pod prices in the uniform-pricing licensing agreement. This also explains the decreasing profits of the Store Brand across royalty rates. Indeed, if we compare the optimal pod prices in the independent-pricing licensing agreement (which we can interpret to be approximately the optimal prices that the Store Brand would choose if it was able to set the prices of its own coffee pods) with those in the uniform-pricing licensing agreement, both reported in panel (a) of Figure 6, we conclude that the Store Brand's pod prices are too high when the royalty rate is low (that is, when the royalty rate is less than 22%) and too low when the royalty rate is high (that is, when the royalty rate is higher than 22%).

7.3. Summary of the Main Effects

Taken together, the overall effects of licensing on equilibrium variables are complex and usually depend on the agreed royalty rate and on the type of licensing agreement. Despite the complexity of the effects, however, we can reach several robust conclusions about the effect of licensing on equilibrium outcomes.

First, the model allows us to identify the ranges of royalty rates that could potentially lead to a beneficial licensing agreement between the licensor and the licensee.

Second, we show that the relationship between the profits of the licensee and the royalty rate is not always monotonic. In certain situations, the licensee can benefit from an increase in royalty rates. This counterintuitive result follows from the fact that an higher royalty rate increases the profits for the licensor in the aftermarket. This motivates the licensor to further reduce the price of the primary good, which in turn increases the licensor's (and the licensee's) installed customer base.

Third, we find that the profits of the licensee are always smaller in the uniform-pricing licensing agreement case than in the independent-pricing licensing agreement case. This result is intuitive because in the licensing agreement with independent pricing, the licensee has the flexibility to set coffee pod prices to maximize its profits. In fact, the profits of the licensee are smaller in the uniform-pricing licensing agreement than in the nonlicensing agreement. This suggests that the ability of the licensee to set its own prices is an important determinant of licensing in equilibrium.

Fourth, for the licensor, the choice between independent or uniform pricing depends on the royalty rate. Uniform pricing is preferred when the royalty rate is low as it avoids price competition. When the royalty rate is high, however, independent pricing is preferred as it facilitates price discrimination.

Finally, licensing seems to have important effects on price competition. Within the range of royalty rates for which the licensor and licensee could reach a beneficial licensing arrangement (with independent pricing) we see two effects. For coffee pods, we observe a convergence between the licensor and the licensee coffee pod prices (despite the independent pricing), which suggests that the independent-pricing licensing agreement leads to less price dispersion in the aftermarket. For coffee machines, prices are lower in the independent-pricing licensing agreement case than in the nonlicensing scenario. This result suggests that the independent-pricing licensing agreement can lead to an increase in the customer base of the two brands because, with lower coffee machines prices, the cost of entry of new customers is lower.

8. Conclusions

We develop and estimate a structural model of demand and supply for both coffee machines and coffee pods that incorporates key features of tied-goods markets. We then use the model to quantify, through policy simulations, the impact of different licensing strategies on equilibrium outcomes (prices and profits) in this market. We solve for the counterfactual market equilibrium in which we force one of the incumbents (DeltaQ) to enter a licensing agreement with one of the followers (the Store Brand), keeping the other competitors with their own system. With certain assumptions, the model allows us to evaluate the trade-offs between the licensing and the no-licensing strategies and to see for which range of royalty rates the licensor and licensee could potentially reach a beneficial licensing agreement.

Our results show that the relationship between the licensee's profits and the royalty rate is not always monotonically decreasing. In addition, even though the licensee always prefers an independent-pricing licensing agreement to a uniform-pricing licensing agreement in this market, the relative preference of the licensor depends on the agreed-upon royalty rate. Finally, we find that licensing has an important impact on price competition in the market. Within the relevant range of royalty rates in which both brands have an incentive to enter a licensing agreement, the independent-pricing agreement is associated with less price dispersion in the aftermarket, and with lower prices of the primary good (coffee machines) of the licensor relative to the nonlicensing scenario. There could, of course, be several reasons why we do not observe licensing in this market. First, firms may be operating under objective functions that differ from those we consider. Next, the store brand may see traffic-generating benefits from carrying its own coffee machine. Also, licensing its technology to the retailer may dilute the DeltaQ brand. In addition, our analysis abstracts away from other firm's strategic considerations such as the timing of entry and firms' product quality choice and variety. The investigation of how these considerations are affected by licensing arrangements (and vice versa) we leave to future research.

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Endnotes

[1] Henceforth, we will refer to the Pingo Doce brand as the Store Brand.

[2] Because the combined quantities of noncoffee drinks represent less than 7% of the total sales of coffee pods for DolceGusto, we choose to focus our study on espresso-coffee options.

[3] During the time period studied, all brands had two categories of pods ("premium" and "regular") with the exception of DeltaQ, which had only one category with prices similar to the Store Brand's premium pods and to DolceGusto's regular pods.

[4] We face two data-related limitations. First, no coffee pod sales nor prices are available for Nespresso because all of their coffee pod sales occur through their own channels (online and own brick-and-mortar stores). We discuss how we deal with this limitation in the identification section. Second, the time coverage for the data for machines and pods is not the same. Coffee machine data are available from January 2007 to April 2012, while the data for coffee pods is available from April 2008 to April 2012. To better capture the dynamics of the industry since its inception, we choose to study the period from January 2007 to April 2012. To deal with the latter limitation, whenever needed for the model estimation, we assume that, for the months in which the data are missing, the number of coffee blends available is the same as in the first time period for which we have data available. For prices, we assume they are the same as the average for the first six time periods for which we have data. This seems to be a reasonable assumption given that pod prices do not change very frequently. Note that we do not need to make an assumption regarding the quantities sold of pods from January 2007 to April 2008 because we only estimate pod market-share moments for the periods for which we have pod sales.

[5] The machine sales data refers to offline sales and is collected by GfK from several retail channels (e.g., supermarkets, hypermarkets, independent retailers, and big box chains). According to GfK, their data covers 80% of the total offline machine sales in Portugal. Conversations with industry sources revealed that the share of sales of machines through the online channel is negligible and estimated at 2% of total sales. Regarding the coverage of the pod sales data, Nielsen estimates that their sales data covers roughly 80% of the industry sales. Further, Euromonitor reports that "Internet retailing of coffee remained insignificant in 2010 with only 1% of sales" (Coffee Portugal, Euromonitor International: Country sector Briefing, February 2011, p. 2).

[6] The brands introduce new coffee machine models to the market every 1.5 years on average. But, unlike what happens with other new durable goods such as camcorders, there are minimal improvements in the functionality of the coffee machines from one model to the next. Newer models consist more of a restyling of previous models, and coffee pods are compatible across different models of the same brand. Note also that there is little exit of models during the period studied (only one model belonging to DeltaQ leaves the market), and the entry of new models does not correspond to "upticks" in sales. As a result, in our empirical analysis, we aggregate coffee machine demand to the brand level (in each period, prices at the brand level are calculated as weighted prices, by sales, of individual machine models). In the demand estimation, we include a brand-level variable with the number

of models as a utility shifter to control for the number of choices/models available.

[7] The research report provided by Nielsen mentioned here is proprietary so this source is not public. The International Coffee Organization's research report is public and has the following reference: "Trends in coffee consumption in selected importing countries," Document ICC-109-8, International Coffee Council (109th session, London, September 2012).

[8] There is suggestive evidence that prices do not change in holiday seasons, which justifies why we do not de-seasonalize the price data. Following Gowrisankaran and Rysman (2012), we run two regressions to check that prices do not change in holiday seasons. For coffee machines we regress the brand-level prices on brand dummies, number of models, a trend, and a holiday dummy that equals one if it is November or December, and zero otherwise. The coefficient for the holiday dummy is not statistically significant. And for coffee pods we regress prices on brand dummies, a trend, and a holiday dummy. Again, the holiday dummy coefficient is not significant. We note that the lack of seasonality in the brand-level price data mirrors that in the disaggregate data at the pod and machine-model levels, so the lack of seasonality is not driven by our aggregation.

[9] A reader may notice that there are a couple of spikes in the pod sales series that persist after applying the smoothing procedure suggested by Gowrisankaran and Rysman (2012). A potential concern is that these outliers affect the parameter estimates. However, we find our results to be robust to local smoothing of the data series.

[10] A Nielsen survey administered to 3,000 representative panelists of the Nielsen Homescan panel in Portugal at the end of 2008 reports that, conditional on owning a coffee maker, the average number of coffee makers a household owns (including electric kettles, non-pod espresso machines, filter coffee makers, etc.) is about 1.8. Thus, the average number of coffee-pod machines per household has to be significantly less than 1.8. This implies that it is rare for a household to own more than one coffee-pod machine.

[11] As a robustness check we estimated a demand model with additional unobserved heterogeneity in the coffee-machines demand by allowing the intercept in the utility function to vary across consumers according to a normal distribution with unknown mean and variance parameters. Given that the price elasticities were unchanged and the computational cost of using such a model for the counterfactual analyses we decided to retain the more parsimonious specification discussed above.

[12] We have also tried estimating the model using discount factors of 0.95 and 0.995, and obtained qualitatively similar results.

[13] This is consistent with our conversation with a Nespresso manager that confirmed that consumers replace their coffee machine when the machine is about three years old. We have also estimated our demand and supply models assuming a 30-month and a 42-month lifespan for coffee machines and obtained qualitatively similar results.

[14] Given our assumption of independent consumption occasions, this form of aggregation is consistent with the approach used by other aggregate logit demand models (e.g., Berry 1994 and Besanko et al. 1998). Note that, because $Pr^{\text{pod}}_{i,j,k,t}$ captures the share of consumer i's pod purchases of coffee pod k during month t, derived from the consumer's share of C consumption occasions in that month, this implies that a consumer is allowed to purchase more than one pod type/blend within a given month. This means that consumers prefer variety because the extreme value is increasing in the number of independent draws and because of temporal variation in taste shocks but not because they have an inherent desire to consume multiple varieties—for example, on a given day. Clearly a more comprehensive model of variety would explicitly incorporate features such as satiation or variety seeking (e.g., Hoch et al. 1999 and Kim et al. 2002). However, since we do not have access to individual-level data, such a model would not be feasible.

[15] Note that we write Equations (15)–(17) in general form using both t and l as time indices because we will need to keep track of when consumers entered the market (i.e., when they purchased their coffee machines, as captured by the superscript new_t) in some of the derivations that will follow.

[16] In technical terms, this simplification implies that when we calculate the first-order conditions with respect to prices—discussed in the next subsection—we assume that the derivatives of ② and ③ with respect to today's prices are approximately zero.

[17] In applications in which consumers exhibit forward-looking behavior in the purchase of the consumable goods (the coffee pods in this case) such that there is stockpiling, for example, our simplified formulation may not be as appropriate as in our context where this feature is not present (see Section 4.1.2).

[18] By March 2012, there was still 63% of the market of coffee machines left (we obtain this number based on the evolution of the market size given by Equation (29), which we discuss in Section 5.1). In a setting or application in which the market size left is small and/or there is no base product replacement, or that replacement is not very frequent, our approximation might not work so well. That is because in that case firms will probably put more weight on the future market size (and on how many consumers of each type will be left) when making their pricing decisions today.

[19] The results for this robustness check are available upon request from the authors.

[20] Note that our demand formulation assumes that consumers (who have not purchased a coffee machine yet) form beliefs regarding the evolution of the coffee pods' inclusive value (based on an AR(1) process) but not regarding the specific path of prices. Thus, the assumption that prices are constant during a machine's lifetime does not contradict the formulation of the consumers' optimization problem.

[21] The first-stage F-statistics on excluded instruments are 29.9 and 35.8 for machines' and pods' prices, respectively, thus suggesting that the instruments are strong (Staiger and Stock 1997). First-stage estimates of the pricing instruments are available upon request from the authors.

[22] This number is obtained by multiplying an estimated 50% penetration rate for coffee machines by the number of households in Portugal (four million). We estimate the penetration rate by using Nielsen and Euromonitor data as follows. A Nielsen survey administered to 3,000 representative panelists of the Nielsen Homescan panel in Portugal at the end of 2008 reports that 69% of households in Portugal own a coffee machine (including electric kettles, non-pod espresso machines, filter coffee makers, etc.). Euromonitor International estimates a penetration rate of electric coffee machines of around 44% in 2009 (Euromonitor International Passport Statistics). The number of households is then estimated by dividing the population size by the average household size in Portugal (Source: Statistics Portugal). We have also estimated our demand model assuming an initial market size of 1.5 million and 2.5 million households, and obtained qualitatively similar results.

[23] According to industry reports, the only brand present in the market at the beginning of 2007 (when our data start), Nespresso, did not have a significant presence in the market at the time. In robustness checks we find that the results are not sensitive to reasonable alternative assumptions regarding Nespresso's initial installed customer base.

[24] The estimated household consumption of six pods per day is obtained based on the average annual coffee consumption per capita in Portugal of 4.3 kg. Source: "Trends in coffee consumption in selected importing countries," Document ICC-109-8, International Coffee Council (109th session, London, September 2012), International Coffee Organization.

[25] Note that Υ is a composite measure and, thus, assuming that Υ is the same for both firms is not the same as assuming that each of the components of Υ (pod variety, pod prices, and pod fixed effects) are

the same for both firms. We use DolceGusto because both brands belong to the same parent company, Nestlé. We conducted several sensitivity analyses to check the robustness of our results to this identification assumption, including using other brands' inclusive values as proxies, and alternative ways of estimating $\Upsilon_{i,NP,t}$ using additional hand-collected data on the evolution of prices and variety for Nespresso's pods. These analyses are detailed in Online Appendix B.

[26] To verify that there is no autocorrelation more formally, and because $\xi_{j,t}^{\text{mac}}$ and $\xi_{j,t}^{\text{pod}}$ do not have any assumed functional forms, we use a nonparametric "runs up and down" test (Madansky 1988) that has been shown to perform well when testing for autocorrelation (Levene 1952). We perform separate tests for machines and pods. We find that the p-values for these tests are all greater than 0.24, implying that we cannot reject the null hypothesis that the unobservables are not serially correlated.

[27] To verify this formally, we follow Gowrisankaran and Rysman (2012) and estimate the covariance of ϕ with its lagged value and test whether the estimated covariance is zero using a t-test. We do this separately for δ^{mac}, and for δ^{pod} for the median consumer, and find p-values greater than 0.19, implying that we cannot reject the null hypothesis that the residuals are not serially correlated.

[28] Source: "Innovation and Renovation: The Nespresso Story," International Institute for Management business case #IMD046.

[29] Sources: "International Report on Coffee Trends, 2014," Competitive Intelligence Coffee Bureau (Brazil), and "Coffee pods: Why we all want what George Clooney is having," The Independent online edition, September 27, 2012.

[30] We calculate price elasticities for machines in the same manner as Gowrisankaran and Rysman (2012) calculate 1% permanent price increases. More specifically, the price increase takes place at time t and is unexpected before then. Also, consumers know that the price increase is permanent. Using the estimated AR(1) coefficients (which are kept fixed), consumers' future expectations (the predicted δ's) are updated based on the change in today's prices. Using the updated δ's, we calculate the change in the value of waiting and thus on market shares at time t. Note that the cross-price elasticities between DolceGusto and DeltaQ and the Store Brand, are the same as those between Nespresso and these two latter brands. This is due to the assumption, discussed in Section 5.2, that the expected utility from coffee pods for Nespresso is the same as that for DolceGusto in each time period.

[31] In principle one could consider more strategies. To make the analysis more focused we consider only these two strategies, which are the two most common types of pricing agreements observed in practice in this type of markets.

[32] Note that in the counterfactuals we condition on the available set of Store Brand's blends and port over all pod blends from the Store Brand to DeltaQ. We do not carry out a formal analysis regarding the entry of these blends into the market. Further, recall that, because of the incompatibility among the different coffee systems during the period studied, we only observe purchases of pods of a given brand for consumers that have purchased that same brand of machine. This means that the $\alpha_{j,k}$ blend fixed effects are estimated relatively to the outside good and that in the counterfactuals, by using these estimated parameters, we implicitly make the assumption that the preferences for the pods are maintained when the Store Brand's pods become compatible with DeltaQ's machines.

[33] A licensing agreement between Nespresso and DolceGusto is not a natural choice because both these brands belong to the same parent company, Nestlé. Indeed, the main reason for the launch of DolceGusto was to create an alternative to Nespresso that could target the lower end of the market.

[34] The fact that these brands target similar consumer segments is consistent with the observation that, when the Store Brand entered the market, DeltaQ was the brand that responded with the most significant price drop for coffee machines, bringing its machines to the same price level as the Store Brand's.

[35] This is a conservative approach because ignoring this effect will bias against finding an incentive to licensing—that is, by ignoring these costs we are computing a lower bound on the potential (if any) increase in the profits from moving from a nonlicensing scenario to a licensing scenario.

[36] According to Keurig's licensing agreements in the United States, Keurig is responsible for some of its licensees' packaging and quality monitoring costs. (Source: U.S. Securities and Exchange Commission website.)

[37] We have also conducted robustness checks using marginal costs of 0, 0.05, 0.15, and of 0.25 euros per package of 10 pods and obtained qualitatively similar results.

[38] Profits for machines and pods in each period are calculated by multiplying margins (price minus marginal costs of production, minus royalty fees or monitoring costs when applicable) by quantities sold. That is, total firm profits are computed as in Equation (14) with the appropriate adjustments related to royalty fees and monitoring costs.

[39] The coffee machine prices are averages weighted by monthly sales to better capture the decreasing trend in coffee machine prices and the increasing trend in machine sales. The patterns in the plots are qualitatively similar if we use unweighted prices for machines. The coffee pod prices are a simple time series average of coffee pod prices over time.

[40] We do not report here the total sales of coffee machines and pods for the different scenarios because the sales patterns are approximately the mirror images of the price patterns.

[41] We infer the implied average Keurig royalty rate from sales data obtained from industry reports. According to the industry report BidnessETC (April 2, 2014) "Keurig Green Mountain: It's a hold" (available at http://www.bidnessetc.com/business/keurig-green-mountain-inc-nasdaq-gmcr-stock-analysis-we-rate-it-as-a-hold/ and accessed on June 11, 2015), in 2013, the sales from Keurig's own K-Cups accounted for 73% of net sales while royalties from licensing agreements accounted for 8% of revenues. Also, according to the Forbes (August 28, 2014) article "Distribution deals with major coffee brands to help Keurig Green Mountain gain market share" (available at https://www.forbes.com/sites/greatspeculations/2014/08/28/distribution-deals-with-major-coffee-brands-to-help-keurig-green-mountain-gain-market-share and accessed on June 26, 2015), "In September 2013, Keurig branded K-Cups accounted for 45% of the total K-Cup volume share, which shoots up to 79% when combined with its licensed brands' K-Cup sales." (Unlicensed K-Cup compatible cartridges represented the remaining 21% share). Using this data, we can infer that the average royalty rate charged by Keurig is about 15%. The details of this computation are available upon request from the authors.

[42] This scenario may be construed as involving some sort of Resale Price Maintenance (RPM) practice that during the time of our data period was illegal in Portugal. Nevertheless, our objective here is merely to illustrate the consequences of such an arrangement in which the licensor and the licensee practice the same prices for their add-on products, rather than to focus on the legality of such a policy.

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