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## Abstract

We study a major new entry in the French mobile telecommunications market, followed by the introduction of fighting brands by the three incumbent firms. Using an empirical oligopoly model with differentiated products, we show that the incumbents' launch of the fighting brands can be rationalized only as a breakdown of tacit collusion. In the absence of entry the incumbents successfully colluded on restricting their product variety to avoid cannibalization; the new entry of the low-end competition made such semi-collusion more difficult to sustain because of increased business stealing incentives. Consumers gained considerably from the added variety of the new entrant and the fighting brands, and to a lesser extent from the incumbents' price response to the entry.



JEL Classification: L13, L96

Keywords: Entry, fighting brand, semi-collusion, product variety, Mobile telecommunications



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# Market Entry, Fighting Brands and Tacit Collusion:

## Evidence from the French Mobile Telecommunications Market*


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**Abstract**

We study a major new entry in the French mobile telecommunications market, followed by the introduction of fighting brands by the three incumbent firms. Using an empirical oligopoly model with differentiated products, we find that the incumbents' fighting brand strategies cannot be rationalized as unilateral best responses to new entry in a static game. Instead, we show how the incumbents' strategies can be rationalized as a breakdown of tacit collusion: in the absence of entry, the incumbents could successfully collude on restricting their product variety to avoid cannibalization; the new entry of the low-end competition made such semi-collusion harder to sustain because of increased business stealing incentives. Consumers gained considerably from the added variety of the new entrant and the fighting brands, and to a lesser extent, from the incumbents' price response to the entry.



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# 1 Introduction

In many concentrated markets, new entrants challenge incumbent firms by offering a relatively low quality brand at a competitive price. Instead of merely lowering the price of their existing products, the incumbents often respond by introducing *fighting brands*. As shown by Johnson and Myatt (2003), a monopolistic incumbent may have a strategic interest in introducing such a brand to accommodate new entry in the low-end segment, which it would not want to serve otherwise. There are plenty of markets where new entry was followed by the introduction of fighting brands. For example, when the dominant microprocessor producer, Intel, was challenged by new entrant AMD, it introduced a low-cost brand (Celeron) to preserve its market leadership. The largest European airlines, such as Lufthansa and Air France, have also established independent low-cost subsidiaries (Germanwings and HOP!, respectively) in an effort to cope with the competition from an increasing number of low-cost carriers. In the Canadian mobile telecommunications industry, the three largest mobile service providers (Rogers, Bell, and Telus) launched subsidiary brands (Chatr, Koodo, and Solo, respectively) to discourage the growth of new low-cost entrants in 2010 (Marlow, 2010). Many other examples on the success and failure of fighting brands can be found in the management literature.[1]

While the prior literature has provided theoretical insights on the market primitives that can prompt an incumbent firm to respond to entry through product line expansion, there exists no empirical analysis that rationalizes such strategies. Furthermore, the existing theoretical literature has mostly limited its attention to the analysis of a monopolist incumbent. Hence, it is unclear whether the fighting brand strategy can emerge as an equilibrium under oligopolistic competition among multiple incumbent firms.

To fill this gap, we examine the French mobile telecommunications market where incumbent operators introduced new subsidiary brands in response to the arrival of a fourth entrant in 2012. Since 2001, 3G mobile services in France had been supplied by three mobile network operators (MNOs): Orange, SFR, and Bouygues Telecom. To stimulate competition in the mobile sector, the French regulatory authority, ARCEP, granted the fourth 3G radio spectrum license to Free Mobile in 2010 (ARCEP, 2013, p. 81). Within a few months prior to the anticipated entry in early 2012, all three incumbents introduced subsidiary brands to provide low-cost services.[2] The price and quality levels of the subsidiary brands were closely matched to Free Mobile's once the entrant started offering its service to consumers (ARCEP, 2013, p. 83).

The (almost) simultaneous introduction of subsidiary brands by the incumbents, along with its timing, suggests a possibility that their product line expansions were strategically motivated in the face of entry. This is also indicated in the statements from the businesses. For example, Orange's CEO announced at the launch of Sosh, "this is our 'low cost' answer, but not 'low service' or 'low value' vis-à-vis our customers"; and in the context of Free Mobile's entry: "We have been thinking of a whole arsenal of projects to maintain our leadership, to go further in the segmentation of the mobile market. That's why we decided to launch a new brand."[3]

[1] Ritson (2009) covers cases relating to cigarettes (Marlboro), beer (Anheuser-Busch), pharmaceuticals (Merck), and other markets (films, cars, paper notes and airlines). In an analysis of brand portfolios, Barwise and Robertson (1992) discuss the launch of a low-cost brand by the UK juice producer Ribena. Berman (2015) considers Dow-Corning's introduction of Xiameter in the market of silicone-based specialty chemical products.

[2] Orange, SFR, and Bouygues Telecom introduced brands named *Sosh*, *RED*, and *B&You*, respectively. The launch was on a very limited scale until Free Mobile finally entered (Berne, Vialle and Whalley, 2019).

[3] The quotes are available from Les Echos 28/07/2011 and Le Point 7/09/2011. The business press referred to the low-cost services of the incumbents as "Free killer offers" (Nouvel Observateur, 15/12/2011) and "anti-Free weapon" (Les Echos, 28/07/2011).

The first objective of our paper is to closely examine the incumbents' incentives to engage in such product strategies by analyzing the profitability of their counterfactual product line decisions in the absence of entry. Our second objective is to assess the welfare implications of the fighting brand strategy in the context of entry of a new market player: i.e., to quantify the size of its welfare impact in comparison to the standard price and variety effects from entry.

To address these questions, we construct a dataset on the French mobile telecom industry for 2011–2014. In the first step, we estimate a differentiated products demand model and consider an oligopoly setting where the network service providers compete in both the wholesale and retail markets. In the second step, we use the empirical model to examine the fighting brand theory. We compute the counterfactual profits under alternative product line and entry decisions to assess whether and to what extent the incumbents had a strategic incentive for launching their subsidiary brands in response to the entry of Free Mobile. In the final step, we compute the impact of entry on consumers and total welfare and decompose it into three different sources: (i) a variety effect that stems from the availability of the entrant's new differentiated service; (ii) a price competition effect due to the incumbents' price responses; and (iii) (potentially) a fighting brand effect from the incumbents' new subsidiary brands.

We find empirical support for the fighting brand theory, but the main intuition requires extending the monopoly story of Johnson and Myatt (2003). The crucial difference derives from the strategic interactions among multiple incumbent firms in our analysis. In particular, we find that the incumbents' fighting brand strategies cannot be rationalized as unilateral best responses to new entry in a static game. Instead, we show how their strategies can be rationalized as a breakdown of tacit collusion: in the absence of entry, the incumbents could successfully collude on restricting their product lines to avoid cannibalization; the new entry of the low-end competition made such semi-collusion harder to sustain because of increased business stealing incentives.

To establish these findings, we first consider a simultaneous one-shot game where each incumbent firm unilaterally decides whether to introduce a low-quality brand, before and after the entry of Free Mobile. This static model does not provide support for the fighting brand hypothesis. On the one hand, the static model requires sufficiently low fixed costs for operating a fighting brand to rationalize its launches as a Nash equilibrium outcome after entry. But on the other hand, the model also needs sufficiently high fixed costs to explain the absence of fighting brands without entry. However, it turns out that there exists no viable range of fixed costs supporting both restrictions. Intuitively, with multiple incumbent firms, there are already strong unilateral incentives to introduce fighting brands even without entry because the gain from business stealing is stronger than the loss from cannibalization.

We therefore consider a game-theoretic framework of repeated interactions to explore the view that the incumbents were colluding on restricting their product lines to avoid cannibalization while competing on prices with differentiated products. Firstly, we investigate whether such product collusion can emerge as an equilibrium in the market without entry, and secondly whether the new entry can lead to a breakdown of the collusive equilibrium. We find that there is a non-empty range of fixed costs under which the product-line collusion can be sustained in the absence of entry, while it becomes harder to be sustained after entry. As such, this finding supports a coordinated strategy interpretation of the fighting brand hypothesis: incumbents may be able to tacitly collude on restricting product variety in an uncontested market, and a new market entry can lead to a breakdown of such semi-collusion. We hasten to add that our conclusion does not necessarily imply illegal conduct, as our evidence is only indirect (relating to incentives). Nevertheless, the possible existence of product-line collusion is consistent with the earlier conclusions of the French competition authority on anticompetitive agreements in the mobile telecom market. On December 1, 2005, the competition authority decided to impose a fine of €534 million to the three incumbent operators for engaging in two kinds of anticompetitive behavior: (i) sharing strategic information on new subscriptions and cancellations; (ii) an agreement from 2000 to 2002 to stabilize market shares based on jointly-defined targets, through a coordination of their commercial and marketing strategies.[4]

Finally, it seems rather difficult to reconcile the incumbents' new product releases with an alternative view that they were merely a marketing or product innovation that may have coincided with the new entry. The low-cost product strategy was no longer a novelty since similar products had already been offered many years earlier in most other European countries, which we will document in our discussion section. In addition, all three incumbents not only introduced their subsidiaries simultaneously just before the entrant's arrival, but they also revamped their tariff offerings immediately upon the entry (Berne et al., 2019). We will also discuss why other factors, such as a freeing up of the incumbents' network capacity after the loss of subscribers, appear to be unlikely explanations for the emergence of the fighting brands in our setting.

After establishing evidence for the fighting brands as strategic responses to new entry, we proceed to examine the impact of entry on consumers and total welfare. We find that the entry of Free Mobile considerably increased consumer surplus (by about €4.6 billion or about 7.7% of industry sales during the period 2012–2014). Consumers mainly benefited from the increased variety offered by Free Mobile and from the fighting brands (each responsible for 51% and 31% of the gains, respectively), and to a lesser extent from the existing operators' intensified price competition (accounting for only 18% of the consumer gains approximately). However, the entry of Free Mobile led to large losses in gross producer surplus, so that the total gross welfare benefits were more modest, estimated to be about €2.2 billion (or 3.7% of industry sales). These gross welfare gains can be attributed almost equally to the variety increase by Free Mobile and to the fighting brands (while the increased price competition made a negligible welfare impact). The net welfare gains would be mitigated if we take into account the fixed costs of the entrant and fighting brands.

**Related literature** Our paper provides new insights into the question of how market structure may affect tacit collusion. From the repeated games literature, it is well known that increased concentration may facilitate collusive behavior in prices or quantities (e.g., Friedman (1971) and Tirole (1988)). Competition authorities in both the U.S. and Europe have accordingly been concerned with "coordinated effects" from mergers. Miller and Weinberg (2017) provide evidence showing how the MillerCoors joint venture facilitated price coordination with the main rival Anheuser-Busch Inbev. Our paper shows how changes in market structure may also affect semi-collusion, where firms compete in the product market (in prices or quantities), while colluding in other dimensions such as R&D (Fershtman and Gandal, 1994), capacity (Osborne and Pitchik, 1987), or location choices (Friedman and Thisse, 1993).[5]

Our paper also contributes to the literature on adjusting product lines as a fighting brand strategy, which

[4] A press release of the 2005 from the French Competition Authority is available in English at: `http://www.autoritedelaconcurrence.fr/user/standard.php?id_rub=160&id_article=502`.

[5] There is also an empirical literature that considers collusion in the absence of changes in market structure. Most notably, in an interesting recent paper Sullivan (2017) considers the combination of both price and product space collusion. In his setting, the two firms collude on staying in segments differentiated from each other, while in our case they may collude on remaining in the same premium-quality segment (without entry).

has up to now been largely theoretical. Johnson and Myatt (2003) develop a model of vertical differentiation where a fighting brand arises as a monopolist's best response to entry in the low-quality segment and yet does not arise in the absence of such entry. Denicolò et al. (2007) find that the intensity of competition, measured by product differentiation or cost efficiency, can determine an incumbent monopolist's optimal response to entry.[6] More recently, Nocke and Schutz (2018) find that the fighting brand equilibrium can be supported in a wide range of oligopoly models with horizontally differentiated products. Our study complements this theoretical literature by empirically analyzing the fighting brand strategy in a non-cooperative setting with *multiple* incumbents and measuring its implications for consumer and total welfare effects of entry.

While previous empirical work has studied price responses to entry (e.g. Goolsbee and Syverson (2008)), there exists no evidence on product line responses to entry.[7] There is however a broader literature on the relationship between concentration and product variety, which also highlights the importance of business stealing and cannibalization forces. In the radio broadcasting industry, Berry and Waldfogel (2001) find that mergers increase aggregate product variety, which is consistent with strategic product positioning to deter entry. In the same industry, Sweeting (2010) shows how merging firms reposition their products to avoid cannibalization without affecting aggregate product diversity. Davis (2006) finds that new movie theaters mainly steal business from competitors rather than cannibalizing sales from the chain's own existing theaters.

Several studies have considered the impact of entry and concentration in the telecommunications industry. Economides et al. (2008) measure the welfare impact of entry in the U.S. long distance telecommunications industry, but they do not consider the incumbent's strategic reaction to entry. Xiao and Orazem (2011) analyze the broadband network services market to find that the fourth entrant had only marginal impact on the market competition. In a study of the U.S. mobile telecommunications market, Seim and Viard (2011) show how entry reduced prices and induced firms to offer a greater variety of pricing plans. Nicolle et al. (2018) use hedonic regressions to quantify the price impact of Free Mobile's entry in the same French mobile market analyzed in this paper. Genakos et al. (2018) study the impact of entry and mergers in mobile telecommunications markets for a panel of OECD countries. They find that increased concentration raises not only prices but also investment per operator. Most recently, Lin et al. (2020) study the incentives to invest in 4G-LTE deployment after the T-Mobile and Sprint merger. The question on how changes in market structure in the mobile telecommunications industry, whether through entry or mergers, affect consumers and welfare continues to be central in the current policy debate.[8]

The rest of the paper is organized as follows. In Section 2, we present the data and in Section 3 the model of demand and oligopoly price-setting. Section 4 reports the empirical results. In Section 5, we analyze the profit incentives to expand product lines both in the absence and the presence of entry. In Section 6, we measure the consumer and total welfare effects of entry and decompose them by various sources. Finally, we conclude in Section 7.

[6] Earlier theoretical work by e.g. Brander and Eaton (1984) and Judd (1985) studied product line decisions of competing firms, but they did not consider new market entry in their analysis.

[7] Some empirical work (in particular Eizenberg (2014)) has studied product line decisions without entry considerations.

[8] There is also a literature estimating the demand for mobile telecom services. We will compare this work with our own findings in the empirical results section.

# 2 French mobile market and data

We first present relevant industry background on Free Mobile's entry in the French mobile telecom market. Next, we discuss the dataset on the demand and tariff characteristics for mobile services and additional data on network coverage for the period 2011-2014. Finally, we provide a preliminary description of the evolution of the market during the considered period.

## 2.1 Industry background

Before the arrival of the new entrant Free Mobile in 2012, there were three large incumbent mobile network operators (MNOs): Orange, SFR, and Bouygues. In addition, there was a multitude of small-scale mobile virtual network operators (MVNOs), which entirely relied on wholesale access from the three incumbent networks. The mobile operators offer three broad tariff types: prepaid, postpaid, and forfait bloqué. Prepaid is at the lowest end of the product line and involves only usage fees. In contrast, the latter two also include fixed fees and consumption allowances, as will be explained in more detail in the data discussion. With a large share of the retail and wholesale markets under control, the incumbent MNOs had been able to sustain relatively high prices for the postpaid contracts by charging a high premium for volumes consumed under other tariffs.[9] Concerned by the weak competition, the government eventually facilitated the entry of the fourth network in January 2012.[10]

The new entrant Free Mobile introduced a new class of products offering full-featured postpaid services comparable to the incumbents' mainstream products, yet at a disruptive price level undercutting even the most competitive low-end prepaid services. In addition to the price, the entrant's products were distinguished from the incumbents' standard postpaid services by their SIM-only plans, eliminating both bundled handset and contractual commitment. Furthermore, they included unlimited consumption allowances, while retail and customer services were limited exclusively to the online channel. Within days after the launch of the entrant's new products, the three incumbents immediately matched the product strategy by releasing their own branded counterparts, namely Sosh, SFR, and B&You (Berne et al., 2019). The incumbents' new services were made available exclusively through their newly introduced subsidiary brands operating separately from the existing product lines. These new brands were differentiated from the prepaid plans as they offered attractive pricing to heavy-usage customers, while the prepaid plans appealed mostly to low-volume users such as the elderly, foreign visitors, or those with low credit. Despite the introduction of these new subsidiary brands, the incumbents reportedly lost substantial revenues by about 30% from each subscriber during the first two years since the entry of Free Mobile (UFC-Que Choisir, 2014).

## 2.2 Data

We collect data on the consumption of mobile services in France during 2011–2014 from Kantar, a UK-based market research firm. This dataset contains information on consumers' choice of network operator, product

[9]For example, Orange offered 2GB data allowance under a 24-month commitment to postpaid contracts at a monthly price of €33, while a comparable consumption would cost at least €100 for the prepaid cards according to its retail brochure published during April–June 2011.

[10]The government opened a process for comparative tender (i.e., beauty contest) to invite a potential licensee of the spectrum for UMTS (3G) standard (Hocepied and Held, 2011). It prescribed various regulations for the incumbents' call termination rates, for example, wholesale access to the legacy data network (2G).

brand, type of service contracts (e.g., prepaid or postpaid), service quality (measured as allowances for call and data), and price. We also observe demographics such as age and income distributions for approximately 6,000 consumers across 22 metropolitan areas classified by the local administration and jurisdiction systems. The geographic areas are aggregated to 13 region blocks following the legislation that came to effect in 2016.

The consumer database covers virtually all network operators in France. This includes all three incumbent MNOs (Orange, SFR, and Bouygues), their respective lower quality subsidiary brands (Sosh, Red and B&You), the entrant (Free Mobile) and the MVNOs. Since the MVNO market is highly fragmented, we group the MVNOs by their wholesale host networks (i.e., MVNOs for Orange, SFR and Bouygues). This approach reduces the dimension of the choice set, thus helping to avoid the problem of sparse observations for the small scale operators. Considering the MVNO's limited capacity for product differentiation during the sampling period, this simplifying assumption does not appear to be overly restrictive.[11]

The dataset contains information on the monthly subscription of each consumer. In any given time period, a vast number of tariff varieties were available in the market due to the high frequency of new product arrivals. For example, 1,112 unique tariffs were offered by Orange alone during the same period (Nicolle et al., 2018). Yet, they are broadly categorized in three distinct tariff types: prepaid, postpaid, and *forfait bloqué*. These differ in their level of fixed, variable and overusage fees, which implies different schedules for the marginal prices of consumption.[12] While the tariff categories are reported in the data, no information is available on the consumer's actual usage of voice calls, mobile data, or other services but their consumption allowances only. This poses a challenge to a panel data analysis of individual consumers since it would require detailed usage information to infer the effective prices of all possible choices for each consumer. Without such details, we can only obtain aggregate prices, which may lead to a bias for the micro-level analysis due to the resulting measurement error. Hence, we choose to analyze the consumption at the aggregate level by focusing on the consumer's subscription choices among the above three tariff categories.

We will thus define a mobile service product as a tariff category available within each brand of an MNO or an MVNO operator. The corresponding price is measured by the total expected revenue from the average consumer of each service product on a monthly basis.[13] Our price measure thus includes the overuse fee, which applies to the postpaid tariff. This measurement approach later implies a modeling restriction, namely that consumers are indifferent about how a given total service charge is distributed among the different parts of the tariff. The price is assumed to be uniform across the regions to be consistent with the fact that there is no geographic price discrimination. Our measurement approach is not ideal, but developing a price index is by itself a complex and resource-intensive task in the telecommunications markets (Nicolle et al., 2018).

While one may instead consider a price basket approach for measuring the price, this relies on representative usage profiles calibrated from individual consumption decisions, which are endogenous to the price itself. Given the lack of such usage data, we account for possible changes in the composition of users by aggregating the tariffs across a predetermined set of price tiers whenever feasible. In addition, we control for

[11] Most MVNOs were simply a reseller of the contracts offered by their hosting network around the time of the entry. While MVNOs were usually hosted by a single network, Virgin mobile was the exception as it had been multihoming with all three incumbent MNOs for a limited period of time. Our solution is to randomly assign the subscribers to different MVNO groups in proportion to the share of the MNO cellular antenna stations operating in the region.

[12] The original French terms are *prépayé*, *forfait*, and *forfait bloqué*. The prepaid service plans do not charge a fixed access fee but only usage fees for voice, data or text services. In contrast, the postpaid plans are three-part tariffs defined by a fixed access price, consumption allowances, and a usage fee for any consumption in excess of these allowances. Forfait bloqué has the same tariff structure as the postpaid plan, except that it does not practically allow usage beyond the allowances allocated each month.

[13] The same approach is also used by Weiergraeber (2019).

tariff characteristics that may coincide with price changes over time, such as the consumption allowances for voice calling and mobile data. Because the dataset records the allowances only from the last quarter of 2011, we start our working sample at this quarter and drop the first three quarters from the analysis. These steps help obtaining a robust measure of price, which shows a similar overall trend as reported by the alternative approach in a French study (UFC-Que Choisir, 2014, p.26).

We merge the consumption dataset with a national database on network infrastructure facilities obtained from *L'Agence nationale des fréquences* (ANFR), a public authority overseeing the operation of radio communications facilities. The database covers the location, the date of activation, and the technology generation (2G, 3G, and 4G) of base transceiver stations. The base stations, often called cell towers or antennas, provide wireless connections for mobile devices. They therefore constitute an integral part of the mobile network for improving the connectivity and speed of mobile communications. Hence, we collect the cumulative number of cellular antennas activated by each network operator to measure the network quality per technology generation and geographic region.

Combining the two databases yields a panel of 22 mobile service products in 13 regions over 13 quarters spanning from 2011 Q4 to 2014 Q4, generating a total of 3,324 observations. For each mobile service product (i.e., each tariff type and operator brand) in a market (region) and time period (quarter), we observe the number of subscribers, price, tariff characteristics and network quality. To measure the potential market size of each region, we use the regional population from the 2012 census survey conducted by *L'Institut national de la statistique et des études économiques* (INSEE), the national statistics agency in France. Table 1 provides an overview of the main variables and their summary statistics.

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Subscriber (1,000) | 3,324 | 243 | 352 | 2 | 3,041 |
| Price (€) | 3,324 | 18.69 | 8.76 | 3.55 | 56.26 |
| 2G antenna | 3,324 | 902 | 987 | 0 | 3,704 |
| 3G antenna | 3,324 | 721 | 755 | 0 | 2,905 |
| 4G antenna | 3,324 | 113 | 266 | 0 | 2,055 |
| Prepaid | 3,324 | 0.28 | 0.45 | 0 | 1 |
| Postpaid | 3,324 | 0.46 | 0.50 | 0 | 1 |
| Forfait bloqué | 3,324 | 0.27 | 0.44 | 0 | 1 |
| Call allowance (min) | 3,324 | 658 | 820 | 0 | 3,259 |
| Data allowance (MB) | 3,324 | 622 | 666 | 0 | 2,327 |

Based on samples of mobile services in 13 region blocks from 2011 Q4 to 2014 Q4

*Table 1:* Summary statistics of the dataset

## 2.3 Descriptive analysis

Table 2 provides more detailed information about the mobile market broken down by network operator and brand: the number of antenna stations, price, and the share of subscribers. The table reports only the total number of proprietary antenna stations: the incumbents' subsidiary brands share the network with the existing product lines, and the MVNOs pay a wholesale price to use the incumbent's network. The entrant

Free Mobile operates its own antenna network. It also temporarily rented 3G antennas from Orange through a roaming agreement to compensate for its low coverage and quality, but the regulator ARCEP demanded the agreement to be gradually phased out. In our empirical analysis, we will distinguish between the proprietary and roaming antennas to account for the difference in service quality between MNOs and MVNOs. Generally speaking, Table 2 reveals that the incumbent MNOs tend to be more expensive than their subsidiary brands and the new entrant Free Mobile. Since the incumbent services under their operator brands represent high quality products relative to the new subsidiaries, we will use the term *premium* products throughout the paper to distinguish them from the low-cost alternatives.

| Network operator | Product group | Antenna stations 2G | 3G | 4G | Price (€) | Market share |
|---|---|---|---|---|---|---|
| Orange | Orange | 1,908 | 1,330 | 243 | 31.71 | 0.289 |
| | Sosh | | | | 16.65 | 0.039 |
| SFR | SFR | 1,363 | 1,205 | 86 | 25.99 | 0.229 |
| | Red | | | | 15.53 | 0.024 |
| Bouygues | Bouygues | 1,421 | 1,119 | 232 | 30.74 | 0.137 |
| | B&You | | | | 15.99 | 0.025 |
| Free | Free | 0 | 380 | 50 | 11.53 | 0.135 |
| Orange | MVNO | 0 | 0 | 0 | 17.58 | 0.043 |
| SFR | MVNO | 0 | 0 | 0 | 16.08 | 0.089 |
| Bouygues | MVNO | 0 | 0 | 0 | 17.58 | 0.014 |

Based on the dataset of 3,324 observations (mobile service products in 13 region blocks from 2011 Q4 to 2014 Q4).
Market shares are the average share of subscribers across regions.

*Table 2:* Overview of the mobile services market

Figure 1 shows the price changes of the incumbents' classic premium product lines, their subsidiary brands and the entrant Free Mobile. Note that the launch of the incumbent's subsidiary brands (Sosh, Red, and B&You) essentially coincides with the entry of Free Mobile in the first quarter of 2012.[14] The new entrant Free charges a much lower price than the incumbents, whereas the subsidiary brands charge prices somewhere in between. Note that the incumbents' prices move in opposite directions: both SFR and Bouygues lower their prices during the period, while Orange maintains or slightly raises its price level. However, the rising price does not necessarily imply a higher unit cost of consumption for consumers since both the consumption speed and allowances have also increased, particularly with the introduction of the 4G technology around 2014 (Nicolle et al., 2018). Figure A.1 in the appendix reveals a similar pattern for the MVNOs: they have lowered their prices over time, which appears to be at least partially attributable to the increased competition among other factors.

One might be tempted to interpret the low prices of the incumbents' subsidiary brands as predatory actions to drive out the new entrant. However, this is unlikely because according to Figure 1 their prices remained higher than those of Free mobile during the entire period. Furthermore, Free Mobile in fact did not exit but continues to operate as a major operator as of 2020. To appreciate the disruptive change of market structure,

[14]While the subsidiaries had already been introduced one quarter before the entry of Free (B&You in July, and Sosh and RED in October), we lacked sufficient sample size for the quarter due to their limited availability, and therefore, removed them from the analysis.

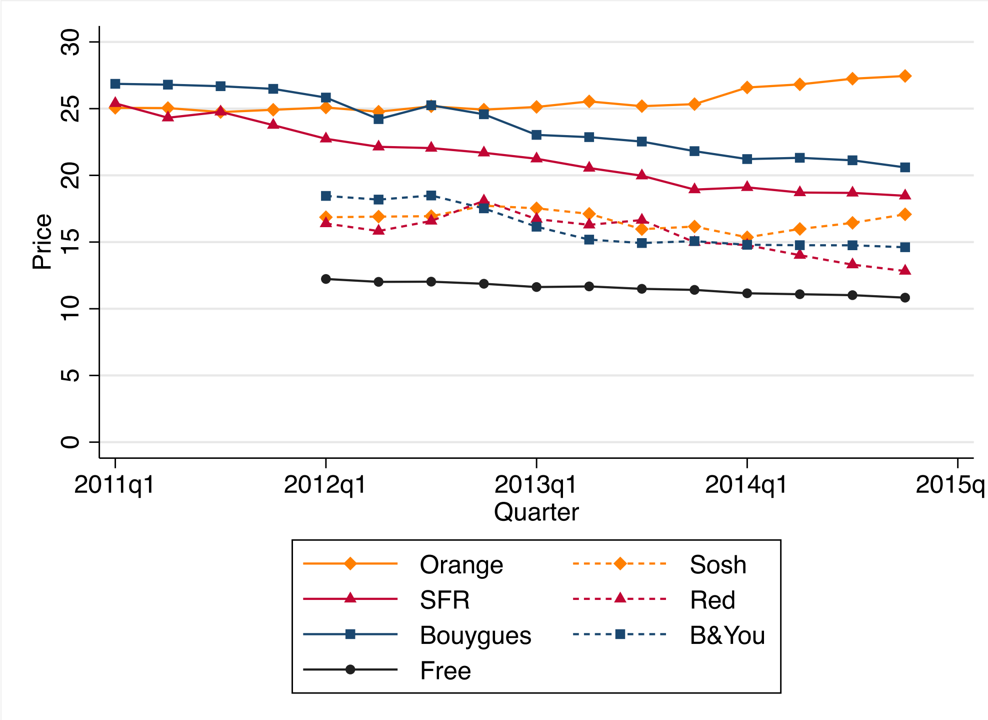



*Figure 1:* Prices of mobile services by product line brands

Figure 2 displays the market shares of the MNOs during our sample period. From the first quarter of 2012, the market shares of the incumbents' existing brands declined in favor of Free Mobile, which eventually overtakes the product line of the second largest incumbent (SFR). The incumbents' losses were only partly compensated by the gains of their three subsidiary brands.

Table 3 provides a more detailed description of how the entry of Free Mobile has affected the market competition asymmetrically. It displays the subscriber shares in the first and last quarters of our working sample divided into the three tariff categories (prepaid, postpaid, and *forfait bloqué*). In the first quarter of our sample (2011 Q4), when Free Mobile had not yet entered, the prepaid and forfait bloqué plans generated large sales for the premium product lines of the incumbent MNOs, collectively accounting for about 47%–95% of the postpaid sales of each operator. By the final quarter of 2014, however, Free Mobile had gained a considerable market share of 19.8%, while the incumbents' subsidiary brands had also become important as a whole with a combined share of 14.3%. While Free Mobile and the subsidiary brands only offered postpaid plans, they did not steal as much market share from the incumbents' postpaid tariff plans as from their prepaid and *forfait bloqué* services. With their aggressive prices, Free Mobile and the fighting brands appear to have appealed to a market segment previously served by the incumbents' prepaid and *forfait bloqué*, differentiating themselves from the premium postpaid services.

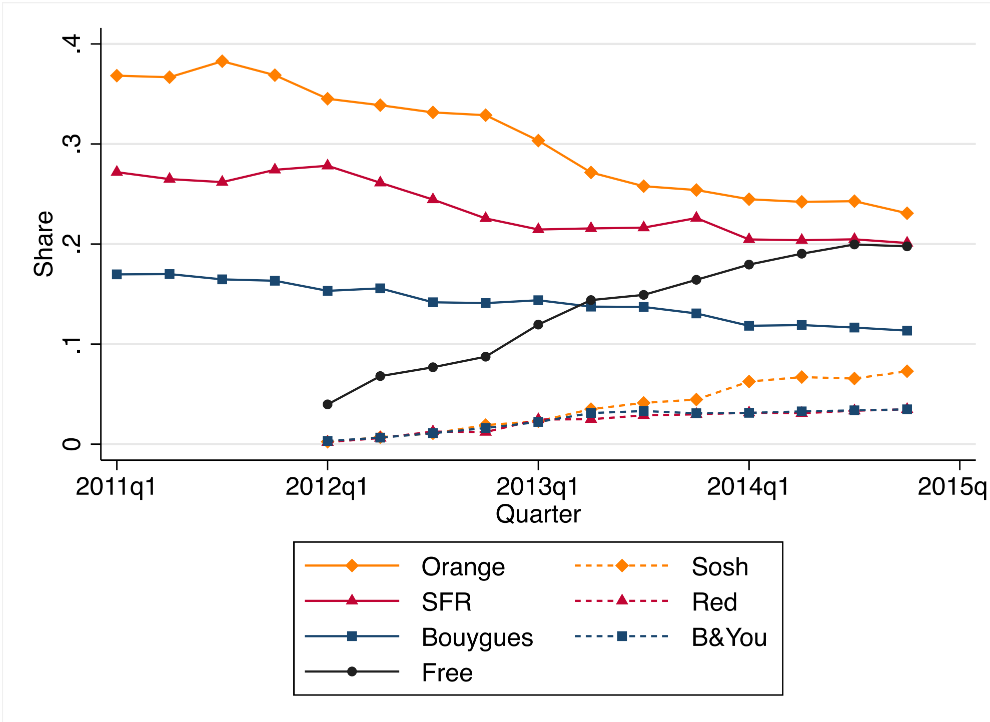



*Figure 2:* Market shares of mobile services by product line brands

# 3 Model

## 3.1 Demand

We employ the standard discrete choice framework of Berry, Levinsohn and Pakes (1995) (henceforth BLP) to model the demand for mobile network services in each regional market. Our modeling approach is motivated by the overarching goal of measuring both the incumbents' market power and the competition effects from the new products in a parsimonious framework. We thus focus on measuring flexible substitution patterns by allowing for unobserved taste correlations; we abstract away from potential demand-side dynamics from network effects or switching costs, as it is challenging to identify the different sources while also allowing for unobserved heterogeneity especially in aggregate demand estimation.[15] In particular, the gradual transition of the market demand after entry may not be solely attributable to network effects or switching costs, but is also compatible with other explanations such as consumer learning of quality and growing product awareness and brand reputation, to name a few (Dubé, Hitsch and Rossi, 2010). Our model does not attempt to distinguish between these sources of temporary dynamics but rather aims to control for them without taking a particular view.

Our model assumes that each consumer $i$ receives indirect utility $u_{ijt}$ from consuming mobile service product $j$ among the set of $J$ services available in market $t$ during a given quarter. The market $t$ refers to the

[15] A large literature has been devoted to estimating different types of demand-side dynamics. Recent examples include Dubé, Hitsch and Rossi (2009), Dubé, Hitsch and Chintagunta (2010), Shcherbakov (2016),Weiergraeber (2019). In our setting however, it is unlikely that Free followed a typical strategy of introductory pricing under switching costs because Free's prices were not considerably lower in the first months after its launch.

| Network operator | Product group | Market share (2011Q4) | | | Market share (2014Q4) | | |
|---|---|---|---|---|---|---|---|
| | | Prepaid | Postpaid | F. bloqué | Prepaid | Postpaid | F. bloqué |
| Orange | Orange | 0.085 | 0.192 | 0.098 | 0.024 | 0.171 | 0.041 |
| | Sosh | | | | | 0.073 | |
| SFR | SFR | 0.036 | 0.185 | 0.057 | 0.011 | 0.170 | 0.023 |
| | Red | | | | | 0.035 | |
| Bouygues | Bouygues | 0.030 | 0.114 | 0.024 | 0.011 | 0.094 | 0.009 |
| | B&You | | | | | 0.035 | |
| Free | Free | | | | | 0.198 | |
| Orange | MVNO | 0.008 | 0.008 | 0.015 | 0.003 | 0.022 | 0.010 |
| SFR | MVNO | 0.027 | 0.064 | 0.024 | 0.012 | 0.064 | 0.007 |
| Bouygues | MVNO | 0.008 | 0.002 | 0.015 | 0.004 | 0.007 | 0.001 |

F. bloqué denotes *forfait bloqué*, a postpaid service with fixed consumption allowances (or infinite variable price implicitly).

*Table 3:* Change of market shares by the service pricing types

geographic area (region) of the consumer; we suppress the index for time periods to simplify the notation. Each mobile service product $j$ is defined by tariff type (prepaid, postpaid or *forfait bloqué*) and product brand (operator or subsidiary) following the structure of Table 3.[16] As Berry et al. (1995), we take the Cobb-Douglas specification for $u_{ijt}$:

$$u_{ijt} = \alpha \log(y_{it} - p_j) + \beta'_{it} x_{jt} + \xi_{jt} + \epsilon_{ijt}, \tag{1}$$

where $y_{it}$ is the income of consumer $i$ in market $t$, $p_j$ is the total consumption price of product $j$, which is uniform across markets (regions) $t$, though it may vary over time.[17] The vector $x_{jt}$ includes observable controls of product quality: network quality (number of antenna stations for the three different generations in a given region) and tariff characteristics (such as call and data consumption allowances). For a subset of $x_{jt}$, the vector $\beta_{it}$ represents the heterogeneous taste of consumer $i$ in market $t$ and is specified as

$$\beta_{it} = \beta + \pi d_t + \nu_{it},$$

where $d_t$ contains the aggregate demographics of market $t$, and $\nu_{it}$ is a vector of tastes that vary across consumers and markets, which may depend on individual demographics as in Nevo (2001). The income and tastes $(y_{it}, \nu_{it})$ are assumed to jointly follow an underlying probability distribution $\mathcal{P}_t$ specific to each market $t$. The residual component $\xi_{jt}$ captures the mean unobserved quality of mobile service $j$ in market $t$ (the econometric error term), and $\epsilon_{ijt}$ is an idiosyncratic unobserved taste shock by consumer $i$ for service $j$ and is assumed to follow an iid extreme value type I distribution.

The outside good is denoted by $j = 0$ and represents a collection of options that range from relying on the Wi-Fi technology to adopting mobile services other than those supplied by the domestic mobile networks;

[16]Specifically, both operator and subsidiary brands are available from the three incumbent MNOs, while all products are supplied under a single product brand for the new entrant Free Mobile and the MVNO groups.

[17]As discussed in the data section, the consumption price encompasses the monthly subscription and usage fees of all component services such as voice call, mobile data, text messages and various other services, excluding the payment for handset devices.

it is assumed to yield indirect utility $u_{i0t} = \alpha \log(y_{it}) + \xi_{0t} + \epsilon_{i0t}$, where $\xi_{0t}$ captures the evolution of the technology of the outside good.

To derive the aggregate market share, we follow the convention of decomposing $u_{ijt}$ as

$$u_{ijt} = \delta_{jt} + \mu_{ijt} + \epsilon_{ijt}, \tag{2}$$

where $\delta_{jt}(\beta, \pi) = (\beta + \pi d_t)' x_{jt} + \xi_{jt}$ is the quality valuation of product $j$ common to all consumers in market $t$; $\mu_{ijt}$ denotes the net heterogeneous component defined as

$$\mu_{ijt}(y_{it}, \nu_{it}; \alpha) = \alpha \log(y_{it} - p_j) + \nu_{it}' x_{jt},$$

and correspondingly $\mu_{i0t} = \alpha \log(y_{it})$. Given the extreme value error assumption, we obtain the probability of product $j$ generating maximal utility for consumer $i$ in market $t$ as the logit choice probability (McFadden, 1973), which yields the aggregate the market share in region $t$:

$$s_{jt}(\alpha, \beta, \pi) = \int \frac{\exp\left(\delta_{jt}(\beta, \pi) + \mu_{ijt}(y_{it}, \nu_{it}; \alpha)\right)}{\sum_{k=0}^{J} \exp\left(\delta_{kt}(\beta, \pi) + \mu_{ikt}(y_{it}, \nu_{it}; \alpha)\right)} d\mathcal{P}_t(y_{it}, \nu_{it}).$$

In the following section, we express the market share $s_{jt}(\boldsymbol{p})$ as a function of the (uniform) retail prices $\boldsymbol{p} = (p_1, ..., p_J)$. We then obtain the total national demand by aggregating the local demands across all 13 regions, i.e.

$$D_j(\boldsymbol{p}) = \sum_t s_{jt}(\boldsymbol{p}) M_t, \tag{3}$$

where $M_t$ is the population size in region $t$.

## 3.2 Supply

There are two types of network operators: MNOs and MVNOs. The MNOs possess their own network of antenna stations and may choose to sell access to MVNOs who do not operate their own network infrastructure. In practice, all the incumbent MNOs, Orange, SFR and Bouygues, provide wholesale access to MVNOs, whereas the entrant MNO, Free Mobile, does not do so by setting prohibitively high access prices.

We model the supply side as a two-stage game. In the first stage, the MNOs simultaneously set wholesale prices for access services to the affiliated MVNOs. In the second stage, given the observed wholesale prices, the MNOs and MVNOs simultaneously set retail prices for mobile services to consumers. Both wholesale and retail prices are nondiscriminatory across geographical regions as discussed in Section 2. To be consistent, we make the simplifying assumption that the marginal cost of services is uniform across regions but may differ by product lines. Furthermore, the MVNOs are considered as a single price-setting entity as mentioned earlier.

Let $L_f \subset \mathcal{J} = \{1, ..., J\}$ represent the set of retail product lines served by MNO $f \in \mathcal{F} = \{1, ..., F\}$. The set $\mathcal{J}$ can in principle include up to six alternatives depending on the MNO: the three tariff types at either the MNO's premium product line or at its subsidiary brand. In practice, the number of alternatives is smaller, as evident from Table 3. Furthermore, we denote by $f_0$ the product line of MVNO hosted by its wholesale firm $f$. While the MVNO can also carry up to three tariff plans, the description below assumes the MVNO to be a single-product firm for expositional convenience. Lastly, since our focus in this section is on pricing and not product line decisions, we omit the fixed cost of operating a subsidiary brand, a subject that we will introduce later when examining the incentives for the fighting brands in Section 5.

The total profits of host MNO $f$ are the sum of the profits from its own retail product line and the profits from providing access to MVNO $f_0$:

$$\Pi_f = \sum_{l \in L_f} (p_l - c_l) D_l\left(\boldsymbol{p}\right) + (w_{f_0} - c_{f_0}) D_{f_0}\left(\boldsymbol{p}\right), \tag{4}$$

where $w_{f_0}$ is the wholesale price for the product of MVNO $f_0$; $c_l$ and $c_{f_0}$ are the marginal costs of $l$ and $f_0$, respectively; $D_l$ and $D_{f_0}$ are the national demand for MNO $f$'s product $l$ and MVNO $f_0$'s product hosted on MNO $f$'s network, respectively. The retail profits of MVNO $f_0$ are

$$\Pi_{f_0} = (p_{f_0} - w_{f_0}) D_{f_0}\left(\boldsymbol{p}\right). \tag{5}$$

Note that we normalize $f_0$'s retail marginal cost to zero; it is implicitly included in both $c_{f_0}$ and $w_{f_0}$ (as further clarified in Appendix A).

We first derive the conditions for the optimal retail prices conditional on wholesale prices. Next, we derive the conditions for the optimal wholesale prices chosen in the first stage. Taken together, these conditions enable us to back out the unobserved marginal costs and wholesale prices, as in e.g. Sudhir (2001), Brenkers and Verboven (2006) and Villas-Boas (2007).

Conditional on the wholesale prices $\{w_{f_0}\}$ for $f \in \mathcal{F}$, the second-stage retail prices are characterized by the following first-order necessary conditions:

$$\frac{\partial \Pi_f}{\partial p_j} = D_j + \sum_{l \in L_f} (p_l - c_l) \frac{\partial D_l}{\partial p_j} + (w_{f_0} - c_{f_0}) \frac{\partial D_{f_0}}{\partial p_j} = 0, \qquad j \in L_f, f \in \mathcal{F}, \tag{6}$$

$$\frac{\partial \Pi_{f_0}}{\partial p_{f_0}} = D_{f_0} + (p_{f_0} - w_{f_0}) \frac{\partial D_{f_0}}{\partial p_{f_0}} = 0, \qquad f \in \mathcal{F}. \tag{7}$$

It is implicit in the notation of Equation (6) that $f = f(j)$, where $f(j)$ denotes the host network supplying product $j$. Likewise, $f_0$ implicitly denotes $f_0(j)$ in Equation (7), i.e., the MVNO product hosted by network $f(j)$. Equations (6) and (7) implicitly define the equilibrium retail prices as a function of the wholesale price vector, $\boldsymbol{p(w)}$.

To characterize the wholesale prices $\boldsymbol{w}$, we first define the derivatives $\partial p_{f_0}/\partial w_{f_0}$ as referring to own pass-through rate, i.e., the rate at which MVNO $f_0$ passes the change of wholesale price $w_{f_0}$ through to retail price $p_{f_0}$. The derivative $\partial p_j/\partial w_{f_0}$ for $j \neq f_0$ refers to cross pass-through rate, i.e., the pass-through of the wholesale price for MVNO $f_0$ into the retail price of other mobile services.

The first-stage wholesale prices can then be determined by the following first-order condition for $f \in \mathcal{F}$:

$$\begin{aligned}
\frac{d\Pi_f}{dw_{f_0}} &= \frac{\partial \Pi_f}{\partial w_{f_0}} + \sum_{j \in \mathcal{J}} \frac{\partial \Pi_f}{\partial p_j} \frac{\partial p_j}{\partial w_{f_0}} \\
&= D_{f_0} + \sum_{j \in \mathcal{J} \setminus L_f} \frac{\partial \Pi_f}{\partial p_j} \frac{\partial p_j}{\partial w_{f_0}} \\
&= D_{f_0} + \sum_{j \in \mathcal{J} \setminus L_f} \left( \sum_{l \in L_f} (p_l - c_l) \frac{\partial D_l}{\partial p_j} + (w_{f_0} - c_{f_0}) \frac{\partial D_{f_0}}{\partial p_j} \right) \frac{\partial p_j}{\partial w_{f_0}} = 0.
\end{aligned} \tag{8}$$

In the above, the second equality follows from the envelope theorem. The third equality describes the tradeoff for an MNO when deciding on the wholesale price $w_{f_0}$ it charges to its hosted MVNO. This condition is easier to interpret in the special case where there is only a single MNO $f$ (and hence one associated MVNO $f_0$). In this case, the set of products $\mathcal{J} \setminus L_f = \{f_0\}$, so that the first-order condition becomes:

$$D_{f_0} + \left( \sum_{l \in L_f} (p_l - c_l) \frac{\partial D_l}{\partial p_{f_0}} + (w_{f_0} - c_{f_0}) \frac{\partial D_{f_0}}{\partial p_{f_0}} \right) \frac{\partial p_{f_0}}{\partial w_{f_0}} = 0.$$

Intuitively, the MNO faces the following tradeoff. On the one hand, an increase in the wholesale price $w_{f_0}$ raises wholesale profits proportional to the current demand of the MVNO (first term). On the other hand, an increase in the wholesale price raises the MVNO's retail price ($\partial p_{f_0} / \partial w_{f_0}$): this implies wholesale losses from a demand reduction of the MVNO (through $\partial D_{f_0} / \partial p_{f_0}$), which are partly compensated by a demand increase for MNO $f$'s own retail products (through $\partial D_l / \partial p_{f_0}$). In the more general case with competing MNOs (Equation (8)), there are further indirect demand effects because the wholesale price increase is also passed through onto the other MNOs' retail prices.

In the appendix, we provide further details on the computation of the pass-through rates $\partial p_j / \partial w_{f_0}$. One can then invert the system given by Equations (6), (7) and (8) to back out the marginal costs and the wholesale prices.

The above exposition assumes that the MNOs and MVNOs set wholesale prices and retail prices independently, so that there are both vertical and horizontal externalities. As an alternative to this independent pricing model, we will also consider a simpler supply model of vertical integration. In this scenario, each MNO directly sets the retail price of its hosted MVNO to maximize joint profit

$$\Pi_f = \sum_{l \in L_f} (p_l - c_l) D_l (\boldsymbol{p}) + (p_{f_0} - c_{f_0}) D_{f_0} (\boldsymbol{p}), \tag{9}$$

and the wholesale price follows an (implicit) sharing rule depending on the parties' bargaining power. The retail prices satisfy the first-order conditions for profit maximization as in a standard multi-product Bertrand Nash equilibrium:

$$\frac{\partial \Pi_f}{\partial p_j} = D_j + \sum_{l \in L_f} (p_l - c_l) \frac{\partial D_l}{\partial p_j} + (p_{f_0} - c_{f_0}) \frac{\partial D_{f_0}}{\partial p_j} = 0, \qquad j \in L_f, f \in \mathcal{F}, \tag{10}$$

$$\frac{\partial \Pi_{f_0}}{\partial p_{f_0}} = D_{f_0} + \sum_{l \in L_f} (p_l - c_l) \frac{\partial D_l}{\partial p_{f_0}} + (p_{f_0} - c_{f_0}) \frac{\partial D_{f_0}}{\partial p_{f_0}} = 0. \tag{11}$$

From these conditions we can again back out the marginal costs of both the MNOs and MVNOs. We will use this vertical integration model as a robustness check to our independent pricing model in the subsequent analysis. It implies that there are no "double marginalization" effects, and it may arise under various circumstances: perfectly competitive MVNOs, some forms of (unobserved) non-linear contracting or some equilibria with interlocking relations (see, e.g., Rey and Vergé (2010)).

# 4 Empirical results

## 4.1 Demand specification

Our econometric model is based on the utility specification (1) of Section 3. Specifically, the vector $x_{jt}$ contains the network quality variables: the number of proprietary 2G, 3G and 4G antennas for the MNOs and the corresponding roaming antennas for the MVNOs. It also contains tariff characteristics: dummy variables for the forfait bloqué and prepaid plans (with postpaid as the base), and consumption allowances for voice call minutes and data downloads. Finally, we include fixed effects for brands and geographic regions, a full set of time fixed effects and the inverse of time elapsed since first entry of each product. The latter mainly varies for the new entering brands and not for the incumbents as they have been around since the 1990s. Taken together, these variables also intend to capture unobserved forms of quality differentiation, such as handset subsidies, availability of offline retail channels and add-on services which were typically available only for the contract-based plans (postpaid and forfait bloqué) of the incumbents' premium brands.[18] For all these variables we estimate mean valuations ($\beta$). Furthermore, we interact the brand fixed effects with average age and the three tariff service plans with age categories ($\pi$).

We employ a more parsimonious specification to account for consumer heterogeneity $\mu_{ijt}$. We begin by expanding the log price term in $u_{ijt}$ for $j \in \mathcal{J} = \{1, ..., J\}$ as $\alpha \log(y_{it} - p_j) \approx \alpha \log(y_{it}) - \alpha_{it} p_j$, where $\alpha_{it} = \alpha / y_{it}$. Then, without loss of generality, $u_{i0t}$ can be normalized up to the extreme value error by dropping $\alpha \log(y_{it})$ everywhere. We correspondingly modify the net heterogeneous utility term into

$$\mu_{ijt} = -\alpha_{it} p_j + \nu_{it}' x_{jt} \qquad j \in \mathcal{J}.$$

For the heterogeneous tastes $\nu_{it}$, we start with a parsimonious specification (RC logit I) that includes random coefficients for the frontier mobile network technology (the combined number of 4G and its roaming antennas) and for the forfait bloqué service plans. Price, 4G network quality and forfait bloqué jointly reflect the key sources of differentiation between the incumbents' premium and low-cost brands. We allow the preference for network quality and forfait bloqué plans to vary by income in the same way as the price parameter $\alpha_{it}$. More precisely, we parameterize $(\alpha_{it}, \nu_{it})$ as $(\alpha, \sigma_\nu)/y_{it}$ for a real-valued vector $\sigma_\nu \in \mathcal{R}^2$ . Hence, $\alpha_{it} = \alpha / y_{it}$ implies that an individual with a high income draw is less price sensitive (as in BLP's original specification),

[18]Unobserved add-on services include for example preloaded carrier mobile apps, cloud storage, roaming connection, and free access to popular social networking services.

while $\nu_{it} = \sigma_\nu / y_{it}$ allows for a positive or negative taste correlation between price and the other characteristics (so $\sigma_\nu$ may be positive or negative).[19] Intuitively, we want to measure whether less price sensitive consumers tend to have a higher or lower valuation for network quality and budget-oriented postpaid plans through the common income term $y_{it}$. This thus aims to capture the main dimensions of differentiation between the premium and low-cost brands in a flexible yet parsimonious way.

We also estimated a more flexible specification (RC logit II) that in addition includes random coefficients for the prepaid service plans and for the intercept, using the same income interactions. Finally, we have estimated various alternative specifications, including a specification where the random coefficients for the other characteristics than price are not interacted with income. We briefly discuss these below and report them in Appendix F. The market share function is given by

$$s_{jt}(\delta_t, \alpha, \sigma_\nu) = \int \frac{\exp\left(\delta_{jt} + \mu_{ijt}(y_{it}; \alpha, \sigma_\nu)\right)}{1 + \sum_{k=1}^{J} \exp\left(\delta_{kt} + \mu_{ikt}(y_{it}; \alpha, \sigma_\nu)\right)} d\mathcal{P}_t(y_{it}), \tag{12}$$

where $y_{it}$ is drawn from a known empirical distribution $\mathcal{P}_t$ in market $t$.[20]

## 4.2 Estimation

To estimate the parameters, we use the generalized method of moments (GMM) following the literature (Berry et al., 1995). The main identifying assumption is that the error term $\xi_{jt}$ is mean independent of the observed product characteristics other than price, i.e., $E\left[\xi_{jt} \middle| x_t\right] = 0$. Based on this assumption, Berry et al. (1995) suggest using flexible functions of the exogenous characteristics across products and firms as instruments $z_t$, i.e., sums of characteristics of other products of the same firm and different firms. In subsequent work, Berry et al. (1999) use Chamberlain's (1987) optimal instruments. The optimal instrument is a specific function of the product characteristics (i.e., the expected derivative of the error term with respect to parameters) and provides an asymptotically efficient estimator. Using a Monte Carlo analysis, Reynaert and Verboven (2014) document how the optimal instruments can deliver considerably more efficient estimates in finite samples, and therefore at the same time improve the stability of the estimation by avoiding convergence to the boundary of the parameter space, as is often experienced with the standard BLP instruments.

The vector of optimal instruments takes the form

$$h_{jt}(z_t, \theta) \equiv E\left[\frac{\partial \xi_{jt}(\theta)}{\partial \theta} \middle| z_t\right]$$

for a given parameter vector $\theta$, where $\xi_{jt}(\theta) = \delta_{jt}(s_t, \theta) - \beta x_{jt}$, and $\delta_{jt}(s_t, \theta)$ can be obtained by inverting the demand system (12) at a given $\theta$ using the BLP contraction mapping. BLP's mean independence assumption then implies a conditional moment restriction $E\left[\xi_{jt}(\theta_0) \middle| h(z_t, \theta_0)\right] = 0$ for the true parameter $\theta_0$. If the moment restriction is satisfied uniquely at $\theta = \theta_0$, we can obtain a consistent estimate by GMM from the unconditional moment condition $g(\theta_0) \equiv E\left[\xi_{jt}(\theta_0) h(z_t, \theta_0)\right] = 0$. Reynaert and Verboven (2014) use a standard non-optimal BLP instruments in first stage to obtain consistent parameter estimate $\hat{\theta}$. In second

[19]This formulation thus uses the same specification as for the price coefficient and applies this to other characteristics to allow for taste correlation (as done in Nevo (2001) with a different functional form).

[20]Specifically, $y_i \sim \max\{\underline{y}, N(\bar{y}, \sigma_y^2)\}/100$, where the mean $\bar{y}$ and the standard deviation $\sigma_y$ are calibrated from the data for each corresponding region, and $\underline{y}$ is set to be €300 based on the minimum observed in the sample.

stage, they then compute approximately optimal instruments $h(x, \hat{\theta})$ and re-estimate the model by minimizing the GMM objective function:

$$\min_{\theta} \xi(\theta)' h(z, \hat{\theta})' h(z, \hat{\theta}) \xi(\theta)'.$$

Nonetheless, the two-step approach may lose efficiency gains due to the finite-sample bias in the first stage estimation. Furthermore, reliance on a specific choice of non-optimal instruments may be a source of lack of robustness. To address these issues, we propose a one-step estimator that continuously updates the optimal instruments $h(z, \theta)$. The one-step estimation is then equivalent to

$$\min_{\theta} \xi(\theta)' h(z, \theta)' h(z, \theta) \xi(\theta)'.$$

Our approach is analogous to the continuous-updating GMM estimator of Hansen et al. (1996) although it has no need to update the GMM weight since in our setting the moments are just identified under optimal instruments.[21] Minimizing the GMM objective function then involves two consecutive fixed point procedures. The first loop inverts the demand system to obtain $\delta(s, \theta)$ through the BLP contraction mapping. The second loop solves for the optimal instruments $h(z, \theta)$ such that it would be consistent with the parameters entering the linear part of the utility function in (1). We discuss the approach more formally in Appendix B.2.[22] To minimize the GMM objective function in the outer loop, we employ the Nelder-Mead simplex method since the continuous updating makes it difficult to obtain analytic derivatives.[23] While the continuous updating procedure significantly increases the overall computational cost, it has the advantage of eliminating the small-sample bias introduced in the first-stage estimates $\hat{\theta}$.

One potential concern for the estimation arises from the possible serial correlation in the unobserved quality $\xi_{jt}$. For the simple logit specifications, we addressed this problem by aggregating the moments across time periods following Berry et al. (1995). For the random coefficients logit, we adopt the more efficient approach of Newey and West (1987) by formulating a heteroscedasticity and autocorrelation consistent GMM estimator, implying clustered standard errors at the product–region level.[24]

Finally, we approximate the market share function (12) through Monte Carlo integration using 200 quasi-random draws generated by Latin hypercube sampling.[25] This has been found to offer superior sampling efficiency over simple random draws (Brunner et al., 2017). We use error tolerances of $10^{-14}$ and $10^{-8}$ for the contraction mapping and optimal IV procedures, respectively. While there has been a concern for numerical bias attributed to the nested fixed point algorithm in the literature (Dubé et al., 2012), Lee and Seo (2016) show that the numerical error in the fixed point solutions does not propagate into the parameter estimates. Rather, they prove that the bounds of the parameter bias is within the order of square root of the inner loop tolerance (see also Lee and Seo (2015) for Monte Carlo analysis). Hence, we expect the error tolerances to have a limited impact on our GMM estimates.

[21] Nevertheless, the optimal GMM weight is still used for estimation efficiency.

[22] Intuitively, the second loop recovers the parameters entering the linear part of the utility following the practice of Nevo (2000): it starts from BLP's earlier mentioned sums of other product characteristics to account for price endogeneity and then evaluates the optimal instruments conditional on those obtained parameters. This procedure is repeated until convergence is reached for the parameters of the linear utility components.

[23] The global convergence was checked by running the estimation procedure from multiple starting points.

[24] Although the point estimates are unaffected by the GMM weight under optimal instruments, the standard errors will still be biased unless the weight is robust to the serial correlation.

[25] Increasing the number of draws implied virtually no change in our estimates.

### 4.3 Demand parameter estimates

Table 4 presents the main estimation results for the consumer demand model. The full set of parameter estimates, including the brand fixed effects and service plans interacted with consumer demographics, is available in Table A.1 of the appendix. Before we turn to the full random coefficients models, we first briefly comment on the results from simpler logit specifications.

| Estimate | Logit | IV logit | RC logit I | RC logit II |
|---|---|---|---|---|
| Price/$y_{it}$ ($-\alpha$) | | | -3.333*** | -3.914*** |
| | | | (0.345) | (0.630) |
| Log 4G/$y_{it}$ | | | -2.728*** | -3.495** |
| | | | (0.577) | (1.624) |
| Forfait bloqué/$y_{it}$ | | | 36.421*** | 37.670*** |
| | | | (3.928) | (5.549) |
| Prepaid/$y_{it}$ | | | | -6.415 |
| | | | | (4.996) |
| Intercept/$y_{it}$ | | | | 27.628* |
| | | | | (14.998) |
| Price/$\bar{y}_t$ | -0.288*** | -1.593*** | | |
| | (0.093) | (0.505) | | |
| Log(2G antenna) | 1.466*** | 1.572*** | 0.987*** | 0.781** |
| | (0.129) | (0.249) | (0.295) | (0.315) |
| Log(2G roaming) | 1.401*** | 1.370*** | 0.958** | 0.743 |
| | (0.185) | (0.398) | (0.444) | (0.484) |
| Log(3G antenna) | 0.142 | 0.281* | 0.508*** | 0.618*** |
| | (0.097) | (0.160) | (0.182) | (0.188) |
| Log(3G roaming) | -0.048 | 0.182 | 0.209 | 0.341 |
| | (0.161) | (0.350) | (0.370) | (0.408) |
| Log(4G antenna) | -0.216*** | -0.183*** | 0.245** | 0.345* |
| | (0.032) | (0.057) | (0.106) | (0.178) |
| Log(4G roaming) | -0.171*** | -0.173*** | 0.140 | 0.301 |
| | (0.036) | (0.066) | (0.124) | (0.221) |
| Forfait bloqué | -6.001*** | -6.977** | -11.778*** | -11.352*** |
| | (1.253) | (3.392) | (2.847) | (2.869) |
| Prepaid | -4.654*** | -8.409*** | -10.623*** | -10.653*** |
| | (1.262) | (2.862) | (2.524) | (2.646) |
| Call allow. (1,000 min) | 0.145*** | 0.446*** | 0.580*** | 0.615*** |
| | (0.047) | (0.095) | (0.099) | (0.104) |
| Data allow. (1,000 MB) | 0.193*** | -0.003 | 0.105 | 0.012 |
| | (0.057) | (0.101) | (0.112) | (0.131) |
| 1/Time since entry | -2.883*** | -2.800*** | -2.522*** | -2.352*** |
| | (0.097) | (0.153) | (0.220) | (0.246) |
| Observations | 3,324 | 3,324 | 3,324 | 3,324 |
| $J$ statistic | | 50.88 | 0.00 | 0.00 |
| D.F. | | 7 | 0 | 0 |
| Age heterogeneity | Yes | Yes | Yes | Yes |
| Product, region & time fixed effects | Yes | Yes | Yes | Yes |
| Own price elasticity | | -1.010 | -2.530 | -3.028 |
| Market elasticity | | -0.024 | -0.092 | -0.109 |

Standard errors in parentheses (clustered at the product–region level): * p<0.10, ** p<0.05, *** p<0.01. $y_{it}$ & $\bar{y}_t$ denote individual & mean incomes scaled by the €100 units. Time trend, intercept, and other demographics controls are included in all specifications. The first-stage robust $F$ statistic for IV logit is 47.49 with $p$ value<1e-4 under clustered errors.

*Table 4:* Estimation of mobile services demand

We begin with a simple logit demand in the first column (Logit) without accounting for the price endogeneity. The price is normalized by the average population income of each regional market in the scale of €100s. The price coefficient is negative and significant, but its magnitude is small. Furthermore, the coefficients for most network quality variables are imprecisely estimated, sometimes with negative sign. The model also includes fixed effects for tariff types and product brands as well as a constant, which normalizes the utilities with respect to the postpaid plan of Bouygues MVNOs.

The second column (IV logit) instruments for the endogenous price variable by formulating BLP instruments as the sum of the characteristics across the products of the same and rival firms, respectively. The list of the characteristics includes the network antennas of the three generations and the number of available products. As the two variables represent product quality and product line size, they are important considerations for the firms' pricing. The price instruments aggregate over the regions to conform to the uniform pricing that is typical in the mobile market. Hence, the variation in the instruments primarily comes from changes over time since the entry of Free mobile and fighting brands. The validity of these instruments stems from the timing of decisions on network investment and product portfolio, which are assumed to take place prior to the pricing decisions.

We find that the estimated price coefficient increases in size from -0.288 to -1.593 after instrumenting for the price. While the 4G network coefficients remain negative, the positive 3G antenna coefficient becomes marginally significant. These changes are already more in line with what one might expect from the sample period of 2011–2014. Nevertheless, the own-price elasticities implied by the estimates (on average -1.01) are still far below the estimates from the previous literature on the mobile telecom markets (see Section 4.4 for more discussion of the literature).

The third column (RC logit I) displays the estimates of the parsimonious random coefficients model that incorporates consumer heterogeneity in the valuation of price, forfait bloqué service, and 4G network quality.[26] The simulated income draws are divided by €100 for consistency with the scaling of the previous columns. The estimated random coefficients $(\alpha, \sigma_\nu)$ are presented in the top three rows. The price coefficient (-3.33) is larger than the IV logit estimate, generating simulated draws of $-\alpha/y_{it}$ ranging between -8.90 and -2.04 for the 10th and 90th percentiles, respectively.[27] This translates into higher own-price elasticities (on average -2.53) than in the IV logit specification. We also find significant heterogeneity in the valuation of both the 4G networks and forfait bloqué services. The signs of the heterogeneity parameters indicate that high-income consumers, who have a low price sensitivity (low $\alpha/y_{it}$), highly appreciate network quality while having a low valuation for forfait bloqué services relative to other consumers.

We now turn to the remaining estimates of the RC logit I specification. Consumers have a high mean valuation for denser 2G proprietary and roaming networks, and for denser 3G and 4G proprietary networks. The mean valuation for call allowance is strongly positive, while not precisely estimated for data allowances (perhaps because this valuation is captured by the network quality variables). We also include the variable "Time since entry" as an additional control, defined as the inverse of time elapsed since market entry of each product. The coefficient estimate is strongly negative and significant. This shows it takes some time to build market share, which may be driven by various factors as discussed earlier in the previous section.

Finally, the fourth column of Table 4 (RC logit II) shows the estimates of an extended model with additional random coefficients. The estimates remain very similar to the previous specification, including the one for the forfait bloqué service plan. The added random coefficient for prepaid service is not significant, while the random coefficient for the intercept is significant at the 10 percent level.

The random coefficients in Table 4 include interaction terms with income draws to capture taste correlation for the characteristics. As a way to validate this specification, we calculate the model's predicted average incomes per buyer group (operator and tariff type). We find that these are of a comparable magnitude as the observed ones; see Table A.2 in Appendix C. The approximations do show some differences between

[26] The variable Log 4G/$y_{it}$ combines both Log 4G and its roaming antennas.

[27] This range is obtained after normalizing the draws of $y_{it}$ with respect to national average income $\bar{y}$.

groups, which can be interpreted as suggesting that the income draws also capture other unobservable factors that affect choices through taste correlation. As a robustness check, we have nevertheless also estimated a specification without the interactions in the random coefficients. These are reported in the third column of Table A.15 in Appendix F. This also reveals significant unobserved heterogeneity in various dimensions. The next columns of Table A.15 show additional robustness analysis: a specification with a 50% higher potential market size, and a specification without the allowance variables (which also enables a slightly increased sample to include the earlier months). These specifications generate broadly comparable parameter estimates.

Recall that all these specifications use the continuous updating GMM estimator. Appendix G discusses estimators based on non-optimal instruments (BLP and differentiation IVs). While this gives comparable results for the random coefficients and the implied substitution patterns, the estimates for the price coefficient tend to be somewhat sensitive with respect to the specific choice of instruments. We therefore focus our analysis on the efficient continuous updating GMM estimator, which does not rely on the specific choice of instruments for the random coefficients in a first stage.

## 4.4 Substitution patterns and markups

We first compare the implied price elasticities of the various models in Table 4 with other empirical work. Next, we focus on the preferred extended model (RC logit II) to discuss the specific substitution patterns and markups.

**Comparison of elasticities with previous literature** Our demand model abstracted away from detailed fee structures within each given tariff type by aggregating the fixed and variable fees. As a way to validate our estimates, it is therefore instructive to compare the implied price elasticities with other estimates in the literature on the demand for mobile telecom services.

As shown in the bottom rows of Table 4, the simple logit model implies very low estimates for the own-price elasticity of demand (very inelastic for OLS logit and around -1 for IV logit). The random coefficients logit models imply much larger elasticities at around -3.0 on average in the RC logit II model. The own-price elasticities vary between -1.5 and -5.3 according to the matrix of own- and cross-price elasticities presented in Table A.4 in the appendix. The estimates of the random coefficients model are broadly in line with other empirical findings, including studies that incorporate the usage decision. Huang (2008) finds elasticities ranging between -4 and -7 for Taiwan (an earlier period when demand was not yet saturated). His elasticity estimates based on subscribers and traffic are very close to each other, which is consistent with Kim et al. (2010) who find very inelastic mobile usage demand. Our estimates are also roughly in line with those of Grzybowski and Pereira (2007) for Portugal (in the range of -2.6 and -6.4) and slightly higher than the average of -2.6 obtained by Gagnepain and Pereira (2007).[28]

**Substitution patterns** To discuss the specific substitution patterns between brands and tariff types, it is most informative to use diversion ratios. The diversion ratio $DR_{jk} = (\partial D_k/\partial p_j)/(\partial D_j/\partial p_j)$ is the fraction of lost sales from product $j$ that flows towards product $k$ after a price increase by $j$. Table 5 shows the diversion ratios for the postpaid tariff plans, while Table A.3 in Appendix C shows the full matrix of diversion ratios for

[28] We estimate a market level price elasticity of around -0.1, which is lower than in Huang (2008). However, he considered a much earlier period when demand had not yet reached maturity.

all tariff plans (including prepaid and forfait bloqué, and the MVNOs and the outside good).[29] Both tables should be read by column.

| Network | Product | Orange | | SFR | | Bouygues | | Free |
|---|---|---|---|---|---|---|---|---|
| operator | group | Postpaid | Sosh | Postpaid | Red | Postpaid | B&You | Postpaid |
| Orange | Prepaid | 5.43 | 5.22 | 5.70 | 4.99 | 4.91 | 5.13 | 5.95 |
| | Postpaid | -100.00 | 11.84 | 24.40 | 10.05 | 25.80 | 10.98 | 6.95 |
| | Forfait bloqué | 6.64 | 7.89 | 7.30 | 7.92 | 5.90 | 7.65 | 11.17 |
| | Sosh | 3.62 | -100.00 | 3.92 | 3.49 | 3.32 | 3.70 | 3.88 |
| SFR | Prepaid | 2.02 | 2.10 | 2.24 | 2.34 | 1.88 | 2.09 | 2.51 |
| | Postpaid | 28.05 | 15.07 | -100.00 | 13.36 | 24.40 | 14.21 | 10.22 |
| | Forfait bloqué | 2.54 | 4.40 | 3.08 | 5.17 | 2.35 | 4.70 | 11.13 |
| | Red | 2.21 | 2.68 | 2.55 | -100.00 | 2.14 | 2.72 | 3.50 |
| Bouygues | Prepaid | 2.14 | 2.03 | 2.23 | 1.93 | 1.96 | 2.10 | 2.34 |
| | Postpaid | 18.18 | 7.73 | 14.98 | 6.71 | -100.00 | 7.63 | 4.81 |
| | Forfait bloqué | 1.21 | 1.77 | 1.41 | 1.97 | 1.15 | 1.94 | 3.59 |
| | B&You | 2.83 | 3.33 | 3.18 | 3.16 | 2.80 | -100.00 | 3.91 |
| Free | Postpaid | 10.97 | 19.07 | 13.85 | 20.98 | 10.87 | 20.91 | -100.00 |

Percentage of sales diverted toward products (rows) due to price increase (columns). Columns limited to postpaid products; the full matrix is in Table A.3 in Appendix.

*Table 5:* Diversion ratios (from postpaid products)

According to Table 5, the operator-branded postpaid tariffs mainly divert sales from each other: Orange mainly from SFR (28.1%), and SFR and Bouygues mostly from Orange (24.4% and 25.8%, respectively). In sharp contrast, the fighting brands draw the most consumers from Free Mobile: Sosh, Red and B&You take 19.1%, 21.0% and 20.9% away from Free, respectively. Finally, Free mainly captures sales from both the postpaid and forfait bloqué plans of Orange and SFR. The complete Table A.3 shows additional intuitive results regarding the diversion from the prepaid and forfait bloqué tariff plans. More specifically, the incumbents' prepaid and forfait bloqué tariffs tend to lose sales mainly to Free Mobile.

In sum, the diversion ratios are intuitive and consistent with the earlier documented market share changes after the introduction of Free Mobile and the fighting brands. Free Mobile mainly steals business from the incumbents' premium brands, while the incumbents' fighting brands mainly steal business from Free Mobile (and would mainly cannibalize sales in the absence of Free Mobile). These substitution patterns can have important implications for the profit incentives and welfare effects, which will be evaluated in the next sections.

**Markups** Table 6 presents a summary of the profit margins recovered from the estimates of the extended model (RC logit II) in Table 4. For the MVNO products, these refer to the retail margins.[30] We find that the markups tend to be lowest for the prepaid and forfait bloqué tariffs (especially those of the MVNOs). The markups are also low for Free Mobile's postpaid and the incumbents' fighting brands (Sosh, Red and B&You). In contrast, the markups of postpaid services are considerably higher for the incumbents' premium

[29] Table A.4 uses a similar structure to show the full matrix of own-and cross-price elasticities, which is useful for comparison with past (and future) empirical literature on the demand for mobile telecom services.

[30] Recall that we recover the retail and wholesale margins from the first-order conditions, as given by Equations (6), (7) and (8). More details on the solution procedure are available in the appendix.

products. These differences in markups across brands and tariffs are consistent with expectations, based on the substitution patterns examined above.

| Network operator | Product group | Price | | | Markup | | |
|---|---|---|---|---|---|---|---|
| | | Prepaid | Postpaid | F. bloqué | Prepaid | Postpaid | F. bloqué |
| Orange | Orange | 13.56 | 39.04 | 22.56 | 8.70 | 14.00 | 7.60 |
| | Sosh | | 16.67 | | | 9.37 | |
| SFR | SFR | 13.33 | 28.86 | 18.62 | 7.94 | 11.50 | 5.38 |
| | Red | | 15.54 | | | 8.32 | |
| Bouygues | Bouygues | 13.53 | 35.12 | 19.89 | 6.68 | 10.90 | 4.63 |
| | B&You | | 16.07 | | | 7.24 | |
| Free | Free | | 11.54 | | | 5.62 | |
| Orange | MVNO | 9.27 | 19.04 | 18.27 | 4.32 | 6.88 | 3.59 |
| SFR | MVNO | 6.34 | 18.89 | 17.26 | 3.51 | 6.84 | 3.45 |
| Bouygues | MVNO | 4.40 | 32.92 | 19.79 | 2.76 | 8.74 | 3.82 |

Average retail prices and margins of mobile services across times and regions (in euro). For MVNO products, these refer to retail margins. F. bloqué denotes forfait bloqué service. See the note of Table 3 for its definition.

*Table 6:* Estimated markups

These results show that the incumbents earn higher markups in their premium postpaid segment even after the release of fighting brands. Nevertheless, Table 6 highlights that the higher markups for the incumbents' premium products do not entirely explain their higher prices. The remaining part of the price premium is due to the higher marginal costs associated with providing the premium quality postpaid services. For example, the premium postpaid services operated physical retail channels for offline customer support, which was not offered for the low-cost services. The premium postpaid products also used the most recent mobile technologies and made the most intensive use of the network infrastructure. Moreover, the premium products included some costly services that were either unavailable or unnecessary under the low-cost offers (e.g., an optional extra SIM card, real-time billing, etc.).

Finally, as a way to validate our estimates, it is useful to compare the computed markups with external information on EBITDA margins at the operator level from the companies' financial reports. Our estimates imply an average markup of 38% for Orange, 40% for SFR and 33% for Bouygues. These estimates show a similar pattern albeit at a somewhat higher level than the ones obtained from financial reports (34% for Orange, 31% for SFR and 22% for Bouygues in 2011). However, these accounting margins may include fixed cost components and would thus likely be higher without them. In further support of our assumption on non-cooperative price-setting behavior, note that the firms had earlier been convicted of price collusion in 2005, and despite likely further monitoring, there have been no claims on such practices since then. Furthermore, the average EBITDA margin of the French operators of 31.7% is only slightly above the European average of 28.8% in 2012 (HSBC, 2014).

In sum, our findings imply that the higher prices for the incumbents' premium postpaid products are partly due to higher markups and partly due to higher marginal cost of service. This contrasts with what would be found in a simplified logit demand specification, where a multiproduct firm obtains identical markups for all of its products.[31] Hence, in a simplified logit any observed price differences between products of the same firm would have to be attributed entirely to cost differences.

# 5 Incumbents' incentives for product line expansion

In the previous section, we estimated consumer demand and recovered marginal costs from our oligopoly model. In this section, we use these estimates to investigate whether we can rationalize the three incumbents' new subsidiary product lines after the entry by Free Mobile as a fighting brands strategy in the spirit of Johnson and Myatt (2003).[32] Depending on the outcome of this analysis, we will then determine whether to take the fighting brands into account in the welfare analysis of the next section.

To assess whether we can rationalize the incumbents' product line expansions as a fighting brand strategy, we calculate the equilibrium variable profits for all 16 combinations of product line strategies, i.e. entry or not by Free Mobile and by the three subsidiary brands of the incumbents. These counterfactuals amount to solving the retail and wholesale price equilibrium after eliminating Free and/or each of the incumbents' subsidiary brands. This implies solving Equations (6), (7) and (8), where the pass-through rates in (8) are obtained from Equations (17) and (18) in Appendix A. Table A.6 of the appendix displays the payoffs for each of the three incumbents under all 16 combinations. We will also perform a robustness analysis using our vertically integrated pricing model (based on Equations (10) and (11)), which assumes no double marginalization effects for the MVNOs.

To extend Johnson and Myatt (2003)'s monopoly analysis to our setting with multiple incumbents, we proceed as follows. In Subsection 5.1, we examine the incumbents' *unilateral* incentives for product line extension by formulating their product line decisions as a static simultaneous-move game. We do not find a range of fixed costs that can rationalize, as unilateral best responses, both the absence of fighting brands before entry and their introduction after entry. In Subsection 5.2, we therefore explore a dynamic approach to examine the possibility that the incumbents collude on their product line strategies within an infinitely repeated game framework. More precisely, we ask whether the incumbents were able to tacitly collude on withholding low-cost brands before the entry of Free Mobile, and whether such collusion became more difficult to sustain after entry. Within this modified framework, we aim to identify a non-empty set of fixed costs for the low-cost brands that would generate the same predictions made by Johnson and Myatt (2003).[33]

## 5.1 Unilateral incentives for product line extension

Johnson and Myatt (2003) asked whether an incumbent monopolist has an incentive to introduce a low-quality fighting brand after the entry of a new competitor. In this subsection, we extend their framework to examine,

[31] See for example, Nevo and Rossi (2008). Nocke and Schutz (2018) generalize this principle to a wide class of models satisfying the independence of irrelevant alternatives property.

[32] Johnson and Myatt (2003) also consider product line "pruning," where an incumbent withdraws an existing product as a reaction to entry. In this paper, we limit our attention to product line expansion decisions since no product line pruning is observed during our observation period.

[33] We base our analysis on the parameter estimates of the extended random coefficients model, i.e., the third column in Table 4 (RC logit II). We calculate profits as the net present value from January 1, 2012 (when Free Mobile entered the market) until December 2014 (the last month of our data). This approach has the advantage of simplicity and transparency; in our collusion analysis we also consider an extension where we allow for non-stationary payoffs.

within a static game framework, whether the three incumbent firms have unilateral incentives to introduce their low-quality fighting brands after entry.[34]

Based on the incumbents' observed product line strategies, we posit the following. In the absence of entry, the candidate Nash equilibrium is such that none of the incumbents releases a low-quality brand. Conversely, after the entry of Free Mobile, the candidate equilibrium is such that all incumbents launch a subsidiary brand. More formally, let $\Pi_j^{d,e}$ be incumbent firm $j$'s variable profit when operating a fighting brand or not: $d \in \{FB, noFB\}$. Likewise, the index $e$ indicates the market entry ($E$) or absence ($N$) of Free Mobile: $e \in \{E, N\}$. We use $f_j$ to denote $j$'s fixed cost of operating its fighting brand. With these notations, "no fighting brands" is a Nash equilibrium in the case of absent entry if $\Pi_j^{noFB,N} \geq \Pi_j^{FB,N} - f_j$ for each $j$. Analogously, in the presence of entry, "fighting brands" is a Nash equilibrium if $\Pi_j^{FB,E} - f_j \geq \Pi_j^{noFB,E}$ for each $j$. The range of fixed costs satisfying both restrictions is then given by

$$\Pi_j^{FB,N} - \Pi_j^{noFB,N} \leq f_j \leq -(\Pi_j^{noFB,E} - \Pi_j^{FB,E}). \tag{13}$$

Table 7 uses the payoff matrix of Table A.6 to calculate the deviation payoffs to the individual incumbents when they unilaterally deviate from the candidate Nash equilibrium product line strategies as expressed in (13). Bootstrapped standard errors are shown in parentheses.[35]

| | Entry of Free Mobile | |
|---|---|---|
| | No | Yes |
| Incumbent network | Equilibrium: no FB $(\Pi_j^{FB,N} - \Pi_j^{noFB,N})$ | Equilibrium: FB $(\Pi_j^{noFB,E} - \Pi_j^{FB,E})$ |
| Orange | 429 | -354 |
| | (60) | (53) |
| SFR | 289 | -230 |
| | (45) | (37) |
| Bouygues | 402 | -311 |
| | (58) | (48) |

The figures represent the incumbents' profit changes in million euros, resulting from unilateral deviations from the observed candidate Nash equilibrium: no fight brands (no FB) without the entry by Free Mobile, fight brands (FB) in the presence of entry. The calculations are based on the payoffs from Table A.6 of the appendix. Standard errors from a parametric bootstrap are in parentheses.

*Table 7:* Unilateral incentives to deviate from candidate equilibrium product lines

According to the first column of Table 7, each incumbent would experience a (statistically significant) *increase* in variable profits if it unilaterally releases a subsidiary brand when there is no entry. Based on the left side of (13), our non-cooperative framework rationalizes the market outcome that no incumbent launches

[34]As a benchmark for comparison with the monopoly set-up of Johnson and Myatt (2003), Appendix D also examines the three incumbents' joint (as opposed to unilateral) incentives to introduce low-quality brands after the entry of Free Mobile. We find that these joint incentives are strongly negative before entry, and they increase substantially to a negligible positive amount after entry. While this exercise provides useful economic intuition on the role of cannibalization effects before entry and business stealing after entry in the spirit of Johnson and Myatt's (2003) monopoly analysis, it is not realistic because it relies on explicit contracting.

[35]We draw 200 parameter values from a normal distribution using the point estimates and covariance matrix of our extended random coefficients model (RC logit II).

a low-cost brand in the absence of entry if the fixed costs of operating such a brand exceed the deviation payoff of the first column. For example, since the variable profit gains for Orange amount to €429 million, its fixed cost must be of at least this amount for Orange not to introduce its low-quality brand (Sosh) in the absence of entry.

The second column of Table 7 finds that the incumbents' gross variable profits *decrease* if they unilaterally withhold a subsidiary brand when Free Mobile enters. Based on the right side of (13), we can characterize as an equilibrium the market outcome that all incumbents release a low-cost brand if the fixed costs of subsidiary brands are less than the variable profit losses in absolute terms (since the incumbents would save these fixed costs if they do not launch their new brands). For example, for Orange, the fixed cost of its subsidiary brand Sosh must be smaller than €354 million, since otherwise Orange would not have introduced it upon the entry of Free Mobile.

The first and second columns (in absolute value) thus respectively characterize lower and upper bounds on the incumbents' fixed costs that are necessary to rationalize the fighting brand strategy as a unilateral best-response. When the two are compared, the lower bound turns out to be higher than the upper bound by significant margins for all three incumbents.[36] Hence, it is clear that there are no levels of fixed costs that simultaneously explain why the incumbents introduced subsidiary brands upon the entry of Free Mobile, and why they would not have done so already in the absence of entry.[37]

To sum up, we do not find support for the non-cooperative view of the fighting brands as the incumbents' unilateral best response strategy.[38] However, our analysis has so far limited attention to simultaneous product line decisions in a static game and, in doing so, ignored the possibility that the incumbents could react to the competitors' unilateral expansion of their product portfolio. Hence in the subsequent analysis, we will consider a dynamic approach that allows for the competitors' reactions within an infinitely repeated game framework to examine whether we can find support for the fighting brand theory in the oligopoly setting.

## 5.2 Collusion in product line strategies

We now examine whether the incumbents can tacitly collude on restricting their product lines and how entry affects the sustainability of such form of collusion. We first develop a tractable model of collusion in product line strategies under simplifying assumptions. We then calibrate this model based on our estimates.

**Model.** We consider an industry with three incumbent firms, $j = O, S, B$ named after the initial of the incumbents, and a potential entrant, now denoted as firm $F$, competing in prices with differentiated products. Each incumbent firm $j$ sells a premium service and has the possibility to expand its brand portfolio by introducing a new low-cost service. To operate the new brand, incumbent firm $j$ has to incur a per-period fixed cost $f_j$. In contrast to the incumbent firms, the entrant $F$ is a single-product firm, which offers only a low-cost service.

[36] The $t$ statistic for the difference is higher than 7 ($p$<0.0001) for all the incumbents.

[37] We obtain the same conclusions in the vertically integrated pricing model, as shown in Table A.12 of the appendix: the lower bounds on fixed costs to rationalize no fighting brands in the absence of entry are always higher than the upper bounds to rationalize fighting brands in the presence of entry.

[38] This finding does not necessarily contradict the theoretical analysis of Nocke and Schutz (2018), where product lines can (weakly) expand as competition intensifies. The discrepancy may arise because of two distinct features in our model. First, our random-coefficients demand specification includes aspects of both horizontal and vertical differentiation. Second, our supply-side model incorporates the fixed operating costs of subsidiary brands to account for the restricted product lines observed before the entry.

The three incumbent firms play an infinitely repeated game.[39] At each date, they simultaneously decide whether to launch a new low-cost brand (if they have not launched one yet), in addition to their existing premium brand. Once it is launched, an incumbent cannot withdraw its low-cost brand, for example due to high exit costs.[40] We postulate that while firms can potentially collude on their product line strategies, they compete in prices. That is, we consider a context of semi-collusion, where firms collude in one dimension and compete in another.[41]

Each firm $j = O, S, B$ maximizes the present discounted value of its profits, with a discount factor $\delta_j \in (0, 1)$. Firm $j$'s profit at a given date depends on its own product line and that of its competitors, as well as on the equilibrium prices of the one-stage price game given the firms' brand portfolios.

We assume that the one-stage brand expansion game has an equilibrium in which all incumbents decide to launch a new brand. We will infer an upper bound on the fixed costs below which our assumption holds true given our parameter estimates. To define model primitives, we denote by $\Pi_j^{N,e}$ firm $j$'s gross profit in this non-collusive (Nash) outcome, with $e = E$ in case of entry and $e = N$ without entry. The profit is gross of the per-period fixed cost $f_j$ of operating the new brand. All incumbents' launching a new brand constitutes an equilibrium of the one-stage game if and only if $\Pi_j^{N,e} - f_j > \hat{\Pi}_j^e$ for all $j$, where $\hat{\Pi}_j^e$ denotes firm $j$'s profit if it does not launch a new brand and the two other incumbents would still do so. This condition thus defines an upper bound for the fixed cost, $\bar{f}_j^e \equiv \Pi_j^{N,e} - \hat{\Pi}_j^e$. Intuitively, if firm $j$'s fixed costs are sufficiently low ($f_j < \bar{f}_j^e$), it has no incentive to deviate from the one-stage equilibrium where all incumbents launch a new brand.

On the other hand, we examine whether the incumbent firms can tacitly collude on restricting their product lines. To sustain such collusive outcome, firms adopt the punishment strategy of infinite reversion to the one-stage equilibrium in case any incumbent firm deviates from the collusive equilibrium by unilaterally expanding its brand portfolio. Similarly as above, we denote by $\Pi_j^{C,e}$ firm $j$'s profit in the collusive outcome, and by $\Pi_j^{D,e}$ its gross profit if it deviates from it.

We will say that entry facilitates collusion in product line strategies if it reduces the threshold discount factor above which the collusive outcome can be sustained, and otherwise that it makes collusion more difficult to sustain.

In what follows, we first determine the condition under which collusion on restricting product lines is sustainable. Next, we identify the condition under which collusion becomes more difficult to sustain after entry ($e = E$). Finally, we calibrate this model of semi-collusion using our estimates of operators' profits (for which we continue to rely on Table A.6 of the appendix).

**Sustainability of collusion.** In both cases, with entry ($e = E$) and without ($e = N$), tacit collusion is sustainable if the sum of discounted profits from collusion is higher than the discounted profits obtained by deviating. If incumbent firm $j$ deviates from the collusive outcome by launching a new brand, it earns the net profit $\Pi_j^{D,e} - f_j$ for one period. In the ensuing punishment phase, the deviating firm makes the profit $\Pi_j^{N,e} - f_j$ in each period. Firm $j$ would thus have no incentives to deviate from the collusive outcome when

[39] In our context, it is helpful to think that this infinitely repeated game is played within a specific time period, for example, the month of January, 2012, when entry took place.

[40] Withdrawing the low-cost brand could imply a large reputation cost for the incumbent. See, e.g., Chiou and Scarpa (1992) for a model where withdrawing a new brand has a negative reputational effect on an incumbent's legacy product.

[41] The literature has analyzed semi-collusion in settings where firms compete in the product market (in prices or quantities), while colluding in R&D (Fershtman and Gandal, 1994), capacity (Osborne and Pitchik, 1987), or location choices (Friedman and Thisse, 1993).

the per-period payoffs are stationary if the following condition holds:

$$\frac{\Pi_j^{C,e}}{1-\delta_j} \geq \Pi_j^{D,e} - f_j + \frac{\delta_j}{1-\delta_j}(\Pi_j^{N,e} - f_j). \tag{14}$$

Condition (14) holds if and only $\delta_j \geq \underline{\delta}_j^e$, where $\underline{\delta}_j^e$ is the threshold discount factor for firm $j$, defined by

$$\underline{\delta}_j^e(f_j) \equiv \frac{\Pi_j^{D,e} - \Pi_j^{C,e} - f_j}{\Pi_j^{D,e} - \Pi_j^{N,e}}. \tag{15}$$

There exists a non-empty set of discount factors for the three incumbents such that collusion is sustainable only if $\underline{\delta}_j^e < 1$ for all $j = O, S, B$. Since the threshold discount factor (15) is decreasing in $f_j$, we have $\underline{\delta}_j^e < 1$ if $f_j$ is sufficiently large. The intuition is that, as the fixed cost of operating a new brand increases, both the deviation and punishment profits decrease, which makes collusion on withholding fighting brands easier to sustain.

Formally, from (15) we have $\underline{\delta}_j^e < 1$ if and only if $f_j > \underline{f}_j^e \equiv \Pi_j^{N,e} - \Pi_j^{C,e}$. Obviously, if the gross payoff from collusion is larger than the gross punishment profit (i.e., $\Pi_j^{C,e} \geq \Pi_j^{N,e}$), there always exists a range of discount factors that sustain collusion for all fixed costs $f_j \geq 0$. However, as we will see below with our estimates, the gross profit from collusion can be lower than the gross punishment profit, because under punishment a firm derives additional revenues from its low-cost brand. In this case, a sufficiently high fixed cost of brand operation is necessary to sustain collusion.

To summarize, if for all incumbents $j = O, S, B$ we have $f_j \in (\underline{f}_j^e, \bar{f}_j^e)$, then there is a range of discount factors such that firms can coordinate via repeated interactions on not launching low-cost brands, with or without entry of the competitor. The lower bound on fixed costs guarantees that firms are willing to collude on withholding low-cost brands, whereas the upper bound guarantees that firms are willing to punish by also releasing a low-cost brand when one of the firms deviates.

**The impact of entry on collusion incentives.** We now discuss the impact of entry by firm $F$ on the possibility of collusion in product line strategies. Entry has countervailing effects on the ability of the incumbent firms to tacitly collude on restricting their product line. On the one hand, entry lowers the collusion profit, which makes collusion harder to sustain. On the other hand, entry also lowers the deviation and punishment profits, which facilitates collusion.

Overall, entry makes collusion more difficult to sustain if and only if $\underline{\delta}_j^E > \underline{\delta}_j^N$. One can easily verify that

$$\underline{\delta}_j^E(f_j) - \underline{\delta}_j^N(f_j) \equiv \Delta_j(f_j) = \frac{(\Pi_j^{D,E} - \Pi_j^{N,E}) - (\Pi_j^{D,N} - \Pi_j^{N,N})}{(\Pi_j^{D,E} - \Pi_j^{N,E})(\Pi_j^{D,N} - \Pi_j^{N,N})} f_j + \Delta_j(0), \tag{16}$$

with

$$\Delta_j(0) \equiv \frac{\Pi_j^{D,E} - \Pi_j^{C,E}}{\Pi_j^{D,E} - \Pi_j^{N,E}} - \frac{\Pi_j^{D,N} - \Pi_j^{C,N}}{\Pi_j^{D,N} - \Pi_j^{N,N}}.$$

Entry makes collusion in product line strategies more difficult to sustain if, for all $j = O, S, B$, one of the following conditions holds:[42]

1. $\Delta_j(0) > 0$ and $\Pi_j^{D,E} - \Pi_j^{N,E} > \Pi_j^{D,N} - \Pi_j^{N,N}$;
2. $\Delta_j(0) > 0$, $\Pi_j^{D,E} - \Pi_j^{N,E} < \Pi_j^{D,N} - \Pi_j^{N,N}$ and $f_j$ is sufficiently low ($f_j < \bar{\bar{f}}_j$);
3. $\Delta_j(0) < 0$, $\Pi_j^{D,E} - \Pi_j^{N,E} > \Pi_j^{D,N} - \Pi_j^{N,N}$ and $f_j$ is sufficiently high ($f_j > \bar{\bar{f}}_j$).

Otherwise, entry facilitates collusion.[43]

Hence, for entry to make collusion more difficult to sustain, there may be an additional upper bound on the fixed costs (in Case 2) or an additional lower bound (in Case 3). Note that these bounds may be more or less tight than the earlier bounds for sustainability ($\underline{f}_j^e$ and $\bar{f}_j^e$), and we will verify them from our parameter estimates.

**Calibration.** We can now evaluate whether: (i) the three incumbent operators could tacitly collude on restricting their product lines before the entry of Free Mobile; and (ii) whether such collusion became more difficult to sustain after the entry of Free Mobile. Table 8 computes the lower and upper bounds on fixed costs for which collusion is sustainable before entry (i.e., $\underline{f}_j^N$ and $\bar{f}_j^N$) and the bounds for which it becomes more difficult to sustain after entry (i.e., $\bar{\bar{f}}_j$). These are computed from the above definitions, using the incumbents' payoffs under the alternative market configurations shown in Table A.6.

| Operator | $\underline{f}_j^N$ (collusion) | $\bar{f}_j^N$ (punishment) | $\bar{\bar{f}}_j$ (breakdown) | $\bar{f}_j^N - \underline{f}_j^N$ | $\bar{\bar{f}}_j - \underline{f}_j^N$ |
|---|---|---|---|---|---|
| (O)range | -204 | 389 | 285 | 593 | 489 |
| | (21) | (58) | (43) | (76) | (61) |
| (S)FR | -327 | 263 | 175 | 590 | 502 |
| | (33) | (42) | (30) | (74) | (63) |
| (B)ouygues | 145 | 369 | 194 | 224 | 49 |
| | (20) | (56) | (35) | (36) | (15) |

Lower and upper bounds on fixed costs for which collusion in restricting product lines is sustainable before entry ($\underline{f}_j^N$ and $\bar{f}_j^N$) and upper bounds for which collusion becomes more difficult to sustain after entry ($\bar{\bar{f}}_j$) in million euros. Standard errors from a parametric bootstrap are in parentheses.

*Table 8:* Bounds on fixed costs supporting fighting brands in response to entry

The first column of Table 8 computes the lower bounds on fixed costs ($\underline{f}_j^N$) above which firms are willing to collude before the entry of Free Mobile (given their punishment strategies). Formally, these are lower bounds on fixed costs such that $\underline{\delta}_j^N < 1$. Orange and SFR are willing to collude by withholding fighting brands for any level of fixed costs (as the lower bounds are negative). Intuitively, this is because their collusion profits are already higher than their gross profits of punishment (so they would certainly be higher after

[42] Since the denominator of the coefficient of $f_j$ in (16) is positive, the sign of $\Delta_j(f_j)$ depends on the sign of the numerator of the coefficient of $f_j$ and the sign of $\Delta_j(0)$.

[43] The upper bound $\bar{\bar{f}}_j$ is derived as:

$$\bar{\bar{f}}_j = \frac{\Pi_j^{C,E}(\Pi_j^{D,N} - \Pi_j^{N,N}) - \Pi_j^{C,N}(\Pi_j^{D,E} - \Pi_j^{N,E}) + \Pi_j^{D,E}\Pi_j^{N,N} - \Pi_j^{D,N}\Pi_j^{N,E}}{(\Pi_j^{D,E} - \Pi_j^{D,N}) - (\Pi_j^{N,E} - \Pi_j^{N,N})}.$$

accounting for the fixed costs under punishment).[44] Bouygues is willing to collude provided its fixed costs are above €145 million. Intuitively, a sufficiently high fixed cost reduces Bouygues' profits from deviating and also makes its punishment more severe.

The second column of Table 8 presents the upper bounds on fixed costs ($\bar{f}_j^N$) below which the incumbents are willing to carry out the punishment outcome as an equilibrium to the one-stage game. The outcome in which all three operators punish by releasing a low-cost brand is a one-stage equilibrium provided that the fixed costs are below €389 million for Orange, below €263 million for SFR and below €369 million for Bouygues. It is worth noting that with our estimates, the punishment outcome always corresponds to the harshest (symmetric or asymmetric) punishment for the deviating firm.[45]

Taken together, for each incumbent there is a non-empty range of fixed costs for which both collusion and punishment are sustainable. So, we can rationalize the incumbents' decisions to avoid introducing fighting brands in the absence of entry by Free Mobile as a tacitly collusive strategy.

The third column of Table 8 presents the fixed cost bounds for which such collusion becomes more difficult to sustain after the entry by Free Mobile. As shown above, this may either imply further upper or lower bounds on fixed costs. Table A.7 of the appendix shows that for our estimates, we have $\Delta_j(0) > 0$ and $\Pi_j^{D,E} - \Pi_j^{N,E} < \Pi_j^{D,N} - \Pi_j^{N,N}$ for each incumbent $j = O, S, B$. We are therefore in Case 2 defined above. This means that entry makes collusion in product line strategies more difficult to sustain if the fixed costs are sufficiently low, i.e. $f_j < \bar{\bar{f}}_j$: fixed costs should be below €285 for Orange, below €175 for SFR and below €194 for Bouygues.

Note that the upper bounds $\bar{\bar{f}}_j$ are tighter than the earlier upper bounds $\bar{f}_j$ to sustain punishment, but they are still above the lower bounds $\underline{f}_j$ to sustain collusion in the absence of entry. The last two columns confirm that the margins between the lower and upper bounds are all significantly positive.

We can therefore conclude that there is a non-empty set of discount factors such that collusion on restricting product lines is sustainable before entry, but becomes more difficult to sustain after entry if the following conditions on fixed costs hold:

$$f_O \in (0, 285), \quad f_S \in (0, 175), \quad f_B \in (145, 194).$$

We obtain the same conclusions in the model of vertically integrated pricing instead of independent wholesaler-retailer pricing, as shown in Table A.13 of the appendix.

The analysis of Table 8 has focused on establishing the relevant ranges of fixed costs that may rationalize the fighting brand story for some discount factor. To make this more concrete, it is also of interest to examine the precise threshold discount factors $\underline{\delta}_j^e(f_j)$, based on (15), for given fixed cost levels (within our just obtained ranges). Figure 3 shows, for each firm $j$, the threshold discount factor to sustain collusion without entry (dashed line) and with entry (solid line), as a function of the fixed cost $f_j$, for the relevant range of fixed costs, i.e. for $f_j \in \left[\max\{0, \underline{f}_j\}, \min\{\bar{f}_j, \bar{\bar{f}}_j\}\right]$. For each given fixed cost $f_j$ of firm $j$, any point between the two discount factor curves ensures that collusion is sustainable without entry but not with entry.[46] The

[44] This can be verified from inspecting the collusion and punishment profits of Orange and SFR in the absence of entry by Free in Table A.6.

[45] Therefore, the trigger strategies with infinite reversion to the one-stage equilibrium of the game (Friedman, 1971) coincide with Abreu's optimal punishment.

[46] The two lines cross at the upper bound $\bar{\bar{f}}_j$ for the fixed costs as it is the highest fixed cost that ensures that collusion is easier to sustain without entry.

outward rotation of the threshold discount factor curves thus indicates that entry has made it more difficult to sustain collusion in restricting product lines.

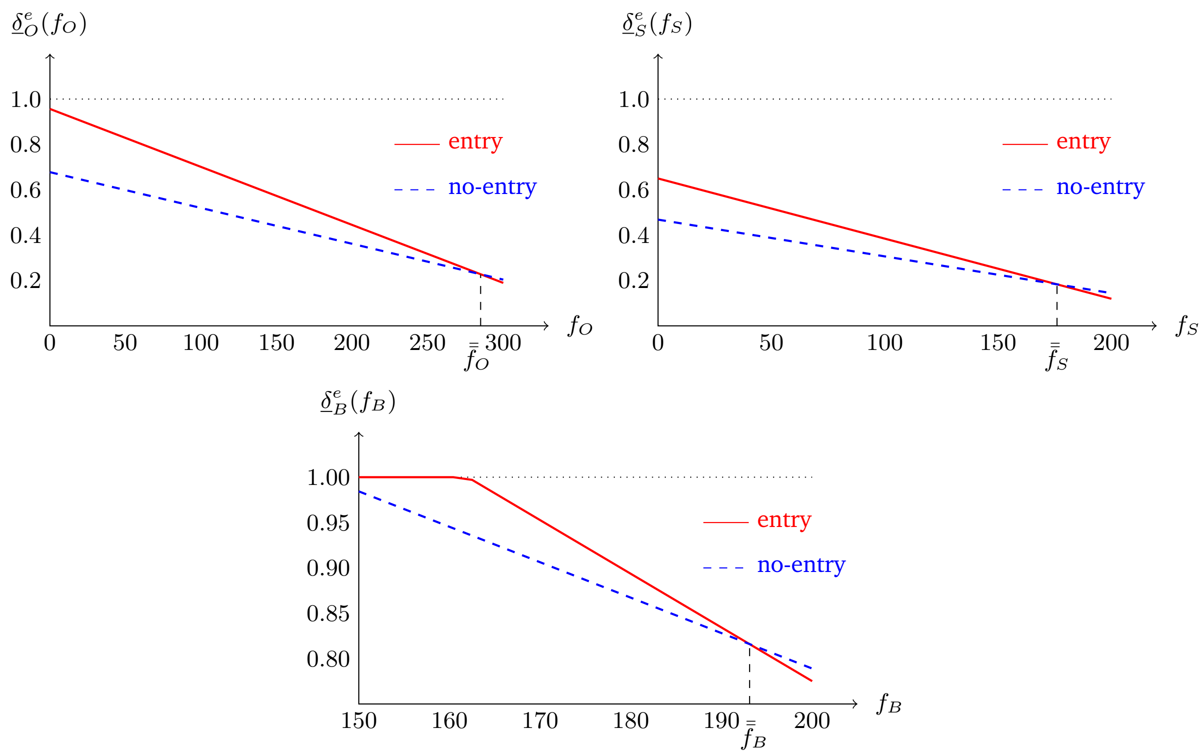



*Figure 3:* Threshold discount factors for Orange (top left), SFR (top right), and Bouygues (bottom).

To sum up, we find evidence that the introduction of new low-cost brands can be rationalized as "fighting brand" strategies within a repeated game framework of tacit collusion. There indeed exists a plausible range of fixed costs and discount factors such that the incumbents can collude on restricting their product lines in the absence of Free Mobile's entry, whereas such collusion can break down after entry.[47]

**Robustness.** So far, our analysis of collusion has relied on the simplifying assumption that the payoffs would remain stationary within and beyond the three years of our sample period. Our data confirm that the mobile market has nearly stopped growing in France with over 99% of mobile service adoption rate. Nevertheless, the data also indicate a gradual shift in demand towards the new products since their entry, with the change dissipating over time as the market finally approached a steady state near the end of the sample period (Figure 2). As discussed earlier in Section 3, such transition process may stem from various factors.

To assess the consequence of the nonstationary transition, we perform two sensitivity analyses. First, we focus on the last two-quarter period, around which the market appears to be mostly stabilized. Second, we adjust our stationary model of collusion to accommodate the nonstationary game structure by distinguishing

[47]As an alternative to our repeated game approach, we could have also considered that incumbent firms take into account their rivals' sequential reactions when they decide unilaterally to deviate from the candidate equilibrium, i.e., no introduction of low-cost brands if there is no entry, and introduction of low-cost brands in case of entry. This approach has a similar intuition and leads to similar findings.

between two phases: an interim transition phase that lasts only until the first half of 2014, which is then followed by the stationary phase in the last two quarters that is assumed to be repeated afterwards. Both extensions give robust conclusions regarding our earlier obtained fixed cost bounds. We discuss these extensions and findings in Appendix H.

## 5.3 Alternative explanations

In the previous subsections, we showed how we can rationalize the fighting brands as a break-down of semi-collusion in restricting product lines after entry occurs. We also ruled out the possibility that the fighting brands were unilateral best responses to entry in a static game framework. However, one may still reason that the incumbents' new product releases were merely a product or marketing innovation in response to an unrelated event that may have coincided with the new entry. While this is in principle possible, it appears to be rather unlikely in practice.

First, the differentiating features of the incumbents' new products are relatively straightforward, and similar low-cost brands had in fact already been introduced in most other countries. To assess this systematically, we collected data for the OECD countries over the last 20 years.[48] Figure 4a shows the number of low-cost subsidiary brand entries per year for the OECD countries, excluding France (for which we indicate the timing of entry by the vertical line). As the figure shows, in many markets the incumbent MNOs had already been operating low-cost subsidiary brands by the time when the French incumbents finally introduced their fighting brands in 2011. Interestingly, if we consider the *earliest* entry in each country, as shown in Figure 4b, there are only 3 out of 23 countries where the first low-cost brands were launched after 2011: New Zealand (2012), Poland (2013), and Italy (2017).[49] In the other 20 OECD countries, the first brands were launched earlier than 2011. The average year of entry of the first low-cost brand, conditional on launching one, is 2006.

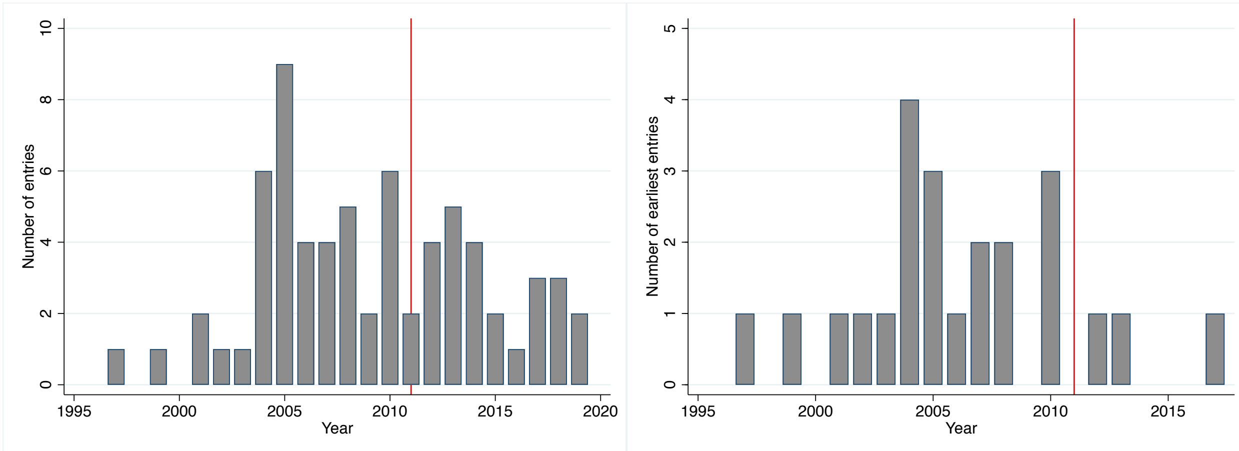
A second general reason why other explanations for the incumbents' low-cost subsidiary brands are unlikely is that all three incumbents released them into the market almost simultaneously and right before the entrant's arrival. Besides, they also revamped the tariff terms immediately upon Free's entry (Berne, Vialle and Whalley, 2019).[50] France was in fact one of few countries where the low-cost brands were introduced at the same moment (i.e. the same year). Excluding France, this was the case in only 5 OECD countries (Austria, Germany, Norway, Portugal and Spain) among the 23 countries where we observe fighting brands.

In sum, this cross-country analysis shows that most other countries already had low-cost brands for years by the time the French MNOs launched their fighting brands. With France being to some extent an outlier, this further supports our explanation that the fighting brands were a break-down of tacit collusion after entry,

[48]We collected data on the timing of entry from a combination of public sources, proprietary databases, or discussions with industry experts from the countries. A detailed explanation is available on request in our separate note "Introduction of Low-Cost Subsidiary Brands by Incumbent Mobile Network Operators in OECD Countries."

[49]Italy is an interesting case, which resembles the French setting (with entry at an even later point) but with some differences. It is a market where low-cost subsidiary brands were introduced late (in 2017), similar to France. The incumbent MNOs launched their low-cost brands as a response to the entry threat of *Iliad/Free*—the same operator which entered the French market in 2012. Iliad entered the Italian market in May 2018 with an aggressive pricing strategy. Telecom Italia (TIM) launched its low-cost brand *Kena* in March 2017 prior to entry while Vodafone launched its low-cost brand *Ho Mobile* in June 2018. The third incumbent MNO *Wind Tre* did not introduce any low-cost brand. Italian observers argue that this is because consumers already perceived Wind Tre as a low-cost operator. So while the case of Italy shows some similarity to France, it is possible that the fighting brand story in that market is not a break-down of tacit collusion in product lines, but rather a unilateral response to entry (as in the original Johnson-Myatt setting).

[50]One event around the time of the entry by Free was the introduction of the EU regulation for price ceilings on wholesale roaming charges (2010 and 2011). But even if such an event would induce incumbents to simultaneously introduce their own low cost brands, it does not explain why such brands were already introduced in other countries.




*(a)* Timing of entry

*(b)* Timing of first entry

*Figure 4:* Years of entry by low-cost brands in the OECD countries

rather than a mere marketing innovation coinciding with the new entry.

Two specific alternative explanations for the launch of the low-cost fighting brands after Free's entry deserve a further discussion. A first hypothesis is that Free relieved the constraints on the incumbent's network capacity by stealing market share. However, capacity constraints in the mobile market are typically only temporary, as operators invest and install new sites to cope with increased traffic.[51] Second, operators can use additional spectrum, when licensed, to increase their capacity.[52] In any case, spectrum management is harmonized to some extent in the European Union, so that changes in spectrum capacity for mobile services are correlated across countries. If French MNOs did not introduce fighting brands with lower prices due to capacity constraints, it is hard to see why it was not a relevant constraint in other European countries, where we commonly observe the launch of fighting brands before 2011.

Another interpretation for the incumbents' launch of the low-cost fighting brands is the following. Before Free's entry, the incumbents used to offer different quality plans as a way to price discriminate, with a distorted low-quality plan (i.e. prepaid). When Free entered with a low-price option of better quality, this forced the incumbents to adjust their plans and prices. Stole (1995) provides a theoretical analysis of how entry can reduce such price discrimination and the associated quality distortions. In the French mobile market, this interpretation appears to be unlikely. First, we do not observe that the incumbent MNOs dropped their low-end (prepaid) brands upon the entry of Free mobile. They kept operating these brands, with a similar quality, and introduced new (differentiated) low-cost brands. In other words, the new fighting brands are not the result of a repositioning of existing brands (with reduced quality distortions), but they are entirely new brands. Second, we do not observe a price decrease of all premium brands, as would be predicted under a reduction of price discrimination.

[51]For example, over the course of the period 2012Q1–2014Q2, we observe in our data set an increase by 6% of 2G sites and by 18% of 3G sites for the three incumbent MNOs.

[52]For example, Orange and SFR were awarded an additional 5MHz of spectrum already in May 2010 in the 2.1 GHz band (for about 300 million euros each), but this increase in spectrum capacity did not lead them to launch fighting brands.

## 6 Impact of entry on consumers and welfare

We are now in a position to evaluate the impact of entry by Free Mobile on consumers and welfare. In our setting with differentiated products, there exist three different channels through which the entry effects may operate. First, entry has a direct variety effect from the arrival of the entrant's differentiated new services. Second, entry may intensify price competition, leading to lower prices for the incumbents' premium brands. Third, as shown in the previous section, entry may result in a breakdown of semi-collusion, thus inducing the incumbents to release low-quality fighting brands. This may further improve welfare through increased variety and lower prices.

To assess the relative importance of these three channels, we decompose the consumer and welfare impacts of Free Mobile's entry by considering alternative counterfactual scenarios. First, we consider that Free Mobile enters the market while assuming that the incumbent MNOs do not respond by adjusting prices or by introducing fighting brands. This is the pure variety effect from entry. Second, we assume that the incumbents optimally adjust their prices while their product portfolio is held fixed. This refers to the price effect from entry. Third, we account for the breakdown in the semi-collusion and allow the incumbents to introduce their fighting brands. Technically, we perform these counterfactuals based on the post-entry samples for 2012–2014, since this gives us estimates of the consumer valuations and marginal costs of the new entrant and the fighting brands. Using the post-entry data, our measurement approach thus proceeds as follows. First, we eliminate the fighting brands and compute the new equilibrium wholesale and retail prices. Second, we additionally eliminate Free Mobile, holding the prices of the incumbent MNOs and MVNOs constant. Third, we additionally allow the incumbents and MVNOs to adjust their prices and compute the new Nash equilibrium.

Table 9 summarizes the surpluses measured by this decomposition. The first column reports the impact on consumer surplus over the considered period. The total consumer surplus gains from the changes in market structure amount to €4.6 billion (with a standard error of 0.9). To put this figure in perspective, the size of the gains is equivalent to 7.7% of the total €60.1 billion industry retail sales. The consumer surplus gains from the pure variety effect of Free Mobile (holding fixed the price and product line responses) constitute €2.3 billion, or about half of the total consumer gains. The additional consumer gains from the incumbents' and MVNOs' price responses, over and above the variety effect, are rather modest, about €854 million. This corresponds to price reductions by 1.3% for Orange and 2.4% for SFR, and a price increase by 0.7% for Bouygues. Finally, the additional consumer gains from the fighting brands are estimated to be around €1.4 billion, or more than 30% of the total consumer gains. Note that the gains from the fighting brands are mainly obtained from the additional variety offered by themselves, but not from further price responses by Free or other operators (not shown in the table).

The second column of Table 9 measures the impact of entry on producer surplus. Total producer surplus decreases by €2.2 billion: the incumbents and MVNOs collectively lose €4.0 billion, of which Free Mobile only recaptures €2.1 billion. Producer surplus mainly drops due to the direct variety effect (by €1.2 billion): this is due to the reallocation of sales from the high margin incumbent MNOs to the low margin entrant Free Mobile (held fixed in this part of the decomposition). Producer surplus also decreases as a result of the price competition (by €698 million). Finally, producer surplus is further reduced by the incumbents' fighting brands (by €340 million). This is again due to a reallocation effect from the high margin incumbents to the lower

| Source | Consumer | Producer | Total |
|---|---|---|---|
| **Free's entry** | 3,124 | -1,901 | 1,222 |
| | (689) | (379) | (312) |
| Variety | 2,270 | -1,204 | 1,066 |
| | (441) | (180) | (263) |
| Price | 854 | -698 | 156 |
| | (254) | (206) | (55) |
| **Fight brands** | 1,439 | -340 | 1,099 |
| | (240) | (32) | (214) |
| Total | 4,562 | -2,241 | 2,321 |
| | (928) | (405) | (524) |

Impact of entry on consumers and welfare, broken down by different sources (in million euro). Standard errors from a parametric bootstrap are in parentheses.

*Table 9:* Sources of consumer and welfare impact from entry

margin fighting brands.

Finally, the total welfare impact of entry is computed in the third column of Table 9. The total gross welfare increase is estimated to reach €2.3 billion. Interestingly, about half of these welfare gains stem from the variety effect induced by Free and the other half from the fighting brands. Only a small part is obtained from the increased price competition (€156 million). Intuitively, this just constitutes a transfer between firms and consumers given that total demand for mobile services is relatively inelastic as the mobile market was already saturated before entry.

As a robustness analysis, we have also evaluated the impact of entry on consumer surplus and welfare under the vertically integrated pricing model instead of the independent retailer-wholesaler pricing model. The results are shown in Table A.14 of the appendix. We find that the impact of Free and the fighting brands is similar. Hence, we conclude that our findings are not sensitive to the pricing assumptions.

Overall, we conclude that the entry of Free Mobile has made a large contribution to consumer surplus, about half of which is due to the increased variety from the new entrant, and 30% is due to additional gains from the fighting brands (with the rest of the gains, albeit of more modest size, from the competitive price responses of the existing firms). At the same time, the entry of Free has led to large losses in gross producer surplus due to inefficient reallocation, implying that the total gross welfare benefits are only half of the consumer benefits.

# 7 Conclusion

We have analyzed the impact of new entry in the mobile telecommunications market in France. Using detailed information on the demand of network services at the local market level, we estimate a flexible differentiated products demand model to capture rich substitution patterns. Taking as input the price elasticity estimates, we use an oligopoly model of wholesale and retail price competition to infer wholesale prices and marginal costs of production. These estimates allow us to evaluate the incumbents' profit incentives to introduce fighting brands and to decompose the welfare impact of entry stemming from different sources.

We find empirical evidence for the fighting brand theory, but our framework departs from the existing theory by taking into account strategic interactions among multiple incumbent firms. We cannot rationalize the incumbents' fighting brand strategies as unilateral best responses to the new entry in a static game. Instead, we show that the incumbents' launch of the fighting brands can be rationalized as a breakdown of tacit collusion in product lines: before entry, the incumbents can collude on suppressing low-cost brands to avoid cannibalization, and after entry, this semi-collusion becomes more difficult to sustain because of increased business stealing incentives.

Our findings have implications for the consumer and welfare effects from new entry. We find that the entry of Free Mobile has considerably contributed to consumer welfare, mainly through the increased variety offered by the new entrant and through the incumbents' fighting brands (responsible for, respectively, 50% and 32%, of the consumer consumer gains), and much less by the intensified price competition (responsible for only 18% of the consumer gains). The welfare effects of entry are mitigated by producer surplus losses associated with inefficient reallocation. A general conclusion from our analysis is that concentrated market structures may facilitate tacit collusion on restricting product variety. This adds to traditional concerns that increased concentration may facilitate collusion in prices or quantities, with the potential of generating considerably larger losses to consumers and welfare.

As discussed at the beginning of this paper, the launch of fighting brands is a typical response to entry in many markets where firms operate product portfolios. In future research, it would be interesting to study other cases in more depth to learn whether they can be explained as a breakdown of tacit collusion in product lines by incumbent firms, or rather as unilateral best responses to new entry, or as managerial decisions that coincided with new entry for no strategic reasons.

## References


**ARCEP**, "ARCEP Annual Report 2012," June 2013.

**Barwise, Patrick and Thomas Robertson**, "Brand Portfolios," *European Management Journal*, 1992, *10* (3), 277–285.

**Berman, Barry**, "How to Compete Effectively against Low-Cost Competitors," *Business Horizons*, 2015, *58* (1), 87–97.

**Berne, Michel, Pierre Vialle, and Jason Whalley**, "An Analysis of the Disruptive Impact of the Entry of Free Mobile into the French Mobile Telecommunications Market," *Telecommunications Policy*, 2019, *43* (3), 262–277.

**Berry, Steven, James Levinsohn, and Ariel Pakes**, "Automobile Prices in Market Equilibrium," *Econometrica*, July 1995, *63* (4), 841–90.

**_ , _ , and _** , "Voluntary Export Restraints on Automobiles: Evaluating a Trade Policy," *American Economic Review*, 1999, *89* (3), 400–430.

**Berry, Steven T. and Joel Waldfogel**, "Do Mergers Increase Product Variety? Evidence From Radio Broadcasting," *Quarterly Journal of Economics*, 2001, *116* (3), 1009–1025.

**_ and Philip A. Haile**, "Identification in Differentiated Products Markets Using Market Level Data," *Econometrica*, 2014, *82* (5), 1749–1797.

**Brander, James A. and Jonathan Eaton**, "Product Line Rivalry," *American Economic Review*, 1984, *74* (3), 323–334.

**Brenkers, Randy and Frank Verboven**, "Liberalizing a Distribution System: The European Car Market," *Journal of the European Economic Association*, 2006, *4* (1), 216–251.

**Brunner, Daniel, Florian Heiss, André Romahn, and Constantin Weiser**, "Reliable Estimation of Random Coefficient Logit Demand Models," *Working Paper*, 2017.

**Bun, Maurice J.G. and Monique De Haan**, "Weak Instruments and the First Stage F-Statistic in IV Models with a Nonscalar Error Covariance Structure," *Amsterdam School of Economics, Discussion Paper 2010/02*, 2010.

**Chamberlain, Gary**, "Asymptotic Efficiency in Estimation with Conditional Moment Restrictions," *Journal of Econometrics*, 1987, *34* (3), 305–334.

**Chiou, Chong Ju and Carlo Scarpa**, "Credible Spatial Preemption Through Reputation Extension," *International Journal of Industrial Organization*, September 1992, *10* (3), 439–447.

**Davis, Peter**, "Measuring the Business Stealing, Cannibalization and Market Expansion Effects of Entry in the US Motion Picture Exhibition Market," *The Journal of Industrial Economics*, 2006, *54* (3), 293–321.

**Denicolò, Vincenzo, Michele Polo, and Piercarlo Zanchettin**, "Entry, Product Line Expansion, and Predation," *Journal of Competition Law and Economics*, 2007, *3* (4), 609–624.

**Dubé, Jean-Pierre, Günter J Hitsch, and Peter E Rossi**, "Do Switching Costs Make Markets Less Competitive?," *Journal of Marketing research*, 2009, *46* (4), 435–445.

**Dubé, Jean-Pierre H., Günter J. Hitsch, and Pradeep K. Chintagunta**, "Tipping and Concentration in Markets with Indirect Network Effects," *Marketing Science*, 2010, *29* (2), 216–249.

— , **Jeremy T. Fox, and Che-Lin Su**, “Improving the Numerical Performance of BLP Static and Dynamic Discrete Choice Random Coefficients Demand Estimation,” *Econometrica*, 2012, *80* (5), 2231–2267.

**Dubé, Jean-Pierre, Günter J. Hitsch, and Peter E. Rossi**, “State dependence and alternative explanations for consumer inertia,” *The RAND Journal of Economics*, 2010, *41* (3), 417–445.

**Economides, Nicholas, Katja Seim, and V. Brian Viard**, “Quantifying the Benefits of Entry into Local Phone Service,” *RAND Journal of Economics*, 2008, (3), 699–730.

**Eizenberg, Alon**, “Upstream Innovation and Product Variety in the U.S. Home PC Market,” *Review of Economic Studies*, 2014, *81* (3), 1003–1045.

**Fershtman, Chaim and Neil Gandal**, “Disadvantageous semicollusion,” *International Journal of Industrial Organization*, 1994, *12* (1), 141–154.

**Friedman, James W.**, “A Non-cooperative Equilibrium for Supergames,” *Review of Economic Studies*, 1971, *38* (1), 1–12.

— **and Jacques Thisse**, “Partial Collusion Fosters Minimum Product Differentiation,” *RAND Journal of Economics*, 1993, *24* (4), 631–645.

**Gagnepain, Philippe and Pedro Pereira**, “Entry, Costs Reduction, And Competition in the Portuguese Mobile Telephony Industry,” *International Journal of Industrial Organization*, 2007, *25* (3), 461–481.

**Gandhi, Amit and Jean-François Houde**, “Measuring Substitution Patterns in Differentiated-Products Industries,” *Working Paper*, 2016.

— **and** — , “Measuring Substitution Patterns in Differentiated-Products Industries,” *Working Paper*, 2019.

**Genakos, Christos, Tommaso Valletti, and Frank Verboven**, “Evaluating Market Consolidation in Mobile Communications,” *Economic Policy*, 2018, *33* (93), 45–100.

**Goolsbee, Austan and Chad Syverson**, “How Do Incumbents Respond to the Threat of Entry? Evidence from the Major Airlines,” *The Quarterly Journal of Economics*, 2008, *123* (4), 1611–1633.

**Grzybowski, Lukasz and Pedro Pereira**, “Merger Simulation in Mobile Telephony in Portugal,” *Review of Industrial Organization*, 2007, *31* (3), 205–220.

**Hansen, Lars Peter, John Heaton, and Amir Yaron**, “Finite-Sample Properties of Some Alternative GMM Estimators,” *Journal of Business & Economic Statistics*, 1996, *14* (3), 262–280.

**Hocepied, Christian and Ansgar Held**, “The Assignment of Spectrum and the EU State Aid Rules: The Case of the 4th 3G License Assignment in France,” *Competition Policy Newsletter*, 2011, (3), 26–30.

**Huang, Ching-I**, “Estimating Demand for Cellular Phone Service under Nonlinear Pricing,” *Quantitative Marketing and Economics*, 2008, *6* (4), 371–413.

**Johnson, Justin P. and David P. Myatt**, “Multiproduct Quality Competition: Fighting Brands and Product Line Pruning,” *American Economic Review*, 2003, *93* (3), 748–774.

**Judd, Kenneth L.**, “Credible Spatial Preemption,” *RAND Journal of Economics*, 1985, (2), 153–166.

**Kim, Youngsoo, Rahul Telang, William Vogt, and Ramayya Krishnan**, “An Empirical Analysis of Mobile Voice Service and SMS: A Structural Model,” *Management Science*, 2010, *56* (2), 234–252.

**Lee, Jinhyuk and Kyoungwon Seo**, “A Computationally Fast Estimator for Random Coefficients Logit Demand Models Using Aggregate Data,” *RAND Journal of Economics*, 2015, *46* (1), 86–102.

— **and** — , "Revisiting the Nested Fixed-Point Algorithm in BLP Random Coefficients Demand Estimation," *Economics Letters*, 2016, *149*, 67–70.

**Lin, Zhongjian, Xuan Tang, and Mo Xiao**, "Endogeneity in Discrete Baysesian Games: U.S. Cellphone Service Deployment," *Working Paper*, 2020.

**Marlow, Iain**, "Rogers Launches Discount Cellphone Brand Chatr," *The Globe and Mail*, July 2010. `https://www.theglobeandmail.com/technology/rogers-launches-discount-cellphone-brand-chatr/article1213891/`.

**McFadden, Daniel**, "Conditional Logit Analysis of Qualitative Choice Behavior," in Paul Zarembka, ed., *Frontiers in Econometrics*, New York: Academic Press, 1973, pp. 105–142.

**Miller, Nathan H. and Matthew C. Weinberg**, "Understanding the Price Effects of the MillerCoors Joint Venture," *Econometrica*, 2017, *85* (6), 1763–1791.

**Nevo, Aviv**, "A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand," *Journal of Economics & Management Strategy*, December 2000, *9* (4), 513–548.

— , "Measuring Market Power in the Ready-To-Eat Cereal Industry," *Econometrica*, March 2001, *69* (2), 307–342.

— **and Federico Rossi**, "An Approach for Extending Dynamic Models to Settings with Multi-Product Firms," *Economics Letters*, 2008, *100* (1), 49–52.

**Newey, Whitney K. and Kenneth D. West**, "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 1987, *55* (3), 703–708.

**Nicolle, Ambre, Lukasz Grzybowski, and Christine Zulehner**, "Impact of Competition, Investment, and Regulation on Prices of Mobile Services: Evidence from France," *Economic Inquiry*, April 2018, *56* (2), 1322–1345.

**Nocke, Volker and Nicolas Schutz**, "Multiproduct-Firm Oligopoly: An Aggregative Games Approach," *Econometrica*, 2018, *86* (2), 523–557.

**Osborne, Martin J. and Carolynn Pitchik**, "Cartels, Profits and Excess Capacity," *International Economic Review*, 1987, *28* (2), 413–428.

**Rey, Patrick and Thibaud Vergé**, "Resale Price Maintenance and Interlocking Relationships," *Journal of Industrial Economics*, 2010, *58* (4), 928–961.

**Reynaert, Mathias and Frank Verboven**, "Improving the Performance of Random Coefficients Demand Models: The Role of Optimal Instruments," *Journal of Econometrics*, 2014, *179* (1), 83–98.

**Ritson, Mark**, "Should You Launch a Figher Brand," *Harvard Business Review*, October 2009.

**Sanderson, Eleanor and Frank Windmeijer**, "A Weak Instrument $F$-Test in Linear IV Models with Multiple Endogenous Variables," *Journal of Econometrics*, 2016, *190* (2), 212–221.

**Seim, Katja and V. Brian Viard**, "The Effect of Market Structure on Cellular Technology Adoption and Pricing," *American Economic Journal: Microeconomics*, 2011, *3* (2), 221–251.

**Shcherbakov, Oleksandr**, "Measuring Consumer Switching Costs in the Television Industry," *The RAND Journal of Economics*, 2016, *47* (2), 366–393.

**Staiger, Douglas and James H. Stock**, "Instrumental Variables Regression with Weak Instruments," *Econometrica*, 1997, *65* (3), 557–586.

**Stole, Lars**, “Nonlinear Pricing and Oligopoly,” *Journal of Economics and Management Strategy*, 1995, *4* (4), 529–562.

**Sudhir, Karunakaran**, “Competitive Pricing Behavior in the Auto Market: A Structural Analysis,” *Marketing Science*, 2001, *20* (1), 42–60.

**Sweeting, Andrew**, “The Effects of Mergers on Product Positioning: Evidence from the Music Radio Industry,” *RAND Journal of Economics*, 2010, *41* (2), 372–397.

**Tirole, Jean**, *The Theory of Industrial Organization*, MIT Press, August 1988.

**UFC-Que Choisir**, “Concurrence dans la téléphonie mobile: Un bilan sans appel. La ligne consumériste ne doit pas être coupée,” April 2014.

**Villas-Boas, Sofia Berto**, “Vertical Relationships between Manufacturers and Retailers: Inference with Limited Data,” *Review of Economic Studies*, 2007, *74* (2), 625–652.

**Weiergraeber, Stefan**, “Network Effects and Switching Costs in the US Wireless Industry,” *Working paper*, 2019.

**Xiao, Mo and Peter F. Orazem**, “Does the Fourth Entrant Make Any Difference? Entry and Competition in the Early U.S. Broadband Market,” *International Journal of Industrial Organization*, 2011, *29* (5), 547–561.

# Appendix A Details on the supply model

**MVNOs' retail marginal cost** We first derive our model in the text from a model that does not normalize the MVNO's marginal cost to zero. The profits of an MNO $f$ and its affiliated MVNO $f_0$ are:

$$\Pi_f = \sum_{l \in L_f} (p_l - c_l) D_l(\boldsymbol{p}) + (\overline{w}_{f_0} - c^w_{f_0}) D_{f_0}(\boldsymbol{p}),$$

$$\Pi_{f_0} = (p_{f_0} - \overline{w}_{f_0} - c^r_{f_0}) D_{f_0}(\boldsymbol{p}).$$

where $\overline{w}_{f_0}$ denotes the actual wholesale cost paid by $f_0$ to $f$, $c^w_{f_0}$ denotes $f$'s wholesale marginal cost of serving $f_0$, and $c^r_{f_0}$ denotes $f_0$'s retail marginal cost.

The first-order conditions for the retail and wholesale prices are analogous to those obtained in the text:

$$\frac{\partial \Pi_f}{\partial p_j} = D_j + \sum_{l \in L_f} (p_l - c_l) \frac{\partial D_l}{\partial p_j} + (\overline{w}_{f_0} - c^w_{f_0}) \frac{\partial D_{f_0}}{\partial p_j} = 0, \qquad j \in L_f, f \in \mathcal{F},$$

$$\frac{\partial \Pi_{f_0}}{\partial p_{f_0}} = D_{f_0} + (p_{f_0} - \overline{w}_{f_0} - c^r_{f_0}) \frac{\partial D_{f_0}}{\partial p_{f_0}} = 0, \qquad f \in \mathcal{F}.$$

$$\frac{d \Pi_f}{d w_{f_0}} = D_{f_0} + \sum_{j \in \mathcal{J} \setminus L_f} \left( \sum_{l \in L_f} (p_l - c_l) \frac{\partial D_l}{\partial p_j} + \left(\overline{w}_{f_0} - c^w_{f_0}\right) \frac{\partial D_{f_0}}{\partial p_j} \right) \frac{\partial p_j}{\partial w_{f_0}} = 0$$

We can make the following changes in variables: $c_{f_0} = c^w_{f_0} + c^r_{f_0}$ and $w_{f_0} = \overline{w}_{f_0} + c^r_{f_0}$. These definitions imply that $\overline{w}_{f_0} - c^w_{f_0} = w_{f_0} - c_{f_0}$ and $p_{f_0} - \overline{w}_{f_0} - c^r_{f_0} = p_{f_0} - w_{f_0}$. Substitution of these margins results in the same profit expressions and first-order conditions as in the text (i.e. (4)–(8)).

In sum, this shows that the marginal cost we identify, $c_{f_0}$, is the sum of the MNO's marginal cost of serving the MVNO plus the MVNO's retail marginal cost, $c_{f_0} = c^w_{f_0} + c^r_{f_0}$; and the wholesale price we identify, $w_{f_0}$, is the sum of the wholesale price actually paid by the MVNO plus its marginal cost, $w_{f_0} = \overline{w}_{f_0} + c^r_{f_0}$. However, the wholesale markup is identified since the MVNO's retail cost (included implicitly in the wholesale price and wholesale marginal cost) is cancelled out (i.e. $\overline{w}_{f_0} - c^w_{f_0} = w_{f_0} - c_{f_0}$).

**Further details on the solution** Based on the first-order conditions (6)–(8) in the text, we now discuss further details on the solution of the wholesale prices and marginal costs.

We first differentiate Equation (6) for all $f \in \mathcal{F}$ with respect to the wholesale price $w_{g_0}$ of network $g \in \mathcal{F}$, so that we obtain the following equations: for $j \in L_f$ and $f \in \mathcal{F}$,

$$\sum_{k \in J} \left[ \frac{\partial D_j}{\partial p_k} + \sum_{l \in L_f} (p_l - c_l) \frac{\partial^2 D_l}{\partial p_j \partial p_k} + (w_{f_0} - c_{f_0}) \frac{\partial^2 D_{f_0}}{\partial p_j \partial p_k} \right] \frac{\partial p_k}{\partial w_{g_0}} + \sum_{l \in L_f} \frac{\partial p_l}{\partial w_{g_0}} \frac{\partial D_l}{\partial p_j} = b^1_j, \tag{17}$$

where $b^1_j = -\frac{\partial D_{f_0(j)}}{\partial p_j}$ if $g = f(j)$, and 0 otherwise. Likewise, we differentiate Equation (7) w.r.t. $w_{g_0}$ to obtain

$$\sum_{k \in \mathcal{J}} \left[ \frac{\partial D_{f_0}}{\partial p_k} + (p_{f_0} - w_{f_0}) \frac{\partial^2 D_{f_0}}{\partial p_{f_0} \partial p_k} \right] \frac{\partial p_k}{\partial w_{g_0}} + \frac{\partial p_{f_0}}{\partial w_{g_0}} \frac{\partial D_{f_0}}{\partial p_{f_0}} = b^2_f, \tag{18}$$

for all $f \in \mathcal{F}$, where $b^2_f = \frac{\partial D_{f_0}}{\partial p_{f_0}}$ if $g = f$, and 0 otherwise.

The solution procedure begins by solving the wholesale prices $w_{f_0}$ for $f \in \mathcal{F}$ from Equation (7). Given the wholesale prices, we subsequently solve Equations (6), (8), (17), and (18) to obtain the marginal costs $c_j$ for $j \in L_f$ and $c_{f_0}$ for all $f \in \mathcal{F}$. The solution of the marginal costs in the second step relies on the trust region algorithm.

For each MNO $g \in \mathcal{F}$, we first solve (17)–(18) for the pass-through rates $\partial p_j/\partial w_{g_0}$ for all $j \in \mathcal{J}$, taking the marginal costs as input. To write the equations in matrix form, we let $J$ denote the number of elements in $\mathcal{J}$ and $L$ the number of products contained in $\bigcup_{f\in\mathcal{F}} L_f$, the complete set of the MNO product lines. This convention implies that $L + F = J$. Under these notations, (17) and (18) can be expressed as

$$Ax = b, \qquad A = \begin{bmatrix} A^1 \\ A^2 \end{bmatrix}, \quad b = \begin{bmatrix} b^1 \\ b^2 \end{bmatrix},$$

where $x = [\partial p_1/\partial w_{g_0}, ..., \partial p_J/\partial w_{g_0}]$, $b^1 = [b^1_1, ..., b^1_L]'$, $b^2 = [b^2_1, ..., b^2_F]'$, and the submatrix $A^1$ is defined as:

$$A^1_{ij} = \frac{\partial D_i}{\partial p_j} + \sum_{l \in L_{f(i)}} (p_l - c_l)\frac{\partial^2 D_l}{\partial p_i \partial p_j} + (w_{f_0(i)} - c_{f_0(i)})\frac{\partial^2 D_{f_0(i)}}{\partial p_i \partial p_j} + 1\{j \in L_{f(i)}\}\frac{\partial D_j}{\partial p_i},$$

for $j = 1, ..., J$ and $i = 1, ..., L$. The submatrix $A^2$ is defined as

$$A^2_{fj} = \frac{\partial D_{f_0}}{\partial p_j} + (p_{f_0} - w_{f_0})\frac{\partial^2 D_{f_0}}{\partial p_{f_0} \partial p_j} + 1\{j = f_0\}\frac{\partial D_{f_0}}{\partial p_{f_0}},$$

for $f \in \mathcal{F}$ and $j \in \mathcal{J}$.

Then, by plugging the derivatives $\partial p/\partial w$ obtained from (17) and (18) into (8), we can fully characterize the marginal costs by jointly solving Equations (6) and (8).

# Appendix B Computational details

## B.1 Simulation

Given the estimates for the wholesale prices and marginal costs, we use the same FOCs to solve for the equilibrium retail and wholesale prices. Specifically, the second-stage game is solved by Equations (6) and (7). This solution step is nested in the computation procedure for the first-stage game solved by (8). Given the retail prices and marginal costs, the pass-through rates in Equation (8) can be obtained from Equations (17) and (18). Due to numerical instability caused by extremely low income draws, we adjust the lower bound $\underline{y}$ of the simulated incomes to be €700 on average to ensure the convergence of the solution procedure.

## B.2 Continuous updating procedure for optimal instruments

For given nonlinear parameters $\theta_2 = (\alpha, \sigma_\nu)$,

1. BLP contraction loop

   (a) Solve for BLP fixed point $\delta(\theta_2) = (\delta_{jt})_{j,t}$ s.t. $s_{jt}(\delta_t, \theta_2) = s_{jt}$ for all $j, t$ .

2. Optimal instruments loop

   (a) Given $\delta$ in step 1 and the optimal instrument $z^{k-1}$ from the previous $(k-1)$-th iteration, obtain linear parameter estimates $\theta_1^k$ from the linear IV regression of Nevo (2000).
   (b) Obtain $z^k = E\left[\frac{\partial \hat{\delta}(\theta_1^k, \theta_2)}{\partial \theta} \middle| z^{k-1}\right]$ using the implicit function theorem, where $\hat{\delta}$ is the inverse of predicted demand $\hat{s} = E_\xi[s(\xi, \theta_1^k, \theta_2)|z^{k-1}]$.
   (c) Repeat (a) and (b) until $\|\theta_1^k - \theta_1^{k-1}\| < 10^{-8}$.

# Appendix C Supplementary tables

| Estimate | Logit | IV logit | RC logit I | RC logit II |
|---|---|---|---|---|
| *Random coefficients* | | | | |
| Price/$y_{it}$ ($-\alpha$) | | | -3.333*** | -3.914*** |
| | | | (0.345) | (0.630) |
| Log 4G/$y_{it}$ | | | -2.728*** | -3.495** |
| | | | (0.577) | (1.624) |
| Forfait bloqué/$y_{it}$ | | | 36.421*** | 37.670*** |
| | | | (3.928) | (5.549) |
| Prepaid/$y_{it}$ | | | | -6.415 |
| | | | | (4.996) |
| Intercept/$y_{it}$ | | | | 27.628* |
| | | | | (14.998) |
| Price/$\bar{y}_t$ | -0.288*** | -1.593*** | | |
| | (0.093) | (0.505) | | |
| Log(2G antenna) | 1.466*** | 1.572*** | 0.987*** | 0.781** |
| | (0.129) | (0.249) | (0.295) | (0.315) |
| Log(2G roaming) | 1.401*** | 1.370*** | 0.958** | 0.743 |
| | (0.185) | (0.398) | (0.444) | (0.484) |
| Log(3G antenna) | 0.142 | 0.281* | 0.508*** | 0.618*** |
| | (0.097) | (0.160) | (0.182) | (0.188) |
| Log(3G roaming) | -0.048 | 0.182 | 0.209 | 0.341 |
| | (0.161) | (0.350) | (0.370) | (0.408) |
| Log(4G antenna) | -0.216*** | -0.183*** | 0.245** | 0.345* |
| | (0.032) | (0.057) | (0.106) | (0.178) |
| Log(4G roaming) | -0.171*** | -0.173*** | 0.140 | 0.301 |
| | (0.036) | (0.066) | (0.124) | (0.221) |
| Forfait bloqué | -6.001*** | -6.977** | -11.778*** | -11.352*** |
| | (1.253) | (3.392) | (2.847) | (2.869) |
| Prepaid | -4.654*** | -8.409*** | -10.623*** | -10.653*** |
| | (1.262) | (2.862) | (2.524) | (2.646) |
| Call allow. (1,000 min) | 0.145*** | 0.446*** | 0.580*** | 0.615*** |
| | (0.047) | (0.095) | (0.099) | (0.104) |
| Data allow. (1,000 MB) | 0.193*** | -0.003 | 0.105 | 0.012 |
| | (0.057) | (0.101) | (0.112) | (0.131) |
| Orange | -0.965 | -1.611 | -1.387 | -0.881 |
| | (1.019) | (1.816) | (1.731) | (1.630) |
| SFR | -0.786 | -0.664 | -1.231 | -1.221 |
| | (1.025) | (2.249) | (2.311) | (2.286) |
| Bouygues | -1.327 | -1.061 | -2.012 | -1.838 |
| | (1.046) | (3.532) | (2.223) | (2.217) |
| Free | 40.473*** | 43.439** | 29.541 | 31.092* |
| | (13.051) | (21.697) | (19.567) | (18.769) |

(Table continues on the next page.)

*Table A.1:* Full results for Table 4

| Estimate | Logit | IV logit | RC logit I | RC logit II |
|---|---|---|---|---|
| Sosh | 39.782*** | 43.849** | 30.264 | 32.401* |
| | (13.056) | (22.057) | (19.655) | (18.699) |
| B&You | 41.519*** | 44.941** | 28.826 | 30.958* |
| | (13.059) | (21.700) | (19.512) | (18.682) |
| Red | 37.970*** | 44.121** | 25.115 | 27.135 |
| | (13.046) | (22.429) | (19.602) | (18.818) |
| MVNO:Orange | 0.193*** | -0.067 | 0.705*** | 0.839*** |
| | (0.059) | (0.132) | (0.181) | (0.272) |
| MVNO:SFR | 1.020*** | 0.671*** | 0.912*** | 0.940*** |
| | (0.051) | (0.136) | (0.141) | (0.159) |
| Postpaid: age≤20 | -9.998*** | -18.710** | 23.601*** | 6.007 |
| | (3.203) | (8.002) | (7.390) | (17.141) |
| Postpaid: 21≤age<30 | -2.680 | -4.402 | 9.507*** | 2.677 |
| | (1.746) | (4.483) | (3.571) | (9.314) |
| Postpaid: 30≤age<45 | 2.232* | 0.280 | 20.609*** | 12.018 |
| | (1.259) | (3.044) | (3.201) | (9.278) |
| Postpaid: 45≤age<60 | -3.778 | -7.717 | 47.772*** | 24.053 |
| | (2.566) | (5.988) | (7.039) | (24.991) |
| Prepaid: age≤20 | -10.134*** | -16.673** | 29.854*** | 10.198 |
| | (3.216) | (7.468) | (7.955) | (17.526) |
| Prepaid: 21≤age<30 | 1.574 | 4.125 | 18.915*** | 12.740 |
| | (1.751) | (3.547) | (4.006) | (9.198) |
| Prepaid: 30≤age<45 | 6.619*** | 7.053** | 27.650*** | 18.985** |
| | (1.361) | (3.002) | (3.616) | (9.022) |
| Prepaid: 45≤age<60 | 0.846 | 1.408 | 56.639*** | 32.582 |
| | (2.587) | (5.881) | (7.722) | (24.934) |
| F. bloqué: age≤20 | -3.525 | -12.170 | 36.716*** | 17.820 |
| | (3.222) | (8.578) | (8.462) | (16.694) |
| F. bloqué: 21≤age<30 | 2.477 | 2.217 | 19.415*** | 12.299 |
| | (1.755) | (4.891) | (4.755) | (9.714) |
| F. bloqué: 30≤age<45 | 8.376*** | 6.575* | 28.346*** | 19.060** |
| | (1.324) | (3.612) | (3.668) | (8.747) |
| F. bloqué: 45≤age<60 | 1.581 | -1.291 | 55.991*** | 30.950 |
| | (2.585) | (7.174) | (8.295) | (24.982) |
| Low cost: age≤20 | -45.705*** | -58.941*** | -2.629 | -24.165 |
| | (11.133) | (19.132) | (18.767) | (27.418) |
| Low cost: 21≤age<30 | -29.968*** | -34.263** | -10.899 | -17.746 |
| | (8.437) | (14.662) | (12.835) | (16.480) |
| Low cost: 30≤age<45 | -15.709** | -20.146* | 6.620 | -2.636 |
| | (6.407) | (11.064) | (10.180) | (14.548) |
| Low cost: 45≤age<60 | -19.084*** | -23.212*** | 34.540*** | 11.688 |
| | (4.193) | (8.264) | (8.718) | (25.620) |
| Orange*age | 0.630** | 0.779* | 1.122*** | 1.098*** |
| | (0.262) | (0.471) | (0.433) | (0.426) |
| SFR*age | 0.542** | 0.440 | 0.858 | 0.924 |
| | (0.263) | (0.578) | (0.589) | (0.593) |
| Bouygues*age | 0.578** | 0.497 | 1.052* | 1.098* |
| | (0.266) | (0.908) | (0.568) | (0.579) |
| Free*age | -5.016*** | -5.600* | -3.793 | -4.154 |
| | (1.934) | (3.197) | (2.898) | (2.787) |
| Sosh*age | -5.337*** | -6.159* | -4.275 | -4.701* |
| | (1.936) | (3.260) | (2.935) | (2.794) |
| B&You*age | -5.749*** | -6.456** | -4.008 | -4.446 |
| | (1.937) | (3.190) | (2.884) | (2.774) |
| Red*age | -4.827** | -6.207* | -2.953 | -3.373 |
| | (1.934) | (3.357) | (2.910) | (2.808) |
| 1/Time since entry | -2.883*** | -2.800*** | -2.522*** | -2.352*** |

(Table continues on the next page.)

*Table A.1:* Full results for Table 4

| Estimate | Logit | IV logit | RC logit I | RC logit II |
|---|---|---|---|---|
| | (0.097) | (0.153) | (0.220) | (0.246) |
| Observations | 3,324 | 3,324 | 3,324 | 3,324 |
| $J$ statistics | | 50.88 | 0.00 | 0.00 |
| D.F. | | 7 | 0 | 0 |
| Region & time fixed effects | Yes | Yes | Yes | Yes |

Standard errors in parentheses : p<0.10, ** p<0.05, *** p<0.01.
Standard errors are clustered at the product–region level.
$y_{it}$ & $\bar{y}_t$ denote individual & mean incomes scaled by €100.
Tariff types are interacted with the proportion of each age group in the local population.

*Table A.1:* Full results for Table 4

| | Observed income | | | Predicted income | | |
|---|---|---|---|---|---|---|
| Network | Prepaid | Postpaid | F. Bloqué | Prepaid | Postpaid | F. Bloqué |
| Orange | 2,763 | 3,052 | 2,892 | 2,600 | 3,831 | 2,368 |
| SFR | 2,595 | 2,936 | 2,829 | 2,529 | 3,455 | 1,578 |
| Bouygues | 2,528 | 2,895 | 2,755 | 2,643 | 3,734 | 2,013 |
| Free | | 3,023 | | | 2,186 | |
| Sosh | | 3,199 | | | 2,814 | |
| B&You | | 2,959 | | | 2,776 | |
| Red | | 3,058 | | | 2,668 | |
| MVNO:Orange | 2,715 | 2,861 | 2,596 | 2,082 | 2,953 | 1,521 |
| MVNO:SFR | 2,927 | 2,923 | 2,796 | 1,042 | 2,830 | 1,017 |
| MVNO:Bouygues | 2,709 | 2,767 | 2,753 | 548 | 3,517 | 2,056 |

The predicted income is generated by 200 random draws of income from Model RC logit II of Table 4.

*Table A.2:* Average incomes conditional on observed and predicted product choice

| Network operator | Product group | Orange Prepaid | Orange Postpaid | Orange F. bloqué | Orange Sosh | SFR Prepaid | SFR Postpaid | SFR F. bloqué | SFR Red | Bouygues Prepaid | Bouygues Postpaid | Bouygues F. bloqué | Bouygues B&You | Free Postpaid |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Orange | Prepaid | -100.00 | 5.43 | 6.59 | 5.22 | 6.04 | 5.70 | 5.68 | 4.99 | 6.16 | 4.91 | 5.68 | 5.13 | 5.95 |
| | Postpaid | 10.66 | -100.00 | 8.46 | 11.84 | 9.50 | 24.40 | 3.98 | 10.05 | 10.31 | 25.80 | 5.06 | 10.98 | 6.95 |
| | F. bloqué | 9.86 | 6.64 | -100.00 | 7.89 | 8.96 | 7.30 | 10.41 | 7.92 | 9.10 | 5.90 | 9.80 | 7.65 | 11.17 |
| | Sosh | 3.10 | 3.62 | 3.00 | -100.00 | 3.09 | 3.92 | 1.85 | 3.49 | 3.07 | 3.32 | 2.09 | 3.70 | 3.88 |
| SFR | Prepaid | 2.46 | 2.02 | 2.43 | 2.10 | -100.00 | 2.24 | 2.25 | 2.34 | 2.37 | 1.88 | 2.17 | 2.09 | 2.51 |
| | Postpaid | 12.99 | 28.05 | 10.86 | 15.07 | 12.20 | -100.00 | 5.50 | 13.36 | 12.45 | 24.40 | 6.77 | 14.21 | 10.22 |
| | F. bloqué | 6.12 | 2.54 | 7.72 | 4.40 | 6.09 | 3.08 | -100.00 | 5.17 | 5.81 | 2.35 | 9.87 | 4.70 | 11.13 |
| | Red | 2.28 | 2.21 | 2.32 | 2.68 | 2.42 | 2.55 | 1.98 | -100.00 | 2.25 | 2.14 | 1.93 | 2.72 | 3.50 |
| Bouygues | Prepaid | 2.44 | 2.14 | 2.38 | 2.03 | 2.30 | 2.23 | 2.05 | 1.93 | -100.00 | 1.96 | 2.19 | 2.10 | 2.34 |
| | Postpaid | 6.84 | 18.18 | 5.31 | 7.73 | 6.28 | 14.98 | 2.60 | 6.71 | 6.65 | -100.00 | 3.39 | 7.63 | 4.81 |
| | F. bloqué | 2.43 | 1.21 | 2.84 | 1.77 | 2.31 | 1.41 | 3.78 | 1.97 | 2.43 | 1.15 | -100.00 | 1.94 | 3.59 |
| | B&You | 2.74 | 2.83 | 2.65 | 3.33 | 2.76 | 3.18 | 1.95 | 3.16 | 2.70 | 2.80 | 2.09 | -100.00 | 3.91 |
| Free | Postpaid | 17.98 | 10.97 | 21.10 | 19.07 | 18.91 | 13.85 | 28.38 | 20.98 | 17.93 | 10.87 | 23.94 | 20.91 | -100.00 |
| MVNO:Orange | Prepaid | 0.90 | 0.47 | 1.09 | 0.67 | 0.82 | 0.54 | 1.22 | 0.69 | 0.87 | 0.43 | 1.11 | 0.71 | 1.21 |
| | Postpaid | 2.44 | 3.14 | 2.28 | 2.62 | 2.24 | 3.10 | 1.38 | 2.49 | 2.37 | 2.77 | 1.64 | 2.51 | 2.39 |
| | F. bloqué | 2.26 | 0.91 | 2.92 | 1.65 | 2.21 | 1.09 | 4.78 | 1.87 | 2.24 | 0.82 | 3.81 | 1.75 | 4.29 |
| MVNO:SFR | Prepaid | 2.50 | 0.73 | 3.57 | 1.60 | 2.36 | 0.90 | 5.16 | 1.92 | 2.34 | 0.66 | 4.12 | 1.54 | 4.32 |
| | Postpaid | 5.20 | 6.46 | 4.98 | 5.70 | 5.05 | 6.71 | 3.71 | 5.52 | 4.94 | 5.66 | 3.82 | 5.09 | 5.50 |
| | F. bloqué | 1.79 | 0.54 | 2.64 | 1.18 | 1.76 | 0.67 | 4.00 | 1.59 | 1.55 | 0.47 | 3.01 | 1.17 | 3.33 |
| MVNO:Bouygues | Prepaid | 0.77 | 0.14 | 1.13 | 0.45 | 0.75 | 0.19 | 1.73 | 0.59 | 0.68 | 0.15 | 1.42 | 0.51 | 1.61 |
| | Postpaid | 0.27 | 0.54 | 0.23 | 0.30 | 0.22 | 0.46 | 0.09 | 0.27 | 0.22 | 0.45 | 0.11 | 0.28 | 0.23 |
| | F. bloqué | 1.02 | 0.49 | 1.19 | 0.66 | 0.92 | 0.55 | 1.31 | 0.66 | 0.94 | 0.45 | 1.18 | 0.68 | 1.14 |
| Outside good | | 2.95 | 0.74 | 4.31 | 2.04 | 2.81 | 0.95 | 6.21 | 2.33 | 2.62 | 0.66 | 4.80 | 2.00 | 6.02 |
| Outside good ($M \times 1.5$) | | 3.11 | 0.61 | 4.65 | 2.02 | 2.96 | 0.83 | 6.79 | 2.37 | 2.75 | 0.57 | 5.22 | 2.02 | 6.26 |

Percentage of sales diverted toward products (rows) due to price increase (columns). The row "Outside good ($M \times 1.5$)" is the diversion toward the outside good under the counterfactual where the market size is increased by 50%.

*Table A.3:* Diversion ratios

| Network | Product | Orange | | | | SFR | | | | Bouygues | | | | Free |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| operator | group | Prepaid | Postpaid | F. bloqué | Sosh | Prepaid | Postpaid | F. bloqué | Red | Prepaid | Postpaid | F. bloqué | B&You | Postpaid |
| Orange | Prepaid | -2.271 | 0.874 | 0.268 | 0.195 | 0.033 | 0.435 | 0.058 | 0.072 | 0.033 | 0.271 | 0.025 | 0.097 | 0.600 |
| | Postpaid | 0.046 | -2.892 | 0.099 | 0.109 | 0.014 | 0.441 | 0.009 | 0.035 | 0.015 | 0.339 | 0.005 | 0.051 | 0.165 |
| | F. bloqué | 0.112 | 0.797 | -4.245 | 0.204 | 0.036 | 0.409 | 0.094 | 0.081 | 0.036 | 0.231 | 0.033 | 0.099 | 0.790 |
| | Sosh | 0.084 | 0.888 | 0.211 | -2.327 | 0.029 | 0.457 | 0.042 | 0.072 | 0.029 | 0.270 | 0.017 | 0.097 | 0.505 |
| SFR | Prepaid | 0.102 | 0.826 | 0.266 | 0.212 | -2.446 | 0.428 | 0.072 | 0.088 | 0.034 | 0.260 | 0.027 | 0.107 | 0.686 |
| | Postpaid | 0.059 | 1.156 | 0.130 | 0.144 | 0.019 | -3.042 | 0.016 | 0.048 | 0.019 | 0.335 | 0.008 | 0.070 | 0.248 |
| | F. bloqué | 0.130 | 0.475 | 0.478 | 0.209 | 0.048 | 0.251 | -5.353 | 0.107 | 0.045 | 0.132 | 0.087 | 0.113 | 1.550 |
| | Red | 0.089 | 0.813 | 0.235 | 0.205 | 0.034 | 0.433 | 0.066 | -2.512 | 0.030 | 0.262 | 0.023 | 0.109 | 0.631 |
| Bouygues | Prepaid | 0.099 | 0.881 | 0.259 | 0.201 | 0.033 | 0.430 | 0.066 | 0.073 | -2.345 | 0.264 | 0.025 | 0.104 | 0.605 |
| | Postpaid | 0.050 | 1.197 | 0.100 | 0.116 | 0.015 | 0.453 | 0.010 | 0.040 | 0.016 | -3.513 | 0.006 | 0.062 | 0.192 |
| | F. bloqué | 0.136 | 0.608 | 0.411 | 0.210 | 0.046 | 0.320 | 0.231 | 0.095 | 0.042 | 0.185 | -5.071 | 0.108 | 1.172 |
| | B&You | 0.082 | 0.827 | 0.198 | 0.190 | 0.029 | 0.434 | 0.047 | 0.076 | 0.029 | 0.282 | 0.018 | -2.352 | 0.558 |
| Free | Postpaid | 0.112 | 0.584 | 0.352 | 0.218 | 0.041 | 0.344 | 0.148 | 0.097 | 0.037 | 0.194 | 0.044 | 0.124 | -1.559 |
| MVNO:Orange | Prepaid | 0.121 | 0.655 | 0.404 | 0.214 | 0.040 | 0.368 | 0.160 | 0.086 | 0.041 | 0.201 | 0.045 | 0.110 | 1.048 |
| | Postpaid | 0.085 | 1.025 | 0.217 | 0.170 | 0.025 | 0.460 | 0.037 | 0.061 | 0.028 | 0.294 | 0.016 | 0.084 | 0.418 |
| | F. bloqué | 0.129 | 0.500 | 0.450 | 0.213 | 0.047 | 0.265 | 0.321 | 0.104 | 0.044 | 0.141 | 0.083 | 0.115 | 1.477 |
| MVNO:SFR | Prepaid | 0.145 | 0.398 | 0.576 | 0.208 | 0.052 | 0.234 | 0.339 | 0.101 | 0.048 | 0.115 | 0.093 | 0.105 | 1.703 |
| | Postpaid | 0.083 | 0.967 | 0.216 | 0.206 | 0.027 | 0.464 | 0.052 | 0.070 | 0.027 | 0.276 | 0.020 | 0.092 | 0.474 |
| | F. bloqué | 0.132 | 0.365 | 0.571 | 0.194 | 0.044 | 0.219 | 0.369 | 0.100 | 0.042 | 0.107 | 0.089 | 0.113 | 1.793 |
| MVNO:Bouygues | Prepaid | 0.147 | 0.268 | 0.514 | 0.208 | 0.058 | 0.190 | 0.308 | 0.121 | 0.042 | 0.103 | 0.105 | 0.131 | 2.107 |
| | Postpaid | 0.055 | 1.119 | 0.117 | 0.123 | 0.017 | 0.462 | 0.015 | 0.046 | 0.018 | 0.347 | 0.007 | 0.068 | 0.227 |
| | F. bloqué | 0.099 | 0.406 | 0.516 | 0.125 | 0.027 | 0.194 | 0.229 | 0.095 | 0.027 | 0.096 | 0.055 | 0.066 | 1.094 |

Percentage of change in sales of products (rows) due to price increase (columns)

*Table A.4:* Elasticity of retail demand

| Upstream network | Downstream network | Wholesale price | | | Wholesale markup | | |
|---|---|---|---|---|---|---|---|
| | | Prepaid | Postpaid | F. bloqué | Prepaid | Postpaid | F. bloqué |
| Orange | MVNO | 4.95 | 12.16 | 14.69 | 5.38 | 9.59 | 4.58 |
| | | (0.64) | (1.03) | (0.62) | (0.71) | (1.19) | (0.72) |
| SFR | MVNO | 2.83 | 12.05 | 13.82 | 4.47 | 9.01 | 4.51 |
| | | (0.63) | (1.04) | (0.64) | (0.71) | (1.15) | (0.73) |
| Bouygues | MVNO | 1.64 | 24.18 | 15.97 | 2.66 | 10.24 | 3.47 |
| | | (0.52) | (1.21) | (0.63) | (0.44) | (1.23) | (0.51) |

MNO's average wholesale prices and margins on MVNO products across quarters and regions. Standard errors in parenthesis. Implied marginal costs statistically insignificant for prepaid.

*Table A.5:* Estimated wholesale prices and markups on MVNO products

| | | SFR | | | |
|---|---|---|---|---|---|
| | | Fight | | Not | |
| | | Orange | | Orange | |
| Bouygues | Payoffs | Fight | Not | Fight | Not |
| **Entry of Free mobile** | | | | | |
| Fight | Orange | 9,761 | 9,406 | 9,895 | 9,532 |
| | SFR | 7,490 | 7,652 | 7,260 | 7,414 |
| | Bouygues | 3,929 | 4,030 | 3,995 | 4,098 |
| Not | Orange | 10,009 | 9,644 | 10,152 | 9,778 |
| | SFR | 7,694 | 7,867 | 7,458 | 7,622 |
| | Bouygues | 3,618 | 3,707 | 3,676 | 3,767 |
| **No entry of Free mobile** | | | | | |
| Fight | Orange | 11,223 | 10,834 | 11,415 | 11,011 |
| | SFR | 8,753 | 8,990 | 8,490 | 8,715 |
| | Bouygues | 4,613 | 4,765 | 4,714 | 4,869 |
| Not | Orange | 11,651 | 11,242 | 11,856 | 11,427 |
| | SFR | 9,116 | 9,370 | 8,843 | 9,081 |
| | Bouygues | 4,244 | 4,379 | 4,332 | 4,467 |

Equilibrium profits for 2011Q4–2014Q4 in million euros

*Table A.6:* Equilibrium profits under all entry and product line strategies

| Operator | $\Delta_j(0)$ | $\Pi_j^{D,E} - \Pi_j^{N,E}$ | $\Pi_j^{D,N} - \Pi_j^{N,N}$ | $\bar{\bar{f}}_j$ |
|---|---|---|---|---|
| (O)range | 0.28 | 392 | 633 | 285 |
| | (0.01) | (53) | (79) | (43) |
| (S)FR | 0.18 | 377 | 617 | 175 |
| | (0.01) | (48) | (78) | (30) |
| (B)ouygues | 0.39 | 168 | 256 | 194 |
| | (0.02) | (24) | (38) | (35) |

First column is a ratio, other columns are in million euros.

*Table A.7:* Impact of entry on collusion: background conditions

| Operator | Product | Retail price | Change(%) | Change |
|---|---|---|---|---|
| Orange | Prepaid | 13.85 | 1.89 | 0.26 |
| Orange | Postpaid | 39.53 | 1.00 | 0.40 |
| Orange | F. bloqué | 22.83 | 1.11 | 0.25 |
| Sosh | Postpaid | 16.90 | 1.33 | 0.23 |
| SFR | Prepaid | 13.56 | 2.15 | 0.29 |
| SFR | Postpaid | 28.73 | 1.26 | 0.35 |
| SFR | F. bloqué | 18.95 | 3.62 | 0.64 |
| Red | Postpaid | 15.83 | 1.94 | 0.30 |
| Bouygues | Prepaid | 13.21 | -1.93 | -0.25 |
| Bouygues | Postpaid | 34.85 | 0.20 | 0.07 |
| Bouygues | F. bloqué | 19.66 | 0.10 | 0.01 |
| B&You | Postpaid | 15.77 | -2.05 | -0.31 |

Percentage change in prices due to the incumbent's response to entry. The change is measured by the subtracting the observed prices under entry from the counterfactual prices under no entry in equilibrium and divided by the observed price. The unit is in euros.

*Table A.8:* Price effects of entry

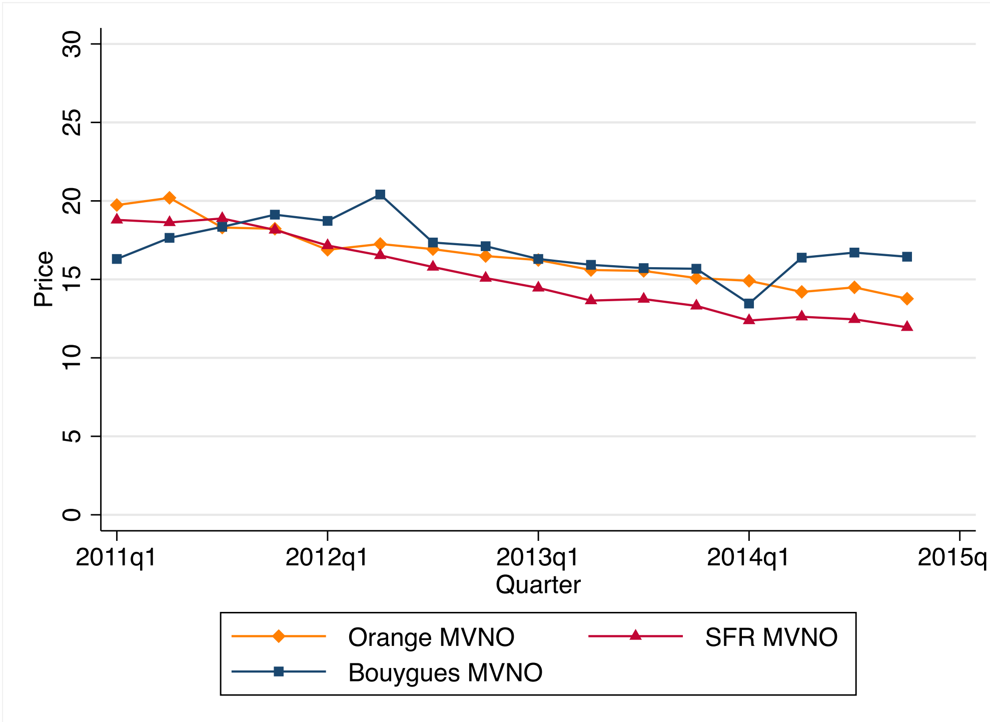



*Figure A.1:* Prices of the MVNO services

## Appendix D Joint incentives for product line extension

In Section 5.1, we examined within a static framework whether the three incumbent firms have *unilateral* incentives to introduce their low-quality fighting brands. In this appendix, as a benchmark for comparison with Johnson and Myatt's (2003) theoretical monopoly analysis, we explore the incumbents' *joint* incentives to introduce low-quality brands after the entry of Free Mobile. Based on the payoff matrix of Table A.6, Table A.9 quantifies the incremental changes in variable profits when all incumbents jointly switch from withholding the subsidiary brands to releasing them in the absence of entry (first column) and in the presence of entry (second column), respectively.

According to the first column, in the absence of entry the incumbents would lose considerably from jointly releasing the subsidiary brands. The low-quality brands would reduce their joint profits by €386 million (significant with a standard error of €35 million), or by even larger amount if we were to take into account the fixed costs of launching or operating them. Intuitively, the low-quality brands cannibalize the sales of the high-quality brands, which lowers the incumbents' joint profits. There is therefore no strategic incentives for them to jointly release the subsidiary brands in the absence of entry.

In contrast, according to the second column, if Free Mobile enters the market, the incumbents would gain a positive amount (€12 million) from jointly releasing the subsidiary brands. Entry thus raises the incumbents' incentives for the fighting brands by €398 million (at the expense of Free Mobile which would lose €238 million because of the fighting brands). Nonetheless, the incumbents' joint incentives for the fighting

| | Entry of Free Mobile | |
| --- | --- | --- |
| Network | No | Yes |
| Orange | -204 | -18 |
| | (21) | (7) |
| SFR | -327 | -132 |
| | (33) | (9) |
| Bouygues | 145 | 162 |
| | (20) | (26) |
| **Total incumbents** | -386 | 12 |
| | (35) | (22) |
| Free | 0 | -238 |
| | (0) | (33) |

The figures represent the profit changes (in million euro) of the incumbents and Free Mobile, when the incumbents jointly introduce their low-cost brands. The calculations are based on the payoffs from Table A.6 of the appendix. Standard errors from a parametric bootstrap are in parentheses.

*Table A.9:* Joint profit incentives for the incumbents' fighting brand adoption

brands after entry are small and statistically insignificant: business stealing from Free Mobile essentially just compensates for the cannibalization of the premium brands. Note that the findings are very similar in the vertically integrated pricing model (see Table A.11). As a footnote, Table A.9 also suggests that the incumbents may disagree over their desirable choice of collective actions: Bouygues would prefer all incumbents to launch a subsidiary low-quality brand regardless of Free Mobile's entry.

In sum, this cooperative setting provides intuition in line with Johnson and Myatt's monopoly theory. The incumbents' joint incentives for releasing the low-quality brands are substantially negative before entry because of cannibalization, and they increase considerably to a negligible positive amount after entry because of business stealing.

# Appendix E Profit incentives and welfare effects under vertically integrated pricing

| | | SFR | | | |
|---|---|---|---|---|---|
| | | Fight | | Not | |
| | | Orange | | Orange | |
| Bouygues | Payoffs | Fight | Not | Fight | Not |
| **Entry of Free mobile** | | | | | |
| Fight | Orange | 9,918 | 9,555 | 10,054 | 9,683 |
| | SFR | 7,604 | 7,779 | 7,373 | 7,541 |
| | Bouygues | 3,966 | 4,066 | 4,033 | 4,134 |
| Not | Orange | 10,159 | 9,787 | 10,303 | 9,921 |
| | SFR | 7,809 | 7,993 | 7,573 | 7,749 |
| | Bouygues | 3,649 | 3,736 | 3,707 | 3,796 |
| **No entry of Free mobile** | | | | | |
| Fight | Orange | 11,356 | 10,960 | 11,540 | 11,130 |
| | SFR | 8,864 | 9,112 | 8,603 | 8,841 |
| | Bouygues | 4,640 | 4,790 | 4,738 | 4,890 |
| Not | Orange | 11,767 | 11,354 | 11,959 | 11,529 |
| | SFR | 9,226 | 9,488 | 8,957 | 9,206 |
| | Bouygues | 4,259 | 4,392 | 4,344 | 4,477 |

Equilibrium profits for 2011Q4–2014Q4 in million euros

*Table A.10:* Equilibrium profits under all entry and product line strategies

| | Entry of Free Mobile | |
|---|---|---|
| Network | No | Yes |
| Orange | -173 | -4 |
| | (23) | (8) |
| SFR | -343 | -145 |
| | (40) | (15) |
| Bouygues | 163 | 170 |
| | (21) | (26) |
| **Total incumbents** | -354 | 21 |
| | (45) | (20) |
| Free | 0 | -221 |
| | (0) | (32) |

The figures represent the profit changes (in million euros) of the incumbents and Free Mobile, when the incumbents jointly introduce their low-cost brands. The calculations are based on the payoffs from Table A.10 of the appendix.

*Table A.11:* Joint profit incentives for fighting brand adoption: vertically integrated pricing

| | Entry of Free Mobile | |
|---|---|---|
| | No | Yes |
| Network | Equilibrium: no fighting brands | Equilibrium: fighting brands |
| Orange | 429 | -354 |
| | (60) | (53) |
| SFR | 289 | -230 |
| | (45) | (37) |
| Bouygues | 402 | -311 |
| | (58) | (48) |

The figures represent the incumbents' profit changes (in million euros), resulting from unilateral deviations from the observed candidate Nash equilibrium: "no fighting brands" without the entry by Free Mobile, "introduce fighting brands" in the presence of entry. The calculations are based on the payoffs from Table A.10 of the appendix.

*Table A.12:* Unilateral incentives to deviate from candidate equilibrium profit lines: vertically integrated pricing

| Operator | $\underline{f}_j^N$ (collusion) | $\bar{f}_j^N$ (punishment) | $\bar{\bar{f}}_j$ (breakdown) | $\bar{f}_j^N - \underline{f}_j^N$ | $\bar{\bar{f}}_j - \underline{f}_j^N$ |
|---|---|---|---|---|---|
| (O)range | -173 | 397 | 297 | 570 | 470 |
| | (23) | (59) | (47) | (79) | (68) |
| (S)FR | -343 | 260 | 181 | 603 | 523 |
| | (40) | (41) | (31) | (81) | (71) |
| (B)ouygues | 163 | 380 | 185 | 218 | 22 |
| | (21) | (58) | (38) | (37) | (18) |

Lower and upper bounds on fixed costs for which collusion in restricting product lines is sustainable before entry ($\underline{f}_j^N$ and $\bar{f}_j^N$) and upper bound for which collusion becomes more difficult to sustain after entry (i.e., $\bar{\bar{f}}_j$) in million euros.

*Table A.13:* Bounds on fixed costs supporting fighting brands in response to entry: vertically integrated pricing

| Source | Consumer | Producer | Total |
|---|---|---|---|
| **Free's entry** | 3,072 | -1,612 | 1,460 |
| | (677) | (373) | (305) |
| Variety | 2,266 | -875 | 1,391 |
| | (445) | (164) | (284) |
| Price | 805 | -737 | 69 |
| | (235) | (215) | (24) |
| **Fight brands** | 1,400 | -200 | 1,200 |
| | (240) | (25) | (222) |
| Total | 4,472 | -1,812 | 2,660 |
| | (916) | (392) | (526) |

Impact of entry on consumers and welfare broken down by different sources (in million euros).

*Table A.14:* Sources of consumer and welfare impact from entry: vertically integrated pricing

# Appendix F Model extensions

| Estimate | RC logit I | RC logit II | Normal RC logit | Market Size*1.5 | No Allowance | Full sample |
|---|---|---|---|---|---|---|
| *Random coefficients* | | | | | | |
| Price/$y_{it}$ ($-\alpha$) | -3.333*** | -3.914*** | -1.524*** | -2.414 | -3.776*** | -3.313*** |
| | (0.345) | (0.630) | (0.235) | (1.789) | (0.622) | (0.583) |
| Log 4G/$y_{it}$ | -2.728*** | -3.495** | | -7.129** | -3.294** | -4.301*** |
| | (0.577) | (1.624) | | (2.837) | (1.477) | (0.628) |
| Forfait bloqué/$y_{it}$ | 36.421*** | 37.670*** | | 75.336*** | 35.803*** | 30.720*** |
| | (3.928) | (5.549) | | (21.520) | (4.726) | (3.124) |
| Prepaid/$y_{it}$ | | -6.415 | | 45.163 | -6.654 | -14.834*** |
| | | (4.996) | | (31.978) | (7.396) | (4.156) |
| Intercept/$y_{it}$ | | 27.628* | | -15.405 | 23.788 | -3.976 |
| | | (14.998) | | (44.724) | (30.833) | (11.569) |
| Log 4G*$\nu_{it}$ | | | 1.171*** | | | |
| | | | (0.178) | | | |
| Forfait bloqué*$\nu_{it}$ | | | 1.416 | | | |
| | | | (0.924) | | | |
| Prepaid*$\nu_{it}$ | | | 2.740*** | | | |
| | | | (0.864) | | | |
| Intercept*$\nu_{it}$ | | | 0.047 | | | |
| | | | (2.866) | | | |
| Log(2G antenna) | 0.987*** | 0.781** | 1.106*** | 1.118*** | 1.045*** | 1.523*** |
| | (0.295) | (0.315) | (0.229) | (0.281) | (0.296) | (0.294) |
| Log(2G roaming) | 0.958** | 0.743 | 1.097*** | 1.092*** | 0.985** | 1.570*** |
| | (0.444) | (0.484) | (0.310) | (0.414) | (0.491) | (0.426) |
| Log(3G antenna) | 0.508*** | 0.618*** | 0.431** | 0.490** | 0.404** | 0.220 |
| | (0.182) | (0.188) | (0.190) | (0.199) | (0.171) | (0.200) |
| Log(3G roaming) | 0.209 | 0.341 | 0.175 | 0.233 | 0.213 | -0.014 |
| | (0.370) | (0.408) | (0.266) | (0.359) | (0.408) | (0.340) |
| Log(4G antenna) | 0.245** | 0.345* | -0.004 | 0.442* | 0.359* | 0.349*** |
| | (0.106) | (0.178) | (0.061) | (0.249) | (0.191) | (0.107) |
| Log(4G roaming) | 0.140 | 0.301 | -0.007 | 0.540* | 0.242 | 0.227* |
| | (0.124) | (0.221) | (0.071) | (0.303) | (0.253) | (0.116) |
| Postpaid | 10.623*** | 10.653*** | 12.453*** | 8.413*** | 11.321*** | 10.370*** |
| | (2.524) | (2.646) | (3.357) | (2.488) | (2.629) | (2.324) |
| Forfait bloqué | -1.155 | -0.699 | 3.617* | -0.333 | -0.625 | -0.460 |
| | (2.853) | (3.002) | (2.168) | (2.537) | (2.912) | (2.464) |
| Call allow.(1,000 min) | 0.580*** | 0.615*** | 0.458*** | 0.419** | | |
| | (0.099) | (0.104) | (0.149) | (0.175) | | |
| Data allow.(1,000 MB) | 0.105 | 0.012 | 0.315** | 0.135 | | |
| | (0.112) | (0.131) | (0.129) | (0.154) | | |
| Orange | -1.387 | -0.881 | -0.211 | -1.388 | -0.792 | -1.227 |
| | (1.731) | (1.630) | (1.414) | (1.144) | (1.641) | (1.576) |
| SFR | -1.231 | -1.221 | -0.420 | -1.176 | -1.046 | -1.008 |
| | (2.311) | (2.286) | (1.568) | (1.451) | (2.228) | (1.956) |
| Bouygues | -2.012 | -1.838 | -0.591 | -2.331 | -1.885 | -1.575 |
| | (2.223) | (2.217) | (1.858) | (1.601) | (2.226) | (2.037) |
| Free | 29.541 | 31.092* | 44.738** | 38.922** | 30.806 | 14.890 |
| | (19.567) | (18.769) | (17.908) | (15.611) | (22.558) | (20.212) |
| Sosh | 30.264 | 32.401* | 44.606** | 39.742*** | 32.316 | 16.099 |
| | (19.655) | (18.699) | (17.848) | (15.418) | (22.428) | (20.131) |
| B&You | 28.826 | 30.958* | 46.121*** | 39.273** | 31.212 | 16.356 |
| | (19.512) | (18.682) | (17.844) | (15.444) | (22.669) | (20.117) |
| Red | 25.115 | 27.135 | 43.370** | 35.280** | 26.889 | 11.507 |
| | (19.602) | (18.818) | (18.076) | (15.601) | (22.894) | (20.252) |
| MVNO:Orange | 0.705*** | 0.839*** | 0.467*** | 0.542* | 0.543 | -0.076 |

(Table continues in the next page.)

*Table A.15:* Comparison of BLP and Differentiation IVs

| Estimate | RC logit I | RC logit II | Normal RC logit | Market Size*1.5 | No Allowance | Full sample |
|---|---|---|---|---|---|---|
| | (0.181) | (0.272) | (0.119) | (0.315) | (0.405) | (0.159) |
| MVNO:SFR | 0.912*** | 0.940*** | 1.098*** | 0.859*** | 0.801*** | 0.457*** |
| | (0.141) | (0.159) | (0.091) | (0.164) | (0.205) | (0.110) |
| Postpaid: age≤20 | 23.601*** | 6.007 | -7.517 | -20.311*** | 8.698 | 14.204* |
| | (7.390) | (17.141) | (6.252) | (4.840) | (40.728) | (8.133) |
| Postpaid: 21≤age<30 | 9.507*** | 2.677 | 0.148 | 1.149 | 3.369 | 7.868** |
| | (3.571) | (9.314) | (2.785) | (2.830) | (21.528) | (3.512) |
| Postpaid: 30≤age<45 | 20.609*** | 12.018 | 5.889** | 4.565** | 13.274 | 18.235*** |
| | (3.201) | (9.278) | (2.325) | (1.883) | (22.213) | (3.031) |
| Postpaid: 45≤age<60 | 47.772*** | 24.053 | 6.693 | 3.106 | 26.982 | 40.760*** |
| | (7.039) | (24.991) | (4.831) | (4.018) | (59.799) | (6.447) |
| Prepaid: age≤20 | 29.854*** | 10.198 | -3.768 | -18.067*** | 11.553 | 18.086** |
| | (7.955) | (17.526) | (5.484) | (5.041) | (42.362) | (7.591) |
| Prepaid: 21≤age<30 | 18.915*** | 12.740 | 11.261*** | 8.538*** | 14.026 | 17.681*** |
| | (4.006) | (9.198) | (3.225) | (2.908) | (21.178) | (3.255) |
| Prepaid: 30≤age<45 | 27.650*** | 18.985** | 14.378*** | 8.977*** | 20.361 | 25.607*** |
| | (3.616) | (9.022) | (2.567) | (2.149) | (22.036) | (3.002) |
| Prepaid: 45≤age<60 | 56.639*** | 32.582 | 19.238*** | 5.813 | 36.336 | 50.192*** |
| | (7.722) | (24.934) | (4.659) | (3.770) | (60.053) | (6.424) |
| F. bloqué: age≤20 | 36.716*** | 17.820 | 0.824 | -10.384* | 19.113 | 25.035*** |
| | (8.462) | (16.694) | (5.431) | (5.782) | (39.576) | (8.567) |
| F. bloqué: 21≤age<30 | 19.415*** | 12.299 | 8.075** | 7.614** | 13.727 | 16.638*** |
| | (4.755) | (9.714) | (3.240) | (3.291) | (21.961) | (3.942) |
| F. bloqué: 30≤age<45 | 28.346*** | 19.060** | 14.184*** | 8.814*** | 20.528 | 25.072*** |
| | (3.668) | (8.747) | (2.570) | (2.368) | (21.194) | (3.346) |
| F. bloqué: 45≤age<60 | 55.991*** | 30.950 | 15.074*** | 2.347 | 34.766 | 47.663*** |
| | (8.295) | (24.982) | (4.807) | (5.525) | (59.739) | (7.004) |
| Low cost: age≤20 | -2.629 | -24.165 | -45.144*** | -57.744*** | -21.669 | 5.097 |
| | (18.767) | (27.418) | (17.269) | (13.403) | (57.874) | (19.741) |
| Low cost: 21≤age<30 | -10.899 | -17.746 | -30.572** | -24.230** | -16.145 | -2.865 |
| | (12.835) | (16.480) | (11.919) | (9.954) | (30.374) | (12.688) |
| Low cost: 30≤age<45 | 6.620 | -2.636 | -14.556 | -13.111* | -0.961 | 12.489 |
| | (10.180) | (14.548) | (9.196) | (7.566) | (29.383) | (10.360) |
| Low cost: 45≤age<60 | 34.540*** | 11.688 | -9.596 | -10.556** | 15.133 | 31.097*** |
| | (8.718) | (25.620) | (6.919) | (5.301) | (60.400) | (7.784) |
| Orange*age | 1.122*** | 1.098*** | 0.622* | 1.045*** | 1.033** | 0.949** |
| | (0.433) | (0.426) | (0.342) | (0.380) | (0.417) | (0.401) |
| SFR*age | 0.858 | 0.924 | 0.582 | 0.810** | 0.869 | 0.749 |
| | (0.589) | (0.593) | (0.392) | (0.398) | (0.577) | (0.502) |
| Bouygues*age | 1.052* | 1.098* | 0.546 | 1.083** | 1.078* | 0.862 |
| | (0.568) | (0.579) | (0.469) | (0.487) | (0.578) | (0.525) |
| Free*age | -3.793 | -4.154 | -5.915** | -5.032** | -4.074 | -1.983 |
| | (2.898) | (2.787) | (2.698) | (2.266) | (3.337) | (2.971) |
| Sosh*age | -4.275 | -4.701* | -6.213** | -5.622** | -4.679 | -2.537 |
| | (2.935) | (2.794) | (2.671) | (2.252) | (3.361) | (2.968) |
| B&You*age | -4.008 | -4.446 | -6.666** | -5.545** | -4.347 | -2.511 |
| | (2.884) | (2.774) | (2.690) | (2.241) | (3.408) | (2.957) |
| Red*age | -2.953 | -3.373 | -5.830** | -4.432* | -3.295 | -1.331 |
| | (2.910) | (2.808) | (2.729) | (2.289) | (3.456) | (2.987) |
| 1/Time since entry | -2.522*** | -2.352*** | -2.843*** | -2.615*** | -2.489*** | -2.289*** |
| | (0.220) | (0.246) | (0.250) | (0.315) | (0.286) | (0.284) |
| Observations | 3,324 | 3,324 | 3,324 | 3,324 | 3,324 | 3,324 |
| $J$ statistic | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 |

Clustered standard errors in parentheses: p<0.10, ** p<0.05, *** p<0.01. $y_{it}$ & $\bar{y}_t$ are individual & mean incomes in €100s.
Column *Log normal RC* is based on income $y_{it}$ simulated from a log normal distribution.
Tariff types are interacted with the proportion of each age group in the local population.

*Table A.15:* Comparison of BLP and Differentiation IVs

# Appendix G Alternative instrumental variables approaches

In the main text, we estimated the demand models with optimal instruments based on our continuous updating GMM estimator to avoid reliance on the parameter estimates from an inefficient first stage. This appendix provides a further motivation for this approach in our application, by reporting several results from the use of non-optimal instruments. Appendix G.1 discusses the BLP instruments (which we also use for price in our optimal instruments approach). Next, Appendix G.2 discusses tests of weak instruments under various non-optimal instruments (BLP IVs and differentiation IVs). Finally, Appendix G.3 discusses the estimates under various non-optimal instruments and provides a conclusion.

## G.1 BLP instruments

Our price instruments rely on the BLP formulation of instrument basis functions. For a complete characterization, we use $r$ to denote a geographic region, $j$ a product, and $f_r(j)$ the set of products supplied in region $r$ by the firm operating product $j$. The set $f_r(j)$ may differ across regions when the firm operates only in certain regional markets; for example, we can have $k \notin f_r(k)$ if network product $k$ is not offered by its supplier in region $r$, and $k \in f_r(k)$ otherwise. We omit time index $t$ to simplify the notation.

We formulate the price instruments by aggregating the exogenous characteristics $x_{kr}$ over all regions as

$$\sum_r \sum_{k \notin f_r(j)} x_{kr} \qquad \text{and} \qquad \sum_r \sum_{k \neq j, k \in f_r(j)} x_{kr}, \tag{19}$$

where the first and second terms sum over the products of own and rival firms, respectively. The price instruments thus vary along the product and quarter dimensions but remain fixed across regions. The characteristics vector $x_{kr}$ contains the number of available products and antennas of different technology generations, specified as

$$\left[1\{k \in f_r(k)\}, A_{kr}^{2G}, A_{kr}^{3G}, A_{kr}^{4G}\right], \tag{20}$$

and $A_{kr}^{g}$ denotes the antenna of each generation $g$.

## G.2 Test of weak instruments: BLP and differentiation IVs

Identification of the BLP demand system relies on instruments for the inverse market share function (Berry and Haile, 2014). Berry and Haile show that the BLP instruments are sufficient for identifying the parametric demand system in principle. Nevertheless, it is an empirical question whether these instruments provide a sufficient independent source of identification when the model involves multiple random coefficients.

Gandhi and Houde (2016) formalize the weak identification problem in the residual function from the inverted demand

$$\begin{aligned} \xi_{jt}(s_t, x_t, p_t, \theta) &= \sum_{k=1}^{K} (\theta^k - \theta_0^k) \frac{\partial \xi_{jt}(s_t, x_t, p_t, \theta_0)}{\partial \theta^k} + \xi_{jt} + O(\|\theta\|^2) \\ &= J_{jt}(s_t, x_t, p_t, \theta_0) b + + \xi_{jt} + O(\|\theta\|^2), \end{aligned} \tag{21}$$

where $\theta_0$ is the true parameter vector characterizing the random coefficients distribution, $J_{jt}(s_t, x_t, p_t, \theta_0)$ is a Jacobian vector of partial derivative $\partial\xi_{jt}(s_t, x_t, p_t, \theta_0)/\partial\theta^k$ as $k$th element, and $b$ is the coefficient vector with $k$th element $b_k = \theta^k - \theta_0^k$. While our approach explicitly formulates Chamberlain's (1987) optimal instrument based on the Jacobian, Gandhi and Houde (2019) instead develop a reduced-form approach to approximate the optimal instrument function.

They propose *differentiation* IVs as alternative instrument basis functions constructed by the difference in exogenous characteristics to approximate the optimal instrument functions more efficiently than the BLP IVs. Full-scale approximation tends to be infeasible due to high dimensionality since the optimal instruments depend on the characteristics space where its dimension exponentially grows with the number of products and their attributes. Gandhi and Houde's important observation is that the BLP demand system would be symmetric in the difference of characteristics, if the distribution of the unobserved demand shocks $(\xi_{1t}, ..., \xi_{Jt})$ is assumed to be exchangeable. Gandhi and Houde (2019) demonstrate that their reduced-form approximation provides a sparse representation of the optimal instruments and can therefore substantially improve the estimation efficiency in Monte Carlo analysis. Hence, the differentiation IVs offer a useful benchmark to assess the commonly used BLP instruments that have often been found to lack sufficient identifying power (Reynaert and Verboven, 2014; Gandhi and Houde, 2019).

Since the partial derivatives in Equation (21) constitute multiple endogenous variables, Gandhi and Houde perform the Cragg-Donald test to measure the overall strength of the instruments based on a standard rank condition for the correlation matrix between approximate and optimal instruments. In addition, Gandhi and Houde (2016) apply the Sanderson-Windmeijer conditional $F$ test, which generalizes the first-stage $F$ test for each reduced form by conditioning out the exogenous variations induced by the other endogenous partial derivatives (Sanderson and Windmeijer, 2016). Thus, the test can help diagnosing the source of possible weakness in instruments for identifying each individual parameter.

We consider two formulations of the differentiation IVs: quadratic and local (Gandhi and Houde, 2019). The quadratic differentiation IV is defined as the quadratic difference of exogenous characteristics between each product $j$ and the rest, i.e. as

$$\sum_{k\neq j}(x_{jr} - x_{kr})^2,$$

where the vector $x_{jr}$ includes the three antenna variables, tariff type fixed effects, elapsed time since entry, and the expected price of product $j$ at region $r$ (as discussed further below). On the other hand, the local differentiation IV focuses on products within its neighborhood in the product space for measuring the difference. Specifically, it defines the IV as

$$\sum_{k\neq j}(x_{jr} - x_{kr})1\{|x_{jr} - x_{kr}| < sd(x_r)\},$$

where the standard deviation $sd(x_r)$ of $x_r$ regulates the scope of the neighborhood, which is allowed to be heterogeneous across regions. Therefore, both differentiation IVs can effectively instrument for the Jacobian $J_{jt}(s_t, x_t, p_t, \theta_0)$, which varies across geographic markets. For the expected price in the differentiation IVs, we use the predicted price conditional on the same price instruments as used for the optimal IV in Table 4.

Table A.16 summarizes the tests of the BLP and differentiation (diff) IVs conducted in the two models

| | RC logit I | | | RC logit II | | |
|---|---|---|---|---|---|---|
| | BLP | Diff IV quad | Diff IV local | BLP | Diff IV quad | Diff IV local |
| Conv. ratio | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.45 |
| **Cond. 1st-stage $F$-test for random coefficients:** | | | | | | |
| Price | 16.63 | 8.05 | 3.06 | 3.75 | 7.79 | 2.00 |
| | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) | (0.08) |
| 4G antenna | 8.33 | 20.59 | 5.14 | 2.49 | 37.74 | 1.14 |
| | (0.00) | (0.00) | (0.02) | (0.01) | (0.00) | (0.34) |
| F. bloqué | 4.47 | 10.37 | 3.35 | 6.90 | 10.67 | 2.15 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.06) |
| Prepaid | | | | 2.34 | 28.75 | 2.49 |
| | | | | (0.01) | (0.00) | (0.03) |
| Intercept | | | | 2.97 | 19.53 | 2.81 |
| | | | | (0.00) | (0.00) | (0.02) |
| Cragg-Donald statistic | 15.68 | 8.03 | 1.94 | 1.55 | 6.85 | 0.77 |
| Kleibergen-Paap statistic | 3.16 | 7.46 | 2.44 | 1.34 | 4.62 | 0.82 |
| Stock-Yogo size CV (10%) | 10.25 | 9.64 | 9.37 | NA | NA | NA |
| Nb. endogenous variables | 3 | 3 | 3 | 5 | 5 | 5 |
| Nb. excluded IVs | 14 | 10 | 9 | 14 | 10 | 9 |

Conditional 1st-stage $F$-test is based on Sanderson and Windmeijer (2016) with robust standard error ($p$ values in parenthesis). Stock-Yogo CV is the critical values for Cragg-Donald statistic given 10% maximal relative bias of IV (relative to OLS) under the i.i.d. error. The null hypothesis of weak instruments is rejected if the Cragg-Donald statistic is above Stock-Yogo CV.

*Table A.16:* Test of weak instruments

of Table 4—*RC logit I* and *RC logit II*. Each column represents the corresponding model and IV, where the conditional first-stage $F$ statistic and its $p$-value are displayed for each element of the Jacobian $J_{jt}(s_t, x_t, p_t, \hat{\theta})$ at the parameter estimate $\hat{\theta}$. In both RC logit I and II, the Sanderson-Windmeijer tests are highly significant for BLP and quadratic diff IVs in all three (common) parameters. The same test also shows that the local diff IV has overall sufficient identification power, although its significance declines in RC logit II to some extent.

We also run the rank-based tests for further evidence of strong IVs. In addition to the Cragg-Donald statistic, Table A.17 also includes the Kleibergen-Paap statistic, which is a heteroscedasticity-robust version of the Cragg-Donald statistic that relies on the i.i.d. error assumption. If the errors are assumed to be i.i.d., a Cragg-Donald statistic above the Stock-Yogo critical value would indicate significant evidence for rejecting the null hypothesis of weak instruments when the relative expected bias of the IV estimator is about 10% of the OLS estimation bias.

In the RC logit I model, the BLP IV appears sufficiently strong under the Cragg-Donald test. However, the Kleibergen-Paap statistic is well below the Stock-Yogo critical value, failing to reject the null hypothesis of weak instruments. The large gap between the two statistics implies that the weak IV test may be sensitive to the underlying assumption on the error structure. We consider the Cragg-Donald statistic as an upper bound for significance since it tends to overestimate the strength of IVs under non i.i.d. error structure (Bun and Haan, 2010). The differentiation IVs narrow the gap between the two ranks tests considerably. Nonetheless, their robust tests still fail to reject the weakness of the IVs.

The rank tests in the RC logit II model generally show further challenges for the IVs. While the Stock-Yogo critical values are no longer available for the degrees of freedom in our tests, all the rank statistics are substantially below 10, an informal threshold suggested as a rule of thumb for significance of the first-stage $F$ test by Staiger and Stock (1997). Moreover, the Kleibergen-Paap statistics are consistently low, even for the quadratic differentiation IV that has the most promising test results overall.

In summary, the overall tests do not provide robust evidence for the strength of the BLP and differentiation IVs. The lack of agreement among different tests appears to stem at least partly from their reliance on the assumption of the underlying error structure. Both the Cragg-Donald and Kleibergen-Paap tests require independently distributed unobserved demand shocks, a rather strong assumption that our model tries to avoid. In our model where the errors are allowed to be serially correlated, even the robust rank statistics do not provide an unbiased measure of the instrument's strength (Bun and Haan, 2010).

Although Sanderson and Windmeijer (2016) aim to overcome such limitation, their test would be valid only when the parameter estimates are unbiased. With weak instruments, however, there still remains a nontrivial concern for the reliability of the test performed on the potentially biased estimate of Equation (21) (Gandhi and Houde, 2019). Hence, we need to carefully examine the estimation results together with the tests, which is addressed in the next section.

As a final caveat, we acknowledge that there is a scope for improvement over our implementation of the differentiation IV approach. However, exploring more robust differentiation IV is an ongoing research question in the literature and is beyond the scope of our focus in this paper.

### G.3 GMM estimation with BLP and differentiation IVs

Table A.17 presents the GMM estimation results for the BLP and differentiation IVs in the same order as Table A.16. Each column is estimated with the two-step procedure for the efficient GMM estimator.

For the two demand models, the random coefficient for price ($\alpha$) is relatively comparable across the three IV sets, both in terms of the point estimates and their significance. Yet the absolute size of the estimates is well below what is obtained with the optimal instruments. It is not uncommon that the distribution of the price random coefficient tends to be biased toward zero when the reduced-form instruments are relatively weak (Reynaert and Verboven, 2014; Gandhi and Houde, 2019). While this may at first seem like a case of weak price instruments, it is worth emphasizing that the optimal IV uses the same BLP instruments for price without incurring such decrease. Hence, the weak instrument issue appears to relate more to the reduced-form approximation approach based on the non-optimal instruments.

For the RC logit I, the random coefficient estimate of Forfait bloqué lacks consistency among the three IVs with relatively large standard errors. The BLP and quadratic diff IVs produce a lower estimate than the local diff IV, which obtains an estimate relatively close to the optimal IV (Table A.1). The estimate for the Log 4G random coefficient also shows sizable variation across the IVs, albeit to a lesser extent. The estimation of the RC logit II model shows a similar pattern only to an amplified degree. The random coefficients (now also including one for Prepaid and the intercept) exhibit similarly large variation across instruments with inflated standard errors.

We can summarize these findings as follows. First, the weak IV tests in Section G.2 provide only partial support for the non-optimal instruments in our application. The mixed test results appear to be reflected in the relatively imprecise yet sensitive estimation results, especially in the richer RC logit II model. This raises an overall concern for weak identification with the non-optimal instruments. This motivates our optimal instrument approach that does not rely on the first-stage non-optimal IVs: this is not only efficient but also can be more robust to the reduced-form approximation errors and non-symmetric demand structures.

| Model | RC logit I | | | RC logit II | | |
|---|---|---|---|---|---|---|
| | BLP IV | Diff IV quad | Diff IV local | BLP IV | Diff IV quad | Diff IV local |
| *Random coefficients* | | | | | | |
| Price/$y_{it}$ ($-\alpha$) | -1.311*** | -2.190*** | -1.614*** | -1.225*** | -2.122* | -1.552*** |
| | (0.272) | (0.526) | (0.534) | (0.296) | (1.270) | (0.436) |
| Log 4G/$y_{it}$ | -3.945*** | -5.722*** | -2.770 | -4.059*** | -4.665*** | 7.892 |
| | (0.645) | (1.310) | (2.878) | (0.971) | (1.705) | (6.350) |
| Forfait bloqué/$y_{it}$ | 10.220* | 2.020 | 42.430** | -1.051 | -1.266 | 56.391** |
| | (5.950) | (33.711) | (19.056) | (55.943) | (85.024) | (23.231) |
| Prepaid/$y_{it}$ | | | | 12.416 | 2.225 | 49.265*** |
| | | | | (8.143) | (4.475) | (17.352) |
| Intercept/$y_{it}$ | | | | 4.803 | 7.940 | -24.257 |
| | | | | (5.824) | (10.101) | (15.226) |
| Log 2G | 1.220*** | 0.920*** | 1.148*** | 1.340*** | 0.909*** | 1.649*** |
| | (0.198) | (0.272) | (0.301) | (0.227) | (0.291) | (0.352) |
| Log 2G roam | 1.208*** | 0.792** | 1.145*** | 1.336*** | 0.814** | 1.531*** |
| | (0.272) | (0.376) | (0.369) | (0.329) | (0.386) | (0.450) |
| Log 3G | 0.387*** | 0.493** | 0.454** | 0.497*** | 0.519** | 0.050 |
| | (0.137) | (0.193) | (0.203) | (0.175) | (0.214) | (0.272) |
| Log 3G roam | 0.156 | 0.432 | 0.187 | 0.218 | 0.376 | -0.233 |
| | (0.222) | (0.318) | (0.307) | (0.244) | (0.326) | (0.374) |
| Log 4G | 0.354*** | 0.601*** | 0.161 | 0.416*** | 0.544** | -1.045* |
| | (0.106) | (0.188) | (0.308) | (0.093) | (0.254) | (0.556) |
| Log 4G roam | 0.402*** | 0.622*** | 0.082 | 0.417*** | 0.557** | -1.230* |
| | (0.117) | (0.198) | (0.322) | (0.116) | (0.250) | (0.640) |
| F. bloqué | -8.201*** | -8.393*** | -14.956*** | -7.819*** | -8.122** | -12.250*** |
| | (1.832) | (2.545) | (5.110) | (2.689) | (3.931) | (4.536) |
| Prepaid | -7.581*** | -9.039*** | -5.818*** | -9.197*** | -8.547*** | -14.083*** |
| | (1.660) | (2.482) | (1.755) | (2.105) | (3.161) | (4.502) |
| Call allow. (1,000 min) | 0.343*** | 0.270*** | 0.437*** | 0.364*** | 0.280* | 0.730*** |
| | (0.072) | (0.093) | (0.148) | (0.085) | (0.160) | (0.181) |
| Data allow. (1,000 MB) | 0.058 | 0.031 | 0.164* | 0.261* | 0.092 | 0.666*** |
| | (0.083) | (0.115) | (0.098) | (0.147) | (0.122) | (0.224) |
| Orange | 0.097 | 1.172 | -1.849 | 0.047 | 0.557 | -0.155 |
| | (1.081) | (1.641) | (1.543) | (1.176) | (1.586) | (1.995) |
| SFR | -1.110 | -0.421 | -1.638 | -0.790 | -0.699 | -0.631 |
| | (1.317) | (1.694) | (2.150) | (1.255) | (1.588) | (2.300) |
| Bouygues | -1.122 | -0.395 | -2.755 | -1.058 | -0.600 | -1.797 |
| | (1.688) | (2.064) | (2.146) | (1.741) | (2.022) | (2.567) |
| Free | 48.695*** | 35.261** | 41.230*** | 54.769*** | 35.895** | 62.462*** |
| | (14.088) | (17.626) | (15.838) | (17.686) | (17.527) | (19.866) |
| Sosh | 48.854*** | 34.488* | 42.355*** | 55.421*** | 35.008** | 62.949*** |
| | (14.175) | (17.647) | (16.012) | (18.038) | (17.495) | (19.879) |
| B&You | 47.956*** | 34.895** | 40.466*** | 54.407*** | 34.973** | 60.088*** |
| | (14.087) | (17.671) | (15.638) | (17.771) | (17.794) | (19.593) |
| Red | 47.139*** | 32.667* | 36.117** | 52.911*** | 32.585* | 55.808*** |
| | (14.208) | (17.821) | (15.760) | (18.070) | (17.759) | (19.722) |
| MVNO: Orange | 0.261** | 0.623*** | -0.002 | 0.560*** | 0.750** | 0.856** |
| | (0.109) | (0.186) | (0.155) | (0.152) | (0.375) | (0.356) |
| MVNO: SFR | 0.994*** | 1.062*** | 0.560** | 1.171*** | 1.163*** | 1.249*** |
| | (0.085) | (0.115) | (0.221) | (0.106) | (0.131) | (0.287) |
| Postpaid: age$\leq$20 | 2.069 | 6.649 | -13.722 | -8.274 | 0.858 | -11.948* |
| | (6.449) | (11.109) | (9.371) | (9.172) | (13.185) | (7.202) |

(Table continues in the next page.)

*Table A.17:* Comparison of alternative IVs

| Model | RC logit I | | | RC logit II | | |
|---|---|---|---|---|---|---|
| | BLP IV | Diff IV quad | Diff IV local | BLP IV | Diff IV quad | Diff IV local |
| Postpaid: 21≤age<30 | 1.976 | 4.473 | -3.152 | -4.808 | 0.574 | -4.532 |
| | (2.907) | (4.758) | (3.246) | (3.463) | (6.840) | (3.296) |
| Postpaid: 30≤age<45 | 9.504*** | 12.090** | 4.072 | 5.156* | 9.154 | 6.122 |
| | (2.849) | (5.057) | (3.348) | (3.129) | (7.665) | (5.872) |
| Postpaid: 45≤age<60 | 14.695** | 22.626* | 0.954 | 1.885 | 14.131 | -2.789 |
| | (6.801) | (12.767) | (8.949) | (7.884) | (20.426) | (11.660) |
| Prepaid: age≤20 | 3.426 | 9.660 | -11.430 | -3.229 | 3.788 | 3.394 |
| | (6.576) | (12.404) | (9.139) | (8.323) | (15.819) | (7.640) |
| Prepaid: 21≤age<30 | 9.475*** | 12.004** | 2.379 | 3.183 | 7.798 | 7.881* |
| | (2.864) | (5.282) | (3.159) | (2.948) | (8.522) | (4.525) |
| Prepaid: 30≤age<45 | 15.138*** | 18.579*** | 7.953** | 11.188*** | 14.769 | 13.627** |
| | (3.089) | (6.077) | (3.697) | (3.756) | (9.852) | (5.942) |
| Prepaid: 45≤age<60 | 22.322*** | 30.191** | 5.527 | 9.440 | 20.395 | 8.988 |
| | (7.034) | (13.505) | (9.374) | (8.717) | (22.827) | (12.831) |
| F. bloqué: age≤20 | 9.115 | 10.367 | 9.951 | -2.630 | 5.002 | 7.291 |
| | (7.005) | (11.926) | (7.044) | (10.716) | (14.816) | (9.595) |
| F. bloqué: 21≤age<30 | 9.672*** | 13.008** | 6.917* | 3.919 | 9.223 | 6.413 |
| | (3.331) | (5.510) | (4.126) | (3.866) | (8.673) | (4.389) |
| F. bloqué: 30≤age<45 | 16.320*** | 20.091*** | 15.137*** | 12.100*** | 16.861** | 12.905*** |
| | (2.926) | (4.772) | (3.336) | (3.031) | (6.939) | (4.592) |
| F. bloqué: 45≤age<60 | 22.348*** | 31.029*** | 11.525 | 10.906 | 22.322 | 5.723 |
| | (6.948) | (11.697) | (8.081) | (6.682) | (17.971) | (10.651) |
| Low cost: age≤20 | -41.772*** | -24.246 | -50.051*** | -58.343*** | -31.609 | -65.326*** |
| | (13.299) | (19.534) | (17.348) | (19.788) | (22.748) | (18.902) |
| Low cost: 21≤age<30 | -29.057*** | -17.983 | -31.272*** | -39.267*** | -21.812 | -43.801*** |
| | (9.376) | (12.466) | (11.099) | (13.439) | (15.041) | (13.500) |
| Low cost: 30≤age<45 | -13.694* | -4.776 | -14.069 | -20.504** | -7.567 | -21.734* |
| | (7.379) | (10.293) | (8.816) | (9.923) | (12.602) | (11.340) |
| Low cost: 45≤age<60 | -0.435 | 8.559 | -13.910 | -13.814 | 0.805 | -19.622 |
| | (7.681) | (13.929) | (10.495) | (10.238) | (22.288) | (13.286) |
| Orange*age | 0.505* | 0.418 | 0.958** | 0.573* | 0.581 | 0.641 |
| | (0.270) | (0.384) | (0.398) | (0.297) | (0.377) | (0.477) |
| SFR*age | 0.732** | 0.723* | 0.734 | 0.733** | 0.803** | 0.625 |
| | (0.336) | (0.416) | (0.558) | (0.321) | (0.401) | (0.563) |
| Bouygues*age | 0.658 | 0.642 | 0.978* | 0.712 | 0.701 | 0.853 |
| | (0.430) | (0.517) | (0.551) | (0.444) | (0.511) | (0.639) |
| Free*age | -6.457*** | -4.537* | -5.482** | -7.385*** | -4.692* | -8.762*** |
| | (2.094) | (2.616) | (2.381) | (2.611) | (2.554) | (3.000) |
| Sosh*age | -6.899*** | -4.622* | -6.137** | -7.958*** | -4.775* | -9.383*** |
| | (2.119) | (2.621) | (2.431) | (2.688) | (2.571) | (3.028) |
| B&You*age | -6.670*** | -4.723* | -5.714** | -7.706*** | -4.775* | -8.857*** |
| | (2.102) | (2.622) | (2.331) | (2.633) | (2.621) | (2.952) |
| Red*age | -6.399*** | -4.108 | -4.513* | -7.216*** | -4.108 | -7.557** |
| | (2.130) | (2.679) | (2.356) | (2.686) | (2.646) | (2.957) |
| 1/Time since entry | -3.050*** | -2.648*** | -3.121*** | -2.888*** | -2.481*** | -2.816*** |
| | (0.140) | (0.229) | (0.216) | (0.159) | (0.304) | (0.303) |
| Observations | 3,324 | 3,324 | 3,324 | 3,324 | 3,324 | 3,324 |
| $J$ statistic | 88.64 | 22.55 | 15.99 | 72.57 | 15.74 | 6.02 |
| $p$ value | 0.00 | 0.00 | 0.01 | 0.00 | 0.01 | 0.20 |

Clustered standard errors in parentheses: p<0.10, ** p<0.05, *** p<0.01.
$y_{it}$ & $\bar{y}_t$ denote individual & mean incomes scaled by €100.
Tariff types are interacted with the proportion of each age group in the local population.

*Table A.17:* Comparison of alternative IVs

# Appendix H Nonstationary payoffs within repeated game framework

Our analysis in Section 5.2 used a simple collusion model with stationary payoffs aggregated over 2012–2014. In this appendix, we perform two sensitivity analyses to assess the consequences of the nonstationary transition period during which Free mobile and the fighting brands were still growing. First, we apply our collusion model by using the payoffs of the second half of 2014, around which the market had become mostly stabilized. Second, we extend our model to a simple nonstationary structure with two phases: a transitory phase that lasts until the first half of 2014, followed by a steady-state phase during the second half of 2014. This second approach thus explicitly accounts for the nonstationary transition process to test whether strategic incentives may conflict between different stages. For example, if the equilibrium conditions are systematically different between both stages, it may no longer be optimal to punish deviating firms after the interim transition stage has passed.

Our first sensitivity analysis estimates the fixed cost bounds using the expressions of our stationary collusion model derived in the text, but now based on the stationary payoffs in the second half of 2014. Table A.18 shows that the overall results remain largely unchanged from our previous estimates of Table 8, with nonempty and highly significant sets of fixed costs for all three operators.

| Operator | $\underline{f}_j^N$ (collusion) | $\bar{f}_j^N$ (punishment) | $\bar{\bar{f}}_j$ (breakdown) | $\bar{f}_j^N - \underline{f}_j^N$ | $\bar{\bar{f}}_j - \underline{f}_j^N$ |
|---|---|---|---|---|---|
| (O)range | -255 | 712 | 520 | 966 | 775 |
| | (18) | (101) | (77) | (118) | (94) |
| (S)FR | -596 | 441 | 247 | 1038 | 843 |
| | (51) | (67) | (52) | (117) | (103) |
| (B)ouygues | 193 | 606 | 283 | 413 | 90 |
| | (24) | (87) | (53) | (63) | (29) |

The stationary period is assumed to be 2014Q3–2014Q4 (last 2 quarters). The estimates are scaled to the same 3-year period as in our draft. Standard errors from a parametric bootstrap are in parentheses.

*Table A.18:* Fixed cost bounds when stage game is played only in the stationary period

Our second sensitivity analysis considers a nonstationary structure where the transitory stage game is played once at the start, and then a stationary game continues repeatedly afterwards. We first denote the per-period profits in the transitory stage 0 by $\Pi_0$, and the per-period profits in the stationary stage 1 by $\Pi_1$. Given this notation, we can generalize the earlier sustainability condition for collusion (14) to

$$\Pi_0^{C,e} + \frac{\delta}{1-\delta}\Pi_1^{C,e} \geq \Pi_0^{D,e} - f + \frac{\delta}{1-\delta}(\Pi_1^{N,e} - f),$$

where the firm index $j$ is omitted for simplicity and $e$ still denotes the entry status (i.e., $e = E$ if entry occurs, and $e = N$ otherwise). The left hand side is the present value of collusion, which consists of a transitory payoff $\Pi_0^{C,e}$ and a stationary profit stream $\Pi_1^{C,e}$ afterwards. The right hand side consists of the deviation payoff in the transitory stage ($\Pi_0^{D,e}$), followed by the steady-state Nash equilibrium profit stream ($\Pi_1^{N,e}$), both net of fixed costs, throughout the subsequent sequence.

This new sustainability condition redefines the threshold discount factor (15) as

$$\underline{\delta}^e(f) \equiv \frac{\Pi_0^{D,e} - \Pi_0^{C,e} - f}{\Pi_0^{D,e} - \Pi_1^{N,e} + \Pi_1^{C,e} - \Pi_0^{C,e}},$$

for $e \in \{E, N\}$. From this new threshold discount factor, it is straightforward to derive the lower bound of the fixed costs for collusion to be sustainable without entry. This lower bound $\underline{f}^N$ is obtained from the restriction $\underline{\delta}^N < 1$, which implies that

$$\underline{f}^N = \Pi_1^{N,N} - \Pi_1^{C,N}. \tag{22}$$

Furthermore, the upper bound $\bar{f}^N$ follows from the necessary equilibrium condition for firms to have an incentive to punish deviating firms by releasing fighting brands without entry. This requires that no firm can gain from refusing to participate in the punishment after the stage-0 deviation:

$$\Pi_1^{N,N} - f + \frac{\delta}{1-\delta}(\Pi_1^{N,N} - f) > \hat{\Pi}_1^N + \frac{\delta}{1-\delta}(\Pi_1^{N,N} - f),$$

where $\hat{\Pi}_1^N$ is the profit under no entry from deviating from the punishment, i.e. not operating a fighting brand while the others do. By reorganizing the terms, we obtain a similar upper bound $\bar{f}^N$ as before:

$$\bar{f}^N = \Pi_1^{N,N} - \hat{\Pi}_1^N. \tag{23}$$

Lastly, we consider the fixed cost bound for collusion to become more difficult to sustain after entry, i.e. for $\underline{\delta}^E > \underline{\delta}^N$. We can write

$$\begin{aligned}\underline{\delta}^E - \underline{\delta}^N &= \frac{\Pi_0^{D,E} - \Pi_0^{C,E} - f}{\Pi_0^{D,E} - \Pi_1^{N,E} + \Pi_1^{C,E} - \Pi_0^{C,E}} - \frac{\Pi_0^{D,N} - \Pi_0^{C,N} - f}{\Pi_0^{D,N} - \Pi_1^{N,N} + \Pi_1^{C,N} - \Pi_0^{C,N}} \\ &= \left[\frac{1}{A} - \frac{1}{B}\right] f + \Delta(0) > 0,\end{aligned}$$

where $A \equiv \Pi_0^{D,N} - \Pi_1^{N,N} + \Pi_1^{C,N} - \Pi_0^{C,N}$, $B \equiv \Pi_0^{D,E} - \Pi_1^{N,E} + \Pi_1^{C,E} - \Pi_0^{C,E}$, and

$$\Delta(0) \equiv \frac{\Pi_0^{D,E} - \Pi_0^{C,E}}{B} - \frac{\Pi_0^{D,N} - \Pi_0^{C,N}}{A}.$$

From the above inequality, we obtain the following condition for the second upper bound $\bar{\bar{f}}$:

$$\Delta(0) > 0, \quad 1/A - 1/B < 0, \quad \text{and} \quad f < \bar{\bar{f}} = -\left[\frac{1}{A} - \frac{1}{B}\right]^{-1} \Delta(0). \tag{24}$$

Note that the lower bound $\underline{f}^N$ (collusion) and the upper bound $\bar{f}^N$ (punishment) depend only on the payoffs in the stationary stage, whereas the upper bound $\bar{\bar{f}}$ (breakdown) depends on the payoffs in both the transitory and stationary stage.

Table A.19 reports the estimated fixed cost bounds where the stationary period spans the last two quarters

(2014Q3–2014Q4) of the sample.[53] The fixed cost bounds tend to be larger than those in the stationary framework (reported in Table 8 in the text). At the same time, the ranges between the upper and lower bounds also become wider for all three operators with strong statistical significance. Therefore, the equilibrium conditions of collusion and its breakdown continue to hold under the nonstationary game structure.

| Operator | $\underline{f}_j^N$ (collusion) | $\bar{f}_j^N$ (punishment) | $\bar{\bar{f}}_j$ (breakdown) | $\bar{f}_j^N - \underline{f}_j^N$ | $\bar{\bar{f}}_j - \underline{f}_j^N$ |
|---|---|---|---|---|---|
| (O)range | -255 | 712 | 287 | 966 | 542 |
| | (18) | (101) | (43) | (118) | (60) |
| (S)FR | -596 | 441 | 183 | 1,038 | 779 |
| | (51) | (67) | (30) | (117) | (81) |
| (B)ouygues | 193 | 606 | 254 | 413 | 62 |
| | (24) | (87) | (42) | (63) | (19) |

The nonstationary period is 2012Q1–2014Q2, and the stationary period is 2014Q3-2014Q4 (last 2 quarters). The estimates are scaled to the same 3-year period as in our draft. Standard errors from a parametric bootstrap are in parentheses.

*Table A.19:* Fixed cost bounds when the last 2 quarters are assumed to be stationary

For further evidence of robustness, we extend the stationary period to cover the last four quarters (2014Q1–2014Q4) and reduce the transitory period accordingly. The corresponding results are presented in Table A.20. Once again, the overall findings still remain valid under this alternative definition of the stage length.

| Operator | $\underline{f}_j^N$ (collusion) | $\bar{f}_j^N$ (punishment) | $\bar{\bar{f}}_j$ (breakdown) | $\bar{f}_j^N - \underline{f}_j^N$ | $\bar{\bar{f}}_j - \underline{f}_j^N$ |
|---|---|---|---|---|---|
| (O)range | -309 | 648 | 235 | 957 | 544 |
| | (25) | (93) | (35) | (117) | (59) |
| (S)FR | -553 | 426 | 156 | 979 | 709 |
| | (49) | (66) | (25) | (114) | (74) |
| (B)ouygues | 189 | 568 | 235 | 379 | 45 |
| | (24) | (83) | (37) | (59) | (14) |

The nonstationary period is 2012Q1–2013Q4, and the stationary period is 2014Q1-2014Q4 (last 4 quarters). The estimates are scaled to the same 3-year period as in our draft. Standard errors from a parametric bootstrap are in parentheses.

*Table A.20:* Fixed cost bounds when the last 4 quarters are assumed to be stationary

While it would be conceptually straightforward to further extend the model to multiple nonstationary stages before entering the stationary stage game, such extension would involve higher-order polynomials in the discount factor, rendering the bounds conditions too complex to derive analytically. Nonetheless, our first-order extension approach appears to confirm the robustness of the main findings in the nonstationary framework.

[53] We scale the payoffs up to the 3-year time period, similar to the previous bound estimates of Table 8.

# Appendix I First stage price regression

| Variable | Estimate |
|---|---|
| Log(2G antenna) | -2.569*** |
| | (0.685) |
| Log(2G roaming) | -2.727*** |
| | (0.972) |
| Log(3G antenna) | 0.988* |
| | (0.550) |
| Log(3G roaming) | 0.976 |
| | (0.834) |
| log(4G antenna) | -0.081 |
| | (0.223) |
| Log(4G roaming) | 0.762*** |
| | (0.216) |
| Forfait bloqué | -10.477* |
| | (6.304) |
| Prepaid | -25.845*** |
| | (6.342) |
| Call allow. (1,000 min) | 2.508*** |
| | (0.265) |
| Data allow. (1,000 MB) | -2.695*** |
| | (0.304) |
| Orange | -27.614*** |
| | (6.520) |
| SFR | -25.368*** |
| | (5.880) |
| Bouygues | -18.133*** |
| | (5.945) |
| Free | -26.298 |
| | (65.686) |
| Sosh | -40.156 |
| | (65.775) |
| B&You | -38.045 |
| | (65.749) |
| Red | -39.402 |
| | (65.682) |
| MVNO:Orange | -1.262*** |
| | (0.430) |
| MVNO:SFR | -2.969*** |
| | (0.428) |
| Postpaid: age$\leq$20 | 12.067 |
| | (16.171) |
| Postpaid: 21$\leq$age<30 | -5.716 |
| | (8.795) |
| Postpaid: 30$\leq$age<45 | -6.559 |
| | (6.353) |
| Postpaid: 45$\leq$age<60 | -5.227 |
| | (12.961) |
| Prepaid: age$\leq$20 | 11.748 |
| | (16.222) |
| Prepaid: 21$\leq$age<30 | 2.908 |
| | (8.810) |
| Prepaid: 30$\leq$age<45 | 3.421 |
| | (6.860) |
| Prepaid: 45$\leq$age<60 | 3.118 |
| | (13.057) |

(Table continues in the next page.)

*Table A.21:* First stage regression of price: $p_{jt}/\bar{y}_t$

| Variable | Estimate |
|---|---|
| F. bloqué: age≤20 | 11.634 |
| | (16.256) |
| F. bloqué: 21≤age<30 | -2.667 |
| | (8.825) |
| F. bloqué: 30≤age<45 | -5.241 |
| | (6.678) |
| F. bloqué: 45≤age<60 | -5.218 |
| | (13.052) |
| Low cost: age≤20 | 18.848 |
| | (56.062) |
| Low cost: 21≤age<30 | 6.32 |
| | (42.460) |
| Low cost: 30≤age<45 | -1.807 |
| | (32.277) |
| Low cost: 45≤age<60 | -0.529 |
| | (21.169) |
| Orange*age | -1.252 |
| | (1.317) |
| SFR*age | -0.065 |
| | (1.328) |
| Bouygues*age | -1.234 |
| | (1.342) |
| Free*age | 1.409 |
| | (9.730) |
| Sosh*age | 1.437 |
| | (9.741) |
| B&You*age | 1.509 |
| | (9.750) |
| Red*age | 1.259 |
| | (9.735) |
| 1/Time since entry | 4.403*** |
| | (0.686) |
| $\sum_r \sum_{k \notin f_r(j)}$ Ant2G$_{kr}$ | -0.018 |
| | (0.016) |
| $\sum_r \sum_{k \notin f_r(j)}$ Ant3G$_{kr}$ | -0.123*** |
| | (0.017) |
| $\sum_r \sum_{k \notin f_r(j)}$ Ant4G$_{kr}$ | 0.013 |
| | (0.009) |
| $\sum_r \sum_{k \notin f_r(j)} 1\{k \in f_r(k)\}$ | 1.080*** |
| | (0.074) |
| $\sum_r \sum_{k \neq j, k \in f_r(j)}$ Ant2G$_{kr}$ | 0.058** |
| | (0.024) |
| $\sum_r \sum_{k \neq j, k \in f_r(j)}$ Ant3G$_{kr}$ | -0.190*** |
| | (0.025) |
| $\sum_r \sum_{k \neq j, k \in f_r(j)}$ Ant4G$_{kr}$ | 0.037*** |
| | (0.012) |
| $\sum_r \sum_{k \neq j, k \in f_r(j)} 1\{k \in f_r(k)\}$ | 1.361*** |
| | (0.078) |
| Constant | -9.215 |
| | (20.185) |
| Observations | 3,324 |
| $R^2$ | 0.886 |
| $F$ | 354.628 |
| $F$ (excluded instruments) | 47.490 |

Standard errors in parentheses: p<0.10, ** p<0.05, *** p<0.01.
$y_{it}$ & $\bar{y}_t$ denote individual & mean incomes scaled by €100.
Tariff types are interacted with the proportion of each age group.

*Table A.21:* First stage regression of price: $p_{jt}/\bar{y}_t$