Online Appendix for "Market Entry, Fighting Brands and Tacit Collusion: Evidence from the French Mobile Telecommunications Market"

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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:

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

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

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

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, $w_{f_0} = \overline{w}_{f_0} + c^r_{f_0}$. Therefore, the MVNO's retail marginal cost is not separately identified. 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 $f \in \mathcal{F}$,

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

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

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

for all $f \in \mathcal{F}$, where $b_f^2 = \frac{\partial D_{f_0}}{\partial p_{f_0}}$ 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), (1), and (2) 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 (1)–(2) 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, (1) and (2) 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 $x = [\partial p_1/\partial w_{g_0}, ..., \partial p_J/\partial w_{g_0}]$, $b^1 = [b_1^1, ..., b_L^1]'$, $b^2 = [b_1^2, ..., b_F^2]'$, and the submatrix A^1 is defined as:

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

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

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

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

Then, by plugging the derivatives $\partial p / \partial w$ obtained from (1) and (2) 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 (1) and (2). 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 δ in step 1 and the optimal instrument z^{k-1} from the previous $(k-1)$-th iteration, obtain linear parameter estimates θ_1^k from the linear IV regression of Nevo (2000).
   (b) Obtain $z^k = E\big[\frac{\partial \hat{\delta}(\theta_1^k, \theta_2)}{\partial \theta}\big| z^{k-1}\big]$ 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

Table A.1: Full results for Table 4

Estimate	Logit	IV logit	RC logit I	RC logit II
Random coefficients				
Price/y_{it} (–α)			-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

(Table continues on the next page.)

Table A.1: Full results for Table 4

Estimate	Logit	IV logit	RC logit I	RC logit II
	(0.047)	(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)
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)

(Table continues on the next page.)

Table A.1: Full results for Table 4

Estimate	Logit	IV logit	RC logit I	RC logit II
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
	(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 are clustered at the product–region level.
All columns include fixed effects for regions and quarters.
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.2: Average incomes conditional on observed and predicted product choice

	Observed income			Predicted income		
Network	Prepaid	Postpaid	F. Bloqué	Prepaid	Postpaid	F. Bloqué
Orange	2,763	3,052	2,892	2,593	3,829	2,358
SFR	2,595	2,936	2,829	2,520	3,452	1,592
Bouygues	2,528	2,895	2,755	2,636	3,731	2,010
Free		3,023			2,190	
Sosh		3,199			2,819	
B&You		2,959			2,776	
Red		3,058			2,667	
MVNO:Orange	2,715	2,861	2,596	2,087	2,953	1,542
MVNO:SFR	2,927	2,923	2,796	1,127	2,840	1,074
MVNO:Bouygues	2,709	2,767	2,753	631	3,516	2,055

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

Table A.3: Diversion ratios

Network operator	Product group	Orange				SFR				Bouygues				Free
		Prepaid	Postpaid	F.bloqué	Sosh	Prepaid	Postpaid	F.bloqué	Red	Prepaid	Postpaid	F.bloqué	B&You	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

Percentage of sales diverted toward products (rows) due to price increase (columns).

Table A.4: Elasticity of retail demand

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.5: Estimated wholesale prices and markups on MVNO products

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

		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 (total across periods)

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

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.8: Price effects of entry

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.

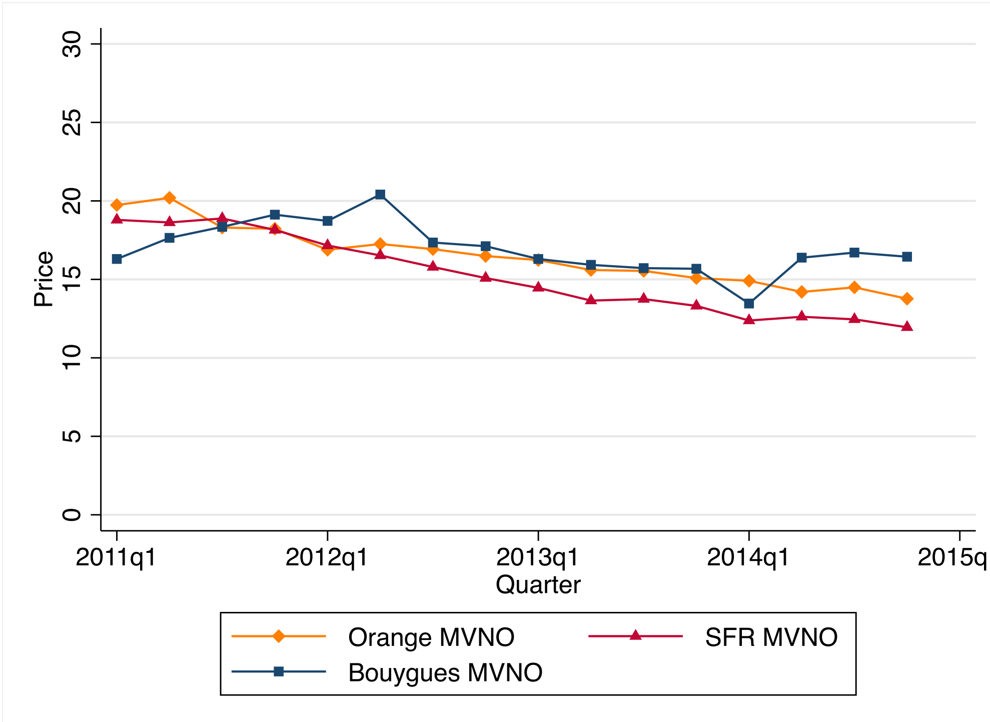

Figure A.1: Prices of the MVNO services

Appendix D Joint incentives for product line extension

In Section IV.A, we examined within a static framework whether the three incumbent firms have *unilateral* incentives to introduce their low-quality fighting brands. In this online 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

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

	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 online appendix. Standard errors from a parametric bootstrap are in parentheses.

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

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

		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 (total across periods)

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

	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 online appendix.

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

	Entry of Free Mobile	
	No	Yes
Network	Equilibrium: no fighting brands	Equilibrium: fighting brands
Orange	429	-362
	(62)	(55)
SFR	282	-231
	(44)	(37)
Bouygues	413	-317
	(60)	(50)

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 online appendix.

Table A.13: Bounds on fixed costs supporting fighting brands in response to entry: 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.14: Sources of consumer and welfare impact from 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).

Appendix F Model extensions

Table A.15: Comparison of alternative demand specifications

Estimate	RC logit I	RC logit II	Normal RC	M*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*ν_{it}			1.171			
			(0.178)			
Forfait bloqué*ν_{it}			1.416			
			(0.924)			
Prepaid*ν_{it}			2.740			
			(0.864)			
Intercept*ν_{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)

(Table continues in the next page.)

Table A.15: Comparison of alternative demand specifications

Estimate	RC logit I	RC logit II	Normal RC	M*1.5	No Allowance	Full sample
MVNO:Orange	0.705	0.839	0.467	0.542	0.543	-0.076
	(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. y_{it} & $\bar{y}_t$ are individual & mean incomes in €100s.
Random draw ν_{it} in Column Normal RC is independently simulated from a normal distribution.

(Table continues in the next page.)

Table A.15: Comparison of alternative demand specifications

Estimate	RC logit I	RC logit II	Normal RC	M*1.5	No Allowance	Full sample

Column M*1.5 is estimated under market size increased by 50%.
Tariff types are interacted with the proportion of each age group in the local population.

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. Online Appendix G.1 discusses the BLP instruments (which we also use for price in our optimal instruments approach). Next, Online Appendix G.2 discusses tests of weak instruments under various non-optimal instruments (BLP IVs and differentiation IVs). Finally, Online 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

$$\sum_r \sum_{k \notin f_r(j)} x_{kr} \quad \text{and} \quad \sum_r \sum_{k \neq j, k \in f_r(j)} x_{kr}, \tag{3}$$

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

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

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

$$\begin{aligned} \xi_{jt}(s_t, x_t, p_t, \theta) &= \sum_{k=1}^{K} (\theta^k - \theta_0^k) \frac{\partial \xi_{jt}(s_t, x_t, p_t, \theta_0)}{\partial \theta^k} + \xi_{jt} + O(\|\theta\|^2) \\ &= J_{jt}(s_t, x_t, p_t, \theta_0) b + + \xi_{jt} + O(\|\theta\|^2), \end{aligned} \tag{5}$$

where θ_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 kth element, and b is the coefficient vector with kth 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 (5) 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

Table A.16: Test of weak instruments

	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	2.45	3.75	7.79	1.52
	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.19)
4G antenna	8.33	20.59	3.18	2.49	37.74	1.16
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.33)
F. bloqué	4.47	10.37	2.27	6.90	10.67	1.76
	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.13)
Prepaid				2.34	28.75	2.34
				(0.01)	(0.00)	(0.05)
Intercept				2.97	19.53	3.09
				(0.00)	(0.00)	(0.01)
Cragg-Donald statistic	15.68	8.03	1.83	1.55	6.85	0.75
Kleibergen-Paap statistic	3.16	7.46	1.74	1.34	4.62	0.60
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.

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 (5) (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 (α) 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.(1,000min)	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.(1,000MB)	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$20	2.069	6.649	-13.722	-8.274	0.858	-11.948
	(6.449)	(11.109)	(9.371)	(9.172)	(13.185)	(7.202)
Postpaid: 21$\leq$age$<$30	1.976	4.473	-3.152	-4.808	0.574	-4.532

(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
	(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.
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 IV.B 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.

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

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.

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 Π_0, and the per-period profits in the stationary stage 1 by Π_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

$$\underline{f}^N = \Pi_1^{N,N} - \Pi_1^{C,N}. \tag{6}$$

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:

$$\bar{f}^N = \Pi_1^{N,N} - \hat{\Pi}_1^N. \tag{7}$$

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 $\bar{\bar{f}}$:

$$\Delta(0) > 0, \quad 1/A - 1/B < 0, \quad \text{and} \quad f < \bar{\bar{f}} = -\left[\frac{1}{A} - \frac{1}{B}\right]^{-1} \Delta(0). \tag{8}$$

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.[1] 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.

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

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.

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.

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

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.

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.

[1]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

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

Variable	Estimate	Std. error
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$age$<$60	3.118	(13.057)
F. bloqué: age$\leq$20	11.634	(16.256)
F. bloqué: 21$\leq$age$<$30	-2.667	(8.825)
F. bloqué: 30$\leq$age$<$45	-5.241	(6.678)
F. bloqué: 45$\leq$age$<$60	-5.218	(13.052)
Low cost: age$\leq$20	18.848	(56.062)
Low cost: 21$\leq$age$<$30	6.320	(42.460)
Low cost: 30$\leq$age$<$45	-1.807	(32.277)
Low cost: 45$\leq$age$<$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)
$\sum_r \sum_{k \notin f_r(j)}$ 2G antenna	-0.018	(0.016)
$\sum_r \sum_{k \notin f_r(j)}$ 3G antenna	-0.123	(0.017)
$\sum_r \sum_{k \notin f_r(j)}$ 4G antenna	0.013	(0.009)
$\sum_r \sum_{k \notin f_r(j)} 1\{k \in f_r(k)\}$	1.080	(0.074)
$\sum_r \sum_{k \neq j, k \in f_r(j)}$ 2G antenna	0.058	(0.024)
$\sum_r \sum_{k \neq j, k \in f_r(j)}$ 3G antenna	-0.190	(0.025)
$\sum_r \sum_{k \neq j, k \in f_r(j)}$ 4G antenna	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)

(Table continues in the next page.)

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

Variable	Estimate	Std. error
Observations	3,324	
R^2	0.886	
F	354.628	
F (excluded instruments)	47.490	

Standard errors in parentheses.
Fixed effects are included for regions and quarters.
y_{it} & $\bar{y}_t$ denote individual & mean incomes scaled by €100.
Tariff types are interacted with the proportion of each age group.

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