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How Fixed Mobile Usage Interact? Does FTTH deployment influence the Interaction?

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Institutions: Orange S.A.

Published on: 28 Jun 2015 - Social Science Research Network

Topics: Mobile broadband and Consumption (economics)

Liang, Julienne

Conference Paper

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26th European Regional Conference of the International Telecommunications Society (ITS): "What Next for European Telecommunications?", Madrid, Spain, 24th-27th June, 2015

Provided in Cooperation with:
International Telecommunications Society (ITS)

How fixed mobile usage interact? Does FTTH deployment influence the interaction?

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June 6th 2015

Abstract

We estimate the interaction between fixed and mobile usage both for voice and data services using consumer level data from April 2013 to March 2014 in a European country. We find a significant proportion of fixed voice consumption could be substituted by mobile voice, and vice versa. However, a substantial proportion of fixed data consumption, and also mobile data consumption, is generated by fixed-mobile interaction in both directions. FTTH deployment has no significant impact on fixed-mobile voice substitution. The fixed data consumption generated by mobile to fixed interaction appears to increase with FTTH deployment.

Key Words: Fixed mobile *;fixed mobile usage interaction, voice consumption, data consumption, substitution versus complementarity, FTTH deployment*

JEL Classification: L43,L50, L96

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1 Introduction

In this study we empirically estimate the interaction between fixed and mobile usage by using a three-stage least-squares (3SLS) regression. Based on the consumption of 43,069 customers who own both fixed and mobile services, we find causal dependency. Fixed and mobile are substitutes when it comes to voice services, while they complement one another for data services. A substantial proportion of mobile data consumption is causally dependent on fixed broadband consumption (and vice versa). These results suggest that policy makers should support fixed-mobile convergence rather than promote competition between fixed and mobile players.

In recent years, the telecommunications sector has seen the convergence of fixed and mobile services, networks and undertakings. Quadruple play offers, including fixed triple play and mobile packages are becoming more and more popular on European markets. Mobile operators have entered into the fixed market (e.g. Vodafone throughout Europe, Bouygues in France), while fixed operators have begun dealing in mobile services (e.g. Telenet in Belgium, Free in France). Recent mergers have also consolidated fixed and mobile convergence at the market structure level (e.g. planned merger between British Telecom and Everything Everywhere). Are these evolutions pro or anti-competitive? Whether or not they should be supported or blocked by public authorities depends on whether fixed and mobile services are substitutes or complements for the end user.

The trend of convergence between fixed and mobile services is based on innovation and technical progress. The adoption of IP technology within the fixed and mobile core network, as well as the deployment of optical fiber for the traffic backhaul of mobile base stations, led to the replacement of traditional voice networks with data networks. This technological transformation, which was observed in the fixed network in the early 2000s, allows operators to provide voice over IP (VoIP) as a basic and generic component of triple play offers. On the mobile market, voice and SMS services account for a declining share of the cost of mobile plans, and is being taken over by mobile data. However, the scarcity of mobile network resources does not allow carriers to offer unlimited data volume on mobile plans, unlike fixed broadband technology.

Therefore, fixed broadband services provide added value over mobile services in terms of data volume, which is why a growing share of consumers own both fixed and mobile broadband.

The remainder of the article is organized as follows. Section 2 discusses the relevant literature. Section 3 presents the data used in the estimation. Section 4 introduces theoretical utility function. Section 5 presents the econometric framework and identification strategy. Section 6 shows the first stage estimation. Section 7 presents the main results. We add some robustness checks in Section 8. Finally, Section 9 concludes.

2 Literature Review

Fixed broadband technologies have been largely adopted in developed countries for more than 15 years now. Before the recent adoption of mobile data services, fixed mobile interaction was primarily observed on voice services. There are a number of studies focusing on fixed to mobile substitution (FMS), summarized by Vogelsang 2010. Most of these studies are based on cross country or country data. The papers of the review find a decline in subscriptions to fixed services. Some papers empirically study the substitution effect by estimating the cross elasticity of demand between mobile and fixed voice services. Such fixed to mobile voice substitution is supported by the cost reduction of mobile technology, network effects in demand and improvements to the quality of mobile voice services. L. Grzybowski (2014) finds that households keep their fixed line connection to access the Internet.

Since the advent of the mobile 3G network, the adoption and utilization of mobile data, i.e. Internet access through smartphones, has surged significantly. T. J. Gerpott et al. carried out a meta-analysis of the literature on mobile internet usage. Their review summarizes 175 papers on mobile data usage intensity and potential determinants of respective usage behavior by individual subscribers. Their literature summary reveals that in spite of the 175 papers on mobile data usage, there are still at least three unchartered territories, which offer ample opportunities for future empirical studies on mobile data usage intensity and its drivers. The first area relates to the measurement of mobile data usage. The second area looks at the choice of independent factors that explain the variance in the consumption of mobile data. The last area concerns study sampling and design methods. As mobile data came after fixed data, we assume that the mobile data usage can be influenced by fixed services. Inversely, fixed data usage might also be impacted in turn by mobile data consumption. This topic is also, in our view, an area of unchartered research.

The interaction between fixed and mobile data services is often studied separately from voice interaction. Srinuan et al. (2012) indicate that pricing and residential factors are important determinants for broadband subscriptions. By estimating own-price and cross-price elasticities, they show that mobile data may substitute fixed broadband data in most geographic areas of Sweden. The nomadic feature of mobile services is a principal differentiator with respect to fixed access. Nielsen and Fjuk (2010) suggest that the primary motivation for using mobile data is to stay connected when a fixed broadband access is not available. Other papers find that fixed and mobile data services complement one another. For example, De Reuver (2013) shows that consumers will only adopt mobile data if these strongly resemble the services they already use on fixed broadband.

Y.Kim et al (2014) find that fixed and mobile data complement, both affect the consumption of the other. L.Grzybowski, J.Liang (2014) use an individual level tariff choice data to find that mobile data is complementary to fixed broadband for quadruple play subscribers while mobile voice is a substitute for fixed voice services. Based only on the voice and data allowance included in mobile plans, without considering actual consumption, the study finds that there is disutility with subscriptions both to mobile voice allowance and unlimited fixed VoIP included in fixed broadband services. However, there is positive complementary utility when a consumer subscribes to both mobile data and fixed Internet access. The present study seeks to use the consumer's actual consumption to confirm their previous finding.

3 The Data

To estimate empirically the sign and the value of fixed mobile interactions, we used an individual monthly consumption dataset provided by a European country multiproduct operator on 43,069 customers who own both fixed broadband and mobile services from April 2013 to March 2014 (12 months). The link between fixed and mobile usage was made by using the mobile number registered when a consumer subscribed to a fixed broadband service. Firstly, the fixed broadband consumers' data were collected. With the corresponding mobile number, mobile consumption data were then collected. After merging these two datasets, our final dataset includes information on the consumption of mobile voice and mobile data, the age of consumer, their gender, the density and the median household income of the municipality in which the consumer lives. It also includes information on fixed broadband such as the nominal broadband speed, managed fixed VoIP and fixed data consumption. Since the fixed broadband subscription is household based and mobile subscription is individual based, the fixed VoIP and fixed data consumption are divided by the average number of individuals in a household in order to obtain individual consumption. Wi-Fi data consumption using a smartphone at home with a fixed network connection is considered as fixed data consumption. In our dataset, there are mobile consumption observations for only one member for each household.

In order to study the influence of FTTH deployment on FM interaction, we also collected a sample of 14,352 customers who live in FTTH-covered areas so that they are eligible for FTTH broadband access (see Table (2)).

It is worth comparing with summary statistics of 2,106 FTTH subscribers (see Table (3)).

From these summary statistics, we can compare managed fixed VoIP and mobile voice consumption at a national level, in FTTH covered areas and for FTTH subscribers. The average mobile voice consumption is about 167 min per month at a national level, and slightly higher for both FTTH subscribers (211 min) and in FTTH covered areas (198 min). The lower consumption of mobile voice can be explained by the fact that the national-level consumers include rural residents who live in areas with poorer mobile coverage while FTTH covered areas and

Variable	Mean	Std. Dev.	Min.	Max.
mobile voice monthly consumption in minute	166.81	267.15	0	12862.88
fixed VoIP/mobile voice consumption ratio	0.56	0	0.56	0.56
mobile data monthly consumption in GB	0.17	0.58	0	117.72
fixed/mobile broadband consumption ratio	67.45	0	67.45	67.45
density of mobile subscriber's resident municipality	1405.93	3504.87	2.24	22228
age of mobile subscriber	51.31	14.1	18	97
gender of mobile subscriber	0.44	0.5	0	1
median income per household of resident municipality	30281.6	7009.24	13106.5	82812.5
N	428750			

Table 1: Summary statistics for consumers in nation level

Variable	Mean	Std. Dev.	Min.	Max.
mobile voice monthly consumption in minute	198.27	264.63	0	6286.73
fixed VoIP/mobile voice consumption ratio	0.49	0	0.49	0.49
mobile data monthly consumption in GB	0.25	0.89	0	188.34
fixed/mobile broadband consumption ratio	71.7	0	71.7	71.7
density of mobile subscriber's resident municipality	9927.75	8293.69	3.72	22228
age of mobile subscriber	53.35	15.61	19	99
gender of mobile subscriber	0.46	0.5	0	1
median income per household of resident municipality	29689.67	6192.38	17403	73891
N	113196			

Table 2: Summary statistics for consumers in FTTH covered areas

Variable	Mean	Std. Dev.	Min.	Max.
mobile voice monthly consumption in minute	211.29	273.16	0	2395.92
fixed VoIP/mobile voice consumption ratio	0.45	0	0.45	0.45
mobile data monthly consumption in GB	0.28	0.70	0	15.31
fixed/mobile broadband consumption ratio	81.40	0	81.40	81.40
density of mobile subscriber's resident municipality	10282.76	8210.82	6.49	22228
age of mobile subscriber	53.69	15.23	19	95
gender of mobile subscriber	0.44	0.5	0	1
median income per household of resident municipality	29607.92	6033.88	17403	60122
N		2414		

Table 3: Summary statistics for FTTH subscribers

FTTH subscribers include mainly urban dwellers. However the fixed voice over IP consumption is quite similar for all categories of consumers.

The data consumption is quite different between consumers at a national level, consumers eligible for FTTH and FTTH subscribers. The nominal speed of ADSL broadband access depends on the section and the length of copper line (from the subscriber's house to the MDF, or main distribution frame). The nominal speed of ADSL access ranges from 1-20Mbits/s. For FTTH access, the nominal speed is significantly higher, ranging from 100-500 Mbits/s. FTTH deployment is often launched by governmental or private initiatives and driven by economic efficiency. Consequently we nowadays find FTTH coverage only in urban areas while rural people are more willing to pay for FTTH access. The nominal fixed broadband speed is correlated with fixed data volume consumption, but uncorrelated directly with mobile data consumption. We can potentially anticipate that the FTTH deployment and its adoption will not have a significant impact on voice consumption. Indeed, FTTH technology improves Internet access speed, but should not modify voice usage. The lowest data consumption is observed for national-level consumers both for mobile and fixed data. This consumption is higher in FTTH-covered areas.

The highest consumption levels were found among FTTH subscribers.

Tables (1) (2) (3) show that fixed broadband consumption is largely higher than mobile data consumption. The ratio varies from 67.5 for national-level consumers to 81.4 for FTTH subscribers. Such high ratios can be explained by the pricing and the devices specific to fixed and mobile technologies. Firstly fixed broadband is charged at a flat rate, i.e. the price of fixed broadband access is independent of fixed data consumption, while mobile data allowance is still limited and therefore constrains mobile data consumption. The difference in screen size between fixed and mobile devices can also be one explanation for the differences in consumption. Indeed, a smartphone is usually used for mobile data that requires less network speed than a big-screen personal computer on a fixed network.

A simple statistical comparison cannot answer the question of causality. What causes the increase in data consumption? Is it due to the progressive migration of networks technologies, i.e. from ADSL to FTTH for fixed network and from 3G to 4G for mobile network, or is it due to stronger fixed mobile interaction? We are asked ourselves whether each type of consumption is influenced by the other types of consumption, positively, negatively or not at all. To address these questions, we developed a demand model to understand the potential causal effects.

4 Demand model

We use a standard quadratic utility specification for an individual i consuming V_{jk}.(to simplify notation, the individual index i is deleted in this section). The quadratic utility function is widely used in demand literature (Singh and Vives 1984, Economides et al. 2008, Miravete and Roller 2003, Kim et al.2010). The utility of a consumer embeds two interaction terms, firstly the interaction between fixed and mobile data consumption, secondly between fixed and mobile voice consumption. A positive (negative) interaction between fixed and mobile usage leads to a higher (lower) utility.

$$U_{fm} = \sum_{j,k} (a_{jk} V_{jk} - \frac{1}{2} V_{jk}^2) + \gamma_d V_{fd} V_{md} + \gamma_v V_{fv} V_{mv} \tag{1}$$

Here, $j = f, m$ denotes respectively fixed and mobile, $k = v, d$ denotes respectively voice and data. V_{jk} represents four types of consumption : managed fixed VoIP V_{fv}, mobile voice V_{mv}, fixed data V_{fd} and mobile data V_{md}. The coefficient γ_v denotes the interaction term between fixed and mobile voice consumption, γ_d the interaction between fixed and mobile data consumption.

The first term of utility function represents utility from voice and data consumption both for fixed and mobile services. The second and third terms capture utility from the interaction between fixed and mobile consumption, a change in fixed (mobile) consumption can influence mobile (fixed) consumption. γ_v or γ_d measures the substitutive effect (if negative), the complementary effect (if positive), independent (if zero).

By maximizing utility with respect to each type of consumption, the first-order condition, i.e.

$\frac{\partial U_{fm}}{\partial V_{jk}} = 0$ for $j = f, m$ and $k = v, d$, gives following equations

$$V_{md} = a_{md} + \gamma_d V_{fd} \tag{2}$$

$$V_{fd} = a_{fd} + \gamma_d V_{md} \tag{3}$$

$$V_{mv} = a_{mv} + \gamma_v V_{fv} \tag{4}$$

$$V_{fv} = a_{fv} + \gamma_v V_{mv} \tag{5}$$

5 Empirical model and identification strategy

Following our discussion on the demand model, our empirical model is based on the equations (2) (3) (4) (5). It is more general to allowing asymmetric fixed-mobile interaction, namely $\gamma_k^{MtoF} \neq \gamma_k^{FtoM}$. Consequently, the equations (2) (3) (4) (5) from theoretical model become applied empirical equations

$$V_{md} = a_{md} + \gamma_d^{FtoM} V_{fd} + \varepsilon_{md} \tag{6}$$

$$V_{fd} = a_{fd} + \gamma_d^{MtoF} V_{md} + \varepsilon_{fd} \tag{7}$$

$$V_{mv} = a_{mv} + \gamma_v^{FtoM} V_{fv} + \varepsilon_{mv} \tag{8}$$

$$V_{fv} = a_{fv} + \gamma_v^{MtoF} V_{mv} + \varepsilon_{fv} \tag{9}$$

Where $\varepsilon_{md}, \varepsilon_{fd}, \varepsilon_{mv}$ and ε_{fv} are error terms for each equation. The variables V_{md} V_{fd} $V_{mv}V_{fv}$ are simultaneously dependent variables and explanatory variables. We are confronted with two recognized sources of endogeneity: omitted variables such as marginal price for unitary mobile data/voice[1] and simultaneity between dependent variable and explanatory variable.

To identify the causal effects of fixed usage on mobile usage, and also mobile usage on fixed usage, it is important to define identification strategies for above mentioned four interactions, which correspond respectively to managed voice over IP, mobile voice, fixed data and mobile

[1] In our dataset, it is possible to have monthly fees for mobile plan and fixed broadband plan. However a mobile plan is composed of mobile voice and mobile data allowance, a fixed broadband plan includes in general unlimited VoIP and data allowance. So the marginal cost for unitary voice (fixed or mobile) and unitary data (fixed and voice) is not known, and considered as omitted variables in our study.

data consumption. To deal with these challenges. we introduce following instrumental variables as an identification strategy for all interactions.

The first instrumental variable is the median household income of mobile subscriber's residential municipality. It is assumed that fixed and mobile usage could depend on the median household income.

The second instrumental variable is the density of mobile subscriber's residential municipality, Mobile broadband speed is closely linked to the density of municipality. The more dense a municipality is, the higher speed the mobile broadband network due to the easier coverage. With this identification assumption, we suppose that the mobile data consumption is correlated with the density of mobile subscriber's residential municipality.

The third instrumental variable is average maximum temperature in the area where the mobile subscriber lives for each month of observations. We suppose the mobile usage depends on the outdoor temperature. A higher temperature favors outdoor activity, resulting in more mobile usage.

The fourth instrumental variable is the age of mobile subscriber, which is correlated with mobile voice consumption. It has been observed that young people use mobile services more than fixed services.

The dummy for gender of mobile subscriber is also used as exogenous variable. The dummy takes value of one for women and zero for men.

For empirical regressions, we use three-stage least-squares (3SLS) regression simultaneously with four equations. The endogeneity is overridden by the introduction of instrumental variables described above in 3SLS regression. Hausman tests between 3SLS vs. OLS reject exogenous hypothesis of OLS (see Appendix). Overidentification tests are conducted with a randomly reduced dataset (see Appendix).

6 First Stage

The following tables show the first-stage estimates for mobile data, fixed data, mobile voice and fixed VoIP consumption using exogenous variables introduced in Section 5.

Table 4: The first-stage estimates for mobile data consumption

First-stage regressions

Source	SS	df	MS
Model	4869.77781	5	973.955561
Residual	138186.494	428744	.32230537
Total	143056.271	428749	.33365972

Number of obs	= 428750
F(5,428744)	= 3021.84
Prob > F	= 0.0000
R-squared	= 0.0340
Adj R-squared	= 0.0340
Root MSE	= .56772

vmd	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
hh_income	5.91e-07	1.24e-07	4.77	0.000	3.48e-07	8.33e-07
density	.0000106	2.48e-07	42.85	0.000	.0000101	.0000111
tempmax_moy	.000832	.0001404	5.93	0.000	.0005569	.0011072
age_mob	-.0069827	.0000619	-112.82	0.000	-.007104	-.0068614
sexe_mob	-.0739423	.0017557	-42.12	0.000	-.0773834	-.0705013
_cons	.5143643	.0055756	92.25	0.000	.5034364	.5252922

Table (4) shows the first-stage estimates for mobile data consumption. The median household income of mobile subscribers' residential municipality has positive impact on mobile data consumption. For the variable "density", the coefficient is also positive which indicates that urban people use more mobile data than rural people. The positive coefficient of variable "tempmax_moy" suggests that the mobile data usage increases with outdoor temperature. The negative coefficient of variable "age_mob" can be interpreted as higher appetence for mobile services among young people. Finally the negative coefficient for the variable "sexe_mob" can be explained as a lower usage of mobile data by women compared to men.

Table 5: The first-stage estimates for fixed data consumption

Source	SS	df	MS
Model	6167215.19	5	1233443.04
Residual	346959836	428744	809.247093
Total	353127051	428749	823.621864

Number of obs	= 428750
F(5,428744)	= 1524.19
Prob > F	= 0.0000
R-squared	= 0.0175
Adj R-squared	= 0.0175
Root MSE	= 28.447

vfd	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
hh_income	.0000328	6.21e-06	5.28	0.000	.0000206	.0000449
density	.0003128	.0000124	25.20	0.000	.0002885	.0003371
tempmax_moy	-.1305287	.007034	-18.56	0.000	-.1443151	-.1167423
age_mob	-.2420708	.0031012	-78.06	0.000	-.2481491	-.2359924
sexe_mob	-2.883685	.0879731	-32.78	0.000	-3.05611	-2.711261
_cons	25.6405	.2793798	91.78	0.000	25.09292	26.18807

Table (5) above shows the first-stage estimates for fixed data consumption. We can observe same sign of coefficients as the first-stage estimates for mobile data consumption except for the variable "tempmax_moy". This result indicates that a higher outdoor temperature has negative impact on fixed data consumption.

Table 6: The first-stage estimates for mobile voice consumption

Source	SS	df	MS		
Model	707038614	5	141407723	Number of obs =	428750
Residual	2.9892e+10	428744	69720.1782	F(5,428744) =	2028.22
				Prob > F =	0.0000
				R-squared =	0.0231
				Adj R-squared =	0.0231
Total	3.0599e+10	428749	71368.4387	Root MSE =	264.05

vmv	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
hh_income	-.0003445	.0000576	-5.98	0.000	-.0004574	-.0002316
density	.0058515	.0001152	50.79	0.000	.0056257	.0060773
tempmax_moy	.4889304	.0652891	7.49	0.000	.3609657	.6168951
age_mob	-2.483285	.0287855	-86.27	0.000	-2.539703	-2.426866
sexe_mob	8.621274	.8165608	10.56	0.000	7.02084	10.22171
_cons	284.4344	2.593186	109.69	0.000	279.3519	289.517

Table (6) above shows the first-stage estimates for mobile voice consumption. Mobile voice consumption is negatively linked to the median household income of mobile subscriber's residential municipality. We observed again a positive coefficient for the variable "tempmax_moy". This result can be explained by a higher mobile voice consumption in areas with higher outdoor temperatures. The coefficient of the variable "sexe_mob" has a positive value. This opposite sign to data consumption suggests higher mobile voice consumption by women.

Table 7: The first-stage estimates for fixex VoIP consumption

```
      Source |       SS       df       MS              Number of obs =  428750
-------------+------------------------------           F(  5,428744) = 1483.56
       Model |   114211603     5  22842320.6           Prob > F      =  0.0000
    Residual |  6.6013e+09428744  15396.9206           R-squared     =  0.0170
-------------+------------------------------           Adj R-squared =  0.0170
       Total |  6.7155e+09428749  15663.1244           Root MSE      =  124.08

------------------------------------------------------------------------------
         vfv |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   hh_income |  -.0000794   .0000271    -2.93   0.003    -.0001324   -.0000263
     density |   .0002828   .0000541     5.22   0.000     .0001767    .0003889
 tempmax_moy |   -.576448   .0306816   -18.79   0.000    -.6365831   -.5163129
     age_mob |   1.119713   .0135273    82.77   0.000       1.0932    1.146226
    sexe_mob |   8.471026   .3837304    22.08   0.000     7.718926    9.223126
       _cons |   46.57677   1.218628    38.22   0.000      44.1883    48.96525
------------------------------------------------------------------------------
```

Table (7) above shows the first-stage estimates for fixed voice consumption. The coefficient is also negative for the median household income. The coefficient of the variable "tempmax_moy" is negative, which suggests that a higher outdoor temperature has a negative impact on fixed VoIP consumption. The age has a positive impact on fixed VoIP consumption. We again observed a positive coefficient for the variable "sexe_mob". This result can be explained by a higher fixed voice consumption among women.

7 Main results

We find robust evidence of positive interaction between fixed and mobile data consumption (complementarity); however fixed mobile interaction reveals negative for voice services (substitution). The impact of fixed data consumption on the consumption of mobile data is highly significant: a substantial proportion of mobile (fixed) data consumption is causally dependent on fixed (mobile) broadband consumption. Regarding fixed and mobile voice interaction, We find a significant proportion of fixed (mobile) voice consumption could be substituted by mobile (fixed) voice.

Here we have summarized the estimated coefficients for $\gamma_d^{FtoM}\gamma_d^{MtoF}\gamma_v^{FtoM}\gamma_v^{MtoF}$ in following tables for the national consumers, FTTH covered areas and for FTTH subscribers.

Detail regression results are placed in Appendix.

Table 8: FtoM data interaction

	Nation	FTTH coverd Area	FTTH subscribers
VARIABLES	vmd	vmd	vmd
vfd	0.0169***	0.0152***	0.0132***
	(9.03e-05)	(8.71e-05)	(7.50e-05)
Observations	428750	113196	91617
Standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			
nation_3sls ftthcov_3sls ftthsub_3sls			

In Table (8) above, we see a positive, statistically significant coefficient suggesting that fixed data consumption has positive impact on mobile data consumption. What are the quantitative implications of the estimates, for instance the coefficient $\gamma_d^{FtoM} = 0.0169$? By applying equation $V_{md} = a_{md} + \gamma_d^{FtoM} V_{fd}$, each GB of fixed data consumption V_{fd} will generate ~17 MB mobile data consumption. For a average of 11GB fixed data consumption at nation level, the volume generated from fixed-mobile interaction is about 0.18 GB, very close to the total mobile data consumption of 0.17 GB (cf. Table (1) in Section 3). This result suggests that all mobile data consumption is generated by fixed to mobile interaction.

Secondly the deployment of FTTH has no significant impact on the volume generated from FM interaction. For instance, The coefficient γ_d^{FtoM} (mobile data in GB generated by 1GB fixed data), is 0.169 GB in nation wide, compared to 0.152 GB in FTTH covered areas and 0.0132 GB for FTTH subscribers. The constant term is absent in the regression results. In fact, by adding a constant term the regressions give negative values for a constant term which is not consistent for data consumption.

Table 9: MtoF data interaction

	Nation	FTTH coverd Area	FTTH subscribers
VARIABLES	vfd	vfd	vfd
vmd	53.14***	65.68***	75.87***
	(0.199)	(0.363)	(0.397)
Constant	1.319***	0.0543	0.0487
	(0.0359)	(0.0497)	(0.0485)
Observations	428750	113196	91617
Standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			
nation_3sls ftthcov_3sls ftthsub_3sls			

In opposite direction mobile to fixed interaction, the coefficient γ_d^{MtoF} in Table (9) have higher values than γ_d^{FtoM}. What are the quantitative implications of the estimates, for instance the coefficient $\gamma_d^{MtoF} = 53$? By applying equation $V_{fd} = a_{fd} + \gamma_d^{MtoF} V_{md} + \varepsilon_{fd}$, each GB of V_{md} will generate ~53 GB fixed data consumption. For a average of 0.17 GB mobile data consumption at nation level (cf. Table (1) in Section 3), the volume generated from mobile to fixed is about 9 GB while the total fixed data consumption is about 11.2 GB.

Then we can compare the estimation for Nation level, FTTH covered area and for FTTH subscribers. Fixed data consumption generated by 1GB mobile data consumption, is 53 GB in nation wide, compared to 65.68 GB in FTTH covered areas and 75.87 GB for FTTH subscribers. The increasing values for mobile to fixed data interaction , γ_d^{MtoF}, suggest that FTTH deployment strengthens the positive interaction between mobile and fixed data.

Table 10: FtoM voice interaction

	Nation	FTTH coverd Area	FTTH subscribers
VARIABLES	vmv	vmv	vmv
vfv	-2.352***	-1.785***	-1.831***
	(0.0129)	(0.0188)	(0.0204)
Constant	393.5***	371.5***	383.8***
	(1.360)	(2.049)	(2.267)
Observations	428750	113196	91617
Standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			
nation_3sls ftthcov_3sls ftthsub_3sls			

Table (10) above shows a strong negative interaction from fixed VoIP to mobile voice, represented by the coefficient γ_v^{FtoM}. This negative interaction is slightly lower in FTTH covered area. A similar value for the coefficient γ_v^{FtoM} is estimated for FTTH subscribers.

Table 11: MtoF voice interaction

	Nation	FTTH coverd Area	FTTH subscribers
VARIABLES	vfv	vfv	vfv
vmv	-0.414***	-0.549***	-0.535***
	(0.00218)	(0.00594)	(0.00605)
Constant	165.3***	205.7***	207.2***
	(0.431)	(1.285)	(1.359)
Observations	428750	113196	91617
Standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			
nation_3sls ftthcov_3sls ftthsub_3sls			

Table (11) above reports the estimation of the coefficient γ_v^{MtoF}, interaction parameter from mobile to fixed voice interaction. The coefficient is negative in all three estimations. These results suggest that the deployment and the adoption of FTTH do not change the sign for fixed-mobile voice interaction. All the fixed mobile interaction parameters for voice services remain negative, ranging from -2.35 to -0.41.

8 Additional robustness checks

We turn back to the process of our regressions. Instead of 3SLS simultaneous regression for four equations together (6) (7) (8) (9), as an additional check, we run equation by equation, 2SLS regression by introducing an appropriate instrumental variable for each endogenous variable (among all exogenous variables introduced in 3SLS regression). This approach implies that the equations (6) (7) (8) (9) are independent of each other while 3SLS estimation takes into account the dependence between four equations. 3SLS regression is therefore more consistent with theoretical model described in Section 4. We find significant values for all coefficients $\gamma_d^{FtoM}\gamma_d^{MtoF}\gamma_v^{FtoM}\gamma_v^{MtoF}$with same sign and same order of magnitude as the 3SLS estimation.

As expected, the results obtained from the robustness check consolidate main results reported in Section 7.

In this section we propose a 2SLS regression for each equation (consequently four equations with four 2SLS regressions), to check that the results of each 2SLS regression are consistent with 3SLS regression in Section 7.

Firstly, Equation (6) is instrumented by the median household income of municipality in which the consumer lives. This produces the following system of equations:

$$V_{md} = a_{md} + \gamma_d^{FtoM} V_{fd} + \beta_{md} X + \varepsilon_{md} \tag{10}$$

$$V_{fd} = \pi_0^{md} + \pi_1^{md} Z_{hh\_income} + \pi_2^{md} X + \tau_{md} \tag{11}$$

Where the variable Z_{hh_income} represents the median household income of mobile subscriber's residential municipality, the vector of X corresponds to control variables such as gender, age etc. ε_{md} and τ_{md} are error terms.

Table (12) displays the estimation using two-stage least-squares regression for fixed to data mobile interaction.

For fixed to mobile data interaction, we start by showing the basic OLS results, in last column, controlling for age, gender of mobile subscriber and outdoor temperature. We see a positive, statistically significant coefficient suggesting that fixed data consumption has positive impact on mobile data consumption. We then implement our empirical strategy by instrumenting fixed data consumption V_{fd} using the median household income of the municipality in which the consumer lives. First of all, in Column (1), we see a stronger positive and statistically significant effect. The next three columns (2) and (4) then introduce sequentially the controls intended to account for demographic and unobservable trends. We see the results are rather stable across the additional specifications and first-stage F-statistic remains highly significant (largely higher than the threshold of 10 owing to the large number of observations).

Secondly, Equation (7) is instrumented by the density of mobile subscriber's residential municipality. Mobile broadband speed is closely linked to the density of municipality. The more dense a municipality is, the higher speed the mobile broadband network due to the easier coverage.

$$V_{fd} = a_{fd} + \gamma_d^{MtoF} V_{md} + \beta_{fd} X + \varepsilon_{fd} \tag{12}$$

$$V_{md} = \pi_0^{fd} + \pi_1^{fd} Z_{Density} + \pi_2^{fd} X + \tau_{fd} \tag{13}$$

With this identification assumption, we suppose that the mobile data consumption is correlated with the density of mobile subscriber's residential municipality.

	(1)	(2)	(3)	(4)	(5)
	two_SLS_1	two_SLS_2	two_SLS_3	two_SLS	OLS
VARIABLES	vmd	vmd	vmd	vmd	vmd
vfd	0.0152***	0.0219***	0.0222***	0.0200***	0.00135***
	(9.85e-05)	(0.000270)	(0.000272)	(0.000308)	(3.05e-05)
age_mob		-0.00148***	-0.00145***	-0.00205***	-0.000688***
		(5.58e-05)	(5.73e-05)	(5.91e-05)	(4.00e-05)
sexe_mob			-0.00869***	-0.0156***	-0.0132***
			(0.00247)	(0.00236)	(0.00173)
tempmax_moy				0.00348***	0.0104***
				(0.000199)	(0.000120)
Observations	428,750	428,750	428,750	428,750	428,750
R-squared	-0.373	-0.910	-0.930	-0.731	0.076
First-Stage F-statistic	61916	11474	11412	8015	.

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Nation_FtoM_data

Table 12: Fixed to mobile data interaction at nation level. The instrument is the median household income of mobile subscriber's residential municipality. First-Stage F-statistic is the f-statistic of the instruments from the first stage.

	(1)	(2)	(3)	(4)	(5)
	two_SLS_1	two_SLS_2	two_SLS_3	two_SLS	OLS
VARIABLES	vfd	vfd	vfd	vfd	vfd
vmd	29.00***	29.66***	29.74***	29.42***	1.537***
	(1.526)	(1.359)	(1.348)	(1.342)	(0.0764)
age_mob		-0.0337***	-0.0357***	-0.0364***	-0.228***
		(0.00962)	(0.00989)	(0.00986)	(0.00314)
sexe_mob			-0.697***	-0.714***	-2.764***
			(0.142)	(0.141)	(0.0881)
tempmax_moy				-0.155***	-0.134***
				(0.00812)	(0.00703)
Constant	6.257***	7.875***	8.270***	10.97***	26.08***
	(0.264)	(0.716)	(0.773)	(0.765)	(0.211)
Observations	428,750	428,750	428,750	428,750	428,750
R-squared	-0.281	-0.295	-0.297	-0.289	0.017
First-Stage F-statistic	1363	1785	1823	1829	.

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Nation_MtoF_data

Table 13: Mobile to fixed data interaction at nation level. The instrument is the population density of consumer's residential municipality. First-Stage F-statistic is the f-statistic of the instruments from the first stage.

Table (13) displays the estimation using two-stage least-squares regression for mobile to fixed data interaction. First of all, in Column (1), we observe a stronger positive and statistically significant effect. The next three columns (2) and (4) then introduce sequentially the controls. Again we see the results are rather stable across the additional specifications and first-stage F-statistic remains highly significant.

Thirdly, Equation (8) is instrumented by the average maximum outdoor temperature measured in the area where the consumer lives for each month of observations.

$$V_{mv} = a_{mv} + \gamma_v^{FtoM} V_{fv} + \beta_{mv} X + \varepsilon_{mv} \tag{14}$$

$$V_{fv} = \pi_0^{mv} + \pi_1^{mv} Z_{temp\max\_moy} + \pi_2^{mv} X + \tau_{mv} \tag{15}$$

For fixed to mobile voice interaction, we start always by showing in Table (14) the basic OLS results, in Column (5), controlling for age and gender and the density of residential municipality. We see a positive, statistically significant coefficient suggesting at first glance that fixed voice consumption has positive impact on mobile voice consumption. But the OLS result only reflects the correlation and not a causal effect. Indeed, when we implement our empirical strategy by instrumenting fixed voice consumption V_{fv} using outdoor temperature, the sign of $\gamma_v^{FtoM}$is inverted from positive of OLS to negative. We can observe in Column (1) the negative coefficient for fixed mobile interaction parameter. This negative coefficient reflects the real causal impact from fixed voice consumption to mobile voice consumption. The next two columns (2) and (4) then introduce sequentially the controls intended to improve the regressions. The positive coefficient for sexe_mob and density means that the mobile voice consumption is higher for women and positively associated to the density of population .

Finally, Equation (9) is instrumented by the age of mobile subscriber.

$$V_{fv} = a_{fv} + \gamma_v^{MtoF} V_{mv} + \beta_{fv} X + \varepsilon_{fv} \tag{16}$$

	(1)	(2)	(3)	(4)	(5)
	two_SLS_1	two_SLS_2	two_SLS_3	two_SLS	OLS
VARIABLES	vmv	vmv	vmv	vmv	vmv
vfv	-0.653***	-0.795***	-0.788***	-0.862***	0.0981***
	(0.133)	(0.123)	(0.123)	(0.124)	(0.00325)
age_mob		-1.585***	-1.537***	-1.524***	-2.592***
		(0.138)	(0.141)	(0.142)	(0.0290)
sexe_mob			15.83***	16.08***	7.945***
			(1.369)	(1.384)	(0.816)
density				0.00611***	0.00582***
				(0.000132)	(0.000115)
Constant	229.6***	324.6***	314.4***	312.1***	278.7***
	(12.80)	(5.252)	(4.645)	(4.679)	(1.610)
Observations	428,750	428,750	428,750	428,750	428,750
R-squared	-0.112	-0.155	-0.151	-0.174	0.025
First-Stage F-statistic	286.4	350.6	353.7	351.2	.

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Nation_FtoM_voice

Table 14: Fixed to mobile voice interaction at nation level. The instrument is the average maximum temperature in the department where the mobile subscriber lives for each month of observations. First-Stage F-statistic is the f-statistic of the instruments from the first stage.

$$V_{mv} = \pi_0^{fv} + \pi_1^{fv} Z_{Age\_mobSubscriber} + \pi_2^{fv} X + \tau_{fv} \tag{17}$$

For mobile to fixed voice interaction, OLS results, in Column (5) of Table (15), controlling for age and gender of mobile subscriber and the density of residential municipality. We see a positive coefficient suggesting at first glance that the mobile voice consumption has positive impact on fixed voice consumption. Similarly to fixed to mobile voice interaction, when we implement our empirical strategy by instrumenting fixed voice consumption V_{mv} using age of mobile subscriber, the sign of γ_v^{MtoF} is inverted from positive of OLS to negative. We can observe in Column (1) the negative coefficient for mobile to fixed interaction parameter. This negative coefficient reflects the real causal impact from mobile voice consumption to fixed voice consumption.

	(1)	(2)	(3)	(4)	(5)
	two_SLS_1	two_SLS_2	two_SLS_3	two_SLS	OLS
VARIABLES	vfv	vfv	vfv	vfv	vfv
vmv	-0.444***	-0.462***	-0.448***	-0.450***	0.0138***
	(0.00773)	(0.00803)	(0.00770)	(0.00770)	(0.000717)
sexe_mob		12.71***	12.41***	12.44***	5.061***
		(0.563)	(0.553)	(0.554)	(0.385)
density			0.00292***	0.00292***	0.000416***
			(8.70e-05)	(8.71e-05)	(5.46e-05)
tempmax_moy				-0.352***	-0.526***
				(0.0435)	(0.0309)
Constant	170.1***	167.6***	161.3***	167.4***	99.80***
	(1.318)	(1.333)	(1.230)	(1.390)	(0.592)
Observations	428,750	428,750	428,750	428,750	428,750
R-squared	-0.954	-1.030	-0.965	-0.970	0.002
First-Stage F-statistic	7292	7029	7449	7475	.

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Nation_MtoF_voice

Table 15: Mobile to fixed voice interaction at nation level. The instrument is the age of mobile subscriber. First-Stage F-statistic is the f-statistic of the instruments from the first stage.

9 Conclusions

In this study we empirically estimate fixed-mobile interaction by using a three-stage least-square (3SLS) regression. Based on the consumption of 43,069 customers who own both fixed broadband and mobile services, we find causal dependency. Fixed and mobile substitute one another on voice services and complement one another on data services for these customers. We find a significant proportion of fixed (mobile) voice consumptions could be substituted by mobile (fixed) voice. However, a substantial proportion of fixed data consumption, as well as mobile data consumption, is generated by FM interaction in both directions. These results suggest that policy makers should support fixed-mobile convergence rather than promote competition between fixed and mobile players. FTTH deployment has no significant impact on fixed-mobile voice substitution. The fixed data consumptions generated by mobile to fixed interaction appear to increase with FTTH deployment.

The next step could be to study choice and consumption by taking into account of the existence of mobile-only consumers (a low proportion in Western European countries). Indeed, as far as the dataset on the subscribers of both fixed and mobile data suggests, these services complement one another. However, the existence of mobile-only consumers means they can also act as substitutes. Based on the choice of mobile-only or fixed-mobile and their respective consumption, a structural econometric study could deepen our understanding of consumers' choices and behavior.

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Appendix

9.1 3SLS regressions for nation representative consumers, FTTH covered area and FTTH subscribers

3SLS regression for nation representative consumers

```
Three-stage least-squares regression
----------------------------------------------------------------------
Equation          Obs  Parms        RMSE    "R-sq"       chi2        P
----------------------------------------------------------------------
vmd           4.3e+05      1    .7356975   -0.4848   34955.03   0.0000
vfd           4.3e+05      1    40.93202   -1.0430   71710.19   0.0000
vmv           4.3e+05      1    401.4588   -1.2636   32226.03   0.0000
vfv           4.3e+05      1    169.9135   -0.8424   35155.87   0.0000
----------------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
vmd          |
         vfd |   .0168816   .0000903   186.96   0.000     .0167047    .0170586
-------------+----------------------------------------------------------------
vfd          |
         vmd |   53.03441   .1980465   267.79   0.000     52.64624    53.42257
       _cons |   1.327088   .0357711    37.10   0.000     1.256978    1.397198
-------------+----------------------------------------------------------------
vmv          |
         vfv |   -2.33265   .0129941  -179.52   0.000    -2.358118   -2.307182
       _cons |   391.5617   1.363146   287.25   0.000       388.89    394.2334
-------------+----------------------------------------------------------------
vfv          |
         vmv |  -.4166532   .0022222  -187.50   0.000    -.4210085   -.4122978
       _cons |   165.7364   .4357057   380.39   0.000     164.8824    166.5903
------------------------------------------------------------------------------
Endogenous variables:  vmd vfd vmv vfv
Exogenous variables:   age_mob rain_avg tempmax_moy density sexe_mob
```

3SLS regression for FTTH covered area consumers

Three-stage least-squares regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
vmd	1.1e+05	1	1.275726	-0.8913	30434.72	0.0000
vfd	1.1e+05	1	83.86682	-0.7528	32764.38	0.0000
vmv	1.1e+05	1	358.6473	-0.8369	8990.03	0.0000
vfv	1.1e+05	1	198.6515	-1.2053	8531.10	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
vmd						
vfd	.0151998	.0000871	174.46	0.000	.015029	.0153706
vfd						
vmd	65.68259	.3628685	181.01	0.000	64.97139	66.3938
_cons	.0543188	.0496679	1.09	0.274	-.0430285	.1516661
vmv						
vfv	-1.78511	.0188271	-94.82	0.000	-1.822011	-1.74821
_cons	371.4508	2.048551	181.32	0.000	367.4357	375.4658
vfv						
vmv	-.5486972	.0059406	-92.36	0.000	-.5603405	-.5370538
_cons	205.7226	1.284962	160.10	0.000	203.2041	208.2411

Endogenous variables: vmd vfd vmv vfv
Exogenous variables: hh_income density tempmax_moy age_mob sexe_mob

3SLS regression for FTTH subscribers

Three-stage least-squares regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
vmd	91617	1	1.095557	-1.2929	30822.72	0.0000
vfd	91617	1	83.1929	-0.3987	36518.95	0.0000
vmv	91617	1	367.0962	-0.8473	8060.95	0.0000
vfv	91617	1	198.1973	-1.2070	7805.85	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
vmd						
vfd	.0131633	.000075	175.56	0.000	.0130163	.0133102
vfd						
vmd	75.872	.3970291	191.10	0.000	75.09383	76.65016
_cons	.0487464	.0484511	1.01	0.314	-.046216	.1437088
vmv						
vfv	-1.831165	.0203955	-89.78	0.000	-1.87114	-1.791191
_cons	383.8226	2.267224	169.29	0.000	379.3789	388.2663
vfv						
vmv	-.5347698	.0060528	-88.35	0.000	-.5466331	-.5229065
_cons	207.1973	1.359362	152.42	0.000	204.533	209.8616

Endogenous variables: vmd vfd vmv vfv

Exogenous variables: hh_income density tempmax_moy age_mob sexe_mob

9.2 Hausman tests between 3SLS vs. OLS reject exogenous hypothesis of OLS

```
                ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |  nation_3sls   nation_ols     Difference          S.E.
-------------+----------------------------------------------------------------
vmd          |
         vfd |    .0168619     .0028984        .0139635        .0000854
-------------+----------------------------------------------------------------
vfd          |
         vmd |    53.14044     2.534295        50.60615        .1840556
       _cons |      1.3191     10.76137       -9.442272               .
-------------+----------------------------------------------------------------
vmv          |
         vfv |   -2.351967     .0652849       -2.417251        .0125124
       _cons |    393.4746     160.5403        232.9343         1.25865
-------------+----------------------------------------------------------------
vfv          |
         vmv |   -.4140211      .014328       -.4283491        .0020587
       _cons |     165.322     93.71889        71.60316        .3669235
------------------------------------------------------------------------------
                          b = consistent under Ho and Ha; obtained from reg3
           B = inconsistent under Ha, efficient under Ho; obtained from reg3

    Test:  Ho:  difference in coefficients not systematic

                  chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =   361565.27
                Prob>chi2 =      0.0000
                (V_b-V_B is not positive definite)
```

The OLS estimates are in column B, and 3SLS in b. This result is expected because OLS yields inconsistent estimates and so we know the exogeneity hypothesis of OLS is false. Therefore the exogeneity hypothesis of OLS is rejected.

9.3 Over identification test for simultaneous equations from randomly reduced observations

```
Three-stage least-squares regression
----------------------------------------------------------------------
Equation          Obs  Parms        RMSE    "R-sq"       chi2        P
----------------------------------------------------------------------
vmd               643      1    .4235687   -0.3481     162.68   0.0000
vfd               643      1    25.62411   -0.8530     244.13   0.0000
vmv               643      1    461.7856   -2.2560      45.89   0.0000
vfv               643      1    159.7796   -0.5468      60.32   0.0000
----------------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
vmd          |
         vfd |    .015541   .0012185    12.75   0.000     .0131528    .0179291
-------------+----------------------------------------------------------------
vfd          |
         vmd |   57.53269   3.682202    15.62   0.000     50.31571    64.74967
       _cons |    1.32707   .6105056     2.17   0.030     .1305006    2.523639
-------------+----------------------------------------------------------------
vmv          |
         vfv |  -2.852254   .4210252    -6.77   0.000    -3.677449    -2.02706
       _cons |   447.9393   43.98355    10.18   0.000     361.7331    534.1454
-------------+----------------------------------------------------------------
vfv          |
         vmv |  -.3368853   .0433746    -7.77   0.000     -.421898   -.2518726
       _cons |   154.4887    9.24677    16.71   0.000     136.3654    172.6121
------------------------------------------------------------------------------
Endogenous variables:  vmd vfd vmv vfv
Exogenous variables:   hh_income density tempmax_moy age_mob sexe_mob
------------------------------------------------------------------------------

.
.  overid

Number of equations : 4
Total number of exogenous variables in system : 6
Number of estimated coefficients : 7
Hansen-Sargan overidentification statistic :    22.387
Under H0, distributed as Chi-sq(17), pval = 0.1703
```

In this randomly reduced dataset, the estimation gives similar results than the initial dataset. The p-value for the Sargan-Hansen test of overidentifying restrictions is higher than 0.1. This result does not reject joint null hypothesis that the instruments are uncorrelated with the error.