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Intra-operator mobile plan switching: Evidence from linked survey and billing microdata

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A B S T R A C T

This paper examines consumers' intra-operator mobile phone plan switching in Ireland. It models the factors associated with switching outcomes, including the direction of change in expenditure and whether those who are observed to switch plans tend to arrive at more or less optimal plans given their usage. A dataset is employed that combines survey responses from mobile consumers with the same consumers' actual usage data in the period 2017–2019; this was collected by Ireland's national regulatory authority. The cost each consumer would have incurred on every plan offered in the market based on their observed usage is estimated. Using models that allow for selection into switching, associations between switching outcomes and demographic and user characteristics are modelled. Controls are included for plan and user attributes, including demographics and proxies for user sophistication and access to alternative communication options. A substantial proportion of intra-operator switchers in the sample increase expenditures when they switch plan. While many switchers move to plans that are more optimal given their usage, a slight majority move to plans that charge a higher price premium over the best available plan (based on observables) than the consumer's previous plan did. Few observable characteristics of consumers or plans seem to be significantly associated with which switches achieve greater optimality, although fixed operator effects are large and significant. These findings add to the weight of evidence which finds that many consumers fail to arrive at the best price even after switching.

Abbreviations: AIC, The Akaike Information Criterion test; BIC, Bayesian Information Criterion test; Billpay_L, Bill-pay plan in the previous period (lagged); Bundle_L, Bundled plan in the previous period (lagged); CAPI, Computer Aided Personal Interviewing; Coef, Coefficient; dExpenditure, Change in plan expenditure; DV, Dependent variable; Exceed_L, Exceeded allowances in the previous (lagged); Expenditure_L, Plan expenditure in the previous period (lagged); Handset_L, Handset included in plan in previous period (lagged); OLS, Ordinary Least Squares; RLAH, Roam Like at Home; SD, Standard deviation; SE, Standard error; SMS, Short Messaging Service.

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1. Introduction

Mature mobile telecommunications markets tend to be relatively concentrated, with a small number of network operators often accompanied by a set of mobile virtual network operators and resellers (European Commission, 2016). Regulators have made significant efforts over time to remove barriers to consumer search and switching, with a view to facilitating competition; for example, switching costs have been reduced by imposing mobile number portability and informational barriers have been reduced by the emergence of price comparison tools. Nevertheless, rates of inter-operator switching vary across markets and over time, with many jurisdictions seeing relatively little switching and a high proportion of consumers reporting that they never switch operator (Lunn & Lyons, 2018). This phenomenon has been recognised for some time, and the barriers to inter-operator switching have been extensively studied. In contrast, less is known about the factors underlying switching among plans but staying with one's existing operator. This is referred to as intra-operator switching. The extent to which intra-operator switching is common, the mechanisms behind it, and the consumer outcomes associated with it, may have implications for the nature of competition in mobile markets and the distribution of benefits among consumers, particularly in places where the extent of inter-operator switching is low.

This paper asks three main questions: What are the main factors associated with higher probability of switching to another plan with the same operator in the mobile telephony market? Do consumers who switch in this way mainly switch to higher-cost or lower-cost packages? Finally, do consumers generally arrive at more or less optimal plans than the ones they switched from, given their pattern of consumption of services? The current paper addresses these questions using data from Ireland that links a consumer survey with billing data on the same consumers' chosen mobile plans, usage of services and expenditures. The main contributions of the paper are that it adds to the very limited literature on intra-operator (as opposed to inter-operator) switching and that it does this using microdata drawn from all the main service providers in a national market.

The basic mobile phone service offering, including voice calls, SMS (Short Messaging Service) texts and mobile data, may seem broadly similar across providers, but it is subject to considerable differentiation. Varying combinations of services, usage allowances, costs, brand image and contract terms are offered to, and ultimately chosen by, consumers. The retail market also includes important goods and services such as handsets, "over the top" media services such as streaming platform subscriptions and other digital applications that may act as complements or substitutes. Service offerings from different markets are sometimes combined in wider telecommunications bundles (e.g., broadband, fixed-line (landline) phone, television), further complicating the choices available to consumers and the task of analysing consumer responses.

Much of the literature modelling the determinants of consumer demand in mobile telecoms relies on experimental studies of hypothetical choice of consumers in stylised environments, e.g. Friesen & Earl (2015). This approach has advantages in allowing strong control of the choice setting and establishing causality, but some argue that the validity of these hypothetical studies for real world consumer behaviours may be limited (Confraria et al., 2017). In this paper observational data are employed to examine consumer choices from a large set of actual mobile telecommunications packages. This approach can be seen as complementary to experimental studies, as it has advantages in establishing external validity and incorporating the richness of the actual market, though it cannot achieve a fine level of experimental control or claim to have uncovered causality.

In examining consumer choices in the mobile phone market, the motivation for study arises primarily from the regulatory sphere. Regulation of digital networks and services, including telecommunications, encompasses facilitation of competition and protection of consumers, among other mandates. From a regulatory perspective, the findings can provide insight on how consumers make decisions in a complex marketplace and may help regulators establish how well retail markets are working and identify where consumers (or particular consumer groups) may need regulatory or legislative protections. This is particularly important given that the market is mature but still characterised by rapid technical progress. Indeed, the market for mobile phones have been described as technology push-driven, where products are created in advance of the identification of recognised consumer needs (Karjaluoto et al., 2005). Regulators require insights into an evolving market where operators try to efficiently manage churn, acquire new customers and design optimal market offerings.

Understanding consumer choice in the mobile phone plan market has taken on added importance in the context of the COVID-19 pandemic and the rapid move to remote working. For example, a survey revealed that 89% of people in Ireland valued their use of their mobile phone during the pandemic, with 45% of working people using voice calls and SMS for work, and 42% using mobile data for work purposes (ComReg, 2020a). A large majority of respondents were satisfied with their mobile services: 84% believed that their mobile phone voice calling service was adequate for working remotely and 73% found their mobile data adequate; however, around one-in-ten reported that their mobile voice (9%) and data (12%) services were not adequate for their work activities (ComReg, 2020a). Given the policy emphasis on scope for continued remote working beyond the COVID-19 pandemic, the quality of mobile services will likely remain an important enabling factor.

The structure of the paper is as follows. Section 2 reviews the international literature on consumer choices in mobile telecoms and provides a brief description of the Irish mobile telecoms market. Section 3 outlines the methods used, including a description of the data and formulation of econometric models. The results are presented in Section 4. Section 5 discusses the findings considering policy implications, as well as the merits and limitations of the research, concluding the paper.

2. Background

To provide research context, a review of the literature on consumer choice in mobile telecoms services is presented, followed by a brief overview of the market in Ireland.

2.1. Literature on consumer choice in mobile telecoms

There is a substantial body of literature examining consumer choice in mobile telecommunications. The evidence concerning choice of mobile plans and operators is first reviewed, followed by studies investigating switching in these markets.

2.1.1. Consumer choice of mobile phone plans

A large body of literature has used experimental methods to explore how consumers select among mobile phone options. In an early study, Riquelme (2001) considered bounded rationality when choosing from a large array of mobile phone options. Consumers with prior experience could predict their choices relatively well, although knowledge remained imperfect, and respondents tended to both over- and underestimate the importance of certain features. Earl et al. (2019) conducted an experiment whereby consumers had an hour to select the best tariff for specified usage – many discovered the optimal choice, but only one in twenty managed to select it. Friesen & Earl (2015) found that complex tariffs led to sub-optimal decision-making, even after many rounds of feedback. However, numerical literacy and task experience was found to improve decision-making. Martins & Szrek (2019) also found evidence in an experimental setting that people with poor numeracy are less likely to choose the cheapest (optimal) plan.

Experimental evidence reveals important features of consumer preferences and demand; however, observational studies provide complementary empirical evidence on real-world consumer choices and demand. There is a long history of observational studies on tariff choice and its welfare effects in telecoms. One dimension examined in the 1970s onwards was how consumer demand responded to a change from flat-rate to metered service for local fixed line telephony services. While theory implies that metered service should be more efficient as it aligns marginal prices more closely to costs, it was noted at an early stage that consumers generally prefer flat-rate tariffs (Mitchell, 1978). Empirical studies showed the effects on demand from changing this aspect of tariff structure to be modest (Train et al., 1987). Later work considered how well consumers are able to find the optimal plan from a set of alternatives. Some argued that fixed line telephony consumers choose rationally in both static and dynamic terms (Miravete, 2003), whereas others concluded that sub-optimal choices can persist (Mitchell & Vogelsang, 1991; Taylor, 1994). Many of the reasons advanced for suboptimal use of optional tariffs in fixed line telephony services were essentially informational, including uncertainty about future demand; misperception of current consumption and prices; or attempts to limit bill variations in the face of volatility in usage. Other explanations, including inertia or satisfaction from the act of choosing, brought in aspects of consumer preference or behavioural factors. Questions around consumers' abilities to select the best plan and biases at play continue to be explored in the current telecommunications literature, now with a focus on mobile telephony and data services.

Using panel data of the usage of mobile phone services of over 6,800 customers of a single operator in an (unspecified) Asian country in 2002, Kim et al. (2010) analysed a sequential consumer demand model of plan choice and quantity demanded of voice and SMS services. SMS and voice services were found to be weak substitutes, and there was a low own price elasticity of voice calls (inelastic). User sensitivity varied depending on demographic characteristics, with younger users and females exhibiting more inelastic demand. The authors also highlighted that users chose sub-optimal plans among those offered by the operator, with substantial differences between actual and expected consumption.

Demand for mobile services and substitution patterns were also estimated by Ida & Kuroda (2009) in a study which focused on 2G and emerging 3G mobile telephone services among three operators in Japan. Using mobile usage data on 687 customers, discrete choice modelling revealed that substitution across services was stronger within providers than across providers e.g. the closest substitute for operator 1's 3G service was operator 1's 2G service, rather than operator 2's 3G service. The authors suggest that this was driven by switching costs, with subscribers locked-in to providers through telephone numbers, family-member discounts and long-term discounts. Variations in the elasticities of products across the generation of services were also uncovered.

Other studies use operator data to examine how consumers choose between increasingly complex mobile service offerings. Grzybowski & Liang (2015) considered the demand for fixed-mobile bundles, specifically quadruple play tariffs (including mobile voice and data, fixed internet provider voice, fixed broadband and internet provider TV) using data on over 4400 European subscribers. Consumers placed a negative valuation on contractual commitment and a positive marginal value on mobile data and voice minutes included in bundled tariffs, with positive valuations on tariffs with unlimited minutes. The researchers suggested that mobile voice was a substitute for fixed broadband access and consumers reduced their voice consumption once they secure a broadband connection. They also find that consumers value unlimited calls less when fixed Voice Over the Internet Protocol (VoIP) is included in the tariff, which may be driven by consumers using Internet access for voice calls.

Existing literature on the choice of mobile handsets also provides useful background on factors that may underlie choice in the *plan* market. Examples include gender, "tech savviness" and brand familiarity (Karjaluoto et al., 2005), operating system familiarity (Grzybowski & Nicolle, 2021), and user "type" e.g. techno-fun oriented versus value-driven (Mazzoni et al., 2007). Evidence of inertia with respect to handset operating systems and brands has also been documented (Grzybowski & Nicolle, 2021).

2.1.2. Consumer choice of mobile operators

The choice of mobile operator by consumers has also been widely studied. Maicas et al. (2009) found that the probability that a customer selected a specific operator increased with the number of members of their social network already subscribed to that firm. Price, proxied by the average revenue per user for firms, negatively influenced choice of operator, while firm size had a positive influence. The results indicated that more intense users valued their social network more, while users who stayed longer with a network were less sensitive to personal network effects. 'Sophisticated' users, defined as those with 'a deep knowledge of the service offered by the operator', were found to have a higher perception of personal network effects and were better able to select the best option.

Focusing on voice plans, Sobolewski & Czajkowski (2012) modelled operator choice between four operators. Operator brand seemed to affect consumer utility and choice, where operators endeavoured to present themselves as differentiated even though functionally identical services were sold. There was also a significant impact of the "status quo operator" on each of the respondent's choices, where strong loyalty, even in hypothetical choices, increased switching costs.

A substantial amount of research in the area of mobile operator choice has examined the degree to which closed user groups or "network effects" affect choices, both those concerning the size of an operators' network in aggregate and those concerning personal or local network effects e.g. having family and friends on a network (e.g. Karacuka et al., 2013; Kim & Kwon, 2003). These can often be tariff-mediated e.g., induced when operators charge higher prices for off-net and on-net calls (Birke & Swann, 2006).

2.1.3. Search and switching

There is an extensive literature on the factors encouraging or discouraging consumer search and switching between operators, as well as policies such as mobile number portability that are intended to make switching easier and less costly. Much of this research focuses on inter-operator switching as opposed to intra-operator switching.

Switching intentions and the determinants thereof have been empirically explored in several contexts. In the Irish context, Lunn & Lyons (2018) used data from the Irish telecommunications regulator to investigate how consumer and service characteristics relate to switching intentions, using a sample of 1069 customers. Bill shock, having children in the household, expecting large savings (>20%), being younger and in the lowest income group were revealed to be significant positive factors associated with intention to switch mobile provider, while working on home duties and being a long-standing customer had a negative effect. The findings suggested that it may be increasingly challenging to encourage a core group of non-switchers to participate in search and switching activities as time passes.

Kim & Yoon (2004) explored subscriber churn and customer loyalty among customers of five mobile operators in Korea. The probability that a subscriber switched operator was dependent on satisfaction with factors such as call quality, tariff level, and subscription duration. A 'lock in effect' was evident, with consumers sticking with their operator unless they encountered significant flaws or dissatisfaction. The authors propose that consumers have limited ability to discern differences in quality across operators as more technologies are incorporated. Thus, building a distinctive brand name is likely to be a fruitful investment for operators.

Many consumers are reluctant to search and switch in the mobile telecommunications market. This phenomenon is known as consumer inertia, and it is mostly studied in an inter-operator context. Mesquita & Urdan (2019) characterise inertia as "spurious loyalty", prevalent in the provision of ongoing services, and it can also be understood as switching avoidance, passiveness and resistance to change. Several theoretical reasons are proposed for consumer inertia in telecommunications. First, behavioural economics highlights the importance of search costs, heuristics, status quo bias, defaults, and time scarcity in decision making. Harrison et al. (2011) commented that the complexities of telecommunications offerings can lead to stress, confusion, and information overload, as well as indecision and inertia for consumers, resulting in poor outcomes for consumers. Second, any monetary switching or transaction costs will cause inertia (Grzybowski & Liang, 2015). Third, the nature of the market may exacerbate reluctance to switch, in that consumers are not completely free to choose if contractually bound (Birke & Swann, 2006). However, operators also expend effort to retain consumers using personalised pricing among other strategies (Capponi et al., 2021). This may leave consumers vulnerable to exploitation when they do not switch.

While some consumers remain inert, others do switch operator. Indeed, operators may have strong incentives to engage in consumer retention strategies, given the high costs of acquiring new consumers over retaining existing ones (Seo et al., 2008). Operators' efforts to identify churn-prone consumers and discourage them from switching have been well studied using machine learning methods among others (Huang et al., 2015; Lu et al., 2014). Intra-operator churn has also been considered using these methods to consider consumers' propensity to switch between technologies e.g. 4G versus 2G/3G (Zhang et al., 2018, 2020). Machine learning models are well-suited to predicting, and to some degree characterising, switching and churn. However, they are not well placed to examine causal links between propensity to switch and consumer characteristics or the outcomes of such switches. The present paper is the first one to take this approach to date.

2.1.4. Challenges in decision-making

A final relevant strand of the literature focuses on how well consumers make complex choices in the telecoms market. Gerpott & Meinert (2016) examine the factors associated with tariff misfit associated with switches to flat rate plans, and find more misfit among older consumers, as well as those with longer operator tenure, greater usage variation and those whose phone is not an iPhone.

Uncertainty and difficulty in estimating and predicting usage are other reasons why consumers might make poor decisions in the mobile plan market. Han et al. (2021) develop a model of mobile plan choice under uncertainty and use experimental data to argue that consumer choice reflects uncertainty more than can be justified by rational choice. Uncertainty about price components creates disutility for consumers, particularly when usage is also uncertain. Consumers may overestimate how precisely they forecast their usage. In the context of fixed line telephone services, Narayanan et al. (2007), note that consumers are more prone to switch from metered to fixed plans than they are to switch from fixed to metered plans *ceteris paribus*, and they attribute this to uncertainty about usage and slower learning when there is a fixed allowance of service.

Grubb (2009) finds that firms offer tariffs designed to exploit overconfidence about consumer knowledge of usage in the mobile phone market in the USA. Grubb (2015a,b) has also suggested that even where a market has substantial competition, firms may exploit consumer confusion and inertia by obfuscating prices, providing complex pricing schedules which make price comparison difficult and soften competition. Gabaix & Laibson (2006) argue that firms may hide or shroud high add-on prices in the presence of myopic (or unaware) consumers and show that informational shrouding can occur even in highly competitive markets. A related phenomenon is salience bias, whereby consumers are overly influenced by the salience of overusing or underusing their plan allowance, leading to poor choices (Jin et al., 2021).

Consumers may also be willing to pay to avoid variation in billing rates. Lambrecht & Skiera (2006) find evidence of consumers who would be better off on a pay-per-use tariff preferring a flat rate, which they explain by insurance effects, convenience and taxi-meter effects (the idea that consumers enjoy usage more when it is decoupled from payment). In a similar vein, a working paper by Genakos et al. (2015) finds that exceeding the monthly recurrent fee impacts plan switching decisions among a panel of mobile phone users, and interprets the findings as evidence of loss aversion.

The evidence reviewed in this paper documents a strong research interest in choices and issues in mobile telecommunications, which has evolved as the offerings made to consumers advance with technological development. A number of studies explore why consumers may be on suboptimal mobile phone plans, and this paper aims to contribute to an understanding of intra-operator switching with linked billing and survey data from Ireland.

2.2. Mobile telecoms in Ireland

As is the case across the world, mobile phones are ubiquitous in the Ireland of 2022, with a penetration rate of mobile subscriptions of 105 per 100 persons (World Bank, 2020). Following some consolidation, Ireland currently has three mobile networks that own and operate their own network infrastructure - Eir Mobile, Three Ireland and Vodafone Ireland. In recent years, a number of mobile virtual network operators have emerged that operate services using one of these infrastructure providers' radio networks, e.g., Tesco Mobile, Virgin Mobile, Lycamobile and An Post Mobile. SIM-only plans have emerged whereby a consumer retains their handset upon switching. Such developments may be conducive to encouraging competition in the market and facilitating more switching, including between plans with included handsets and those without. There have also been some additional brands launched by network operators such as 48 (launched by Three, introduced in 2012), GoMo (Eir Mobile, in 2019) and Clear Mobile (Vodafone, in 2021) (Godlovitch et al., 2021). The retail market shares of the largest mobile operators in 2019, the period for which we study the mobile plan market in Ireland, were as follows: Vodafone captured 38.3% of the market, Three 35.3%, Eir 17.1% and Tesco 6.3% (ComReg, 2020b).

3. Methods and data

The analytical approach and the main features of the data are described in this section.

3.1. Analytical framework

To fully understand consumer switching decisions, one would ideally like to observe and model the full set of available choices: whether to search for a better service offering, to switch to another operator, to switch to another plan with the same operator or to remain with the current plan. Conditional on those choices, does the consumer arrive at a plan delivering more consumer surplus? The role of handset replacement might also be important, since this can be a trigger for switching operator or plan, and it can amount to a significant portion of the combined cost of mobile service access and use.

Due to data limitations, this paper can explore only a subset of branches in the tree of possible choices about switching. Specifically, the outcomes of *intra*-operator switching are modelled, where a customer decides to remain with the same operator and switch mobile plans. For the purposes of this research, intra-operator switching is defined as a switch between different mobile plans offered by the same service provider under the same brand. The data do not allow an examination of switches between plans of different brands provided by an operator (e.g., the operator Three has the brands Three and 48 – only switches within the Three brand can be observed in these data, not switches among brands from the same operator). It is further noted that *inter*-operator switching decisions are not observed, that is, switches between different service providers (e.g., switching from the operator Three to the operator Vodafone is not observed), and there is little information on the consumer's handset before or after the switch. Nevertheless, the branch of intra-operator switching that can be observed is interesting because it has received little research attention to date. This focus on intra-operator switching implies that only a constrained form of optimality can be tested. Specifically, having decided to switch plan but not switch operator, and taking into account any change in usage, does the consumer's expenditure move closer or further to the cost of their operator's least costly plan? One might envision this as movement relative to an efficient consumption frontier. The plan that yields the lowest bill may change as a consumer's pattern and level of usage vary. The research question asks how the proportional premium paid by a respondent over the lowest available plan cost compares between the post-switching and pre-switching periods.

Due to data limitations, the consumer's rationale for switching plans cannot be examined directly in the current paper. Unobserved non-price factors can encourage a consumer to switch to a higher cost plan, for example to avail of a handset upgrade or service add-on. Changes in such unobserved characteristics may also drive some switches to lower cost plans. However, the scope for inference should be helped by focusing on *changes* in optimality due to switching rather than asking whether any consumer is on an optimal plan in a static sense in any period. For an error in measurement of changes to lead to an incorrect inference, consumers would need to value the unobserved attribute more highly in the post-switching period than before.

To construct a set of hypotheses for analysis, this section first considers some of the many different reasons why consumers might switch plans while staying with their operators. Some switching may be initiated by the consumer. In particular, the consumer's preferences for using mobile services may change in a way that makes their existing tariff plan appear less attractive than others available. This could involve a change in the mix or quantity of service components that the consumer expects to use in future. A similar rational motive for switching plan might be information-driven, as in cases where a consumer discovers they would prefer to be on a different tariff due to bill shock or some other informational reset.

There might also be consumer-initiated switches that are less optimal for the consumer. For example, there might be a change in the consumer's perception of service value that is not necessarily grounded in actual usage. For example, consumers that exceed their plans' fixed allocation of minutes or data might believe it is optimal to switch to a plan with a higher allowance, even in cases where it is not. Salience bias, whereby consumers may be overly influenced by over- or under-use of an allowance may drive this (Jin et al., 2021) as well as fixed-rate bias (risk avoidance) and "taxi-meter" effects where consumers prefer usage to feel decoupled from payment (Lambrecht & Skiera, 2006). The complexity and uncertainty surrounding these choices may exacerbate such biases.

There are also rationales for switching that are supplier-led. An operator might simply change the name and branding of a service, leading to something that looks like a switch of plan in the data but does not change anything substantively for the consumer. This is referred to as a "nominal switch" to distinguish it from a "real" switch. In some instances, suppliers do require customers to change plan; for example, when legacy plans are being dropped. Typically, in such cases the consumer is assigned to a new plan and has the option of accepting it, selecting a new plan from their operator, or switching. The authors are not aware of published evidence on whether default plans offered to customers in such cases tend to be more or less costly or to provide better or worse value. A more defensive strategy might involve offering special deals to consumers who signal a willingness to consider switching operators, as in win-back offers when churn is threatened (Zhang et al., 2020).

Unfortunately, no information was available on whether switchers previously considered or threatened inter-operator churn, and the data do not show whether the switch was initiated by the consumer or was suggested or imposed by the operator. Thus, it is not possible to fully disentangle the relative importance of these reasons for intra-operator switching.

Nevertheless, the current paper can cast some light on some possible reasons for intra-operator switching, by using a mixture of descriptive analysis and multivariate regressions to explore the associations between switching outcomes and demographic and user characteristics. Two types of switching outcomes are examined:

1. Did the consumer's expenditure on mobile services rise or fall after the switch compared to the position before it?
2. Did the consumer arrive at more optimal plan, conditional on usage, after the switch compared to before it? This is assessed by comparing the simulated cost of the chosen plan with the least costly plan offered by the consumer's supplier, conditional on a consumer's current usage in each period. Previous research has indicated that a significant share of consumers may be on sub-optimal plans at any given time, and some may even switch to plans that are less optimal than where they started (Gerpott & Meinert, 2016; Jin et al., 2021; and for energy markets,; Wilson & Waddams Price, 2010).

Four hypotheses that could be diagnostic of the main reasons for switching plan are tested:

Hypothesis 1. if intra-operator switches are mainly driven by a rational and well-informed choice, either because of a change in preferences for use of mobile services or because better information has become available to the consumer, few switches should leave the customer on a less optimal plan relative to their current usage than the one they were on before the switch. Unobserved attributes of plans and measurement error could lead to some optimal switches appearing suboptimal, but if the plan cost model used fits the data adequately these cases should be uncommon. In contrast, rational and well-informed switches may result in a mix of increases and decreases in expenditure as consumer preferences can lead to higher or lower demand for services.

Hypothesis 2. misperceptions of the plan price schedule, e.g., the salience bias emphasised by Jin et al. (2021), should lead to systematic patterns in switching associated with subsets of usage patterns. This is tested by asking whether respondents who exceed an allowance for at least one service component in the pre-switch period are more prone to increasing expenditure and to ending up on a less optimal tariff than before, conditional on current usage, than respondents who did not exceed an allowance.

Hypothesis 3. if variations in consumers' information-processing abilities or experience with mobile services are important drivers of their success or otherwise in selecting the least cost tariff given their usage, respondent characteristics such as educational attainment or proxies for their sophistication in using these services should be positively associated with the probability of choosing a more optimal tariff when switching.

Hypothesis 4. to the extent that the pattern of switching outcomes is materially affected by the market position or strategy of their operator, large and statistically significant differences in average switching outcomes for customers of each operator should be found. This can be examined using operator fixed effects.

3.2. Econometric models

A range of alterative-level attributes may affect a consumer's decision to switch plan while remaining with their operator, and the outcomes of that switch in terms of the consumer's change in expenditure and optimality of the plan selected. These include fixed effects for the operator, the plan type (pre-pay or bill pay), whether a handset was included, contract duration; as well as the characteristics of consumers such as age, gender, socioeconomic status, location (urban/rural) and measures of consumer inertia, the importance of family/friends' networks in influencing plan choices as well as consumers use of applications/functions. The threshold for statistical significance is a p-value of <0.05.

Results are generated using two alternative estimators that make differing assumptions about the underlying processes. Controls for plan and user attributes are included, including demographics, proxies for user sophistication and access to alternative communication options. One approach is to estimate Ordinary Least Squares (OLS) regressions using the sub-sample of switchers. However, intra-operator switching is relatively uncommon in the sample, so the process of selection that leads to consumers becoming switchers might make this an unrepresentative group. Therefore, Heckman selection models are estimated to allow for the factors associated with higher or lower probability of making an intra-operator switch.

To provide further detail, the Heckman selection model (Heckman, 1976; Lewis, 1974) is useful where there are issues of selection, as is the case here, since only a subset of consumers select a new plan, and, as such, the outcomes of interest e.g. the change in plan expenditure, can only be observed for consumers who change their plan. As stated above, this group may not be representative of the entire sample which may bias the estimates, however the Heckman selection model accounts for this possibility.

More formally, a regression of the following form can be specified:

$$y_j^* = x_j\beta + \mu_{1j}$$

Where y denotes the dependent variable, for example a change in plan expenditure, by consumer j. This dependent variable is modelled as a function of a vector of independent variables represented by x_j. The error term, μ_{1j}, is normally distributed with a mean of zero and a variance of σ.

However, the outcome of interest, a change in plan expenditure, is only observed where an intra-operator switch, s_j, takes place, i. e., $y_j^* = y_j$ when $s_j = 1$. The selection equation can be represented as follows, with z_j denoting a vector of controls explaining selection into switching:

$$s_j = \begin{Bmatrix} 1 \ if \ z_j\lambda + \mu_{2j} > 0 \\ 0 \ if \ z_j\lambda + \mu_{2j} \leq 0 \end{Bmatrix}$$

Probit regression modelling estimates $z_j\lambda + \mu_{2j}$, where μ_{2j} is the error term of the selection equation.

The Heckman model provides consistent, asymptotically efficient estimates even where there is correlation between the error terms of the two equations. Estimation is by maximum likelihood, and standard errors are clustered at the customer level. The non-selection hazard or the Inverse Mills ratio is computed from the estimated parameters of the selection equation and is used as an indicator of whether selection is a significant feature of the data generation process.

Exclusion restrictions are imposed to assist with identification of the selection equation; in essence, particular factors are assumed to affect selection into switching but not (directly) the outcome of the switch (akin to an instrumental variable). The choice of factors for exclusion from the second stage regression will vary from case to case (Cameron & Trivedi, 2010).

3.3. Data

The data used in this study originate from Ireland's national regulatory authority for telecommunications, ComReg, who commissioned a face-to-face *Mobile Consumer Experience* survey in June 2019. The interviews were carried out in the homes of respondents via CAPI (Computer Aided Personal Interviewing), capturing 2838 participants. This was a nationally-drawn sample of the adult population (18 years plus), with a higher proportion of interviews administered in areas of lower population density (sampling detailed in (ComReg et al., 2019)).

The CAPI included a consent form enabling ComReg to request the respondent's service usage and billing information from their mobile service provider. It proved possible to link survey responses to objective usage and expenditure data for 1035 customers for billing periods between July 2017 to June 2019. Following the simulation of alternative plan costs (see below Section 3.4) and data cleaning, a final analytical sample of 928 consumers was identified for which all the variables for analysis were available.

Data cleaning involved translating plan descriptions into separate plan characteristics (e.g. allowance of off-net call minutes), as well as identifying and amalgamating plans which were nominally different but the same in terms of plan characteristics. One hundred nominal plan switches were also excluded for the purposes of this analysis, that is, when a change took place only in name - plan expenditure and allowances remained exactly the same.

The data form an unbalanced panel, with periods before and after the switch for those who switch.

3.4. Simulating expenditure under alternative plans

Plans, in the context of this research, are defined as service offerings or contracts that differ in some observable manner. Segmentation of the available data into plans was conducted empirically, by identifying the permutations of operator, contract type (prepay vs. bill pay), usage allowances for various voice call, data and SMS components and cost that occurred within the dataset. From the information provided by the four main mobile service providers in Ireland, 147 mutually exclusive plans were identified. These four services providers represent 97.2% of the market (ComReg, 2020b).

The hypothetical cost the consumer would have incurred had they been using each of the other plans available under their operator was then simulated using a top-down plan cost regression model akin to hedonic regression (see Appendix A.1.). This modelled plan expenditure as a function of plan attributes, such as calls, SMS and data allowances and usage as well as contract length, the inclusion of a handset in the plan, plan type (bill pay v pre-pay), and operator fixed effects among others.

Plan attributes can be binary in nature, e.g., whether or not the plan includes an unlimited data allowance. Such attributes are included in the model using 1/0 dummy variables. Other attributes are continuous, e.g., an off-net calling allowance with a varying number of minutes, and the scale of the attribute can be represented as a continuous variable. By regressing plan price on plan attributes, it is possible to estimate the average price of each binary attribute and the marginal price of each variable attribute. The measured effects are based on what is observed from individuals on their *chosen* plans. The coefficients associated with the attributes can then be applied to the broader choice dataset (e.g., to hypothetical individual-plan combinations, that is, plans that a consumer could but *did not choose*) to simulate the hypothetical cost of each alternative plan to each consumer, given their usage. When doing this, it is assumed that each consumer's usage in a given period is unaffected by the prices, terms and conditions of the plan they are on, a necessary limitation of this approach. The final simulated plan cost was divided by the number of days in the billing period to obtain a daily value. Eight consumers with extreme values in terms of observed plan expenditure (the top and bottom one percentile) were dropped from the dataset to reduce the potential impact of unrepresentative outliers on the results. To provide a normalised distribution of costs for modelling, the natural log of the plan cost variable was employed.

3.5. Definition of key variables

3.5.1. Dependent variables

Two alterative specifications are considered. In each, the first-stage regression outcome variable was a binary variable, equal to one where the consumer switched to another plan on the same operator and zero otherwise. Two second stage dependent variables are described as follows:

1) Change in Expenditure. This is the change in the log of the consumer's actual expenditure between the billing period after the switch and the period before it, which approximates to a percentage change. For example, imagine a consumer who spends €30 per month and then switches to a plan that costs €20 - Table 1 below shows how this corresponds approximately to a 41% decrease in plan expenditure.
2) Change in Premium. The premium is defined as the ratio of the expenditure associated with the plan the consumer is on to what the expenditure would be on the cheapest plan offered by their operator, conditional on their usage. It represents the proportional premium the consumer is paying over and beyond the optimal plan offered by their operator, according to the estimate employed. The change in premium is the difference in this ratio in the billing period after the switch compared to the ratio in the billing period before it. If consumers move to a more optimal plan by switching, this variable is expected to be negative. For illustration, an example is provided in nominal terms and represented in Table 2 (though log values are used in the analysis).

Consider a consumer who is with an operator offering, for simplicity's sake, three plans: Plans Bronze, Silver and Gold. If this consumer were on their operator's cheapest plan, Plan Bronze, the plan would cost them €10,[1] given their usage. Say the consumer is originally on Plan Gold which costs €30. Plan Gold is thus €20 more than the lowest price they could pay. Suppose the consumer then switches to Plan Silver that costs €20, given their new usage. Plan Silver is still €10 more than the minimum. The premium before the switch is the actual expenditure minus minimum expenditure before (€30-€10), divided by the minimum (€10), giving a premium of 2 or a 200% premium. Using the same method, the premium after the switch is 1. The change in premium is therefore −1 or a 100 percentage point decrease in premium after the switch.

3.6. Independent variables

A variety of plan, user and demographic characteristics are considered in the regression analyses. Controls are included for the consumer's operator and plan type (pre-pay or bill pay), contract length, whether a handset is included in the plan cost and whether the consumer's plan is part of a bundle. All these variables are lagged by one period; in effect, they represent the consumer's situation immediately before the switch. An indicator variable for whether a consumer exceeded any of their SMS, call or data allowances during the period before the switch is also included, as well as a lag of the dependent variable (e.g. pre-switch expenditure or plan premium). In the expenditure regressions, the lagged dependent variable controls for whether the consumer is a heavy or light user of services, and in the optimality regressions it controls for how much scope the consumer had before the switch to improve the optimality of their plan.

Demographic characteristics considered in the regression analyses (see Appendix section A.2.1) include dummy variables indicating respondent age group (i. 18–34 years; ii. 35–49 years; iii. 50 years or older) and respondent education level (i. primary education or none; ii. secondary or post-secondary education; iii. undergraduate degree or higher). An indicator of whether a respondent has broadband internet is also considered, which may be associated with increased price sensitivity if it is a substitute for mobile phone usage.

Factors included in the Heckman selection equations but omitted from the second-stage expenditure and premium equations (exclusion restrictions) include an indicator of whether the respondent reported making Wi-Fi calls (e.g. via WhatsApp) at least once a month, which could be considered as a proxy for tech-savviness, and being on a very short (1 month) or no service contract, which might indicate that the respondent faced lower contractual barriers to switching than those on longer contracts.

[1] All costs per month.

Table 1
Worked example of expenditure change variable.

Expenditure before	Expenditure after	Change in log expenditure
€30.00	€20.00	ln (20)-ln (30) ≈ −0.41

Table 2
Worked example of change in plan premium over cheapest plan offered by operator.

A	B	C	D	E	F	G	H
Plan Bronze	Plan Gold	Plan Silver	Gold - Bronze	Silver - Bronze	Gold v Bronze	Silver v Bronze	
Minimum expenditure given usage	Expenditure pre-switch	Expenditure post-switch	(Expenditure - minimum) pre-switch	(Expenditure - minimum) post-switch	Premium pre-switch	Premium post-switch	Change in Premium
€10.00	€30.00	€20.00	€20.00 (€30-€10) (B-A)	€10.00 (€20-€10) (C-A)	2 (€20/€10) (D/A)	1 (€10/€10) (E/A)	−1 (2–1)/1 (F-G)/G

4. Results

4.1. Descriptive statistics

Market shares of operators in the sample broadly matched that of the retail market shares in Ireland, described in Section 2.2. Operator-specific results are redacted for confidentiality reasons.

Table 3 displays descriptive statistics for both the full sample and the sample who switch during this period. A similar share of consumers chose bill pay plans (52%) and pre-pay plans, although among switchers, a higher proportion chose bill pay (62%). Average plan cost per month was €29.65 for the full sample and €33.63 for the sample who switch, with a handset included in plan cost in circa 40% of cases and the mobile plan was part of a bundle in 9% of the full sample, slightly more in the switchers only group.

Over 85% of the sample had broadband internet in both cases and over 38% exceeded at least one of their SMS, call or data allowances in the period before the switch. As a proxy of user sophistication, 42% of the full sample made Wi-fi calls (e.g., using WhatsApp), and this was the case for 35% of switchers.

In terms of the demographic characteristics, the average age was 46 years and 48 years for the full sample and switchers,

Table 3
Characteristics of the analytical sample.

	Full sample			Switches only		
	N	Mean/Share	SD	N	Mean/Share	SD
Plan Characteristics						
Advertised plan cost (avg., € per month)	13899	29.65	14.02	195	33.63	15.43
Customer on bill pay plan	13899	.52	.5	195	.62	.49
Handset included in plan cost	13899	.38	.49	195	.44	.5
Bundled plan	13899	.09	.28	195	.12	.33
User-type Characteristics						
Exceeded allowance in pre-switch	13899	.38	.447	195	.48	.48
Consumer owns broadband internet	13899	.85	.36	195	.9	.3
Consumer makes Wifi calls regularly	13899	.42	.494	195	.35	.48
Demographics						
Age (mean)	12757	46.14	15.53	178	47.97	16.05
Married	13899	.55	.5	195	.55	.5
Rural	13899	.70	.5	195	.71	.45
Primary education or none	13899	.04	.2	195	.05	.22
Secondary/post-secondary education	13899	.58	.5	195	.59	.49
Undergrad/postgrad education	13899	.38	.49	195	.36	.48
Usage variables						
Average SMS usage (per day)	13899	3.19	5.86	195	2.35	3.36
Average total call usage (mins. per day)	13899	8.47	13.34	195	8.84	10.86
Average on-net call usage (mins. per day)	13899	3.55	6.19	195	3.85	7.35
Average off-net call usage (mins. per day)	13899	2.73	6.03	195	1.95	3.56
Average daily Ireland data usage (MBs)	13219	89.29	221.99	192	44.83	110.47
Average daily RLAH data usage (MBs)	13219	1.70	15.27	192	.25	1.51
Number of consumers	928			160		

Note: RLAH refers to Roam Like At Home data (i.e. mobile data usage outside Ireland but within the EU costs the same as it would in Ireland).

respectively. Much of the sample (70%) lived in rural locations, which the authors note were oversampled, and circa 38% had undergraduate or postgraduate education.

5. Summary statistics

5.1. Descriptive analysis of switching outcomes

A total of 160 consumers switched mobile plan in the period of analysis, with 195 switches among them (as some switch multiple times), representing 17% of the sample of 928 consumers for whom all variables were available. The group of switches in which the consumer increased expenditure after the switch was slightly larger than the group where expenditure fell (49% vs. 42%; see Table 4). A significant minority of those switches where expenditures increased also achieved a lower price premium. Nevertheless, compared to the best available plan after switching, many did not achieve a lower price premium. Focusing now on the column totals, Table 4 also shows that overall, a slight majority of switches appear to have increased the premium paid over the best available plan (54% vs. 44%). The relatively large share of switches moving consumers to less optimal plans should not be explained by preference variations alone, to the extent that the models used capture service usage adequately. To explore other possible mechanisms, multivariate analysis is performed.

5.2. Regression results

This section reports the results of multivariate models designed to explore the individual- and plan-level factors associated with changes in consumers' expenditures and in the premium paid compared to the lowest cost plan offered by the relevant operator. This section first shows results for models of the proportional change in expenditure, both allowing for selection into switching (with a Heckman correction) and OLS models focusing on switchers only. In all cases, the modelling allows for clustering of the standard errors at the level of the consumer, because some consumers switched more than once during the sample period.

5.2.1. Change in expenditure

Table 5 shows estimates from a Heckman selection model explaining the proportional change in expenditure on plans after the switch compared to before it. Expenditure in the period before the switch is positively associated with the likelihood of switching and negatively associated with the change in expenditure during the switch.

Consumers who exceed some allowance in the billing period before switching, i.e., those who are likely to face a positive marginal cost for some element of service, are also more likely to switch plans. When these consumers do switch, they are more likely to reduce expenditures, conditional on usage, than those who always stay within their allowances to begin with.

Strong operator-specific effects are found in both switching propensity and the change in expenditure. While consumers with a fixed broadband connection are marginally more likely to switch than those without one, fixed broadband service is not associated with systematically different mobile plan spending after the switch. Consumers who are on a very short contract (or none) are more likely to switch plans.

No significant associations are found for switching propensity or the change in expenditure after switching for those with handsets linked to their plans, on bill pay rather than prepay tariffs, or on bundled plans. There is a small and marginally significant negative effect found on switching propensity for those who report use of WiFi for calls. Other results reported in Appendix section A.2.1 show little evidence that demographic factors are significantly associated with the probability of intra-operator switching or the change in expenditure after switches.

From the diagnostics, it appears that selection has a significant effect on the estimated model for the change in expenditure (the Wald test of independent restrictions can be rejected indicating that there is correlation between the errors and selection is at play). This may help explain why signs and significance are quite different in the OLS switches-only model reported in Table 6.

Table 4
Classification of changes in expenditure and plan premium (% of switches; n = 195).

		Plan premium			
		Down	No change	Up	Total
Expenditure	Down	20.5	1.0	20.0	41.5
	No change	5.1		4.6	9.7
	Up	18.5	1.0	29.2	48.7
	Total	44.1	2.1	53.9	100.0

Table 5
Heckman regression results for change in expenditure (log difference between simulated expenditures on new and old plans).

	First stage (switch = 1)		Second stage (dExpenditure)	
VARIABLES	Coef	SE	Coef	SE
Expenditure_L	0.235	0.0577***	−0.556	0.115***
Handset_L	0.175	0.131	0.207	0.122*
Operator A (ref = OperatorD)	−0.341	0.129***	0.356	0.202*
Operator B (ref = OperatorD)	−0.615	0.108***	0.500	0.232**
Operator C (ref = OperatorD)	−0.599	0.127***	0.411	0.185**
Billpay_L	0.0445	0.125	0.173	0.154
Owns Broadband	0.223	0.122*	−0.0243	0.147
Bundle_L	0.156	0.152	0.293	0.199
Exceed_L	0.359	0.0943***	−0.303	0.134**
Contract = 1m_L	0.322	0.139**		
WiFi	−0.0898	0.0536*		
Constant	−2.576	0.191***	2.192	0.660***
Athrho	−1.547	0.296***		
Lnsigma	−0.0119	0.232		
Observations	13,899		195	
Consumers	928		928	
Switches	195			
Wald test of independent restrictions: $\chi 2$ (1) = 27.35; p = 0.000				
AIC: 2269				
BIC: 2450				

Note: Statistical significance: ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors clustered by respondent.
dExpenditure refers to the proportional change in expenditure after the switch compared to before.
Variables denoted with _L (lagged) refer to the period before the switch e.g., Billpay_L indicates that the consumer's pre-switch plan was bill-pay.

Table 6
OLS regression results for change in expenditure (log difference between simulated expenditures on new and old plans).

VARIABLES	Coef	SE
Expenditure_L	−0.383	0.104***
Handset_L	0.145	0.0997
Operator A (ref = Operator D)	0.0450	0.154
Operator B (ref = Operator D)	0.0227	0.132
Operator C (ref = Operator D)	−0.006	0.129
Billpay_L	0.112	0.121
OwnsBroadband	0.129	0.0810
Bundled_L	0.449	0.155***
Exceed_L	0.009	0.0880
Constant	−0.153	0.0897*
Observations	195	
Consumers	160	
R^2	0.208	
AIC: 317		
BIC: 350		

Note: Statistical significance: ***p < 0.01, **p < 0.05, *p < 0.1.

5.2.2. *Change in premium*

This section reports regression results for the change in the premium paid by the consumer for mobile services, defined as the ratio of the predicted cost of supplying their observed demand under their selected plan to the lowest predicted cost available from their operator. *Ceteris paribus*, and unlike expenditure in general, increases in this metric suggest that the consumer is on a less optimal plan after switching.

Table 7 provides estimates based on a Heckman selection model, and Table 8 shows the corresponding OLS results. In this case, the Wald test of independent restrictions does not reject OLS, and the OLS coefficients are similar to their second stage Heckman counterparts. Therefore, the OLS results are emphasised. Here too, demographic controls do not seem to play an important role (shown in Appendix section A2.2), though there is a weak and marginally significant positive association between living in a rural area and the

Table 7
Heckman regression results for change in plan premium (percentage change between simulated premiums on new and old plans).

	First stage (switch = 1)		Second stage (dPremium)	
VARIABLES	Coef	SE	Coef	SE
Premium_L	0.190	0.0742**	−0.681	0.107***
Handset_L	0.243	0.204	0.0365	0.0638
Operator A (ref = OperatorD)	−0.370	0.132***	−0.341	0.151**
Operator B (ref = OperatorD)	−0.556	0.109***	−0.0648	0.187
Operator C (ref = OperatorD)	−0.792	0.155***	1.143	0.335***
Billpay_L	0.0785	0.183	0.0641	0.0652
Owns Broadband	0.231	0.126*	−0.0471	0.112
Bundle_L	0.326	0.144**	−0.425	0.191**
Exceed_L	0.395	0.099***	−0.0477	0.141
Contract = 1m_L	0.338	0.300		
Wifi	−0.103	0.130		
Constant	−2.760	0.340***	0.609	1.076
Athrho	0.0159	1.568		
Lnsigma	−1.424	0.0755***		
Observations	13,899		195	
Consumers	928		928	
Switches	195			
Wald test of independent restrictions: $\chi2$ (1) = 0.00; p = 0.9919				
AIC: 1999				
BIC: 2180				

Note: Statistical significance: ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors clustered by respondent.

Table 8
OLS regression results for change in plan premium (percentage change between simulated premiums on new and old plans).

	DV: dPremium	
VARIABLES	Coef	SE
Premium_L	−0.681	0.0753***
Handset_L	0.0364	0.0660
Operator A (ref = Operator D)	−0.340	0.0984***
Operator B (ref = Operator D)	−0.0630	0.0594
Operator C (ref = Operator D)	1.145	0.172***
Billpay_L	0.0642	0.0659
OwnsBroadband	−0.0479	0.0752
Bundled_L	−0.426	0.135***
Exceed_L	−0.0490	0.0433
Constant	0.620	0.0969***
Observations	195	
Consumers	160	
R^2	0.397	
AIC: 18		
BIC: 51		

Note: Statistical significance: ***p < 0.01, **p < 0.05, *p < 0.1.

change in premium after switching.

The main associations found in this model are among the operator effects. Paying a high premium before switching is negatively associated with the change in premium, which is expected given the limited scope for increasing high premiums or reducing low (or zero) ones. The strength of this inverse relationship is illustrated by ranking each operator's plans from lowest to highest premium in every billing period and plotting the change in rank after switching against the rank of the pre-switch plan. The relationship is negatively sloped (see Fig. 1).

The only other factor found to have a consistently significant effect on the change in plan premium is being on a bundled plan prior to switching, which displays a strong negative association with the change in premium. In general, however, there is little evidence helping to distinguish those who increase premiums when they switch.

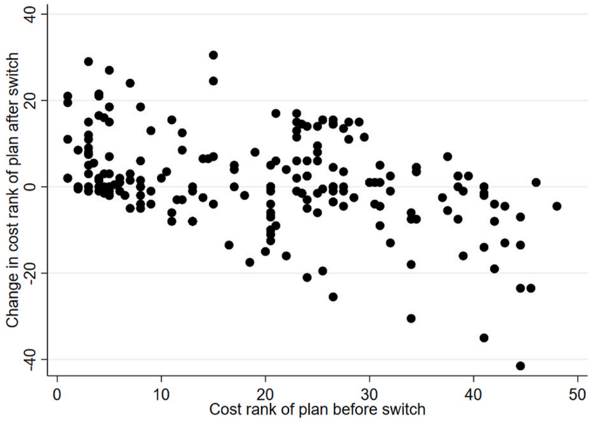

Fig. 1. Relationship of changes in predicted cost rank of operators' plans to their rank before the switch.
Source: analysis by authors of data described in Section 3.3.

6. Discussion and conclusions

This paper adds to the sparse literature on intra-operator switching, which is an important feature of mobile markets but has received much less attention than inter-operator churn. The analysis finds that consumers in the sample who engage in intra-operator switching are slightly more likely to increase their expenditures upon switching than lower expenditures. By itself, this observation of relatively balanced numbers moving up versus moving down in expenditure following switching could be consistent with the idea that changing preferences might play a role (since preferences can fluctuate up or down). However, it is also possible that a mixture of other more directional motives has yielded this relatively balanced outcome.

As expected, the consumer's level of expenditure in the period before the switch is positively associated with the likelihood of switching and negatively associated with the change in expenditure during the switch. Those with higher expenditures prior to switching have more reason to focus on their mobile expenditures and service usage. They are also more likely to be on plans offering relatively generous allowances, so there is more scope to switch to lower cost options than to higher ones.

The results present evidence contradicting Hypothesis 1: a slight majority of switches move consumers to plans that appear to increase the premium paid over the cost of the cheapest offering from their operator, given their observed usage. Some consumers may be making mistakes based on limited information or an imperfect understanding of how plan tariffs work. Previous research has suggested that informational and behavioural factors such as the complexity of plan choices, uncertainty, salience bias, fixed-rate bias, loss aversion and insurance effects can lead to errors in choices among those who switch (Genakos et al., 2015; Gerpott & Meinert, 2016; Han et al., 2021; Jin et al., 2021; Lambrecht & Skiera, 2006).

Informed by empirical studies, Grubb (2015b, 2015a) suggests that consumers make many systematic mistakes and suppliers may take advantage of this. An example of where switching did not result in consumers choosing the best alternative supplier is that of the UK electricity market, where 17–32% of consumers lost surplus when making inter-operator switches (Wilson & Waddams Price, 2010). Moreover, in the fixed line telecoms market in New York state, Economides et al. (2008) found that about 26% of switchers selected a higher cost supplier. In a recent study concerned with these issues, Friesen & Earl (2020) use an experimental setting to compare a number of interventions designed to provide information to consumers about complex mobile tariffs. They find that the quality of a consumer's decision, as measured by choosing the best (cheapest) available option and cost efficiency of choice (percentage of available gain relative to most expensive choice), can be improved where consumers receive literacy training, greater information about plan value is provided and visual feedback is received.

Consumers who have previously exceeded one or more of their allowances are more likely to switch than those who did not exceed an allowance, but they tend on average to switch to lower expenditures and they also tend to experience a decline in the optimality of their tariffs upon switching. This finding contradicts Hypothesis 2, and it stands in contrast with some previous international research (Jin et al., 2021). Exceeding allowances may increase the likelihood of switching plans simply because the consumer uses a relatively large quantity of service and thus has an incentive to economise on bills. It is less clear why exceeding allowances would be associated with a fall in plan optimality among those who switch.

Hypothesis 3 was also not supported by the results. Little evidence of any association between demographic characteristics and the average change in premium from switching is found. This is consistent with a view that a broad-based set of biases are at play among consumers. Such views have found support in previous studies surrounding complex choices in various settings (Lunn et al., 2016). If observable characteristics linked to (sub-)optimal choices could be found, this would be useful for commercial purposes as well as for targeting of consumer protection or "activation" campaigns.

It is also important to note that operators varied considerably in the extent to which their customers increased or decreased both expenditures and the premium compared to the cheapest available plan. This finding provides support for Hypothesis 4. Varying levels of market power or effectiveness of price discrimination strategies could explain some of this variation, or it might reflect unobserved (by us) differences in composition of their user bases. Shrouded attributes, that is hidden information on choices, and "foggy pricing", whereby the operators' tariff options aim to profit from consumers' mistakes, may also be at play (Gabaix & Laibson, 2006). This mechanism cannot be interrogated further in the absence of additional supply-side information.

Few other factors seem to be associated with the optimality metric, although there is some evidence that those on bundled tariffs are more likely than other consumers to reduce the price premium when they switch. This seemingly protective association could be a result of the terms and conditions connected with bundles or it could be to do with higher levels of sophistication or attention among the subset of consumers who tend to adopt them.

6.1. Limitations of the research

Several limitations of this work must also be acknowledged. First, there is a limit to the degree to which the analysis can capture the choice of plans available to all consumers at all times. In the dataset, 147 unique plans are identified across the four service operators and all plans identifiable as business plans are excluded to avoid atypical consumers running small businesses, for example. However, the timeline of the introduction and retirement of plans is not known, meaning that some plans may be modelled as potential choices when they would not have been available in practice.

Second, the lack of survey data on income of customers prevented this factor from being included in the analyses, though educational attainment provides a suitable proxy variable. Further, it was not possible to account for handset costs which may form part of the monthly plan cost for the relevant subscribers since a handset component of the plan cost was not distinguished in the data provided by the operators. It would be interesting to better understand the relationship between the option of a new handset and consumers' additional willingness to pay in a service plan, but this cannot be explored using the data available. A related limitation is that there are likely unobserved plan characteristics that are valued by the consumer but omitted from the available data, e.g., entertainment packages or other value-added services. Omitted characteristics may limit how well the modelling characterises the optimality of plans. Nevertheless, the observed plan features capture 65% of the variation in plan cost.

The exclusion restrictions imposed in the Heckman selection models are based on *a priori* judgement and are limited by the available data. Better indicators of selection would be preferable for the models of the change in expenditure, e.g., if data were available identifying switches that were required or otherwise initiated by suppliers. However, selection does not appear to be important when modelling the change in premium.

6.2. Policy implications and avenues for future research

The research presented in this paper corroborates the view that intra-operator switching provides flexibility and can permit some consumers to arrive at more optimal plans. However, it also raises questions about why some consumers seem to be switching to plans that seem less optimal for them given their usage. These results indicate an important role for provision of information and regulation in this arena, for example via price comparison tools and new regulatory provisions on best tariff advice.

The results show sizeable variations in the average outcomes after switching plans among consumers of different operators. Does this reflect different pricing strategies by these operators, perhaps reflecting variations in their levels of market power or vulnerability to threats of churn? From an operator perspective, optimal rate plan subscribers may contribute less revenue than those on sub-optimal plans, as found by Wong (2010), however Wong argues that this short-term revenue may be offset by loyalty accruing from consumers on optimal plans. To the extent that sub-optimal intra-operator plan switches occur, this could point to a potentially important role for price comparison tools to support consumers in making intra-operator plan changes, as well as inter-operator switches.

These findings may also provide support for more specific forms of consumer protection regulation. In its study of the so called "loyalty penalty"[2] observed in mobile services as well as other sectors, the UK Competition and Markets Agency recommended that "Ofcom should seek to increase the engagement and awareness of consumers by pushing forward with implementing smart data, supporting the development of innovative intermediaries, and tackling low levels of awareness of SIM-only deals" (Competition and Markets Authority, 2018). Awareness-enhancing remedies such as these may also help improve the quality of intra-operator switching decisions. Furthermore, several contributors make a compelling argument for the provision of personal usage information in such areas, given the reversal of information asymmetries with increased data gathering – companies can know consumers' preferences better than consumers know themselves (Bar-Gill & Board, 2012; Kamenica et al., 2011).

More recently, regulatory provisions have been introduced to require suppliers to notify consumers, before a contract is automatically prolonged (rolled over), as to the end of their existing contract and provide the consumer with information on best tariffs available at least on an annual basis (ComReg, 2020c).[3] Similarly, in February 2020 UK regulator Ofcom mandated telecoms providers to actively provide additional notification and advice (OFCOM, 2021). Phone, broadband and pay-TV companies will have to warn customers between 10 and 40 days before their contract comes to an end. These alerts can be sent by text, email or letter, and they must include the contract termination date, information on what the consumer has paid under the current arrangement and what they will

[2] This term describes alleged cases where customers that do not search or switch service providers for extended periods tend to end up on less attractive pricing.

[3] Article 105 of the directive establishing the European Electronic Communications Code (European Commission, 2018) stipulates: "Before the contract is automatically prolonged, providers shall inform end-users, in a prominent and timely manner and on a durable medium, of the end of the contractual commitment and of the means by which to terminate the contract". In addition, and at the same time, providers must give end-users best tariff advice information relating to their services at least on an annual basis.

pay when the contract concludes, details of a notice period for leaving the provider, and the best deals available from the provider including prices available to new customers.

Future research might examine how well the new regulations which require notification of consumers of the end of their contract and offer best tariff advice are implemented in practice and to what extent this informational reset can drive switching. Whether this it improves outcomes for both intra- and inter-operator switchers and mobile plan consumers more generally also merits study. The introduction of 5G services (which happened from summer 2019 onwards in Ireland) also may represent an external impetus for some consumers to switch plans. When later data are available it may be interesting to examine whether patterns of switching determinants and outcomes were changed by this market innovation.

Another element which may provide additional insight into intra-operator switching decisions is handset choice. Consumers may choose a mobile phone plan in order to attain (or indeed finance upfront) a desired handset, and a degree of stickiness may impact switching decisions thereafter. In the present study, insufficient information was available on handset make or cost to fully explore this avenue, but the interaction between the mobile services and handsets markets remains underexplored, particularly on the intra-operator switching front. The data also did not allow for a thorough exploration of bill shock due to low sample sizes, but it would be interesting, from a commercial and regulatory perspective, to understand the characteristics of those who experience bill shock and subsequently change plan but remain on the same operator. In general, a larger sample size and better coverage of plan attributes would assist in improving the precision of the estimates and help ensure that the analysis of optimality includes the full set of attributes that consumers took into account when taking decisions.

The data available in the current study did not permit direct examination of the mechanisms that lead consumers to switch to more or less optimal plans. Behavioural economics research highlights the importance of defaults and status quo bias in consumer choice (Lunn, 2013). Inert consumers may be particularly prone to the cognitive biases, making them reluctant to switch. There are many possible mechanisms that could be considered in future research. Consumers may perceive search costs and transaction costs for switching mobile operator to be higher, and value familiarity with their current arrangement more highly than active consumers. Consumers may also face different trade-offs as regards price and the time and effort taken to find a new suitable phone plan.

To conclude, this study examines a relatively unexplored area of mobile plan choices, that of switching plans within the same operator. Empirical study of survey data linked to billing information reveals that a substantial proportion of customers who switch within the same operator increase expenditures when they switch plan. Though some switchers do move to plans that are more optimal given their usage, a greater proportion move to plans that charge a higher price premium over the best available plan (based on observables) than the consumer's previous plan did. These findings add to a body of evidence which finds that consumers can fail to arrive at the best price even after switching.

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Declaration of competing interest

The authors declare no conflict of interest.

Data availability

The authors do not have permission to share data.

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Appendix

A.1. Plan cost model results

When modelling intra-operator switching in the mobile phone plan market, it is important to consider not only the plan a consumer has chosen and the plan to which they switch (if applicable), but also the alternative plans they could have selected. More specifically, the analysis includes modelling how much a consumer would pay for any plan available from their operator, given their usage (quantity demanded) of various plan dimensions (calls, SMS and data, differing by on- and off-net status, domestic versus international status).

The mobile phone operators provided granular data to ComReg on customers' plan details, usage and associated costs. However, due to data constraints (e.g., missing values and inconsistencies in how the data was provided across operators), there are gaps in the information on the cost of certain plan attributes. This means the precise cost of alternative plans could not be modelled using a "bottom-up" methodology i.e. built up from scratch. Therefore, a top-down approach for the plan cost model is employed, using regression analysis to estimate the marginal contributions to consumer's bills made by a range of plan attributes. This method is similar to hedonic regression, which is widely used in valuation studies. The hedonic regression approach assumes that a good can be viewed as a bundle of attributes, each of which contributes to the commodity's price. In the present context, through regressing plan expenditure on attributes it is possible to estimate the average price of each fixed plan attribute (e.g. unlimited on-net calls allowance) and the marginal price of any continuously-varying attribute. These coefficients can then be used, together with the consumer's actual usage, to simulate the cost of any plan for a given consumer.

The plan cost model regression coefficients can be multiplied by consumers' actual usage in a given billing period simulate how much the customer would have spent on any available plan given their usage of services and the plan's selection of relevant allowances. Regression results for the plan cost model are shown in Table A1.1. The model, which is estimated using OLS, explains about 66% of variation in monthly plan expenditures for the sample of over 15,000 respondent-billing periods.

A.1.1. Plan cost model – OLS regression results

	(1)	(2)
VARIABLES	Coef	SE
Plan expenditure (ln)		
Operator A (Ref =	−1.883	0.188***
Operator B	−1.756	0.203***
Operator C	−1.890	0.212***
Operator D	−1.834	0.202***
Billpay x A	0.395	0.0872***
Billpay x B	0.144	0.0630**
Billpay x C	0.904	0.109***
Billpay x D	0.0559	0.0255**
24m contract x B	0.207	0.0634***
24m contract x D	0.392	0.0502***
24m contract x C	−0.0535	0.126
On-net Calls usage	−0.0171	0.00849**
OffNet Call Usage x A	0.102	0.0731
OffNet Call Usage x B	0.0377	0.0141***
OffNet Call Usage x C	−0.0983	0.0209***
OffNet Call Usage x D	0.0665	0.0115***
Off-net SMS usage	0.0121	0.00629*
Data usage (IRL) x A	0.00464	0.00155***
Data usage (IRL) x B	0.000118	0.000664
Data usage (IRL) x C	0.000104	7.88e-05
Data usage x D	0.000918	0.000191***
Unlimited allowance dummy - OnNet minutes	−0.150	0.0556***
Unlimited OffNet Calls x C	0.179	0.129
Unlimited OffNet Calls x B	0.210	0.0520***
Unlimited OffNet Calls x D	0.135	0.0363***
Unlimited allowance dummy OnNet SMS	0.110	0.0874
Unlimited allowance - OffNet SMS	−0.0668	0.0484
Advertised plan cost (ln)	0.522	0.0627***
Observations	15,339	
R-squared	0.657	

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Standard errors are clustered at the respondent level.

A.2. Additional results from switching models

This section includes regression results for switching models that include demographic controls.

A.2.1. Change in expenditure with demographic controls

Table 9
Heckman regression results for change in expenditure (log difference between simulated expenditures on new and old plans) including demographic controls

	First stage (switch = 1)		Second stage (dExpenditure)	
VARIABLES	Coef	SE	Coef	SE
Expenditure_L	0.242	0.0571***	−0.577	0.117***
Female (ref = Male)	−0.0482	0.0681	0.0208	0.0923
Age18_34 (ref = Age35-49)	0.0298	0.0889	0.133	0.137
Age50plus (ref = Age35-49)	0.125	0.0740*	−0.113	0.109
Married (ref = not married)	−0.0681	0.0387*	0.0815	0.0455*
Rural (ref = urban)	−0.0305	0.0674	0.0246	0.111
Handset_L	0.175	0.131	0.209	0.121*
Operator A (ref = Operator D)	−0.296	0.126**	0.308	0.189
Operator B (ref = Operator D)	−0.610	0.107***	0.485	0.228**
Operator C (ref = Operator D)	−0.567	0.126***	0.370	0.178**
Educ_primary (ref = Educ_secondary)	0.0730	0.139	−0.136	0.173
Educ_tertiary (ref = Educ_secondary)	−0.006	0.0689	0.0166	0.105
Billpay_L	0.0621	0.125	0.182	0.156
OwnsBroadband	0.247	0.129*	−0.0330	0.159
Bundled_L	0.106	0.151	0.353	0.198*
Exceed_L	0.369	0.0940***	−0.331	0.137**
Contract = 1m_L	0.319	0.136**		
Wifi	−0.0914	0.0532*		
Constant	−2.495	0.229***	2.071	0.679***
athrho	−1.572			0.292***
lnsigma	−0.008			0.227
Observations	14,305			
Consumers	928			
Switches	195			
AIC: 2285				
BIC: 2571				

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

Table 10
OLS regression results for change in expenditure (log difference between simulated expenditures on new and old plans) including demographic controls

VARIABLES	Coef	SE
Expenditure_L	−0.402	0.108***
Female (ref = Male)	−0.0627	0.0843
Age18_34 (ref = Age35-49)	0.134	0.108
Age50plus (ref = Age35-49)	−0.0456	0.0939
Married (ref = not married)	0.0431	0.0367
Rural (ref = urban)	0.0173	0.102
Handset_L	0.144	0.104
Operator A (ref = Operator D)	0.0125	0.164
Operator B (ref = Operator D)	0.0247	0.142
Operator C (ref = Operator D)	−0.0410	0.139
Educ_primary (ref = Educ_secondary)	0.0141	0.141
Educ_tertiary (ref = Educ_secondary)	−0.0119	0.101
Billpay_L	0.139	0.133
OwnsBroadband	0.134	0.0879
Bundled_L	0.475	0.168***
Exceed_L	0.0146	0.0978
Constant	−0.231	0.171
Observations	195	
Consumers	160	
R^2	0.22	
AIC: 327.4		
BIC: 383.1		

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

A.2.2. Change in premium with demographic controls

Table 11
Heckman regression results for change in plan premium (percentage change between simulated premiums on new and old plans) including demographic controls

	First stage (switch = 1)		Second stage (dPremium)	
VARIABLES	Coef	SE	Coef	SE
Premium_L	0.206	0.0746***	−0.698	0.0742***
Female (ref = Male)	−0.0556	0.0692	0.0582	0.0395
Age18_34 (ref = Age35-49)	0.082	0.0898	0.0255	0.052
Age50plus (ref = Age35-49)	0.125	0.0738*	0.00537	0.049
Married (ref = not married)	−0.0597	0.041	0.0103	0.0177
Rural (ref = urban)	−0.0142	0.0677	0.0815	0.0447*
Handset_L	0.263	0.145*	0.0399	0.0643
Operator A (ref = Operator D)	−0.325	0.128**	−0.322	0.0966***
Operator B (ref = Operator D)	−0.552	0.107***	−0.00484	0.0605
Operator C (ref = Operator D)	−0.788	0.158***	1.206	0.165***
Educ_primary (ref = Educ_secondary)	0.0651	0.141	0.0426	0.142
Educ_tertiary (ref = Educ_secondary)	−0.00999	0.0699	−0.00058	0.0392
Billpay_L	0.121	0.135	0.064	0.0663
OwnsBroadband	0.245	0.130*	−0.0662	0.062
Bundled_L	0.277	0.138**	−0.427	0.130***
Exceed_L	0.405	0.0998***	−0.0949	0.0406**
Contract = 1m_L	0.374	0.174**		
Wifi	−0.0793	0.0672		
Constant	−2.767	0.258***	0.752	0.113***
Athrho			−0.369	0
Lnsigma			−1.384	0.0778***
Observations	13,899			
Consumers	928			
Switches	195			
AIC: 2010				
BIC: 2289				

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

Table 12
OLS regression results for change in plan premium (percentage change between simulated premiums on new and old plans) including demographic controls

	DV: dPremium	
VARIABLES	Coef	SE
Expenditure_L	−0.681	0.0785***
Female (ref = Male)	0.0524	0.0411
Age18_34 (ref = Age35-49)	0.0297	0.0550
Age50plus (ref = Age35-49)	0.0156	0.0510
Married (ref = not married)	0.00567	0.0176
Rural (ref = urban)	0.0788	0.0462*
Handset_L	0.0409	0.0676
Operator A (ref = Operator D)	−0.347	0.101***
Operator B (ref = Operator D)	−0.0472	0.0628
Operator C (ref = Operator D)	1.145	0.173***
Educ_primary (ref = Educ_secondary)	0.0488	0.150
Educ_tertiary (ref = Educ_secondary)	−0.00129	0.0405
Billpay_L	0.0620	0.0695
OwnsBroadband	−0.0475	0.0606
Bundled_L	−0.402	0.134***
Exceed_L	−0.0624	0.0413
Constant	0.511	0.113***
Observations	195	
Consumers	160	
R^2	0.41	
AIC: 25.2		
BIC: 80.9		

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

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