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EMPIRICAL EVIDENCE OF CONSUMER RESPONSE IN REGULATED MARKETS

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ABSTRACT

The U.K. Competition and Markets Authority has opened two major investigations into the retail energy and banking sectors, and identifies weak consumer response as a potential theory of harm in both sectors. Consumers of many regulated services, including energy and banking, need to make active moves to switch suppliers, with profound consequences for how well the market functions. We identify differences in expected gains across demographic groups, particularly with respect to age and income, the associated changes in activity and implications for policy. We find that potential gains and anticipated switching time are associated with changes in consumer activity, but with differences between markets, demographic groups and individuals. Rather than concentrate on the average consumer response, we find variations across demographic groups, and that well informed vulnerable consumers are not necessarily less responsive than others, once we control for their expectations. We conclude that sector regulators and agencies who wish to encourage consumer action need to differentiate their policies: strategies to emphasize potential gains and reduce anticipated switching time are the most likely to increase consumer activity, but programs need to be tailored to particular markets and target groups if they are to be effective in stimulating consumer activity.

JEL: D12; C35; L40; L50

I. INTRODUCTION

Consumer behavior is increasingly recognized as a key component of competition policy. If markets are to work well, consumers need to seek better deals to

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motivate firms to make such offers available.[1] Buyer response is particularly crucial in those regulated markets where current suppliers have a direct relationship with purchasers, so that the default position is to stay with the current supplier. Consumer welfare and its distribution is especially sensitive in newly liberalized markets, such as energy and telecoms, and in the financial sector, all of which typically retain some form of sector specific regulation.[2] In the U.K., weak consumer response is seen as a major problem in retail energy and banking, both recently referred to the Competition and Markets Authority (CMA)[3] as the first two major market investigations to be undertaken by the newly consolidated competition authority; in both these sectors, on which reports are due in 2016, the CMA has identified barriers to consumer switching as a key potential theory of harm. A similar electricity inquiry is being undertaken across Member States by the European Commission.[4] To understand and, if necessary, rectify such possible harm, Competition and Regulatory Authorities need to understand the drivers of buyer behavior in order to design effective remedies and avoid unintended consequences.

Such understanding is enhanced by empirical evidence on consumer behavior across sectors, including energy and banking. This article identifies the influence on consumers' search and switching activity in eight markets, each involving a default supply relationship and subject to specific regulation, with a sector regulator who has particular duties and instruments. We identify the potential drivers of consumer activity in searching for better deals and switching supplier, in particular exploring the differences both between markets and across demographic groups and individuals, and between those who are well informed and those who have little knowledge about potential gains available.

Using a specially commissioned survey and empirical models to control for underlying factors, and allowing for heterogeneity across individuals, we explore the effect on searching and switching across markets of three "primary" factors that we would expect to drive activity: the expected saving, and the anticipated time required to find a better deal and to change suppliers. We focus on consumers' own expectations of potential gains and time required, enabling us to abstract from direct issues of information by utilizing the respondents' beliefs as reported to interviewers. We identify robust evidence of significant differences

[1] Daniel McFadden, *Free Markets and Fettered Consumers*, 96 AM. ECON. REV. 5 (2006).

[2] See, e.g., Eugenio J. Miravete & Ignacio Palacios-Huerta, Consumer Inertia, Choice Dependence, and Learning from Experience in a Repeated Decision Problem, 96 REV. ECON. & STAT. 524 (2014); Yolanda Polo & F. Javier Sesé, How to Make Switching Costly? The Role of Marketing and Relationship Characteristics, 12 J. SERVICE RES. 119 (2009).

[3] COMPETITION AND MARKETS AUTHORITY, RETAIL BANKING MARKET INVESTIGATION: STATEMENT OF ISSUES (Nov. 2014), https://assets.digital.cabinet-office.gov.uk/media/5462302a40f0b6131200001a/Issues_statement.pdf; OFGEM, STATE OF THE MARKET ASSESSMENT (Mar. 2014), https://www.ofgem.gov.uk/publications-and-updates/state-market-assessment.

[4] Press Release, European Commission, Market Conditions for Consumers Continue to Improve (June 30, 2014), http://europa.eu/rapid/press-release_IP-14-756_en.htm.

in expectations and behavior, not only across markets and demographic groups, but also, even after these are controlled for, across individuals. Our model exhibits some similarities with earlier explanations and provides a good fit with the observations from the survey, as well as identifying new considerations and factors to inform policy. Part II briefly discusses the most relevant literature, and Part III presents the motivation of the model, the survey and the data. Part IV includes the main results and a discussion of selection issues, and identifies persistent differences between markets and across individuals; Part V concludes and discusses policy implications.

II. SELECTED LITERATURE

In modeling search and switching behavior, we draw on literature that focuses on the importance and effect of either search or switching costs or both.[5]

Before starting their search, consumers may be more deterred by expected search costs than anticipated switching costs, partly because any investigation involves search costs for certain, but incurs switching costs only if a better deal is discovered during the search.[6] Nickolay Moshkin and Ron Shachar estimated that 71 percent of consumers' behavior (in television viewing choices) is consistent with the existence of search costs,[7] and much of the evidence points to the importance of considering search cost together with switching cost to understand consumers' switching decisions. Evidence from the energy market suggests that the probability of switching can be over four times higher for those consumers who have actively searched, and that searching costs exert a larger effect than switching costs.[8] Similar evidence that search costs are more important than switching costs is also found in other industries, such as the U.S. auto insurance industry, for example.[9]

Several studies have estimated the decision to switch suppliers as a function of the gains available from doing so (objectively calculated from the researchers' information about opportunities in the market) and a set of demographic and

[5] For the interaction between such costs and market outcomes and empirical studies in different settings, see Paul Klemperer, Competition When Consumers Have Switching Costs: An Overview with Applications to Industrial Organisation, Macroeconomics and International Trade, 62 REV. ECON. STUD. 515 (1995). Joseph Farrell & Paul Klemperer, Coordination and Lock-In: Competition with Switching Costs and Network Effects, in 3 HANDBOOK OF INDUSTRIAL ORGANIZATION 1970 (Mark Armstrong & Robert H. Porter eds., North-Holland 2007).

[6] Chris M. Wilson, Market Frictions: A Unified Model of Search Costs and Switching Costs, 56 EUR. ECON. REV. 1070 (2012).

[7] Nickolay V. Moshkin & Ron Shachar, *The Asymmetric Information Model of State Dependence*, 21 MARKETING SCI. 435 (2002).

[8] Jon T. Sturluson, *Consumer Search and Switching Costs for Competition in Electric Power Retailing*, *in* TOPICS IN THE INDUSTRIAL ORGANIZATION OF ELECTRICITY MARKETS 3 (Stockholm EFI Pub. No. 614, 2003).

[9] Elisabeth Honka, Quantifying Search and Switching Costs in the U.S. Auto Insurance Industry, 45 RAND J. ECON. 847 (2014).

individual variables to proxy search and switching costs, though these often explain little of the observed activity.[10] Demographic characteristics are relatively easily measured in surveys and searching cost proxies appear to be the biggest barriers to changing suppliers, for instance in the newly opened U.K. gas market,[11] where they dominated both switching cost proxies and demographic variables. A study that uses a similar methodology across a series of nine different product markets in Holland compares switching behavior across markets,[12] but is limited by a binary measure for consumer beliefs about gains.

We follow these studies in investigating individual search and switching decisions but using a subjective measure of expected gains, rather than whether the choice of producer is objectively optimal.[13] Our model also differs in identifying the key factors that determine both search and switch activities, rather than focusing on whether search cost is more or less important than switching cost.

This unique use of consumers' estimates of gains rather than researcher calculations from market intelligence enables the exclusion of consumers' (mis) information and enables us to identify the influence of other factors (such as age and gender) in their own right, as well as via any impact that they may have on these "core" expectations.[14] Recognizing which consumers are more likely to search or switch and persistent differences between markets has important implications for regulatory policy in these sectors.

[10] Pei-Yu Chen & Lorin M. Hitt, Measuring Switching Costs and the Determinants of Customer Retention in Internet-Enabled Business: A Study of the Online Brokerage Industry, 13 INFO. SYS. RES. 255 (2002); Elizabeth K. Kiser, Predicting Household Switching Behavior and Switching Costs at Depository Institutions, 20 REV. INDUS. ORG. 349 (2002).

[11] Monica Giulietti, Catherine Waddams Price & Michael Waterson, *Consumer Choice and Competition Policy: A Study of UK Energy Markets*, 115 ECON. J. 949 (2005).

[12] Marc Pomp, Victoria Shestalova & Luiz Rangel, *Switch on the Competition: Causes, Consequences and Policy Implications of Consumer Switching Costs* (CPB, Working Paper No. 97, 2005).

[13] Several papers provide empirical evidence of consumers choosing sub-optimally. For U.S. telecommunications, *see* Nicholas Economides, Katja Seim & V. Brian Viard, *Quantifying the Benefits of Entry into Local Phone Service*, 39 RAND J. ECON. 699 (2006); Eugenio J. Miravete, *Choosing the Wrong Calling Plan? Ignorance and Learning*, 93 AM. ECON. REV. 297 (2003). For U.S. credit cards and credit markets, *see* Sumit Agarwal, Souphala Chomsisengphet, Chunlin Liu & Nicholas S. Souleles, *Do Consumers Choose the Right Credit Contracts?* (Federal Reserve Bank of Chicago, Working Paper 2006-11, 2006); Sumit Agarwal, John C. Driscoll, Xavier Gabaix & David Laibson, *The Age of Reason: Financial Decisions over the Life Cycle and Implications for Regulation*, 40 BROOKINGS PAPERS ON ECON. ACTIVITY 51 (2009). For German internet provisions, *see* Anja Lambrecht & Bernd Skiera, *Paying Too Much and Being Happy About It: Existence, Causes and Consequences of Tariff Choice Biases*, 43 J. MARKETING RES. 212 (2006). For U.K. electricity, *see* Chris M. Wilson & Catherine Waddams Price, *Do Consumers Switch to the Best Supplier?* 62 OXFORD ECON. PAPERS 647 (2010).

[14] An interesting stream of recent empirical studies uses data on observed search and switching behavior in response to market offers. *See*, for example, Ali Hortaçsu, Seyed A. Madanizadeh & Steven L. Puller, *Power to Choose? An Analysis of Choice Frictions in the Residential Electricity Market* (Working Paper, 2012); Babur De los Santos, Ali Hortaçsu & Matthijs R. Wildenbeest, *Testing Models of Consumer Search Using Data on Web Browsing and Purchasing Behavior*, 102 AM. ECON. REV. 2955 (2012).

The growing literature on behavioral economics challenges a perception of consumer decisions based solely on a model of utility maximization that trades off potential gains and losses.[15] The most relevant for consumer activity in relationship markets like those we analyze are choice avoidance and status quo bias.[16] Exploring the rationality of inertia is difficult:[17] such inertia can be related to transaction costs;[18] Stefania Sitzia, Jiwei Zheng, and Daniel Zizzo showed that inattention may be as important as confusion in inertia and poor decisions, in an experiment designed to mimic the circumstances of the U.K. energy market.[19] The confidence of beliefs may also be important in explaining inertia.[20]

Our approach is not to identify whether individual consumers exhibit "non-standard" behavior, but rather to understand the pattern of consumers' responses across markets and their variation, after controlling for potential gains and costs. As outlined in Part III below, we employ an underlying model that balances anticipated gains against expected time commitment of activity, identifying patterns in and across markets that can guide providers, governments and agencies.

III. MODELING AND DATA

In Part III, we first explain the motivation for the model we use and the flexible approach to account for both observed and unobserved consumer heterogeneity, and then describe the survey and the data that it generated.

A. Motivation for Model

In each of the relationship service markets that we study, consumers continue to receive supply from their current provider unless they take action to move away from this default position. We observe whether consumers report that they have searched, switched, or undertaken both activities. As much of the literature recognizes, searching and switching are closely related. Rather than model them sequentially, we recognize that some customers may search for better deals because they are already minded to change providers, while others may initially be more focused on "discovery" and persuaded to switch as a result of finding better deals through their search. Since we cannot distinguish

[15] For an excellent survey of empirical evidence of "non-standard" decision making, *see* Stefano DellaVigna, *Psychology and Economics: Evidence from the Field*, 47 J. ECON. LITERATURE 315 (2009).

[16] For a review, *see* JUDITH MEHTA, BEHAVIOURAL ECONOMICS IN COMPETITION AND CONSUMER POLICY (Centre for Competition Policy 2013).

[17] STEFFEN HUCK, JIDONG ZHOU & CHARLOTTE DUKE, CONSUMER BEHAVIOURAL BIASES IN COMPETITION: A SURVEY—FINAL REPORT (Office of Fair Trading May 2011).

[18] Chris M. Wilson, Luke Garrod & Alistair Munro, *Default Effects, Transaction Costs, and Imperfect Information*, 119 ECON. LETTERS 213 (2013).

[19] Stefania Sitzia, Jiwei Zheng & Daniel Zizzo, *Inattentive Consumers in Markets for Services*, 709 THEORY & DECISION 307 (2014.

[20] Colin F. Camerer, *Prospect Theory in the Wild: Evidence from the Field*, *in* CHOICES, VALUES AND FRAMES 288 (Daniel Kahneman & Amos Tversky eds., Cambridge Univ. Press 2000).

between these approaches, we use similar variables to explain three separate consumer actions: searching, switching, and searching-and-switching, rather than model the order of activities. In this way we allow for the searching and switching activities to be related (because they are determined by the same factors), without specifying the form of that relationship. We define searching as actively looking around for a better deal, rather than the more usual definition in economics of receiving information, whether actively or passively.

Consumers who are maximizing utility in a classic economic model would increase activity as anticipated monetary gains rise and the expected hours needed to search and switch fall. The tradeoff between expected monetary gains and the value of the time varies between consumers according to their circumstances—in particular, income: respondents with higher income would be less likely to switch for given expected gains and anticipated time, since both the value of the monetary gain to them would be lower and the opportunity cost of their time would be greater, raising the disincentive effect of the activity. While any direct influence of more years of formal education on time needed to search and switch should be captured in consumers' direct estimates of anticipated time, higher levels of education may render the time spent less onerous as well as (perhaps) shortening it. Other demographic variables that might affect the trade-off between expected gains and costs include age and gender, either for intrinsic reasons or as a result of targeting by firms that reduces search and switching costs, or raises awareness of potential gains.[21] Differences in homogeneity of products (and the importance of quality) across markets may also be captured by the market dummies; electricity is essentially homogeneous by definition,[22] so we use it as a base case, and anticipate that quality is more likely to be pertinent in telecoms and financial markets.

Consumers' willingness to search and switch will also depend on how confident they are in their estimates of the potential gains and costs, and in their ability to realize them, with a greater willingness to act (for given central expectations of gain and pain) the less variation they perceive around their central estimate. Consumer-specific confidence is likely to be positively related to experience of switching in other markets, and we create a variable of "*switched other*" that equals one if a respondent reports switching in another of the markets in the survey, and is otherwise equal to zero.

A consumer's attitude to search and switching, and to the potential gains available, might vary between markets for several reasons. The searching and switching process may be less psychologically onerous for some products than for others, independently of the time consumers expect to spend; potential

[21] It was found that prepayment consumers were less likely to change suppliers in the early days of the gas market because they were less actively targeted by firms, *see* Giulietti, *supra* note 11.

[22] Reliability depends on the monopoly owner of the distribution wires rather than the retailer chosen by the consumers. Some suppliers do differentiate through associated services such as meter reading, but the product itself is homogeneous.

gains that are a very small proportion of expenditure may be regarded as less motivating than if gains represent a large share of the bill; prices in some markets may be perceived as more changeable; and there may be more knowledge about some markets, for example because of marketing or information campaigns, or because political salience highlights the sector, so that consumers are more confident in their estimates.

We follow the approach of Monica Giulietti, Catherine Waddams Price, and Michael Waterson[23] in using an expenditure function to derive an approximation using the consumer surplus difference between being with the current and a (potential) new supplier. We analyze the process of deciding whether or not to search and switch away from the current supplier in each of the eight markets (k = 8). In addition to allowing for variations in behavior across markets, we also allow for variations in searching/switching decisions across individuals,[24] estimating a random parameter (mixed) probit model to capture both variations related to the observed demographic characteristics of individuals and those related to unobserved characteristics, or random preference variations.[25]

The models used for the probit estimations of the probability of searching, P(se), of switching, P(sw), and of searching-and-switching, P(sesw), were as follows:

$$\Pr[U_i = 1 | X_i, \beta_i]$$

Where $U_i = 1$ if individual i searched/switched/searched-and-switched. Note that we treat a person in each market as a different observation to capture the variation between markets in terms of searching/switching decisions.

As explained above, while the main independent variables expected to drive search and switching behavior are anticipations of gain, search time and switch

[23] Giulietti, *supra* note 11.

[24] Wesley Hutchinson, Wagner Kamakura, and John Lynch demonstrate that effects that are significant in an aggregate analysis may exist separately but not in combination at the segment level; similarly, when effects at segment level are significant, but in opposite directions, they may cancel each other so as to appear insignificant in the aggregate analysis. J. Wesley Hutchinson, Wagner A. Kamakura & John G. Lynch, Jr., *Unobserved Heterogeneity as an Alternative Explanation for "Reversal" Effects in Behavioral Research*, 27 J. CONSUMER RES. 324 (2000).

[25] An early paper to take this into account uses a covariance probit (as opposed to independent probit or logit) model to allow for random taste variations. *See* Jerry A. Hausman & David A. Wise, *A Conditional Probit Model for Qualitative Choice: Discrete Decisions Recognizing Interdependence and Heterogeneous Preferences*, 46 ECONOMETRICA 403 (1978). The development of simulation methods enabled a more general framework with a mixed model of logit or probit allows for random taste variations, based on simulated maximum likelihood estimators. Appendix 1 provides a brief description of the estimation techniques. For technical details, *see* WILLIAM H. GREENE, ECONOMETRIC ANALYSIS (6th ed. Prentice Hall 2008); Hutchinson, *supra* note 24; KENNETH TRAIN, DISCRETE CHOICE METHODS WITH SIMULATION (Cambridge Univ. Press 2002). There is empirical evidence of different behavior both between and within consumer groups in the energy market; *see* Miguel Flores & Catherine Waddams Price, *Consumer Behaviour in the British Retail Electricity Market* (Centre for Competition Policy, Working Paper 13-10, 2013), http://competitionpolicy.ac.uk/publications/working-papers-2013.

time, we would expect the behavior to be affected by "*switched other*," market, income, education, age and gender. We initially allow expected gain, expected search time, expected switch time and switched other to have random parameters (coefficients)—that is, we allow the effect of these variables to vary across individuals, and test the significance of the dispersion of each of these random parameters. If the dispersion is significant we treat it as a random parameter, otherwise we treat it as a fixed parameter and reestimate the model. The outcome of this process is that expected gain, expected switch time and "*switched other*" are treated as random parameters in the search model and the search-and-switch model, with all other independent variables having fixed parameters; in the switching model, expected gain and expected switch time are treated as random parameters, and all other variables are allocated fixed parameters. We also included expectations about suppliers' reluctance to match deals, and how important trust is for each market. These factors are not statistically significant in their own right in any model, and were therefore dropped from the analysis.

Apart from unobserved variations, we also allow for preference heterogeneity around the mean of the random parameter estimate on the basis of the observed covariates (corresponding to the second term in Equation A3 in Appendix I) for both individual and market characteristics, namely income, education, age, gender and market dummies. This is equivalent to introducing interactive terms in the models (see Appendix I for details). If the interaction is not statistically significant then we rely only on the standard deviation of the random parameter estimate—that is, unobserved heterogeneity or random taste variations (the third term in Equation A3 in Appendix I) for sources of preference heterogeneity across individuals. Thus our estimates of random parameters include three main parts: the mean estimates of the random parameter (the first term in Equation A3); the heterogeneity around the mean on the basis of the observed covariates (the second term in Equation A2); and the standard deviation of the random parameter distribution (related to the significance of the random variation, the third term in Equation A3).

B. The Survey and the Data

The data were generated by a large scale survey administered in the summer of 2005, especially commissioned to identify consumers' own estimates of search and switching costs and expected gains from switching. The survey was conducted by Market and Opinion Research International for the ESRC Centre for Competition Policy, and administered to a nationally representative sample of 2027 adults aged 16 or over, interviewed face-to-face, in-home, in 167 sampling points across Great Britain.[26] The survey used quota sampling that followed the Government Office Regions' set quota on demographics (age, gender, class, and others).

[26] Great Britain comprises England, Scotland, and Wales; Northern Ireland was not included in this survey.

Respondents were asked which products the household consumed and paid for, among electricity, mobile phone, fixed phone line rental, national and overseas (fixed line) calls, broadband internet, car insurance, mortgage and current bank account. While these service markets are similar in that all involve a relationship between supplier and consumers that the consumer needs to sever in order to switch to an alternative provider, they differ in the degree of homogeneity of the product and the nature of regulatory oversight, the transparency of prices and in how long choice had been available. Respondents who were aware that choice was available in each market and who were solely or jointly responsible for decisions on who supplied that product to the household, were included in the analysis.

Respondents were asked whether they had searched around for better deals and whether they had switched supplier in each market during the previous three years (other than when moving home). They were also asked how much of their own time such search and switching had taken and whether this was more or less than they had expected; or, if they had no experience, how long they would expect to have to spend on each activity.[27] Participants were asked how much they thought they could save in each market if they shopped around, and to report their current expenditure in each market and their demographic characteristics, including age, gender, and income. The questions and the construction of the variables are reported in Appendix III.

We analyze each household and market as an individual observation—that is, we regard our data as a panel ($\mathcal{J} \times K$) across households ($\mathcal{J}$) and products (K). Each such household/market observation was included only if all the relevant variables described above were known for that case. We discuss the effect of this selection process and other potential selection biases in Part IV.B below. Descriptive data for the "primary" independent variables are shown in Table 1.

IV. RESULTS

A. Main Results

The full results are reported in Table A1 in Appendix II, which is presented in three parts: the first part reports coefficients of variables with fixed parameters; the second shows coefficients of variables with random parameters; and the third part reports statistics related to the performance of the model. For the random parameters (part II), the reported means and heterogeneity in the means correspond to the first and second terms in Equation A3 in Appendix I, while the standard deviations of the random parameter distribution correspond to the third term in the same equation. All the random parameter models are estimated by

[27] Unfortunately, we have been unable to distinguish between any changes in expectations of switching time that resulted from the search process itself. We explore the relationship between expectations and market activity in Part IV.3 below.

Table 1. Average expected savings, search and switch time in each market

Market	*Number of respondents aware and responsible*	Expected maximum gains (£/month)			Expected search time* (hours)		Expected switch time* (hours)	
		Number of respondents	*Mean (standard deviation)*	*Average bill*	*Number of respondents*	*Median* (Standard deviation)*	*Number of respondents*	*Median* (Standard deviation)*
Electricity	1460	617	9.50 (12.99)	35.82	1070	2 (25.67)	1081	1 (29.45)
Mobile phone	1502	686	9.95 (12.66)	25.69	1135	1 (21.42)	1152	1 (19.52)
Fixed phone line	1217	446	7.14 (9.53)	22.27	868	2 (23.80)	891	1 (25.23)
Calls	1160	396	8.14 (10.36)	19.30	845	2 (23.38)	862	1 (24.51)
Broadband	537	236	6.86 (8.78)	19.99	399	2 (22.63)	389	1 (27.21)
Car insurance	984	481	19.60 (34.94)	53.90	758	2 (23.24)	753	1 (19.50)
Mortgage	581	217	44.57 (47.79)	427.89	419	8 (33.33)	413	8 (35.08)
Current bank a/c	1437	313	5.28 (18.65)	7.32	978	6 (29.40)	985	2 (32.18)
Average			**12.22**	**55.37**		**2**		**1**

Note: In our sample, expected search time and switch time take the following values: 0: No time at all; 1: Up to an hour; 2: 1–3 hours; 6: 4–8 hours; 8: about 1 day; 20: 2–3 days; 40: 4–6 days; 80: A week or more. Descriptive statistics for other variables are shown in Appendix III, Table A5. Observed ratio of searching/switching is shown in Table 4 below.

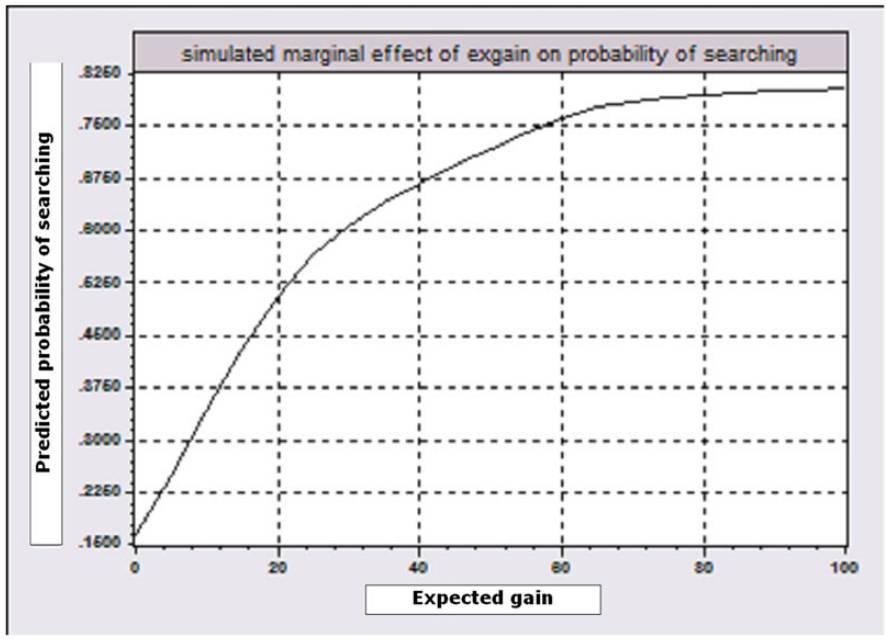

Figure 1A. Simulated effect of expected gain on the probability of searching

throwing different numbers of draws (100, 150, 200, 250, 300) following the Halton sequence (see Appendix I) to achieve a stable set of results.

The large Chi2 values in the third part of Table A1 show that all three models are statistically significant, and the high percentage of correctly predicted observations in the same part of Table A1 demonstrates that predicted probability closely matches the actual searching/switching decisions (a comparison of predicted probability and observed search switching ratios is shown in Table A2 in Appendix II).

We first consider the effect of expected gain and anticipated search and switching time on behavior, noting that the mean estimates of expected gain (the first part in Part II of Table A1, which corresponds to the first term in equation A3) in the random parameter model are statistically significant. Figure 1 shows how expected gains predict the probability of searching or switching. When the expected gain is at the sample mean (around £12 per month), the probability of searching is about 37 percent (panel a). If the expected gain is reduced by about half a standard deviation to zero, the probability of searching falls to 16.5 percent, while a similar *increase* to £24 raises the probability of searching to about 60 percent. The equivalent probabilities of switching are around 18 percent (for zero expected gain), 40 percent (£12 gain), and 66 percent (£24 gain), respectively; and for searching-and-switching are 8 percent, 24 percent, and 46 percent.[28]

[28] These figures are all for the average person in the sample.

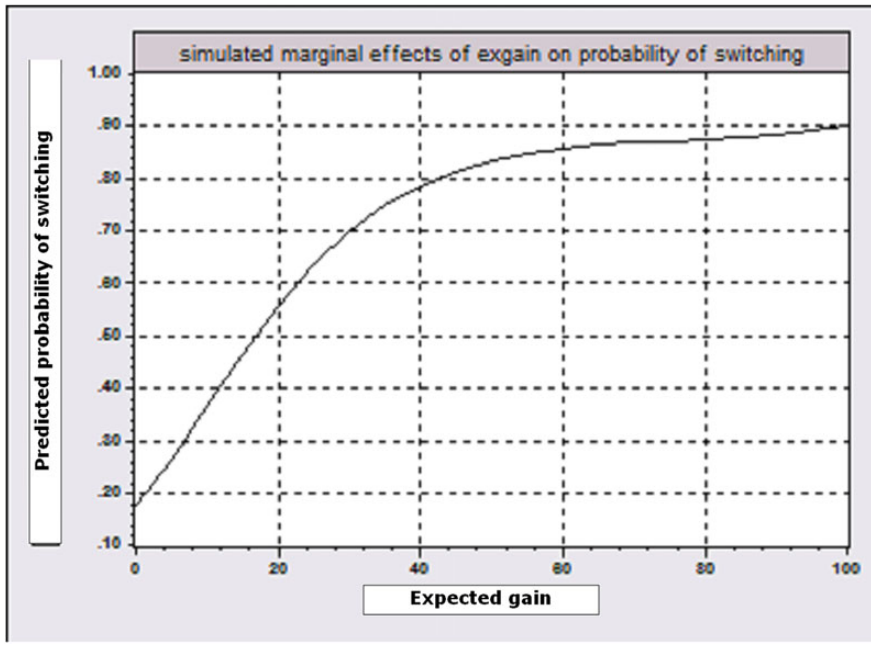

Figure 1B. Simulated effect of expected gain on the probability of switching

The positive switching rate at zero gain may be explained by those who switch for non-financial reasons, and is consistent with the proportion of "pure errors" in switching identified in previous studies.[29] Overall these results confirm that expected gains affect both search and switching decisions positively.

We note that respondents do not seem to be deterred from searching by longer anticipated search times, since the coefficients of this variable are not statistically significant,[30] suggesting that search time may not be the best measure of search cost. However we find that anticipated switching time does have a statistically significant and negative effect on the probability of searching, switching, and searching-and-switching in the random parameter model, perhaps because the switching process is less intrinsically enjoyable and maybe more stressful. Table 3 shows that when anticipated switch time is zero the search model predicts the probability of searching at 62 percent and the probability of switching at around 48 percent; while the predicted probability of undertaking both activities is around 30 percent when it takes no time to switch. As expected switching time increases, the predicted probability of both

[29] Wilson, *supra* note 13.

[30] We report the results related to search time in the searching equation. We also included it in the switching equation but it was not significant and was later dropped from the switching estimation.

searching and switching falls.[31] The mechanism may be that a reduction in expected switch time affects consumers' propensity to switch first, which then promotes consumers' search activity and, in turn, determines the final switch decision. As discussed earlier, we do not attempt to identify how the sequential process may deter search and switching.

While the mean estimates (shown in the first part of Part II in table A1) of switching experience in other markets are not significant in the random parameter model, the effect does vary significantly across markets and individuals. For instance, switching experience has most effect on activity in the fixed phone line, national and overseas calls, car insurance and mortgage markets, with less effect among people who have lower income or are older.

Next we analyze the effect of other demographic factors, in particular age, gender, income and education, both directly and in interaction with expected gain, expected switching time and switching experience in other markets. Here we report these effects when other variables are controlled for, and discuss later the comparison with raw associations, and the policy implications.

We separate out the direct effects of age on behavior from their indirect effects on expectations of gain and effort and, as in other similar surveys, found a U-shaped effect of age on searching/switching (see Figure 2 below for the switching model). In terms of the interactive effects of age with expected gain, switching time and switching experience, we find that older people are likely to value gain more, are more deterred from searching (but less deterred from switching) by longer switching time, and are less affected by their own experience of switching in other markets. The model indicates that switching is least likely around age 56, with its probability increasing as respondents reach and pass retirement age, controlling for other variables. We also find a significant effect of gender in the random parameter models, with males less likely to search and switch than females; from the interaction terms we note that men seem to value gain more and switching time less than women.

Income has on average a negative effect on the probability of activity, showing that respondents with higher income are less likely switch, as we might expect, though the (negative) effect on the probability of searching is not statistically significant. The random parameter model shows that the positive effect of expected gain is more significant for people with higher income,

[31] All the predictions above are based on the population mean estimates, to provide better general estimates, rather than on the individual-level conditional estimates that take account of individual heterogeneity. The use of the individual-level conditional estimates means that the predicted outcome is limited to within the sample drawn as part of the study. These individual-specific estimates are only as good as the data from which they are estimated and may not be ideal for prediction of population behavioral reactions to changes in certain factors, such as expected gains; for details, *see* DAVID A. HENSHER, JOHN M. ROSE & WILLIAM H. GREENE, APPLIED CHOICE ANALYSIS: A PRIMER (Cambridge Univ. Press 2005). Therefore, the above predictions are based on the unconditional (population) mean estimates only. The same problem is also likely to arise in using unconditional mean estimates obtained from non-representative samples.

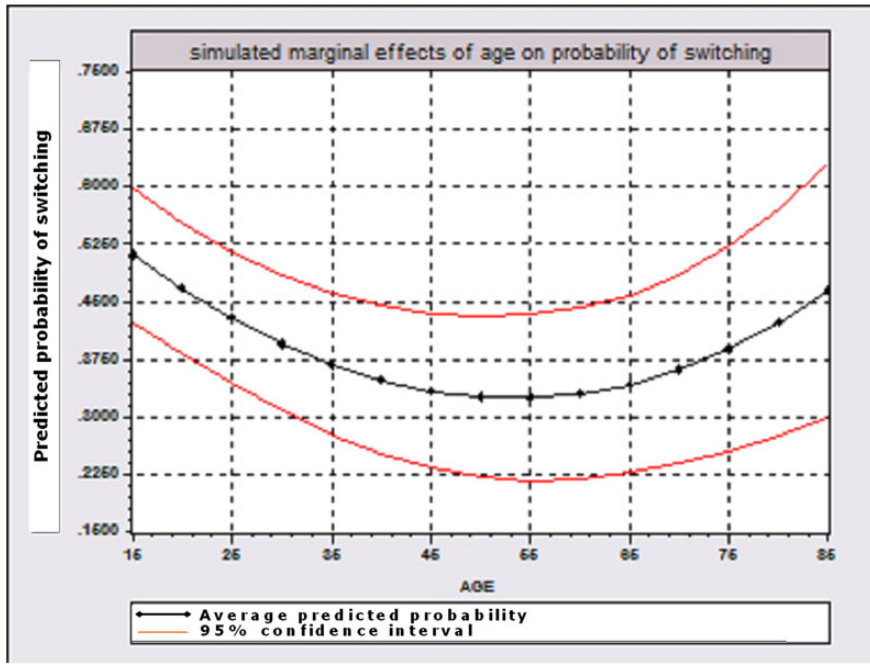

Figure 2. Simulated effect of age on the probability of switching

suggesting that richer households value an additional pound of gain more. We also find that higher income respondents are (rather surprisingly) less likely to value switching time and more likely to be affected by switching experience.

Education seems to have no significant effect on the probability of searching or switching on average in the random parameter model. However, the interaction terms indicate that more educated people are less likely to search or switch for given additional potential gains, and are less likely to be deterred from searching by higher expected switching time. Table 3 summarizes the above results.

1. *Differences Between Markets*

Having discussed the effect of primary variables and their interaction with various demographic variables, we now focus on differences between the markets included in the survey, controlling for these other variables. The market dummies (reported in Table 1A) show large variations across markets: other things being equal, consumers are less likely to search/switch their fixed line suppliers (phone line and calls) and their mortgage providers than they are their electricity provider. Such differences reflect the descriptive data shown in Table 1 and suggest a range of market specific factors, including the presence of intermediaries such as switching web sites, advertising and sales activity, concern about quality issues that might make consumers more reluctant to switch and how long a market had been open to competition at the time of the survey.

Table 3. The effect of demographic factors on the probability of searching/switching

	Probability of Searching	**Probability of switching**	**Probability of searching-and-switching**
Age in years	–0.101*** (0.020)	–0.054*** (0.017)	–0.066*** (0.019)
Age in years squared	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Gender (1 = male, 0 = female)	–0.510*** (0.162)	–0.576*** (0.156)	–0.640*** (0.177)
Income (gross annual household in £000)	–0.008 (0.004)	–0.009* (0.005)	–0.014** (0.006)
Education (in years)	0.053 (0.036)	–0.022 (0.034)	–0.026 (0.041)
Heterogeneity (based on demographic factors) in the Means of Random Parameters			
Expected Gain: Income	0.001*** (0.000)	0.001*** (0.000)	0.002*** (0.000)
Expected Gain: Education	–0.010*** (0.002)	–0.003** (0.001)	–0.005*** (0.002)
Expected Gain: Age	0.002*** (0.000)	0.000 (0.000)	0.001*** (0.000)
Expected Gain: Gender	0.037*** (0.009)	0.035*** (0.007)	0.041*** (0.008)
Expected switch time: Income	0.004*** (0.000)	0.000 (0.000)	0.001*** (0.000)
Expected switch time: Education	0.024*** (0.003)	0.001 (0.001)	0.005** (0.002)
Expected switch time: Age	–0.002*** (0.001)	0.001*** (0.000)	0.000 (0.000)
Expected switch time: Gender	0.105*** (0.015)	–0.000 (0.006)	0.026*** (0.009)
Switched other: Income	0.012** (0.006)	–0.379 (0.256)	0.016*** (0.006)
Switched other: Education	0.014 (0.043)	0.902** (0.358)	0.052 (0.044)
Switched other: Age	–0.022*** (0.007)	1.971*** (0.523)	–0.017*** (0.007)
Switched other: Gender	–0.017 (0.200)	1.272*** (0.440)	0.180 (0.197)

Even after these market variations (and other variables) have been taken into account, differences between markets remain in three important respects: the marginal influence of an additional pound's expected gain; the effect of expected switching time; and the experience of switching in another market.[32] Taking expected gain as an example, Figure 3 shows the estimated coefficients of expected gain of 19 individuals in our data sample who are present in all 8 markets and depicts variations across markets for each individual in relation to the effect of expected gain. The individual estimates for each respondent in each of the 8 markets are shown by the dots with the light lines indicating the lower and upper values. The dark vertical lines separate observations from each of the 19 individuals.

We calculated the variation in the mean and standard deviation of the estimated random parameters of expected gain, switch time and "*switched other*" across markets based on individual-specific mean estimates like those shown in Figure 3,[33] and taking these differences between markets into account. This enables comparison of the different average effect of each of the "primary"

[32] These are shown in the interactive terms with market dummies in Part II in Table A1.

[33] Note that these are means (and standard deviations) of individual-specific conditional estimates of coefficients and should be distinguished from the marginal effects often reported in fixed parameter models such as the bivariate probit model. Standard deviation is computed from the average of the conditional variances plus the variance of the conditional mean.

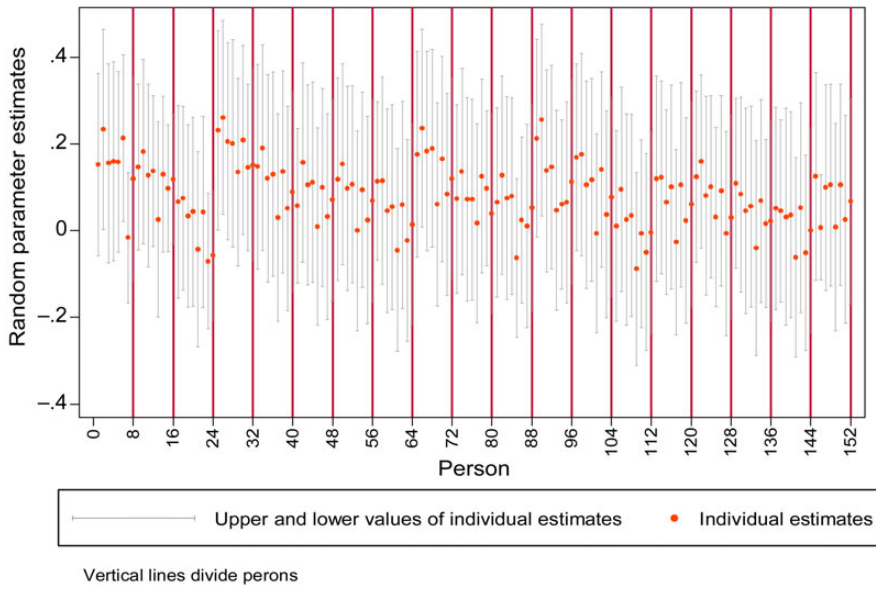

Figure 3. Random parameter of expected gain in the searching model for 19 persons present in all 8 markets
Note: Vertical lines divide persons.

variables on consumer behavior across markets, allowing for the demographic characteristics of individual respondents in the sample.

We observe considerable differences in the simulated conditional coefficients averaged across markets (as well as the standard deviation). An additional pound of expected gain is more likely to stimulate searching for an alternative mobile phone provider than in the electricity, fixed phone and car insurance markets, but is less likely to motivate search or switch activity for broadband, mortgages or current accounts. Expected switching time seems to provide more of a deterrent to searching and switching in fixed phone provision and current bank accounts, but is less off-putting for mobile phones, broadband, car insurance and mortgages. Switching experience is particularly likely to encourage searching and switching for alternative mortgages. These differences suggest that the primary drivers of activity, namely anticipated gain and time needed to switch, have different effects in each market.

2. *Differences Between Individuals*

Finally, we discuss how the estimated effects of expected gain, switching time and experience of switching in other markets vary across individuals, even after controlling for the observed heterogeneity related to markets and to known individual characteristics (the demographics discussed above).The observed heterogeneity in the mean $(\beta + \Delta z_i)$ in equation A2) should reduce the role of the

Table 2. Simulated effect of expected switching time on the probability of searching/switching

Switch time	Simulated probability of searching	Simulated probability of switching	Simulated probability of searching-and-switching
No time at all	0.62	0.48	0.31
Up to an hour	0.48	0.46	0.28
1-3 hours	0.35	0.43	0.26

Note: The majority (66 percent) of the consumers in our sample expect switching time to be less than 3 hours, and so we report simulated probabilities for this range only.

"residual" mean estimate (the third term in equation A2) for random variables including expected gain, switch time and switched other. However we still observe significant dispersions of individual estimates of these coefficients (see the section of Standard Deviation of Random Parameter Distribution in Table 2), and the conditional mean estimates exhibit differences across individuals. To depict the extent of variation in the effect of the same expected gain on different individuals, Figure 4 shows the individual estimates (the dots) and the upper and lower bound of the each individual estimates (the light vertical lines) of the coefficient of expected gain for 331 individuals in the electricity market. The horizontal lines indicate the mean, upper bound and lower bound of the mean of the estimated individual coefficients of expected gain for all 331 individuals. The differences across individuals confirm the importance of taking into account unobserved heterogeneity between consumers that reflects individual-specific preferences in searching and switching decisions.[34] The strategy and policy implications of these variations across individuals, both observed and unobserved, are discussed in Part V.

B. Selection and Interaction Issues

Only about half the respondents were able to provide estimates of all the "primary" variables, namely how much they expected to gain from changing provider and how long they thought searching and switching would take; other data

[34] Using random parameter models as opposed to a fixed parameter model (such as bivariate probit) enables a more realistic assumption and more robust model specification. As an alternative approach for cross-checking we have also undertaken a bivariate probit analysis. Some details are published in Catherine Waddams Price, Catherine Webster & Minyan Zhu, *Searching and Switching: Empirical Estimates of Consumer Behaviour in Regulated Markets* (Centre for Competition Policy, Working Paper 13-11, 2013), http://competitionpolicy.ac.uk/documents/107435/107587/13-11+Complete.pdf/97349ab4-1532-4eb7-a8fc-35fd2c8da011; and the full results are available from the authors. The bivariate probit model confirms the main results from the random parameter model though with lower levels of statistical significance. In particular, the random parameter model highlights the unobserved heterogeneous preferences among consumers regarding their searching/switching decisions made in response to expected gain or switching time.

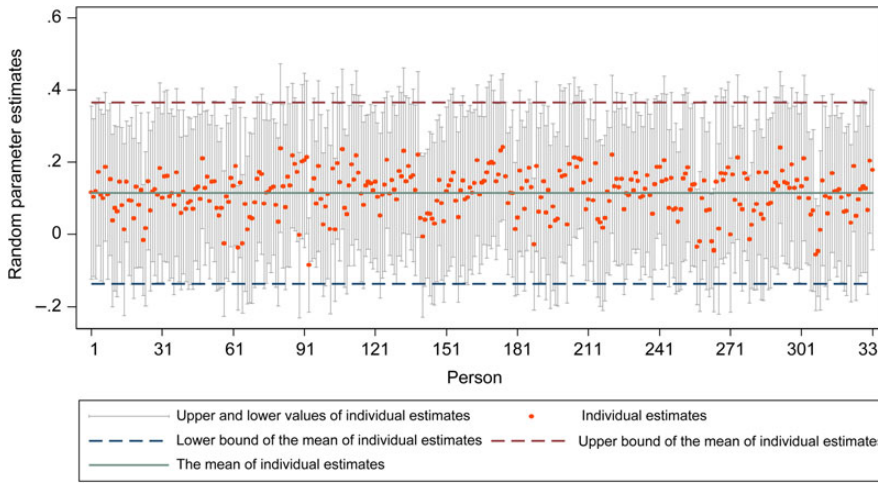

Figure 4. Random parameter of expected gain in search model by individual in the electricity market

sets were incomplete,[35] mainly through refusal to answer the income question.[36] This raises concerns about two potential sources of bias: first, those who could provide estimates may be more likely to be searchers and switchers; second, the searching and switching processes themselves may have resulted in different expectations of potential gain and time required to make the change. Table A6 in Appendix IV and Table 4 below show that those who were included in the analysis were indeed more likely to have searched and switched, confirming the first potential bias, so that the results apply to an untypically "active" subset of the consumers approached, and we take account of this in drawing strategy and policy conclusions in Part V.

We also note that the proportion of each age group that is absent because of missing data is U-shaped, with the youngest and eldest groups least likely to provide complete answers. Selectivity among these respondents is therefore greatest, a factor relevant to our discussion of the interaction between demographics and expectations below.

The second potential bias arises in identifying the causality of the relationship between switching and search activity and expectations of potential gain and effort. Activity in the market could have affected respondents' estimates of

[35] We lost 1556 observations due to missing expected gain and 4690 due to missing expected switch time; 3425 observations were lost due to missing income. The combined effect was that we retained only 1836 out of 8878 potential observations.

[36] An earlier selection process included only those who were responsible for choosing the provider and aware of choice of provider. However, since we are interested in the population that is both responsible and aware of choice, these differences merely show that the population we are sampling differs from a stratified sample of all adults.

gain and time taken to search and switch, rather than vice versa. Cognitive dissonance may also have played a part, with some respondents expressing justification for their (in)activity by understating gains and exaggerating time estimates. The raw associations shown in table A7 (Appendix IV) naturally raise these questions.

We have addressed this issue both by asking those who have switched what they had thought they could save beforehand, and by constructing the expectations of time as far as possible from prior estimates (see Tables A3 and A4 in Appendix III). Among those who have switched, their mean expectations of gain before they switched were significantly higher than the gains they thought they could make by switching again, as one would expect if they believed they had already realized a substantial portion of any potential gains. However, any remaining bias will tend to put more weight on expected gains and time taken than a true underlying distribution would reveal.

While our methodology of basing analysis on consumer expectations rather than market values means that we are unable to match potential gains available in all markets with individual expectations to test any such bias, homogeneity in the electricity market enables some rough estimates. Among consumers who had searched, those who were still with their electricity incumbent expected to be able to save an average of around £4.6 more per month than those who were not. Since incumbents were charging around 10 percent (£3.6 per month) more than non-incumbents at this period,[37] average consumer expectations among searchers reflected these market circumstances surprisingly closely, providing little evidence of "causality" bias.

One important policy relevant aspect is how far consumer searching and switching behavior differs between demographic groups, and our analysis emphasizes both the role of selection in determining the relationships, and how these change when other factors are taken into account, as in the analysis that we have presented.[38] To illustrate and explore this further we present in (Table 4) the search and switching rates according to age and income groups, both for the entire (reasonably representative) sample as a whole, and for the subset of respondents who were included in the analysis because they could provide full answers to all the relevant questions.

We see that for the group as a whole, both switching and searching rates decline with age, though this pattern is less clear cut among the analyzed sample. However, Figure 2 above shows a U-shaped relationship between

[37] OFGEM, ENERGY SUPPLY PROBE (Oct. 2008), https://www.ofgem.gov.uk/ofgem-publications/38437/energy-supply-probe-initial-findings-report.pdf.

[38] Jerry Hausman and Gregory Sidak found similar demographic patterns in the long distance calling charges paid by telephone users, though in their case the actual potential gains available from switching (compared with our self reported anticipated benefits) were greater for low income consumers, *see* Jerry A. Hausman & J. Gregory Sidak, *Why Do the Poor and the Less-Educated Pay More for Long-Distance Calls?*, 3 CONTRIBUTIONS IN ECON. & POL. RES. 1 (2004), http://ssrn.com/abstract=296368.

Table 4. Proportion of each age, income, and education group that has searched and switched

	Switched		Searched	
	Whole group	**Sample included**	**Whole group**	**Sample included**
Age group				
16–24	0.24	0.42	0.33	0.53
25–34	0.21	0.44	0.28	0.51
35–44	0.17	0.35	0.23	0.41
45–54	0.17	0.35	0.22	0.44
55–59	0.13	0.26	0.18	0.33
60–64	0.10	0.40	0.13	0.40
65–74	0.14	0.33	0.16	0.39
75+	0.07	0.39	0.07	0.39
Household Income group*				
low income	0.14	0.32	0.19	0.38
medium income	0.19	0.37	0.27	0.43
high income	0.21	0.43	0.30	0.57
Refused	0.15		0.18	
Education group				
GCSE/O-Level/CSE and below	0.16	0.36	0.20	0.41
Vocational qualifications (= NVQ1+2)	0.17	0.37	0.22	0.42
A-Level or equivalent (= NVQ3)	0.20	0.39	0.27	0.46
Bachelor Degree or equivalent (= NVQ4)	0.18	0.38	0.24	0.45
Masters/PhD or equivalent	0.18	0.44	0.28	0.70
Total	***0.17***	***0.37***	***0.22***	***0.45***

Note: Low income: less than £11,500 per annum; medium income: between £11,500 and £39,999 per annum; High income: more than £40,000 per annum; all total household income from all sources, before tax.

activity and age, with a *higher* likelihood of activity among older respondents than among the middle aged. This results both from the selectivity of inclusion, discussed above and demonstrated in Table 4, and from controlling for other variables in the analysis, in particular the primary factors of expected gain and search and switching time. In terms of income, Table 4 shows a clear inverse relationship between activity and income. Those with higher degrees are more likely to be active, particularly among the sample analyzed. The nature of these relationships is important in identifying appropriate policies to increase activity among a particular demographic group. In particular, the analysis enables us to identify how far inactivity is due to differences in respondents' expectations of gain and time to switch, and how far it is extraneous to these drivers.

Table 5 shows that average gains expected fall markedly for older respondents, and for lower income consumers, in both the full and selected groups. The coefficient for expected gains reflects the lower expectations among older respondents, and so masks the crude effect of age on searching and switching. Interpreting the results and developing appropriate policies (for example, to

Table 5. Expected gain in £ per month for different age and income groups

	Mean (standard deviation)	
	Whole group	**Sample included**
Age group		
16–24	13.05 (26.68)	13.29 (32.05)
25–34	14.34 (22.94)	16.19 (24.28)
35–44	14.82 (25.75)	16.15 (27.01)
45–54	11.09 (23.91)	11.25 (24.92)
55–59	9.30 (18.23)	11.13 (21.93)
60–64	7.45 (10.64)	1.41 (9.81)
65–74	6.47 (12.48)	6.85 (12.07)
75+	2.61 (4.22)	3.58 (4.00)
Income group		
low income	8.10 (13.42)	9.31 (14.70)
medium income	13.63 (23.28)	13.93 (24.05)
high income	14.69 (32.75)	16.19 (35.56)
refused	11.09 (21.18)	
Education group		
GCSE/O-Level/CSE and below	10.11 (20.42)	11.90 (22.86)
Vocational qualifications (= NVQ1+2)	11.90 (17.31)	12.13 (17.49)
A-Level or equivalent (= NVQ3)	14.62 (26.92)	15.45 (29.91)
Bachelor Degree or equivalent (= NVQ4)	15.54 (28.66)	16.82 (30.13)
Masters/PhD or equivalent	12.70 (20.80)	12.24 (20.95)
Total	***12.22 (23.06)***	***13.58 (25.35)***

encourage the less active to become more so) depends on how far these different expectations reflect variations in available gains in the market. For many of these products, for example energy, consumption may depend on income,[39] so lower income groups would be able to gain less in absolute terms because their bills are lower, though lower consumption is unlikely to account for all of the difference in expectations. The relationship between age and consumption is less well established, though the average consumption of pensioner households is likely to be lower.[40] The much lower expectations of gains among older groups is likely to exaggerate any differences in real opportunities, especially because older respondents report less activity in the markets, and are therefore less likely to be on a good deal already. This suggests that one way to encourage more switching in these groups would be to increase their expectations of potential benefits. There does not seem to be a clear relationship between expected gains and educational qualifications, other than a weak inverted U shape: those with least and most qualifications expect lower gains.

[39] *See, e.g.*, Arun Advani, Paul Johnson, Andrew Leicester & George Stoye, Household Energy Use in Britain: A Distributional Analysis (Institute for Fiscal Studies 2013), http://www.ifs.org.uk/comms/r85.pdf.

[40] See, e.g., Catherine Waddams Price & Ruth Hancock, Distributional Effects of Liberalising UK Residential Utility Markets, 19 FISCAL STUD. 295 (1998).

Other primary factors in our analysis also vary by age and income group and statistical tests confirm that expected time for searching and switching are correlated with demographic factors, though the relationships are less clear. Summary charts of expected time to switch for different age and income groups among the sample analyzed are shown in the Appendix IV, Figure A1. The variations in expectations will also be reflected in the coefficients for each of these variables in the analysis reported above, and the implications for policy are discussed further in Part V.

V. DISCUSSION AND CONCLUSION

Our model predicts well the factors associated with consumer market activity in our sample, finding that higher levels of searching and switching are associated with greater anticipated gains and lower expected time needed to switch; this is consistent with anticipated gains stimulating engagement and switching time deterring it. Moreover, while the time to search has little deterrent effect, suggesting that it may be intrinsically more enjoyable or less stressful than the switching process, the expected time to switch seems to discourage both searching and switching. These results confirm the effectiveness of sales tactics that highlight, "Switch to us and save £100 a year on your bills," emphasizing gains and shortening the switching process. Such marketing often aims to bypass the search process altogether by presenting potential buyers with a ready-made offer and encouraging an immediate purchase. Regulators who want to stimulate activity need to emulate such confidence in potential gains, while projecting a short switching process. In practice such messages are often more successfully conveyed to consumers by firms than regulators, whose most important role may lie in ensuring that firms have the incentive and ability to stimulate consumer activity. Avoiding perverse incentives is particularly pertinent in sectors like energy, telecommunications, and finance, which are subject to regulation because of the perceived importance of the service, and where an emphasis on fairness may lead to policies that could discourage consumer activity.

Such concerns with equity may coincide with statutory duties towards particular demographic groups of consumers, in particular the elderly and those with low income, and our results show some differences in both the expectations and the related behavior of these groups. There is a familiar U-shape in the age profile of the underlying propensity to switch, showing the middle aged least active, and the young and old more so, if expectations are controlled for. But we have noted above that this effect is partly the result of differences in anticipation between groups, in particular the lower gains expected among older respondents. These variations in predictions by consumers also explain why the effects of the main drivers of activity seem to be exaggerated among older people—additional gains provide a greater incentive to action, and switching time a greater deterrent to searching; while previous experience of switching has a smaller effect on older respondents, perhaps because they have

a higher level of experience across markets. Efforts to emphasize potential gains and minimize expected time spent in switching would therefore be expected to have a stronger effect among older consumers. However, the activity among those older respondents included in the analysis suggests that any regulatory intervention among this group needs to address the expectations held, rather than be based solely on age.

Lower income respondents are more likely to switch (but not significantly more likely to search) than those with higher incomes, which is consistent with a higher marginal value of savings. This effect is even more marked, given that the smaller expected gains of lower income households have been controlled for. Those with lower income are less responsive to gains (though they expect these to be lower than others do) and more responsive to the length of the process, and may be more risk averse, perhaps because they have more at stake (relatively) than higher income households. The policy implications depend on whether their lower predictions are realistic reflections of market opportunities. If so, the findings suggest that policies that emphasize gains may be less effective among lower income households, and may have to be supplemented with other measures, in particular reducing switching times, which particularly deter these households. Lower income households have less experience of switching in other markets. As with older consumers, we note that a lower proportion of low income consumers could answer all the questions, and so more are missing in the analyzed sample.

Policy makers may also be concerned to increase activity in the market by those with lower educational achievements. While there is no significant difference in the underlying level of searching and switching among such households, they are more responsive both to higher expected gains in encouraging searching and switching, and to anticipated switching time in deterring searching. This indicates the importance of communicating the available gains and any shortening of switching time to this group to encourage them to take advantage of potential gains.

Our findings question the type and value of blanket intervention for groups who may be considered vulnerable because of age, low income or low education achievement. Once other factors are considered, they are neither less active nor less responsive to changes in expected gains and switching time among the group who are knowledgeable about opportunities and costs. Indeed all show signs of responding more to these stimulants than other groups in the population. One particular concern about interventions on behalf of vulnerable consumers arises from positive externalities. Higher switching for one service is associated with switching in others, so protecting individuals in one market may reduce their activity in others among the relatively informed group. The concern arises if the relationship is causal, so that the experience itself affects the activity, rather than that some respondents are inherently more prone to be active. The variation in the effect of experience across markets for the same individual suggests the former explanation, namely that switching in one market does increase

activity in another. Interventions to protect consumers, including aggregated switching for vulnerable groups, may have the unintended consequence of reducing their activity and benefits in other markets, as well as any distortionary effects in the market concerned. However, we should note that these findings refer only to a relatively active subgroup of the sample, as we discuss below.

Activity varies not only between consumers, but also across markets. Consistent differences between markets in the underlying propensity to switch are shown by the market dummies in Table 2 and the interaction with the "primary" variables, after controlling for other known influences. In this context we note no significant difference in searching or switching behavior between electricity, mobile phone, broadband, car insurance and current accounts, but the model predicts lower fundamental activity levels in fixed phone lines and the mortgage market.

Such differences reflect a variety of market specific characteristics, including the amount of advertising and marketing, the length of time for which choice had been available, perceptions of ease of searching and switching (as well as the expected time involved that is directly measured and controlled for) and concern about quality levels, which are common within each market but vary between markets. In the retail banking sector, financial gains do not appear to be the main driver for switching compared to other regulated markets, consistent with the OFT's finding that only 14 percent of the consumers surveyed switch current account for better rates,[41] and perhaps reflecting the greater value to consumers of other services in this sector. However, it seems that expected time to switch may be a major deterrent to changing banks.

Increasing (well founded) consumer confidence in potential gains is likely to be an effective strategy across markets. Authorities who want to increase switching need to engender the same confidence as does the doorstep salesperson, while ensuring that it is based on unbiased information. Initiatives such as those the U.K. energy regulator is taking to simplify tariffs, to develop its own price comparison tool and to administer the confidence code for commercial price comparison websites,[42] are clearly aimed at helping improve both the quality of consumer information and their (justified) confidence levels. However, since anticipated savings will be strongly influenced by the price offers of competitors, policy makers need to ensure they do not dampen competition and so inadvertently reduce the gains that are available from switching supplier (as for example happened with reduced switching rates after introduction of the non-discrimination clause).[43] The significant heterogeneity between consumers and

[41] OFT, PERSONAL CURRENT ACCOUNTS IN THE UK: AN OFT MARKET STUDY (July 2008), http://webarchive.nationalarchives.gov.uk/20140402142426/http:/www.oft.gov.uk/shared_oft/reports/financial_products/OFT1005.pdf.

[42] OFGEM, THE RETAIL MARKET REVIEW—IMPLEMENTATION OF SIMPLER TARIFF CHOICES AND CLEARER INFORMATION (Aug. 2013), https://www.ofgem.gov.uk/sites/default/files/docs/decisions/the_retail_market_review-implementation_of_simpler_tariff_choices_and_clearer_information.pdf.

[43] *See* Morten Hviid & Catherine Waddams Price, *Non Discrimination Clauses in the Retail Energy Sector*, 122 ECON. J. 236 (2012); Catherine Waddams Price & Minyan Zhu, *Non-Discrimination*

across markets means that regulators need to differentiate their strategies. For example the model predicts that (across markets) gains have to be as high as £100 per month (when the sample mean is about £12 per month) to entice the majority of consumers (around 80 percent) to search and switch.

This variation persists even though our analysis includes only the subset of respondents who are able to answer all the relevant questions, and who are more likely to search and switch than the representative group that was interviewed (see Part IV.B above). Our sample therefore consists of the most "active" section of the population. Within this active group virtually all the switchers had looked around for a better deal first, so are likely to make better decisions. Passive consumers who may have been persuaded to switch without first searching were excluded from our analysis because of incomplete answers to the survey, in particular their inability to estimate potential gains.

So while our findings can inform strategies to increase activity among those who are already reasonably well informed about the market, effects may be very different among the more "disengaged" half of households who disproportionately represent lower income and older (and younger) households. If activity among this latter group is to be encouraged, research is clearly needed to understand further the drivers of (in)activity. Field experiments, to confirm the laboratory results of Sitzia, Zheng, and Zizzo, that capture real time responses of consumers facing competing demands on their time and attention in everyday life would provide robust results for this inactive group, and have the benefit of drawing conclusions from observed behavior rather than recall; it would also test among less informed respondents the findings from this study, which, while benefiting from capturing consumers' own expectations and experience, are also subject to the limitations of partial recall and response.

The data on which these findings and conclusions are based are almost a decade old at the time of writing, and services available on the internet, and their usage, have developed significantly in that time, almost certainly reducing the cost of searching, and perhaps lowering the cost of switching to a lesser extent. However, there is increasing concern about a digital divide, in particular that lower income and older consumers may have less access or be less comfortable using such innovations, so the differences that are reported in this article may have been exaggerated by these changes. On the other hand, technical advances and increases in information available should enable policy makers to explore more fully the differences that do exist, and so to design appropriate responses.

Clauses: Their Effect on GB Retail Energy Prices, ENERGY J. (forthcoming 2016). For figures on switching, *see* DEPARTMENT OF ENERGY & CLIMATE CHANGE, QUARTERLY DOMESTIC ENERGY SWITCHING STATISTICS (Mar. 2013), https://www.gov.uk/government/statistical-data-sets/quarterly-domestic-energy-switching-statistics.

Three features that we expected to affect activity, and have been found influential in other studies, are not associated with the searching and switching of the group analyzed here, once other factors are controlled for. The first, expected search time, has already been discussed. The second, whether the respondent expects their existing supplier to match better deals, also has little effect (we had expected that such an expectation would lower the probability of switching). And the third is whether it is important to trust suppliers in a particular market. This has been found to be important in the past, with higher importance of trust associated with lower switching rates within a particular market. It may be that there is little variation within markets in our sample and that between-market variation is captured by the market dummies. The selection issues discussed above may be particularly relevant in interpreting these (non)associations, and each of these factors may well affect the inactive group as a whole, or activity within this excluded group. To the extent that campaigns and policy are directed at the less active in any market, these factors require further exploration.

In conclusion, we have shown that expected gain and anticipated switching time are consistently associated with search and switching in these service markets, that these expectations themselves show differences between groups, and that behavior exhibits distinct patterns and differences across markets, between types of consumers, and between individuals. The model provides initial information to inform market segmentation and regulatory policies to empower consumers, increase (effective) activity in relevant markets, and generate additional competitive pressure on the market.

APPENDIX I. ECONOMETRIC MODEL: THE RANDOM PARAMETER PROBIT MODEL

Suppose the utility associated with the binary decision of searching or switching as evaluated by each individual i is represented in a binary choice model by a utility expression of the form:

$$U_i = \beta_i X_i + e_i,\ e_i \sim N[0,1]. \tag{A1}$$

X_i is a vector of (non-stochastic) explanatory variables that are observed. e_i is independent and identically distributed. β_i and e_i are not observed and are treated as stochastic influences. The parameter vector β_i is assumed to be randomly distributed over individuals according to:

$$\beta_i = \beta + \Delta z_i + v_i = \beta + \Delta z_i + \Gamma \eta_i \tag{A2}$$

where $\beta + \Delta z_i$ is the mean of the distribution (population mean or unconditional mean). β_i depends on individual characteristics as well as parameters yet to be estimated, and the random variation comes from the individual heterogeneity, v_i. This random vector is assumed to have mean zero and covariance

matrix Σ. Now the utility function involves terms:

$$\beta_i X_i = \beta X_i + (\delta' z_i) X_i + \gamma' \eta_i X_i. \tag{A3}$$

As shown in (2) and (3), introducing z_i in (2) to reveal the presence or absence of preference heterogeneity around the mean parameter estimate is equivalent to introducing interactive terms in the utility function as shown in (3). If the interaction is not statistically significant, then we can conclude that there is an absence of preference heterogeneity around the mean on the basis of the observed covariates, z_i. But this does not mean that there is no preference heterogeneity around the mean, but simply that we have failed to reveal its presence in the second term in (3). This means that we rely only on the standard deviation of the parameter estimate—that is, the third term in (3) for sources of preference heterogeneity across individuals.

The conditional density of the parameters is denoted

$$g(\beta_i | z_i, \beta, \Delta, \Sigma) = g(v_i + \beta + \Delta z_i, \Sigma). \tag{A4}$$

The unconditional density for U_i is obtained by integrating over β_i,

$$\begin{aligned} f(U_i | X_i, z_i, \beta, \Delta, \Sigma) &= E_{\beta_i}[f(U_i | X_i, \beta_i)] \\ &= \int_{\beta_i} f(U_i | X_i, \beta_i) g(\beta_i | z_i, \beta, \Delta, \Sigma) d\beta_i. \end{aligned} \tag{A5}$$

The integration will not exist in closed form. They can be estimated by simulation. The simulated log likelihood is

$$\ln L_s = \sum_{i=1}^{n} ln\{\frac{1}{R} \sum_{r=1}^{R} f(U_i | X_i, \beta + \Delta z_i + v_i)\}. \tag{A6}$$

Note that the simulation is over R draws on v_i through β_i as defined in (2). The maximum simulated likelihood estimator is obtained by maximizing (A6) over the full set of structural parameters.

As we are interested in estimating individual-specific parameters, we compute the posterior estimate as follows based on individual information and the prior estimate, $\beta + \Delta z_i$:

$$\hat{E}[\beta_i | \beta, \Delta, X_i, z_i, \Sigma] = \frac{1/R \sum_{r=1}^{R} \hat{\beta}_i f(U_i | X_i, \hat{\beta}_i)}{1/R \sum_{r=1}^{R} f(U_i | X_i, \hat{\beta}_i)} \tag{A7}$$

where $f(U_i | X_i, \hat{\beta}_i)$ is the simulated probability of choice and $\hat{\beta}_i = \hat{\beta} + \hat{\Delta} z_i + v_i$.

In terms of selecting the number of points for the simulation, we follow the Halton sequence.[44] We try different number of draws to secure a stable set of parameter estimates. Estimations are obtained by using NLOGIT 5 software.

[44] *See, e.g.*, KENNETH TRAIN, DISCRETE CHOICE METHODS WITH SIMULATION ch. 9 (Cambridge Univ. Press 2003).

APPENDIX II. FULL RESULTS

To illustrate the interpretation of Table A1, consider the search model, where expected gain, switching time and switching experience in other markets (switched other) demonstrate random coefficients in the probability of searching.[45] The results show that the mean estimator of the coefficient (that is, the first part in Part II of the table, corresponding to the first term in equation A3) of expected gain is positively significant; the mean estimator of the coefficient of expected switching time is negatively significant; and the mean estimator of the coefficient of "switched other" is positively significant (at 10 percent). The terms for heterogeneity in the means of these random parameters show, for example, that the influence of expected gain is more positive with higher income, but less positive with more education; expected gain is most positive among men and older people, and in the mobile phone and electricity markets, and least so in the mortgage and broadband markets.[46]

Table A1. Full results from the random parameter Probit models of searching and switching
Part I: Estimates of the fixed parameters

Dependent Variable → Independent Variable↓	**Probability of searching**	**Probability of switching**	**Probability of searching-and-switching**
Age in years	–0.101*** (0.020)	–0.054*** (0.017)	–0.066*** (0.019)
Age in years squared	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Gender (1 = male, 0 = female)	–0.510*** (0.162)	–0.576*** (0.156)	–0.640*** (0.177)
Income (gross annual household in £000)	–0.008 (0.004)	–0.009* (0.005)	–0.014** (0.006)
Education (in years)	0.053 (0.036)	–0.022 (0.034)	–0.026 (0.041)
Expected search time (hours)	–0.023 (0.025)		–0.014 (0.017)
Switched other	*random parameter*	0.555 (0.591)	*random parameter*
Constant	1.294* (0.684)	0.668 (0.603)	1.004 (0.696)
Market (base case electricity)			
Mobile phone	0.104 (0.241)	0.423* (0.229)	0.313 (0.254)
Fixed phone line	–1.087*** (0.373)	–0.950*** (0.339)	–2.155*** (0.741)
National and overseas calls	–0.768** (0.359)	–1.740*** (0.552)	–1.793*** (0.613)
Broadband internet	–0.144 (0.363)	–1.111*** (0.426)	–0.786* (0.463)
Car insurance	0.022 (0.260)	0.300 (0.235)	0.393 (0.267)
Main mortgage	–4.218*** (1.142)	–1.577*** (0.545)	–16.350*** (2.134)
Current bank account	–0.234 (0.395)	0.073 (0.335)	0.213 (0.391)

[45] A full model was run to include expected searching time with random coefficient but the dispersion of the coefficient (referring to the section of Standard Deviation of Random Parameter Distribution in Table A1) was insignificant, and so expected search time is considered to have a fixed coefficient. The same approach is taken with the switching model and the search-and-switching model.

[46] The interactive terms of expected search time with other factors are not reported as they were not significant.

Part II: Estimates of the random parameters

Dependent Variable → Independent Variable↓	**Probability of searching**	**Probability of switching**	**Probability of searching-and-switching**
Mean estimates			
Expected gain per month (£)	0.105*** (0.032)	0.081*** (0.025)	0.080*** (0.030)
Expected switch time (hours)	–0.619*** (0.060)	–0.102*** (0.024)	–0.126*** (0.033)
Switched other (1 = yes, 0 = no)	1.130* (0.683)	*fixed parameter*	0.419 (0.652)
Standard Deviation of Random Parameter Distribution			
Expected gain per month (£)	0.118*** (0.008)	0.081*** (0.005)	0.113*** (0.007)
Expected switch time (hours)	0.430*** (0.029)	0.071*** (0.006)	0.131*** (0.011)
Switched other (1 = yes, 0 = no)	0.944*** (0.080)	*fixed parameter*	0.521*** (0.062)
Heterogeneity in the Means of Random Parameters			
Expected Gain: Income	0.001*** (0.000)	0.001*** (0.000)	0.002*** (0.000)
Expected Gain: Education	–0.010*** (0.002)	–0.003** (0.001)	–0.005*** (0.002)
Expected Gain: Age	0.002*** (0.000)	0.000 (0.000)	0.001*** (0.000)
Expected Gain: Gender	0.037*** (0.009)	0.035*** (0.007)	0.041*** (0.008)
Expected Gain: Mobile phone	0.042** (0.019)	-0.004 (0.014)	0.007 (0.017)
Expected Gain: Fixed phone line	–0.028 (0.027)	–0.033* (0.020)	–0.036 (0.025)
Expected Gain: National and overseas calls	–0.019 (0.024)	0.005 (0.021)	-0.015 (0.022)
Expected Gain: Broadband internet	–0.117*** (0.035)	–0.062** (0.026)	–0.112*** (0.034)
Expected Gain: Car insurance	–0.014 (0.018)	–0.031** (0.014)	–0.039** (0.016)
Expected Gain: Main mortgage	–0.097*** (0.018)	–0.089*** (0.014)	–0.100*** (0.017)
Expected Gain: Current bank account	–0.059** (0.025)	–0.091*** (0.020)	–0.095*** (0.023)
Expected switch time: Income	0.004*** (0.000)	0.000 (0.000)	0.001*** (0.000)
Expected switch time: Education	0.024*** (0.003)	0.001 (0.001)	0.005** (0.002)
Expected switch time: Age	–0.002*** (0.001)	0.001*** (0.000)	0.000 (0.000)
Expected switch time: Gender	0.105*** (0.015)	–0.000 (0.006)	0.026*** (0.009)
Expected switch time: Mobile phone	0.088*** (0.023)	–0.006 (0.011)	0.012 (0.015)
Expected switch time: Fixed phone line	–0.143*** (0.026)	–0.044** (0.017)	–0.114*** (0.030)
Expected switch time: National and overseas calls	–0.082*** (0.026)	–0.045*** (0.014)	–0.049** (0.019)
Expected switch time: Broadband internet	0.067*** (0.024)	0.052*** (0.012)	0.068*** (0.015)
Expected switch time: Car insurance	0.205*** (0.029)	0.022* (0.012)	0.033** (0.016)
Expected switch time: Main mortgage	0.047** (0.023)	0.029*** (0.010)	0.071*** (0.016)
Expected switch time: Current bank account	–0.272*** (0.031)	–0.050*** (0.013)	–0.088*** (0.018)
Switched other: Income	0.012** (0.006)	–0.379 (0.256)	0.016*** (0.006)
Switched other: Education	0.014 (0.043)	0.902** (0.358)	0.052 (0.044)
Switched other: Age	–0.022*** (0.007)	1.971*** (0.523)	–0.017*** (0.007)
Switched other: Gender	–0.017 (0.200)	1.272*** (0.440)	0.180 (0.197)
Switched other: Mobile phone	–0.351 (0.295)	–0.009 (0.268)	–0.609** (0.284)

Continued

Part II: *Continued*

Dependent Variable → Independent Variable↓	Probability of searching	Probability of switching	Probability of searching-and-switching
Heterogeneity in the Means of Random Parameters			
Switched other: Fixed phone line	1.023*** (0.392)	1.313** (0.571)	1.962*** (0.724)
Switched other: National and overseas calls	0.726* (0.377)	–0.382 (0.406)	1.896*** (0.589)
Switched other: Broadband internet	–0.047 (0.411)	–0.016* (0.006)	0.785 (0.479)
Switched other: Car insurance	0.762** (0.318)	0.220 (0.176)	–0.024 (0.295)
Switched other: Main mortgage	4.062*** (1.073)	0.010* (0.005)	15.117*** (1.987)
Switched other: Current bank account	–0.369 (0.480)	0.043 (0.176)	–0.498 (0.451)

Note: In the switching equation, switched other actually has fixed parameters. So the reported estimates in the third column in the above are from the interactive terms with fixed parameters. It is reported in the same table here to enable easier comparison.

Part III: Model statistics

	Probability of searching	Probability of switching	Probability of searching-and-switching
Log likelihood	–1021.906	–947.839	–899.886
Restricted Log likelihood	–1104.322	–1008.296	–1000.420
Degree of freedom (d.f)	36	24	36
chi2 (d.f)	164.831	120.914	201.069
Goodness of fit†	96.90	89.49	94.50
Observations	1836	1836	1836
Number of draws	250	200	200

Notes: *, **, *** represent significant difference from zero at the 10, 5 and 1% levels respectively. † represents the percentage of correctly predicted observations: If the predicted probability is greater than 0.5, the observation is considered as searched/switched/searched and switched. Standard errors are given in parentheses.

Table A2. Predicted probabilities of activity by market

Market	Search	Switch	Search-and-switch
Electricity	[0.471] 0.475 (0.403)	[0.417] 0.419 (0.337)	[0.372] 0.365 (0.364)
Mobile phone	[0.534] 0.541 (0.392)	[0.475] 0.481 (0.307)	[0.419] 0.413 (0.353)
Fixed phone line	[0.323] 0.316 (0.397)	[0.241] 0.238 (0.288)	[0.194] 0.183 (0.298)
National/overseas calls	[0.383] 0.375 (0.406)	[0.340] 0.341 (0.353)	[0.273] 0.264 (0.343)
Broadband internet	[0.360] 0.347 (0.392)	[0.324] 0.323 (0.320)	[0.252] 0.237 (0.317)
Car insurance	[0.651] 0.670 (0.380)	[0.509] 0.516 (0.332)	[0.480] 0.481 (0.371)
Mortgage	[0.419] 0.418 (0.486)	[0.333] 0.327 (0.443)	[0.295] 0.293 (0.450)
Current bank account	[0.182] 0.167 (0.316)	[0.132] 0.119 (0.203)	[0.132] 0.116 (0.229)
ALL	[0.445] 0.446 (0.420)	[0.374] 0.374 (0.345)	[0.328] 0.321 (0.364)

Note: Observed ratios in [square brackets]; Standard deviations of predicted probability in (round brackets).

APPENDIX III. RELEVANT QUESTIONS FROM THE SURVEY AND CONSTRUCTION OF VARIABLES

Relevant Questions from the Survey:

Q1. In your area, do you have a choice of more than one provider for the following products? (Yes, No, Don't know)

Q2. Which of the following does your household currently have and pay for?

Q4. Using the words on this card, how important or unimportant is it to trust your provider for the following products? (Very important, Fairly important, Neither important nor unimportant, Fairly unimportant, Very unimportant, Don't know)

Q5. Have you looked around for a new provider for any of the following products at any time in the last three years, that is, since May 2002? (Yes, No, Don't know)

Q11. Apart from when moving home, have you switched provider of any of these products in the last three years, that is, since May 2002? (Yes, No, Don't know)

Q15. (Ask all who switched any) Please tell me how much time you spent searching around and looking for the necessary information before you switched each relevant product area? (No time at all, Up to an hour, 1 to 3 hours, 4 to 8 hours, About 1 day, 2 to 3 days, 4 to 6 days, A week or more, Don't know)

Q17. (Ask if any time spent searching at Q15) Would you say it took more time than expected, less time than expected or as long as expected to search for information? (More time than expected, As expected, Less time than expected, Don't know)

Q23. (Ask all who switched any) How much of your own time did it take to switch PRODUCT AREA after you made a decision? (No time at all, Up to an hour, 1 to 3 hours, 4 to 8 hours, About 1 day, 2 to 3 days, 4 to 6 days, A week or more, Don't know)

Q29. (Ask all not switched but searched in any area) How much time did it take you to search for the necessary information on PRODUCT AREA? (No time at all, Up to an hour, 1 to 3 hours, 4 to 8 hours, About 1 day, 2 to 3 days, 4 to 6 days, A week or more, Don't know)

Q33. (Ask all not switched but searched in any area) How long do you think it would have taken of your own time to switch once you had all the necessary information for switching? (No time at all, Up to an hour, 1 to 3 hours, 4 to 8 hours, About 1 day, 2 to 3 days, 4 to 6 days, A week or more, Don't know)

Q35. (Ask all non-switchers who have not searched) How much of your own time did you think it would take you to find enough information to decide whether and to whom to switch PRODUCT AREA? (No time at all, Up to an hour, 1 to 3 hours, 4 to 8 hours, About 1 day, 2 to 3 days, 4 to 6 days, A week or more, Don't know)

Q36. (Ask all non-switchers who have not searched) Once you have found all the necessary information to choose a new supplier, how much of your own time do you think it would take to switch PRODUCT AREA? (No time at all, Up to an hour, 1 to 3 hours, 4 to 8 hours, About 1 day, 2 to 3 days, 4 to 6 days, A week or more, Don't know)

Q38. (Ask all relevant switchers) How much did you originally expect to save per month by switching PRODUCT AREA?

Q43 Approximately how much do you pay on average per month for each of these PRODUCT AREAS?

Q44. (Ask all if answered Q43) To what extent would you agree or disagree that you are confident your estimate for PRODUCT AREAS is accurate?

Q46. (Ask all relevant) How much is the most you think you could save per month if you shopped around for PRODUCT AREA?

Construction of expected time spent searching and switching and expected gains:

The expected search time (*exsetime*) and the expected switching time (*exswtime*) are constructed from different questions for different consumer groups according to the table below.

Table A3. Construction of expected search and switching time

Consumer group	Time spent searching?	More or less than expected?	Expected search time ex ante?	Switching time ex post?	Expected switching time ex ante?
Searched and switched	Q15	Q17	Adjusted Q15 by one scale down or up according to Q17.	Q23	
Searched but not switched	Q29				Q33
Not searched nor switched			Q35		Q36
Not searched (Q15 = 0) but switched	0 from Q15	Q17	Adjusted, but not downwards	Q23	

The construction of the maximum expected gains from switching (*exgainmax*) variable differs by whether or not the consumer was a switcher. Table A4 below describes how this variable was constructed.

Table A4. Construction of expected gains

Consumer group	**Expected gains ex ante**
Switched	Q38
Not switched	Q46

Table A5. Summary statistics

Variables	**Observations**	**Mean/ Median**	**S.D.**	**Min**	**Max**
Expected gain (£ per month)	3392	12.223	23.065	0	400
Expected search time	6472	2* (1–3 hours)	25.583	0	80†
Expected switch time	6526	1* (up to an hour)	27.206	0	80
Age (years)	16216	43.393	17.542	15	99
Gender (1 = male, 0 = female)	16216	0.469	0.499	0	1
Education (years)	16216	12.523	2.377	11	20
Income (household annual gross, £000)	8568	24.483	18.395	2.25	100
Switched in other markets (1 = yes, 0 = no)	16216	0.398	0.489	0	1
Trust important (1 = yes, 0 = no)	9541	0.919	0.273	0	1
Supplier reluctant to match (1 = yes, 0 = no)	9541	0.152	0.359	0	1

Note: * Median (50th Percentile); †80: A week or more.

APPENDIX IV. SELECTION ISSUES

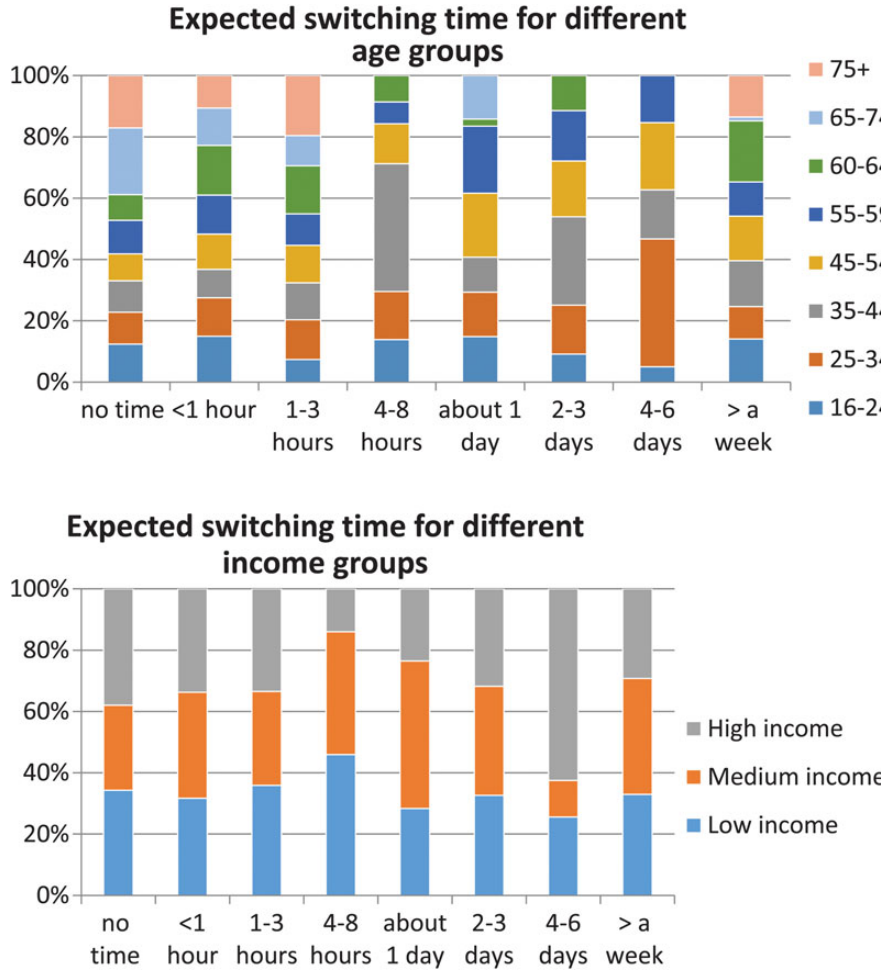

Figure A1: Expected switching time for respondents of different age, income and education groups.

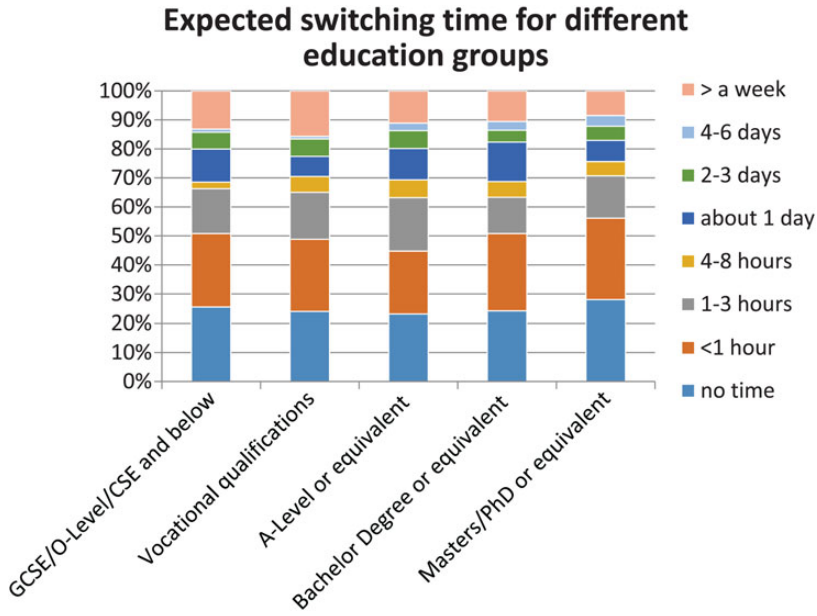

Figure A1: *Continued*

Table A6. Differences between those who are missing any variables used in the estimation and those who are included

Variable		In estimation sample	Not in estimation sample (that is, at least one missing)	Two-tailed sig.
AGE	Mean	40.74	45.48	0.000
	Standard Deviation	13.59	16.10	
	Observations	1836	7705	
GENDER	Female (%)	880 (47.93)	4176 (54.20)	0.000
	Total	1836	7705	
INCOME	Mean	26.99	26.33	0.448
	Standard Deviation	18.09	18.93	
	Observations	1836	3425	
EDUCATION	Mean	12.89	12.73	0.059
	Standard Deviation	2.43	2.55	
	Observations	1836	7705	
SWITCHED OTHER	Yes (%)	1001 (54.52)	3087 (40.06)	0.000
	Total	1836	7705	
RELUCT TO MATCH	Yes (%)	270(14.71)	1177 (15.28)	0.541
	Total	1836	7705	
TRUST IMPORTANT	Yes (%)	1717 (93.52)	7048 (91.47)	0.004
	Total	1836	7705	
EXPECTED GAIN	Mean	13.59	10.61	0.001
	Standard Deviation	25.35	19.92	
	Observations	1836	1556	
EXPECTED SEARCH TIME	Mean	13.54	13.97	0.531
	Standard Deviation	24.46	26.01	
	Observations	1836	4636	
EXPECTED SWITCH TIME	Mean	13.42	14.96	0.035
	Standard Deviation	25.93	27.68	
	Observations	1836	4690	
SEARCHED	Yes (%)	817 (44.50)	1317 (17.09)	0.000
	Total	1836	6388	
SWITCHED	Yes (%)	686 (37.36)	899 (11.85)	0.000
	Total	1836	7585	
Total numbers		1836	7042	

Table A7. Expectation differences between active and inactive consumers

	(1) Yes			(2) No			Mean difference	
Variables	**Observations**	**Mean**	**Standard Error**	**Observations**	**Mean**	**Standard Error**	**t-test**	**d.f.**
Searched								
Expected maximum gain (*£ per month)*	1321	17.033	0.800	2071	9.154	0.386	8.871***	1937
Expected search time (*hours*)	1897	12.741	0.558	4575	14.308	0.386	–2.309**	3778
Expected switch time (*hours*)	1932	10.516	0.533	4594	16.212	0.420	–8.390***	4365
Switched								
Expected maximum gain (*£ per month)*	1110	18.924	0.906	2268	8.978	0.374	10.147***	1497
Expected search time (*hours*)	1476	12.236	0.610	4996	14.325	0.370	–2.757***	6470
Expected switch time (*hours*)	1536	9.341	0.573	4990	16.121	0.401	–9.695***	3171

Note: The number of observations is for the panel ($I \times K$) of individuals (i) across markets (k). The mean difference t-tests were conducted for the base variables without interaction terms. Equal variances were not assumed for all tests other than expected search time (switchers v. non-switchers) where the population variances are not significantly different according to Levene's test. For those tests where equal variances were not assumed, we report Satterthwaite's degrees of freedom. *, **, *** imply t-statistics that have two-tailed significance at the 10-percent, 5-percent, and 1-percent levels respectively.