A STRUCTURAL MODEL OF THE DEMAND FOR TELECARE[1]

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In this paper, we formulate a structural model of the demand for telecare. We show how the Andersen's Behavioral Model of Health Services Use, the Almost Ideal Demand System and the Revealed Preference theory can be combined with microeconomic principles of health production to reason about individuals' utility maximizing behavior. We then estimate the model using a strategy that controls for the effects of both observable and unobservable factors, and later conduct a simulation exercise by way of a decomposition analysis.

Keywords: Telecare, health production, utility maximizing behavior.

1. INTRODUCTION

Telecare refers to the use of devices such as community alarms and automated motion sensors to monitor individuals' health and safety at home. These devices could lead to greater independence for the users by substituting for some social care services; may reduce the need for long term institutional care mainly through delayed admissions, and could lead to fewer unplanned admissions (Clark et al., (2007); Giordano, S., Clark, M. and Goodwin, N. (2011)). While the question of whether or not telecare is actually beneficial to the populace is often an empirical one, the studies in the literature investigating the effectiveness of telecare simply derive an estimate of causal effect without providing a rationale of how telecare use might influence outcomes. Some examples of such studies include: the Whole Systems Demonstrator Cluster Randomized Trials that find telecare users to have comparatively few unplanned hospital admissions (Steventon et al., (2013)) and better mental health related quality of life (Hirani et al., (2013)), and the studies by Akematsu, Y. and Tsuji, M. (2012) and Akematsu, Y. (2013) that use the Propensity Score Matching technique to show a shorter length of stay in hospital for telecare users compared with non-users. This paper therefore fills this knowledge gap by formulating a theoretical model of telecare use and then estimating the impact of telecare in light of the intricacies observed in the model.

The intuition behind the model is that individuals use various goods and services—including telecare—to improve their welfare and, by extension, health status. Here, we adopt the holistic definition of an individual's health that encompasses physical, mental and social well-being in addition to the absence of disease (World Health Organization). Our analytical approach is not new to economic sciences as it follows closely the Human Capital Model by Becker, G. (1965) and the model due to Rosenzweig, M. and Schultz, P. (1983) that explains households' utility maximizing behavior. Accordingly, the use of telecare can be thought of as a utility generating input as well as an input to health and we thus define our model as consisting of a health production function that is embedded in a utility function. Since telecare (unlike some other

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inputs) is purchased from the market, implying that individuals allocate part of their income so as to acquire it; the analysis in this paper takes the form of a constrained utility maximization problem, where the primary objective is to estimate the marginal product of telecare subject to individuals' health status and their prevailing budget constraints.

Such an estimation, however, is not straightforward due to the fact that an individual's true health status is typically unobservable—and hence cannot be identified a priori—and we also need some data to work with, specifically an appropriate outcome measure. Furthermore, the analysis of the utility function in our theoretical model necessitates the consideration of multiple factors that may affect utility and not just telecare use, and we therefore need to further extend the model to cater for these additional influences. In this paper, we link the Scottish Morbidity Records (containing information on acute hospital and psychiatric admissions during the 2010/2011 financial year) to three other data sources i.e. the Scottish Homecare Census (containing data on telecare use collected during the March 2011 census week), Prescribing data (containing information on prescribed and dispensed medications during the 2010/2011 financial year) and Self-Directed Support data (containing information on various demographic characteristics as well as data on the choices made by social care clients in Scotland regarding the provision of their care services during the 2010/2011 financial year), and generate weekly time series data with repeated cross-sections over the financial year. Using the information contained in the pooled dataset, we construct several variables some of which include: telecare use (indicating whether or not a particular individual used telecare devices), female gender (an indicator for females in the dataset), comorbidity (indicating whether a particular individual had three or more comorbid conditions), client group (indicating whether an individual had a mental health problem including dementia, a physical disability or a learning disability), area of residence (an indicator for rural residence), age and living arrangement.

We also categorize the study covariates as 'predisposing', 'enabling' or 'need' factors analogous to the Andersen's Behavioral Model of Health Services Use (see Andersen, R. and Newman, J. (1973); Andersen, R. (1995) for a substantive discussion of these factors). The 'predisposing' factors, in our case, are the factors that are hypothesized to affect a particular individual's utility in some way but cannot be modified by the individual. The 'enabling' factors are those factors that make it possible for individuals to change their utility and are themselves modifiable, unlike the 'predisposing' factors. The 'need' factors, on the other hand, are the non-modifiable factors that reflect on an individual's care needs.

We conceptualize the telecare variable as an 'enabling' factor since individuals use it (telecare) to maximize utility. The variables for age, female gender, client group and area of residence are 'predisposing' factors since we expect variations in individuals' utility in regard to these covariates, whereas the variable for comorbidity is a 'need' factor since it indicates an individual's care needs; in which case the higher the number of comorbid conditions, the higher the level of need, all things equal. An important point to note is that in as much as we consider the variable for area of residence to be a 'predisposing' factor, this is contestable as it is commonplace for individuals to maximize their utility by choosing to live in particular areas. For instance, some people may relocate to urban areas so as to access better care services that would enable them to live independently in their own homes. In this paper, however, the dichotomization of the variable is based on both area level deprivation and population density, and, as such, it follows that the area of residence is to a large extent a 'predisposing' factor since it cannot be modified by any single individual in the dataset.

The outcome measure in this paper is a proximate measure of independent living at home, constructed using information on individuals' living arrangements. We define the outcome measure as a binary variable such that those who were living alone in their private residences or in sheltered housing during the 2010/2011 financial year are coded 1 and those who had different living arrangements are coded 0. Although there are several indicators that have been used by the previous studies to evaluate the effectiveness of telecare e.g. the length of stay in hospital, mental health related quality of life and admission to hospital, our chosen variable has distinct statistical properties, which we would like to exploit, and the analysis of the impact of telecare on independent living at home offers some useful empirical and policy insights. First, against the backdrop of population ageing, multi-morbidity and increasing health care costs in many countries worldwide, the use of telecare devices could help the users manage their chronic conditions and remain independent for as long as possible. Second, the fact that the outcome measure is constructed as a binary variable allows us to conduct a policy simulation exercise by decomposing the treatment effect. We do this by way of the approach due to Sinning, M., Hahn, M. and Bauer, T. (2008). Third, we add to the empirical studies on the effects of telecare, most of which are Randomized Controlled Trials and quasi-experiments (see for example, Steventon et al., (2013); Henderson et al., (2014); Doughty et al., (2010); Peeters, J. (2012); Brownsell, S. (2008)) by conducting our study using large scale non-experimental data.

The rest of this paper is organized around three sections. The next section discusses the model. Section 3 presents the results and Section 4 concludes.

2. SPECIFICATION OF THE MODEL

We begin by defining the utility of a particular individual j (which in our case is an increased likelihood of living independently at home) as a function of 'predisposing' and 'need' factors, telecare use and the individual's health status as shown in Equation 2.1 (see also Figure 1 for an illustration of the individual's utility maximizing behavior). Throughout this paper, the letters X, T, U, V, H, D, M and P respectively denote a vector of 'predisposing' and 'need' factors, telecare use, the individual's utility, the indirect utility function, individual j's health status, a vector of some observable factors that determine health status, the income level for individual j and input prices unless otherwise specified.

$$U = U(X, T, H) \tag{2.1}$$

We let H be such that $H = f(T, D, \mu)$, where μ denotes individual j's biological endowment. We further let M be expressed as a linear combination of some marketed inputs and assume, for expositional simplicity, that X,T and D are marketed, whereas H is not.

$$M = P_x X + P_T T + P_D D \tag{2.2}$$

If we maximize Equation 2.1 subject to $H = f(.)$ and $M = g(.)$ using the Lagrange method and employ total differentiation in order to obtain the critical values, then the reduced form demand functions for X,T and D will be given by:

$$X = X(P_x, P_T, P_D, M, \mu) \tag{2.3}$$
$$T = T(P_T, P_x, P_D, M, \mu) \tag{2.4}$$
$$D = D(P_D, P_x, P_T, M, \mu) \tag{2.5}$$

Notice from Equations (2.3), (2.4) and (2.5) that the demand for a particular input is determined by its own price, the prices of the other utility generating inputs and individual j's income level. This is consistent with the Almost Ideal Demand System (Deaton, A. and Muellbauer, J. (1980)). Since our primary objective in this paper is to provide an estimate of the marginal product of T, where $T = T(.)$ as shown in Equation 2.4 and $T \in U, H$, we first formulate the indirect utility function linking individual j's utility to telecare use and other utility generating inputs, their associated prices and the individual's income level by substituting $D = D(.)$ into $H = f(.)$ and further substituting the resultant equation into $U = U(.)$.

$$V = v(X, T, P_x, P_T, M, \mu) \tag{2.6}$$

We then make four key assumptions that enable us to conduct our analysis:

Assumption 1 *P_x and P_T are implicit in that $P_x \in X$ and $P_T \in T$.*

Assumption 2 *M, X, P_x and P_T are exogenous, whereas μ is unobservable; implying that T is the only endogenous input in Equation 2.6.*

Assumption 3 *$P_T = P_D$. Since individual j maximizes utility by choosing T over D, it follows then that P_D is the relative price of T.*

Assumption 4 *If we let $P_x X + P_T T + P_D D$ be denoted by θ, then M is such that $M \geq \theta$. Stated differently, individual j has sufficient income to purchase the marketed inputs, X, T and D.*

The estimated version of Equation 2.6 can therefore be written as:

$$V_t = \beta_o + \beta_1 X'_t + \beta_2 T + \epsilon \tag{2.7}$$

where ϵ is a stochastic random error term and β' are the estimated coefficients.

Proposition 1 *let the indirect utility function of a typical individual be defined as shown in Equation 2.6. Then, policy makers could increase individuals' utility by promoting policies that reduce the price of telecare.*

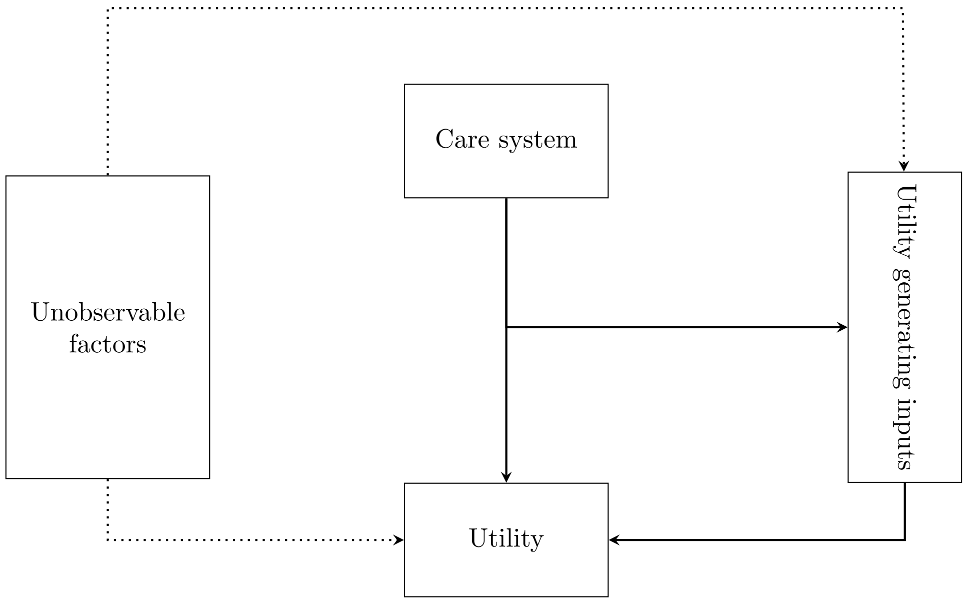

FIGURE 1.— An illustration of individuals' utility maximizing behavior

Recall from section 1 that we use a linked dataset comprising the Scottish Morbidity Records, the Scottish Homecare Census, prescribing data and Self-Directed Support data to generate time series data for the 2010/2011 financial year. Recall also that V_t is such that $V_t = \{0, 1\}$, $X_t' = \{X_{1t}, X_{2t}, X_{3t}, X_{4t}, X_{5t}\}$ and $T = \{0, 1\}$, where X_{1t} is a continuous variable for the age of individual j at time t and the other covariates are defined as follows:

$$V_t = \begin{cases} 1 \text{ if individual } j \text{ was living alone in his or her private} \\ \quad \text{residence or in sheltered housing at time } t, \\ \\ 0 \text{ otherwise.} \end{cases} \tag{2.8}$$

$$X_{2t} = \begin{cases} 1 \text{ if female,} \\ \\ 0 \text{ otherwise.} \end{cases} \tag{2.9}$$

$$X_{3t} = \begin{cases} 1 \text{ if individual } j \text{ had three or more} \\ \quad \text{comorbid conditions at time } t, \\ \\ 0 \text{ otherwise.} \end{cases} \tag{2.10}$$

$$X_{4t} = \begin{cases} 1 \text{ if individual } j \text{ had a mental health problem,} \\ \\ 2 \text{ if individual } j \text{ had a learning disability,} \\ \\ 3 \text{ if individual } j \text{ had a physical disability,} \\ \\ 4 \text{ if individual } j \text{ had no known disability.} \end{cases} \tag{2.11}$$

$$X_{5t} = \begin{cases} 1 \text{ if individual } j \text{ was living in} \\ \quad \text{a rural area at time } t, \\ \\ 0 \text{ otherwise.} \end{cases} \tag{2.12}$$

$$T = \begin{cases} 1 \text{ if individual } j \text{ used telecare devices,} \\ \\ 0 \text{ otherwise.} \end{cases} \tag{2.13}$$

We use Generalized Linear Models (GLMs) to estimate β_o, β_1 and β_2 in Equation 2.7. These models are general in the sense that they allow the outcome variable to be linked to the study covariates via pre-specified link functions which need not be linear. As such, for instance, if we let η denote the linear combination of covariates, then there exists a function, g, such that $E(V_t|X_t', T) = g(\eta)$. This implies that GLMs can be used to model several outcome measures depending on the distribution of g (see McCullagh, P. and Nelder, J. (1989) for a substantive discussion of GLMs). In this paper, we assume that η is unobservable but can be linked to V_t as follows:

$$V_t = \begin{cases} 1 \text{ if } \eta > 0, \\ \\ 0 \text{ otherwise.} \end{cases} \tag{2.14}$$

Because η is linked to V_t as shown in Equation 2.14, substituting Equation 2.8 into Equation 2.14 and further rewriting the resultant equation in terms of probabilities we obtain a function that is given by:

$$Pr(V_t = 1|X', T) = Pr(\eta > 0|X', T) \tag{2.15}$$

or equivalently by Equation 2.16 if we express η as a function of the study covariates.

$$Pr(V_t = 1|X', T) = g(\eta) = g(\beta_o + \sum_{i=1}^{5} \beta_{it} X_{it} + \beta_2 T|X', T) \tag{2.16}$$

If we let g be such that $g(\eta) = \Phi(\eta)$, where Φ is the cumulative distribution function of the standard normal distribution, then Equation 2.16 becomes a probit model. Likewise, specifying g as $g(\eta) = \Lambda(\eta)$, where Λ is the cumulative distribution function of the standard logistic distribution leads to a logit model; writing $g(\eta)$ as $1(\eta)$ implies that the model of interest is a Linear Probability Model, whereas expressing Equation 2.16 as $\frac{1}{\pi}[\tan^{-1}(\eta) + \frac{\pi}{2}]$ results in a cauchit model. If, on the other hand, the equation takes the form $1 - e^{-e(\eta)}$, then the resultant model is a compit model (also known as the complementary log-log model). Although the econometrics literature shows that the model formulations are more or less predictively equivalent, especially for the case of probit and logit models (see for example, Koenker, R. and Jungmo, Y. (2009)); in this paper, we specify the substantive model as a probit model owing to its popularity in demand analyses.

An important issue that arises from the estimation of the model, however, is that the variable for telecare use is potentially endogenous since from Equations (2.1) and (2.4) we can observe that: (i) $T \propto U$, (ii) $T \propto H$ and (iii) $U \propto H$. Stated in words, the use of telecare devices simultaneously improves a particular individual's health status and maximizes his or her utility. Failure to control for the potential endogeneity of telecare use could render our estimated treatment effect inconsistent. We therefore need to employ an appropriate strategy to control for potential endogeneity of T.

The standard approach to dealing with endogeneity bias is to use the Two-Stage Least Squares method (also known as the Two-Stage Predictor Substitution technique when applied to non-linear models; see for example, Angrist, J. and Imbens, G. (1995), Kelejian, H. (1971)) or to estimate β_2 using the Generalized Method of Moments (in which case the population moment condition for exogeneity is replaced with its sample analogue which allows for endogeneity; see for example, Nielsen, H. (2005)). In this paper, however, we take a different approach: the Two-Stage Residual Inclusion approach. Unlike the more popular Two-Stage Least Squares method which entails replacing T with $\hat{T}$ in the substantive model, where $\hat{T}$ are the fitted values obtained from a reduced form model of telecare use; the Two-Stage Residual Inclusion approach controls for endogeneity by including an estimate of the unobservable factors that determine T as an additional regressor in the econometric model of interest. The approach has also been shown to be consistent in non-linear models unlike its comparator (see for example,Terza, J., Basu, A. and Rahouz, P. (2008)).

Let η_1 denote the linear predictor function for the reduced form model of telecare use. Following the logic that was used to link η to V_t, we define the following measurement equation that links η_1 to T.

$$T = \begin{cases} 1 \text{ if } \eta_1 > 0, \\ \\ 0 \text{ otherwise.} \end{cases} \tag{2.17}$$

Since our econometric model of interest in this case is a reduced form model, we can further express η_1 as a linear combination of the exogenous study covariates and some instrumental variables which need to be highly correlated with T but should not be part of Equation 2.16. This is given by:

$$\eta_1 = \alpha_o + \alpha_1 X' + \alpha_2 S + \epsilon_1 \tag{2.18}$$

where S is a vector of instrumental variables and ϵ_1 is a random error term.

If we specify the reduced form model as a probit model, then Equation 2.18 can be linked to the probability of telecare use for given values of X' and S as follows:

$$Pr(T = 1|X', S) = \Phi(\alpha_o + \alpha_1 X' + \alpha_2 S) \tag{2.19}$$

Following the Two-Stage Residual Inclusion approach, we estimate Equation 2.19 and obtain its residuals. These residuals are then included in Equation 2.16 as an additional explanatory variable in order to control for potential endogeneity of T.

Another estimation issue worth considering is sample selection bias which might come about due to the fact that the outcome measure, V_t, may be missing for some observations in the dataset. If we do not correct for sample selection bias if present, then our estimate of the marginal product of telecare would not be generalizable to the wider population. We therefore use the approach due to Olsen, R. (1980). This technique is implemented as follows:

We first define a variable for inclusion into the sample as shown in Equation 2.20.

$$I_t = \begin{cases} 1 \text{ if } V_t \text{ is observed for individual } j, \\ \\ 0 \text{ otherwise.} \end{cases} \tag{2.20}$$

We then link I_t to an unobservable latent variable η_2 as follows:

$$I_t = \begin{cases} 1 \text{ if } \eta_2 > 0, \\ \\ 0 \text{ otherwise.} \end{cases} \tag{2.21}$$

Similar to the Two-Stage Residual Inclusion approach discussed earlier, we express η_2 as a linear combination of the exogenous study covariates and some instruments. This linear predictor function is given by:

$$\eta_2 = \alpha_3 + \alpha_4 X' + \alpha_5 S + \epsilon_2 \tag{2.22}$$

where S is a vector of instruments and ϵ_2 is a stochastic random error term.

An important point to note from Equation 2.22, however, is that S should contain at least two different instrumental variables if we are to simultaneously control for potential endogeneity of telecare use and potential sample selection bias. Upon formulating Equation 2.22 as a Linear Probability Model we obtain:

$$Pr(I_t = 1|X', S) = 1(\alpha_3 + \alpha_4 X' + \alpha_5 S) \tag{2.23}$$

We then estimate the model, obtain its predicted probabilities and construct a variable for the complement of the predicted probabilities which is included in Equation 2.16 as an additional covariate. In formal terms, if $\hat{P}$ denotes the predicted probabilities, then its complement which is given by $\hat{P}-1$ is included in the substantive model as one of the explanatory variables.

So far in this paper, we have controlled for potential endogeneity of telecare use and potential sample selection bias by including appropriate correction terms in the substantive model. However, given that the indirect utility function of a typical individual contains an unobservable component as one of its arguments, the estimated treatment effect could be in error if there are some variations in the outcome measure that emanate from heterogeneity in the unobservable component. In order to obviate this potential bias, therefore, we include an interaction term of the residuals obtained from a reduced form model of telecare use with the variable for telecare use. This approach has also been used by several other studies (see for example, Petrin, A. (2009); Giles, J. (2012); Awiti, J. (2014); Tchetgen, T. (2014)).

Furthermore, the fact that the data in this paper is generated as time series data and is such that the Homecare Census only covers the March 2011 census week, whereas the other three datasets contain information for the entire 2010/2011 financial year also means that the model of interest could suffer from measurement error. Accounting for this additional issue therefore calls for ingenuity on our part to come up with an appropriate control. We impute the missing data with information from the Homecare Census, generate a count variable for the number of weeks before the March 2011 census week and then include it in the substantive model as an additional regressor. Given that the model contains some variables that are potentially measured in error before the March 2011 census; the count variable controls for the changes in the outcome measure before the census week that are not explained by the explanatory variables due to measurement error in addition to unexplained trend variations over the period of analysis. Consequently, Equation 2.16 is extended as follows:

$$Pr(V_t = 1|\mathcal{C}) = \Phi(\beta_o + \beta_1 X_t' + \beta_2 T + \beta_3 \hat{\epsilon} + \beta_4(\hat{P} - 1) + \beta_5 T\hat{\epsilon} + \beta_6 t) \quad (2.24)$$

where $\mathcal{C}$ are the explanatory variables of the model, $\hat{\epsilon}$ are the residuals obtained from a reduced form model of telecare use, $T\hat{\epsilon}$ is an interaction term of the variable for telecare use with its residuals and t is a variable for the number of weeks before the March 2011 census week.

Next, we decompose β_2 following the approach proposed by Sinning, M., Hahn, M. and Bauer, T. (2008). The decomposition analysis presents three scenarios. Call these scenarios "A", "B" and "C". A shows the change in the mean outcomes for telecare users if all the individuals were to have exactly the same characteristics. B shows the change in the mean outcomes for telecare users if the telecare users were to have the predictor levels for non-users and the non-users, in turn, were to have the predictor levels for telecare users, while C shows the change in the mean outcomes for telecare users due to factors operating outside the model. The analysis first involves estimating Equation 2.24 and computing the weighted coefficients[1] for both telecare users and non-users using an identity matrix as the weighting matrix. Let the predictor levels

[1]The weighted coefficients for telecare users are computed by the following formula: $\beta_T^* = \Omega\beta_T + (I - \Omega)\beta_N$, whereas the weighted coefficients for non-users are computed by the

for telecare users be denoted by β_T^* and those for non-users be denoted by β_N^*. We then use the pseudo-random number generator in STATA 14.1 to generate the study covariates in a simulated environment but instead of just using β_T^* to gather data for telecare users, we also use β_N^*(formally written as $E_{\beta_N^*}[Pr(V_t = 1|\mathcal{C})]^T$) and vice versa (formally written as $E_{\beta_T^*}[Pr(V_t = 1|\mathcal{C})]^N$). We then compute the decomposition components as follows:

$$R = A + B + C \tag{2.25}$$

$$A = \{E_{\beta_T^*}[Pr(V_t = 1|\mathcal{C})]^N - E_{\beta_T^*}[Pr(V_t = 1|\mathcal{C})]^T\} \tag{2.26}$$

$$B = \{E_{\beta_N^*}[Pr(V_t = 1|\mathcal{C})]^T - E_{\beta_T^*}[Pr(V_t = 1|\mathcal{C})]^T\} \tag{2.27}$$

$$\begin{aligned} C = \{&E_{\beta_N^*}[Pr(V_t = 1|\mathcal{C})]^N - E_{\beta_T^*}[Pr(V_t = 1|\mathcal{C})]^N\}+ \\ &\{E_{\beta_N^*}[Pr(V_t = 1|\mathcal{C})]^T - E_{\beta_T^*}[Pr(V_t = 1|\mathcal{C})]^T\} \end{aligned} \tag{2.28}$$

where Equation 2.25 is the decomposition equation.

and repeat the procedure 500 times. Since A, B and C are counterfactual, their analytic standard errors do not exist and we thus obtain the bootstrapped standard errors instead.

3. RESULTS AND DISCUSSIONS

This section presents the descriptive statistics of the study variables as well as the empirical results of our econometric models of interest. Table I gives the variable definitions. Table II contains the average values and the number of observations for each variable. Table III contains the average marginal effects[2] computed from the estimated coefficients of the reduced form model of telecare use shown in Equation 2.19 and the sample selection model shown in Equation 2.23. Table IV contains the average marginal effects computed from the estimated coefficients of our main model, while Table V presents the results of the decomposition analysis.

From Table II, we can observe the following: (i) the majority of the observations included in the study sample belonged to female homecare clients; (ii) about 7% of the observations in the study sample belonged to those individuals classified as 'Dementia and Mental Health', 24% belonged to those with learning disabilities, 17% belonged to the physically disabled individuals in the study sample and 52% belonged to the frail elderly; (iii) approximately

following formula: $\beta_N^* = \Omega\beta_N + (I - \Omega)\beta_T$. β_T are the estimated coefficients for telecare users, Ω is the weighting matrix which in our case is an identity matrix, I is an identity matrix and β_N are the estimated coefficients for non-users (see Sinning, M., Hahn, M. and Bauer, T. (2008) for a much more comprehensive discussion). Note that our choice of an identity matrix for Ω enables us to conceptualize β_T as the predictor levels for telecare users and β_N as the predictor levels for non-users. As such, under $\Omega = I$ weighting scheme, β_T^* $=\beta_T$ and $\beta_N^* = \beta_N$.

[2]The average marginal effects show the changes in the probability of observing a particular outcome measure that are induced by unit changes in the covariates, ceteris paribus. They are computed by taking the partial derivatives of the econometric models of interest with respect to the covariates for each observation in the dataset, and then calculating the averages (see Long, J.S. and Freese, J. (2006), for a scholarship on average marginal effects). Because the partial derivatives of the intercept terms in Equations (2.19), (2.23) and (2.24) are zero, the regression results presented in this paper do not include their average marginal effects.

TABLE I
Variable Definitions

Variable	Definition
Age	Age in years at time t.
Female gender	1 if female, 0 otherwise.
Area of residence	1 if a particular individual was living in a rural area at time t, 0 otherwise.
Client group	1 if a particular individual had a mental health problem, 2 if a particular individual had a learning disability, 3 if a particular individual had a physical disability, 4 if a particular individual did not have a disability.
Telecare use	1 if a particular individual used telecare devices, 0 otherwise.
Comorbidity	1 if a particular individual had three or more comorbid conditions at time t, 0 otherwise.
Independent living at home	1 if a particular individual was living alone in his or her private residence or in sheltered housing at time t, 0 otherwise.
Inclusion into the sample	1 if the outcome variable for a particular individual at time t is observed, 0 otherwise.
Propensity of readmission	A variable indicating the likelihood of readmission to hospital or psychiatric care in Scotland computed at the health board level.
Prevalence of telecare use	A variable indicating the proportion of telecare users in each local council area.
Project ID	A unique reference number for each individual in the dataset.
Telecare residuals	The residuals obtained from a reduced form model of telecare use.
Control for sample selection bias	A control for potential sample selection bias following Olsen, R. (1980).
Time trend	A time trend variable where the unit of time is 1 week.
Time trend 1	A count variable for the number of weeks before the March 2011 census.

36% of the observations in the study sample belonged to the individuals with at least three comorbid conditions; (iv) about 19% of the observations in the study sample were for the individuals who were living independently at home, and (v) the average age of the sample is 76 years.

The results presented in the table also show that the study sample is a sub-sample of the study population in that the outcome measure i.e. the variable for independent living at home has only $25,150$ observations yet the study population has $49,025$. Looking closely at the table, we further note that the variables have different number of observations; implying that we do not have information on all the study covariates for some of the observations. For instance, we can observe that while the variable for area of residence has $25,035$ observations, that of telecare use has $25,150$. Similarly, the age variable has $25,115$ observations compared with $25,150$ for the variable for client group.

Turning our attention to the results in Table III, we note that the reduced form model of telecare use (shown in Column 1 of the table) and the sample

TABLE II

Descriptive statistics

	Study population		Study sample	
	N	M	N	M
Age	48,749	75.52	25,115	75.21
Female gender	48,749	0.65	25,115	0.66
Area of residence	48,584	0.09	25,035	0.09
Telecare use	49,025	0.11	25,150	0.10
Dementia and Mental Health	49,025	0.06	25,150	0.07
Learning disability	49,025	0.30	25,150	0.24
Physical disability	49,025	0.16	25,150	0.17
Frail elderly	49,025	0.48	25,150	0.52
Comorbidity	49,025	0.36	25,150	0.37
Independent living at home	25,150	0.19	25,150	0.19
Propensity of readmission	48,616	0.15	25,058	0.15
Trend	49,025	40.0	25,150	32.0
Trend 1	49,025	12.0	25,150	20.0
Number of homecare clients	25,982		14,001	

Notes: N = number of observations; M = arithmetic mean for the age variable and for the variable for propensity of readmission to hospital or psychiatric care, median for the time trend variables and proportion for the other variables.

selection model (shown in Column 2 of the table) contain two explanatory variables in addition to the study covariates i.e. the variable for the propensity of readmission to hospital/psychiatric care in each of the 14 Health boards in Scotland and the variable for the proportion of telecare users in each local council area in Scotland. These variables are the instruments denoted by S in Equations (2.19) and (2.23). A further look at the results in Column 1 shows that the coefficient of the variable for the propensity of readmission to hospital or psychiatric care has a negative sign, whereas that of the proportion of telecare users in each local council area is positive. This implies that there is an inverse relationship between telecare use and the likelihood of readmission to hospital or psychiatric care but a direct relationship between telecare use and the prevalence of telecare.

Other notable results from the table are that: (i) the probability of telecare use increases by 0.006 for every one year increase in an individual's age, ceteris paribus; (ii) the probability of using telecare devices for a female is lower than that of her male counterparts by 0.008 on average, other factors held constant, although the average marginal effect is not statistically significant at 5% level of significance; (iii) individuals with dementia or other mental illnesses and those with learning disabilities are more likely to use telecare than their frail elderly counterparts, holding other factors constant and (iv) rural residents compared with their urban counterparts have a higher likelihood of being telecare users, all things equal. This result, however, as with the result of the effect of female gender, is not statistically significant at 5% level of significance.

Looking at the results in Column 2, we can observe that the physically disabled individuals and those with dementia or other mental illnesses are less likely than the reference group to have been selected into the study sample, holding other factors constant. We can also observe from the results that the higher the proportion of telecare users in a particular local council area, the lower the likelihood that an individual who resides in that local council area

TABLE III

The first stage models

	Telecare use = 1 (1)	Inclusion into the sample = 1 (2)
Age	0.006	0.002
	(5.24)	(1.58)
Square of age	−0.0001	−0.00003
	(5.58)	(3.36)
Female gender	−0.008	0.009
	(1.24)	(1.54)
Area of residence	0.011	−0.009
	(0.97)	(0.89)
Dementia and Mental Health	0.042	−0.183
	(5.81)	(25.76)
Learning disability	0.032	−0.004
	(2.78)	(0.38)
Physical disability	0.001	−0.043
	(0.10)	(5.01)
Comorbidity	−0.005	−0.066
	(0.83)	(11.99)
Propensity of readmission	−2.03	−0.636
	(9.77)	(2.89)
Prevalence of telecare use	1.219	−0.681
	(27.00)	(17.98)
Trend	0.0001	−0.008
	(0.72)	(51.25)
Number of observations	48,571	48,571
Number of homecare clients	25,598	25,598

Notes: The table presents the average marginal effects for the first stage models and the Z statistics in parenthesis. The standard errors used to compute the Z statistics are clustered by Project ID. Z statistics greater than or equal to 1.96 imply statistical significance at 5% level of significance. We include the square of age as an additional regressor so as to control for the non-linear effect of age on telecare use and inclusion into the sample. The reference group for client group is 'Frail elderly'.

was selected into the sample, other factors held constant. This is because the average marginal effect of the variable for 'prevalence of telecare use' is −0.681 and statistically significant at 5% level of significance. The results further show that the higher the propensity of readmission to hospital/psychiatric care in a particular Health board, the lower the probability of sample selection, all things equal.

Focusing on the results in Table IV, we can observe that the average marginal effects are presented for five variants of the substantive model. These model variants are labeled as (1), (2), (3), (4) and (5). The first model contains the results of the estimated effect of telecare on independent living at home, controlling for the other covariates. The second model estimates the treatment effect controlling for other independent variables and time trend. The third model extends the second model by correcting for potential endogeneity of telecare using the Two-Stage Residual Inclusion approach discussed in the previous section. The fourth model estimates the effect of telecare on independent living at home, controlling for other covariates, time trend, potential endogeneity of telecare use and potential sample selection bias using the approach by Olsen, R. (1980). The fifth model estimates the treatment effect

TABLE IV

THE SECOND STAGE MODEL ($V_t = 1$), AVERAGE MARGINAL EFFECTS (Z STATISTICS)

Variable	(1)	(2)	(3)	(4)	(5)
Age	−0.008	−0.006	−0.004	−0.015	−0.015
	(6.11)	(4.70)	(3.67)	(12.53)	(12.46)
Square of age	0.0001	0.0001	0.00003	0.0002	0.0002
	(7.14)	(5.29)	(3.97)	(16.14)	(16.15)
Female gender	0.031	0.027	0.023	0.009	0.008
	(4.65)	(4.41)	(3.80)	(1.49)	(1.41)
Area of residence	0.037	0.027	0.026	−0.007	−0.007
	(3.89)	(3.25)	(3.12)	(0.83)	(0.83)
Telecare use	−0.025	−0.011	0.018	0.015	0.065
	(2.22)	(1.16)	(1.75)	(1.59)	(3.30)
Dementia and Mental Health	−0.128	−0.079	−0.082	0.316	0.321
	(13.96)	(9.02)	(9.50)	(16.41)	(16.57)
Learning disability	0.124	0.107	0.114	0.068	0.068
	(10.50)	(10.28)	(11.13)	(6.99)	(6.97)
Physical disability	−0.107	0.006	0.005	0.108	0.109
	(1.11)	(0.64)	(0.51)	(11.44)	(11.57)
Comorbidity	−0.219	−0.150	−0.145	0.037	0.039
	(33.51)	(26.27)	(25.11)	(3.67)	(3.86)
Trend 1		−0.009	−0.009	−0.027	−0.027
		(58.49)	(58.28)	(35.31)	(35.44)
Telecare residuals			−0.391	1.028	1.074
			(10.85)	(15.64)	(15.90)
Control for sample selection				2.262	2.289
				(23.70)	(23.88)
Telecare interacted with residuals					−0.318
					(2.80)
Wald test for weak					743.12
instruments; $\chi^2(p - value)$					(0.00)
Wald Chi-square	1292	2072	2170	2519	2525
test; $\chi^2(p - value)$	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of observations	25,035	25,035	25,032	25,032	25,032
Number of homecare clients	14,001	14,001	13,998	13,998	13,998

whilst controlling for confounding variables, time trend, potential endogeneity of telecare use, potential sample selection bias and potential unobserved heterogeneity.

The results in the Table show that the model suffers from endogeneity, sample selection bias and unobserved heterogeneity since the corresponding control function variables are statistically significant at 5% level of significance. In particular, we can observe that the residuals obtained from the reduced form model of telecare use are statistically significant in Column (3) and this significance persists even after adding subsequent controls for potential sample selection bias and potential unobserved heterogeneity. Similarly, a close look at Columns (4) and (5) also shows that the correction term due to Olsen, R. (1980) and the interaction term of the variable for telecare use with its residuals are statistically significant at 5% level of significance. We therefore choose the model in Column 5 as the most preferred model and interpret the average marginal effects contained therein.

Looking at the results in Column 5, we note that the average marginal effect

TABLE V

Decomposition analysis

Decomposition component	Results	p-value
A	−0.0440429	0.000
	(0.012)	
B	0.0228529	0.047
	(0.004)	
C	−0.0119349	0.181
	(0.009)	

Note: The bootstrapped standard errors are in parenthesis

of the variable for age has a negative sign and is statistically significant at 5% level of significance (Average Marginal Effect = 0.015; Z-statistic = 12.46). In particular, the results indicate that, controlling for the other covariates in the model, a one year increase in age increases the probability of independent living at home by about 0.02. An even closer look at the results shows that the average marginal effects of the variables for telecare use, client group and co-morbidity are statistically significant at 5% level of significance, whereas those of the variables for female gender and area of residence are not. Specifically, we can observe that the probability of independent living at home for a telecare user is higher than that for a non-user by approximately 0.07, other factors held constant. We can also observe that, all things equal, the individuals with at least three comorbid conditions have a higher probability of living independently at home than their counterparts with fewer comorbidities. Since the average marginal effects of the three client groups have a positive sign, we further note that the individuals with dementia or other mental illnesses, and those with learning or physical disabilities are more likely to be independent than their frail elderly counterparts, holding other factors constant.

We determine whether or not the two instrumental variables in the reduced form model of telecare use are correlated with the variable for telecare use by conducting a Wald test. The null hypothesis of the test is that the coefficients of the two instrumental variables are simultaneously equal to zero. In other words, the two instrumental variables are not significant predictors of telecare use. Looking at the results of the test, we note that this hypothesis is rejected at 5% level of significance ($\chi^2 = 743.12; p - value = 0.00$). A further test for overall model fitness is conducted using the Wald Chi-square test whose null hypothesis is that the coefficients of the covariates included in Table IV are not different from zero. From the results presented in the table, we conclude that the coefficients of the covariates of all the five variants of our main model are different from zero since the null hypothesis is rejected at 5% level of significance throughout. This is indicative of goodness of fit.

The results in Table V show the standard errors and p-values for the decomposition components discussed in Section 2. In particular, we note that the coefficient of component A is −0.0440429 and statistically significant at 5% level of significance. These results, therefore, suggest that telecare users and non-users have different characteristics since assuming homogeneity results in a lower treatment effect than what is reported in Table IV. We also note that the coefficient of component B is statistically significant and carries a positive sign; implying that policy makers could increase the likelihood of independent living by encouraging the non-users to use telecare devices. This could be done, for instance as will later be shown in the proof of Proposition 1 in Appendix A, by reducing the price of telecare. We further observe from the coefficient of component C that part of the observed treatment effect is attributed to factors other than those controlled for in the econometric model of interest, despite the simulated effect not being statistically significant at 5% level of significance.

4. CONCLUSIONS

This paper formulates a structural model that links the demand for telecare to independent living at home and further decomposes the treatment effect in a counterfactual manner using linked administrative health and social care data in Scotland. Our study ties in the econometric analysis of the demand for health and health capital, the revealed preference theory and the Almost Ideal Demand System with the Andersen's Behavioral Model of Health Services Use. This is a novelty. We assume that a typical individual maximizes his/her utility and, by extension, health status by using telecare devices so as to live independently at home. The predictors of independent living at home can be broadly classified into three categories: 'predisposing', 'enabling' and 'need' factors and telecare is conceptualized as an 'enabling' factor. We further assume that telecare is a marketed good and, as such, the theoretical model in this paper takes the form of a constrained utility maximization problem. Due to these assumptions, therefore, it follows that a particular individual's utility maximizing behavior is such that the individual produces his/her own health via the use of inputs e.g. telecare.

Estimating the marginal product of telecare in light of these assumptions, however, is not a straightforward task. First, an individual's true health status is typically unobservable and since telecare use is correlated with both the individual's utility and his/her health status, an endogeneity problem could emerge if the factors determining the individual's decision to use telecare are also correlated with the probability of living independently at home. Second, the fact that telecare use is potentially endogenous implies that the unobservable factors determining whether or not a particular individual uses telecare could also cause the treatment effect to differ across the population hence bringing about unobserved heterogeneity. Third, because we expect a particular individual's true health status to be constantly fluctuating over the individual's lifespan even when the individual is not using any health enhancing inputs, the onus is on us to disentangle this effect from the effects of our study covariates if the empirical model is to have theoretical validity. Fourth, there could be a selectivity issue in our study that is brought about by our inability to observe the outcome measure for all the observations in the dataset.

Our estimation strategy, therefore, systematically derives a consistent treatment effect by simultaneously controlling for the various estimation issues that come with such an endeavor. In order to control for potential endogeneity of telecare use, we use the Two-Stage Residual Inclusion approach; to control for potential selectivity bias, we adopt the approach due to Olsen, R. (1980); to control for unexplained variations in the outcome measure over time, we include, in our econometric model of interest, a variable for time trend as one of the regressors, and to account for potential unobserved heterogeneity, we also include an interaction term of the treatment variable with an estimate of the unobservable factors that determine it. The use of these techniques builds on the empirical studies that employ similar strategies to address their study objectives (see for example, Awiti, J. (2014); Giles, J. (2012); Petrin, A. (2009); Tchetgen, T. (2014); Mwabu, G. (2009)). Our analytical approach also extends the experimental studies in the literature that look into the effectiveness of telecare (see for example, Akematsu, Y. and Tsuji, M. (2012); Akematsu, Y. (2013); Steventon et al., (2013); Henderson et al., (2014); Doughty et al., (2010); Hirani et al., (2013)) by estimating the treatment effect in a non-experimental setting. Furthermore, the econometric model employed in this paper can be generalized to estimate utility functions that are characterized by social care clients maximizing their utility via the use of various utility generating inputs, some of which double up as health enhancing inputs (see Momanyi, K. (2018), for a comprehensive discussion of the econometric model).

The empirical results show that, all things equal, the use of telecare increases an individual's likelihood of living independently at home and this treatment effect is decomposable by way of the approach due to Sinning, M., Hahn, M. and Bauer, T. (2008). The treatment effect, however, could differ among various sub-groups in the population and, as such, future research could focus on conducting a sub-group analysis. The econometric specification could also be amended to include more endogenous variables in addition to telecare. An important point to note is that the decomposition analysis used in this paper is co-opted to enable us to inform policy. For instance, by decomposing the treatment effect, we contribute to knowledge and policy by demonstrating empirically that the likelihood of independent living at home could be increased by promoting telecare use among the non-users.

ACKNOWLEDGEMENTS

I would like to thank the Health Economics Research Unit for their support while undertaking my PhD studies at the University of Aberdeen as well as NHS National Services Scotland for providing the data for this study. I take full responsibility for any errors and omissions.

ENDNOTES

1. As explained in Section 2, the instrumental variables in the reduced form model of telecare use and the sample selection model need to be correlated with the variable for telecare use but should not be determined in the main model. We use a variable indicating the propensity of readmission to hospital or psychiatric care in Scotland computed at the Health board level and another variable for the proportion of telecare users in each local council area in Scotland as instruments. We expect the former to be correlated with telecare use in that the lower the propensity of readmission to hospital or psychiatric care, the higher the likelihood of telecare use all things equal. This is because the use of telecare devices

could substitute for some services that would otherwise be provided in hospital. Similarly, we expect that, holding other factors constant, the higher the proportion of telecare users in a particular local council area, the higher the likelihood of telecare use in that local council area. We however do not expect the propensity of readmission at the Health board level or the proportion of telecare users in a particular local council area to be determined in our substantive model.

2. We assess whether or not it is appropriate to generate time series data by interacting our covariates of interest with the variable for the number of weeks before the March 2011 census, including these interaction terms in our substantive model as additional regressors and then testing for the statistical significance of their estimated coefficients. Significant coefficients for the interaction terms in this case would indicate that the parameter coefficients are not stable over time and hence a time series approach is not appropriate. Upon estimating the model, however, the results (not presented here) showed that the average marginal effects of the interaction terms are not statistically significant at 5% level of significance; implying that using time series analysis does not bias our results.

APPENDIX A: APPENDIX SECTION

In this section, we provide the proof of Proposition 1. The first task is to show that the demand for telecare is inversely related to its price, consistent with the law of demand i.e. $T \propto \frac{1}{P_T}$. We assume, for simplicity, that telecare is a normal good. Recall from Section 2 in the main text that we derive the input demand functions by solving for the critical values of the utility generating inputs and their prices using the Lagrange method. Let the Augmented Objective Function for utility maximization be expressed as:

$$\mathcal{L}(X,T,H:\lambda) = U(X,T,H) - \lambda(P_x X + P_T T + P_D D - M) \tag{A.1}$$

where $\mathcal{L}$ denotes the maximal utility and λ denotes the Lagrange multiplier that indicates the rate of change in the maximal utility when the budget constraints are relaxed.

Taking the total derivative of $\mathcal{L}$ with respect to T and λ we obtain the following differential equations:

$$d\mathcal{L} = \frac{dU}{dX} = \frac{\partial U}{\partial X}dX + \frac{\partial U}{\partial T}dT + \frac{\partial U}{\partial H}dH - \lambda P_T dT \tag{A.2}$$

$$d\mathcal{L} = (P_x X + P_D D + P_T T - M)d\lambda \tag{A.3}$$

To obtain the First Order Conditions (F.O.C) for utility maximization, we set A.2 and A.3 equal to zero. Accordingly, $d\mathcal{L}$ can be written as:

$$d\mathcal{L} = \frac{dU}{dX} = \frac{\partial U}{\partial X}dX + \frac{\partial U}{\partial T}dT + \frac{\partial U}{\partial H}dH - \lambda P_T dT - \Big[(P_x X + P_D D + P_T T - M)d\lambda\Big] = 0 \tag{A.4}$$

If we let $\mathcal{S}$ be such that $\mathcal{S} = \{X,T,H\}$ and ρ be defined as $\rho = \{X,D\}$, and further rewrite the above differential with T on the left hand side, then:

$$T = \Big[\sum_{\mathcal{S}} \frac{\gamma_{\mathcal{S}} d\mathcal{S}}{P_T d\lambda}\Big] - \sum_{\rho} \frac{P_\rho \rho}{P_T} - \frac{\lambda dT}{d\lambda} + \frac{M}{P_T} \tag{A.5}$$

where the notation $\gamma_{\mathcal{S}}$ denotes the marginal products of the utility generating inputs, $\sum_{\mathcal{S}}$ indicates that the summation is conducted over the elements of $\mathcal{S}$, and $\sum_{\rho}$ indicates that the summation is conducted over the elements of ρ.

Note that Equation A.5 is the demand function for telecare since T is related to its price, the prices of the other marketed inputs and the exogenous income level. Note furthermore that this demand can be decomposed into four components. Let the first component be denoted by $C1$, the second by $C2$, the third by $C3$ and the fourth by $C4$. Since the demand relation in Equation A.5 is based on the Almost Ideal Demand System, it follows then that $C1$, $C2$, $C3$ and $C4$ shed light on individuals' relative preference for telecare as observed in the market place. This is consistent with the revealed preference theory.

$C1$– quantifies the maximal utility that results from the consumption of the utility generating inputs when the budget constraints are relaxed (stated differently, when the general economic conditions improve). Notice however that P_T appears in the denominator; implying that the higher the price of telecare, the lower the maximal utility and, by extension, the level of T, other factors held constant.

$C2$– shows the quantity of T that would be demanded by a particular individual if the total amount of money allocated to acquiring the marketed inputs other than telecare was to be reallocated to acquiring T. Since in this paper we assume that an individual is a telecare user because he/she chooses T over its substitutes, it follows then that the higher the value of $C2$, the lower the relative preference for telecare, all things equal.

$C3$– shows the maximal utility that would result from the consumption of T if the budget constraints were to be relaxed. Accordingly, if a particular individual prefers to maximize utility via the use of telecare, then he/she would consume more of it (telecare) relative to its substitutes even under tight budget constraints. It follows then, therefore, that the higher the value of $C3$, the lower the relative preference for telecare, ceteris paribus.

$C4$– is the basic Marshallian demand relation in which case the demand for telecare is inversely related to its price but directly related to the exogenous income level.

Following the reasoning in $C1$, $C2$, $C3$ and $C4$, we can infer, without loss of generality, that the demand for telecare is inversely related to its price i.e. $T \propto \frac{1}{P_T}$. We apply the same logic that is used to derive Equation A.5 to derive the demand functions for X and D. We then substitute the demand function for D into the health production function defined as $H = f(T, D, \mu)$ in the main text and further substitute the resultant equation into the the utility function defined in Equation 2.1 in the main text to formulate a function that takes the following general form:

$$V = v(X, T, P_x, P_T, M, \mu) \tag{A.6}$$

Note that this function is the indirect utility function defined in the main text as Equation 2.6. Now suppose that we take the total derivative of V with respect to P_T assuming that Assumptions (1), (2), (3) and (4) hold. Then:

$$\frac{dV}{dP_T} = \frac{\partial V}{\partial X}\frac{dX}{dP_T} + \frac{\partial V}{\partial T}\frac{dT}{dP_T} \tag{A.7}$$

Given that we have already established that $T \propto \frac{1}{P_T}$, we can observe from Equation A.7 that, holding other factors constant, reducing P_T would result in an increase in T. This is because the differential $\frac{dT}{dP_T}$ gets smaller for marginal increases in P_T and gets larger as P_T decreases. If we let γ_T denote $\frac{\partial V}{\partial T}$, then we can further observe that the larger the value of $\frac{dT}{dP_T}$, the larger the value of γ_T. Said another way, an attempt to reduce P_T would increase a particular individual's demand for T and consequently his/her utility.

Q.E.D

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