New Estimates of the Demand for Physical and Mental Health Treatment

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ABSTRACT

Consumers' price responsiveness is central to current reform proposals to address rapidly escalating health care costs, but the best available estimates of price elasticities of demand are now more than 25 years old. We seek to provide more current estimates of the demand for both mental and physical health treatment using a health care demand model that incorporates the relevant costs influencing consumption decisions, including out-of-pocket payments (cost-sharing) for ambulatory services, out-of-pocket prescription drug costs, and insurance premiums. Following Ellis (1986) and Ellis and McGuire (1986), we use consumers' out-of-pocket payments to derive theoretically appropriate expected end-of-year prices. The demand model is estimated using the 1996-2003 Medical Expenditure Panel Survey (MEPS), a nationally representative survey of the U.S. civilian, non-institutionalized population. We address the potential endogeneity of expected end-of-year prices and health insurance coverage (or adverse selection) by estimating a correlated random effects specification (Chamberlain, 1980). This allows us to relax the untenable assumption of standard random effect models that price and health insurance are uncorrelated with unobserved individual attributes. We find that the price responsiveness of ambulatory mental health visits has decreased substantially in the last 30 years and is now slightly less elastic than visits for physical health problems. However, the demand for both mental health and non-mental prescription drugs is substantially more price elastic. We discuss the implications of our results.

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1. Introduction

Optimal second-best insurance requires balancing the gains from risk-spreading with the welfare losses due to moral hazard (Zeckhauser, 1970). This balancing in health insurance coverage is analogous to Ramsey pricing (Besley 1988; Zeckhauser 1970; Baumol and Bradford 1970). That is, the level of consumer cost-sharing (or the out of pocket price that consumers face) should be positively related to the price elasticity of demand—the higher the price elasticity, the higher the cost-sharing. Current proposals for health care reform, such as Health Savings Accounts, are predicated on the notion that shifting more costs directly to consumers will reduce unnecessary medical use and help restrain rapidly escalating health care costs (Fuchs and James, 2005). Price elasticites are also central to continued debates over benefit mandates, such as requiring insurers to cover particular services such as mammograms or to provide equal coverage for mental health treatment (or mental health parity). Therefore, the question of how elastic the demand for health care is and whether it varies by type of treatment has far reaching implications for private insurers and public policy makers.

The best available evidence on price elasticities for health care comes from the RAND Health Insurance Experiment (HIE), a large-scale randomized experiment conducted from 1977 to 1982 (Manning et al., 1987). The RAND HIE found price elasticities of around -.2 for all types of medical care, but considerable variation for different types of treatment. In particular, the demand for outpatient psychotherapy visits was found to be approximately three times more price elastic than for other medical visits (Keeler, Manning, and Wells, 1988). This important finding, consistent with observational studies from the same period (Horgan, 1986; McGuire 1981), has been used to justify higher cost-sharing for mental health treatment in the years since (Frank, Goldman, and McGuire, 1992).

Many question how relevant the RAND HIE estimates still are today given the rapid advances in medical technology that occurred over the last 25 years and the growth of managed care. Economists (Glied 2003; Cutler 2002; Newhouse 1993) generally credit medical advances with being the major force driving health care expenditures from $255 billion in 1980, or 10.4% of GDP to an estimated $2.1 trillion in 2006, or 16.0% of GDP (Heffler et al. 2005). The development of less-invasive surgical procedures that can be performed on an outpatient basis, new diagnostic and imaging procedures, and new treatments and therapies have all led millions more to seek treatment for their health conditions (Thorpe et al., 2004). Especially important was the introduction of many new classes of prescription drugs, such as lipid-lowering statins and new types of anti-depressants like Prozac and Paxil. As a result, prescription drug spending grew at twice the rate of other types of medical care spending over the last decade (Heffler et al. 2005). Perhaps nowhere is the change in medical technology more evident than in the treatment of mental health problems. Traditional psychotherapy, the standard of treatment during the RAND HIE, has largely given way to prescription drug based treatment, practiced alone or in combination with newer talk therapies, such as cognitive behavioral therapy. As a result, the number of Americans in treatment nearly doubled from 16.5 million in 1987 (Zuvekas, 2001) to 30.5 million in 2001 (Zuvekas, 2005).

Clearly, the demand for mental health treatment and many other types of medical treatment shifted outwards since the RAND HIE twenty-five to thirty years ago. But we might expect the same medical advances that led to demand shifts to also change the shape of the demand curves. The demand for medical care is usually thought of as a derived demand for health, and therefore dependent on the current state of medical technology. In other words, consumers are purchasing entirely different bundles of goods now than they did decades earlier.

Furthermore, changes in the institutional coverage for mental and physical health treatment and their associated prescription medications brought about by managed care and the expanding role of the public sector in health insurance markets could also influence relative demand levels and price responsiveness.

We seek to provide current estimates of the demand for both physical and mental health treatment, and in particular the price elasticity of demand for different types of treatment including prescription drugs.[1] Therefore, we derive a health care demand model that incorporates the relevant costs influencing consumption decisions, including out-of-pocket payments (cost-sharing) for ambulatory services, out-of-pocket prescription drug costs, and insurance premiums. Following Ellis (1986) and Ellis and McGuire (1986), we use consumers' out-of-pocket payments to derive theoretically appropriate expected end-of-year prices for different types of medical care. The demand model is estimated using the 1996-2003 Medical Expenditure Panel Survey (MEPS), a nationally representative survey of the U.S. civilian, non-institutionalized population.

We address the potential endogeneity of expected end-of-year prices and health insurance coverage (or adverse selection), which typically confound observational studies, by exploiting the longitudinal dimension of the MEPS to estimate a correlated random effects specification (Chamberlain, 1980). This allows us to relax the untenable assumption of standard random effect models that price and health insurance are uncorrelated with the unobserved individual attributes, such as unobserved physical and mental health status and preferences for treatment. The specification can also be seen as a reasonable way to account for time invariant measurement error processes.

[1] We differentiate physical and mental health treatment based upon household responses of the type of treatment received and the reasons for seeking care.

The rest of the paper is organized as follows: A presentation of our underlying theoretical model and empirical specification is given in Section 2, followed by our econometric estimation procedure in Section 3. We describe the data used to estimate in empirical model in Section 4 and present the estimation results Section 5. Section 6 concludes with a discussion of the results in light of past findings in this area and current policy issues.

2. Theoretical and Empirical Approach

Following the standard neoclassical approach to consumer demand, suppose that an individual $i = 1,...,N$ in time period $t = 1,...,T$ has preferences over their health, H_t, and a composite commodity of all other goods, C_t, defined by the following utility function:

(1) $$U_{it} = U(H_{it}, C_{it}).$$

Further assume that health is a stock variable defined by an initial level of health carried over from the previous period, investments in health made through the consumption of medical services, m_{kit}, $k = 1,...,K$, and random shocks, ε_{it}, such that

(2) $$H_{it} = h(H_{it-1}, m_{1it},..., m_{Kit}, \varepsilon_{it}).$$

To determine the optimal investment in health and consumption of other goods, the individual maximizes (1) and (2) subject to a budget constraint,

(3) $$\sum_k p_{kt} m_{kit} + C_{it} \leq Y_{it},$$

where Y_{it} represents total disposable income, and the price of the composite commodity has been normalized to one. The resulting demand equations for medical services, which can be easily modified to include exogenous socio-demographic determinants, Z_t, take the form:

(4) $$m_{kit} = q(p_{1t},..., p_{Kt,} Y_{it}, \varepsilon_{it}; Z_{it}), \ \forall k = 1,...,K.$$

Although the above derivation is straightforward, complete specification of the demand equations is complicated by the presence of medical insurance and the nonlinear pricing schedules commonly applied to medical care. In particular, deductibles, coverage ceilings, and non-constant cost sharing between consumers and insurers make it difficult to determine the effective price of medical services. Newhouse, Phelps, and Marquis (1980) have shown that defining p_{kt} in (4) as the average or marginal price of medical care is likely to lead to biased estimates. However, in the absence of wealth effects and risk aversion, Ellis (1986) and Ellis and McGuire (1986) demonstrated that the expected end-of-year price is the effective shadow price for medical care in the presence of nonlinear budget constraints caused by health insurance.[2] For a consumer facing a nonlinear price schedule for medical care with distinct segments $s = 1,...,S$, if their expectation regarding which of these segments their final plan-year medical transaction will fall can be summarized by the probability, π_s, then their expected end-of-year price is defined as

(5) $$p^e_{kit} = \sum_s \pi_{kis} p_{kts} .$$

The empirical model for a demand system composed of K types of medical services can thus be specified to take the form

(6) $$m_{kit} = \alpha_k + \sum_h \eta_{kh} z_{hit} + \sum_l (\gamma_{kl} \log p^e_{lit} + \delta_{kl} pd^e_{lit}) + \beta_k \log Y_{it} + c_i + \varepsilon_{kit} ,$$

where pd^e_{kit} is a binary variable = 1 if the individual *i*'s expected end-of-year price for medical service k is equal to zero and = 0 otherwise, and c_i is a stochastic time-invariant individual

[2] Even after allowing for risk aversion, the expected end-of-year price remains close to the shadow price of medical services. Note that the use of expected end-of-year prices allows one to incorporate supply constraints imposed by insurers into the model that limit the number of covered visits. This is done by estimating each consumer's expectation, or probability, that the coverage limit is exceeded and subsequent expenses not reimbursed.

specific effect measuring unobserved heterogeneity.[3] We interpret c_i as unobserved mental and physical health status and propensity to consume treatment; in cross-sectional formulations of the model, c_i is typically either assumed to be zero or uncorrelated with all other regressors. If the vector of disturbances $\boldsymbol{\varepsilon}_{it} = (\varepsilon_{1it},...,\varepsilon_{Kit})'$ is assumed to be jointly distributed $N(0,\sigma_{\varepsilon}^2)$, then the system of K equations defined by (6) is correlated through both c_i and $\boldsymbol{\varepsilon}_{it}$.

The logarithmic specification of price and income variables in (6) is similar to other commonly used specifications in the empirical demand literature, and is necessary to account for the skewed distributions of these variables. The distribution of medical care prices (expected out-of-pockets costs), however, is not only skewed to the right, but contains a large mass at zero due to the fact that many individuals are enrolled in health insurance plans where the majority of their out-of-pocket costs are zero after paying an annual premium. This may occur, for example, if the some types of medical services require no co-payment (e.g. preventive services), or an individual's expenditures within a plan-year are large enough to exceed a stop-loss provision, whereby all remaining services in any service category do not require a co-payment. We account for this feature of the price distribution through the use of the binary variables to indicate zero expected end-of-year prices and logged positive prices. In contrast to out-of-pocket costs, the health insurance premium is an anticipated expense not linked to any particular health care transaction, and therefore, has been subtracted from total disposable income (that is, $Y_{it} = Y_{it}^{Total} - Premium$).

Given our interpretation of c_i as the individual's unobserved physical and mental health status and propensity to consumer care, we cannot assume that factor is uncorrelated with either

[3] Under this specification $\log p_{kit}^{e}$ is set to zero when p_{kit}^{e} is equal to one.

expected end-of-year prices or several of the socio-demographic variables in the model. Therefore, c_i is modeled as a correlated random effect (CRE), and assumed to be potentially correlated with all the regressors in each time period:

(7) $$c_i = \sum_h \sum_t \lambda_{lt}^1 z_{hit} + \sum_l \sum_t (\lambda_{lt}^2 \log p_{lit}^e + \lambda_{lt}^3 pd_{lit}^e) + \sum_t \lambda_t^4 \log Y_{it} + \upsilon_i ,$$

where υ_i is assumed to be independent of the exogenous regressors and $\boldsymbol{\varepsilon}_{it}$ and is distributed $N(0, \sigma_\upsilon^2)$.[4] This specification was originally derived by Chamberlain (1980) and has been applied to demand systems by Meyerhoefer, Ranney and Sahn (2005). Defining $\mathbf{x}_{it}$ as a row vector containing all the model regressors for time period *t* (plus a constant for the intercept), (7) is substituted into (6) to derive the demand system with reduced form parameter vector $\boldsymbol{\pi}_{kt} = (\boldsymbol{\pi}'_{kt1}, ..., \boldsymbol{\pi}'_{ktT})$ and normally distributed disturbance $u_{kit} = \varepsilon_{kit} + \upsilon_i$:

(8) $$m_{kit} = \mathbf{x}'_{i1}\boldsymbol{\pi}_{kt1} + \mathbf{x}'_{i2}\boldsymbol{\pi}_{kt2} + \cdots + \mathbf{x}'_{iT}\boldsymbol{\pi}_{ktT} + u_{kit} .$$

Econometric estimation of the CRE model generally proceeds by first obtaining consistent estimates of the reduced form parameters in (8) followed by identification of the structural parameters of interest in (6).

3. Econometric Estimation

In comparison to most commodities and many other services, medical services are difficult to measure in homogeneous units. Not only is there wide variation in the quality of medical care, but some medical procedures are very resource intensive while others are easily administered. In order to limit heterogeneity in the type of services provided we focus on ambulatory care and exclude inpatient treatment. We also follow the approach of previous

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[4] If c_i is assumed to be orthogonal to a subset of the demographic variables, then restriction $\lambda^1 = 0$ should be imposed for this subset in (7).

studies (such as Horgan 1986; Zuvekas, 1999; Winkelmann, 2004) in measuring ambulatory medical service use through the number of visits to physicians or other medical personnel, and analogously, measure pharmaceutical consumption through the number of prescription drug fills and/or re-fills during a one year time period. Finally, we disaggregate outpatient treatment into mental health ambulatory care, physical health ambulatory care, mental health related prescription pharmaceuticals, and physical health related prescription pharmaceuticals.

Irrespective of whether the medical service provided is an ambulatory visit or prescribed medicine, the distribution of consumption is highly skewed, particularly for the treatment of less common chronic conditions, such as mental illness. This is because most individuals have very few visits and prescription fills in a given year, while some individuals have a large number. In addition, for services such as mental health care there are a high proportion of non-consumers of both ambulatory treatment and prescription drugs. We use a zero-inflated ordered probit (ZIOP) specification, developed by Harris and Zhao (2004) to model the demand for medical services in the presence of this skewed distribution for ambulatory visits and prescription fills. Doing so allows us to capture the large probability mass at zero as well as define discrete categories containing a range of visit/fill enumerations at the upper end of the consumption distribution rather than just a single number of total visits.

Other popular empirical specifications used to model this type of data generating process include count data models, such as the zero-inflated Poisson or negative binomial specifications. Our choice of the ZIOP model stems primarily from the desire to incorporate correlated random effects into the model, which is more tractably done using an index function with normally distributed disturbances. In addition, we find the ordered probit framework conceptually attractive when modeling numbered outcomes within specified ranges as well as individually.

Both Cameron and Trivedi (1998) and Wooldridge (2002) propose the ordered probit as an alternative to count data models, with the former demonstrating that it fits selected data on the number of doctor visits at least as well as a negative binomial model.

Underlying the ZIOP specification is a latent model of the demand for medical care in which observed consumption levels, m_k, are generated as

$$m_k = r_k \cdot m_k^* . \tag{9}$$

The variable r_k is a binary indicator dividing individuals into "consumers" and non-consumers" and is itself defined by the latent process

$$r_k = \begin{cases} 0 & \text{if} \quad \tilde{r}_k = \mathbf{x}'\boldsymbol{\pi}_k^A + u_k^A \le 0 \\ 1 & \text{if} \quad \tilde{r}_k > 0 \end{cases} . \tag{10}$$

Likewise, m_k^* indicates the chosen consumption level of the individual (including zero consumption) through the latent process:

$$m_k^* = \begin{cases} 0 & \text{if} \quad \tilde{m}_k^* = \mathbf{x}'\boldsymbol{\pi}_k^B + u_k^B \le 0 \\ 1 & \text{if} \quad 0 < \tilde{m}_k^* \le \mu_1 \\ 2 & \text{if} \quad \mu_1 < \tilde{m}_k^* \le \mu_2 \\ \vdots & \\ J & \text{if} \quad \mu_{J-1} < \tilde{m}_k^* \end{cases} \tag{11}$$

where $j = 1,...,J$ indexes ambulatory visit or prescription fill number. Although there is no requirement that the data vector $\mathbf{x}$ be the same in (10) and (11), in our application there are no variables which effect the likelihood of consuming medical services, but not effect the level of their consumption (or vice versa). Under the above formulation a zero outcome is observed if either the individual is a non-consumer of the service in question ($r_k = 0$) or is a consumer, but an infrequent one ($r_k = 1, m_k^* = 0$). Likewise, to observe a non-zero outcome the individual must be a consumer, or market participant, and have a positive consumption level during the respective time period.

Under the assumption that u_k^A and u_k^B are both independently and identically distributed $N(0,1)$, the full unconditional probabilities of the ZIOP model take the form:

$$\Pr(j) = \begin{cases} \Pr(m_k = 0 \mid \mathbf{x}) & = & \left[1 - \boldsymbol{\Phi}(\mathbf{x}'\boldsymbol{\pi}_k^A)\right] + \boldsymbol{\Phi}(\mathbf{x}'\boldsymbol{\pi}_k^A) \cdot \boldsymbol{\Phi}(\mathbf{x}'\boldsymbol{\pi}_k^B) \\ \Pr(m_k = 1 \mid \mathbf{x}) & = & \boldsymbol{\Phi}(\mathbf{x}'\boldsymbol{\pi}_k^A) \cdot \left[\boldsymbol{\Phi}(\mu_1 - \mathbf{x}'\boldsymbol{\pi}_k^B) - \boldsymbol{\Phi}(-\mathbf{x}'\boldsymbol{\pi}_k^B)\right] \\ \Pr(m_k = 2 \mid \mathbf{x}) & = & \boldsymbol{\Phi}(\mathbf{x}'\boldsymbol{\pi}_k^A) \cdot \left[\boldsymbol{\Phi}(\mu_2 - \mathbf{x}'\boldsymbol{\pi}_k^B) - \boldsymbol{\Phi}(\mu_1 - \mathbf{x}'\boldsymbol{\pi}_k^B)\right] \\ \vdots & & \\ \Pr(m_k = J \mid \mathbf{x}) & = & \boldsymbol{\Phi}(\mathbf{x}'\boldsymbol{\pi}_k^A) \cdot \left[1 - \boldsymbol{\Phi}(\mu_{J-1} - \mathbf{x}'\boldsymbol{\pi}_k^B)\right] \end{cases} \tag{12}$$

As Harris and Zhao point out, this specification is analogous to other Zero Inflated models (see, for example, Mullahy (1986, 1997), Greene (1994), and Pohlmeier and Ulrich (1995)) and is directly comparable to the double hurdle models following from Craig (1971).

Estimation of the medical services demand system using the ZIOP specification is a multi-step process in which the reduced form parameter estimates in equation (8) are obtained in two stages. In the first stage the ZIOP model is used to generate predicted probabilities for different numbers of visits or fills that are multiplied by consumers reported out-of-pocket costs to construct the expected end-of-year prices in (5). The price variables are then added to the model and it is re-estimated equation-by-equation to obtain the full set of reduced form parameter estimates. Because some of the data on out-of-pocket costs is imputed, we add labor market variables for industry category, occupation category, and whether the individual works in a firm with a retirement plan to the first stage model in order to strengthen identification in the second stage estimation of the reduced form.[5] These variables are assumed appropriate for this

[5] Note that the *reduced form* expected price parameters are identified through the non-imputed data even without these exclusion restrictions. The power of the exclusions is high due to the large number of observations used to estimate the model (N=201,166). Under the null hypothesis that the coefficient vector corresponding to the industry and occupation variables is zero, the Wald statistics for the ambulatory mental health equation, mental health drug

purpose because they influence medical care demand primarily through price (because they are correlated with the generosity of health insurance coverage). Assuming that the model regressors in equation 8 are exogenous after substituting the right-hand-side of equation 7 for c_i, single equation ZIOP estimation yields consistent estimates of the reduced form parameters. The structural parameters of interested are then identified using the panel dimension of the data.

Meyerhoefer, Sahn, and Ranney demonstrate how identification of the structural parameters in equation (6) is achieved through the use of a minimum distance estimator of the form:

$$\min D(\boldsymbol{\psi}) = [\hat{\boldsymbol{\pi}} - \mathbf{H}\boldsymbol{\psi}]'\hat{\boldsymbol{\Omega}}^{-1}[\hat{\boldsymbol{\pi}} - \mathbf{H}\boldsymbol{\psi}]\,. \tag{13}$$

Here $\boldsymbol{\psi}$ denotes the vector of structural parameters, $\hat{\boldsymbol{\Omega}}$ is the estimated covariance matrix of the reduced form parameter estimates, and $\mathbf{H}$ is a design matrix mapping the structural parameters to the reduced form estimates. In this case, the estimated covariance matrix $\hat{\boldsymbol{\Omega}}$ is adjusted using the formulae derived by Wooldridge (2002, pp.354-56) to account for the first-stage estimation of the predicted probabilities used to construct the expected price variables. The minimum distance framework provides a means of testing the validity of restrictions on the model as well as other nested or non-nested specifications through the use of the chi-squared distributed test statistic $ND(\hat{\boldsymbol{\psi}})$.

4. Data

The data source for our empirical application is the 1996 – 2003 Medical Expenditure Panel Survey (MEPS). The MEPS is a comprehensive, nationally representative survey of the

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equation, ambulatory physical health equation and physical health drug equation are 3756, 3078, 3417, and 2608, respectively. The corresponding critical value is $\chi^2_{22} = 40$ at the 1 percent level of significance.

U.S. civilian non-institutionalized population, conducted annually since 1996 using a rotating panel design. Respondents are interviewed about their characteristics and health care use and expenses over the course of two years through five interview rounds. In addition, information from the household survey is supplemented by expenditure data collected directly from respondents' medical service providers and pharmacies through a Medical Provider Component (MPC).

Appendix Table A1 lists descriptive statistics for all of the variables used in the medical services demand model. Socio-demographic controls include race, gender, age and its square, years of completed education, self-reported physical and mental health status, the Columbia impairment scale for children, and a deterministic time trend. The insurance variables are dichotomous and indicate whether the respondent was fully or partially enrolled in a private insurance program (including TRICARE), or one of two categories of public insurance: Medicare or Medicaid / other state program.[6] We also include an indicator for whether the private or public insurance program was administered through an HMO or managed care organization. Employment related variables include indicators for whether the respondent received paid sick leave and paid vacation at their current job. All of the price variables and logged family income have been adjusted for inflation and are reported in 2003 USD. In addition, the family's annual out-of-pocket premium has been subtracted from income, which is deflated by the square root of household size in order to adjust for household economies of scale. We do not age-restrict the sample, and therefore, use the parent's labor market and education information for respondents under the age of 18. Variables marked by an * in Table A4 are those that we have specified as correlated with the random effect in our empirical specification.

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[6] Due to similarities in cost-sharing and the incidence of illness we include the Medicare/Medicaid dual eligible population and the under-65 Medicare population in the Medicaid / other public program category.

Table A2 contains detailed distributions on the components of expected end-of-year prices for the full sample. These include (pre-imputation) unit prices at each point on the eight segment price schedule as well as the predicted probabilities of facing an end-of-year price on each segment.

The dependent variables in the correlated random effects ZIOP model are the number of mental health and physical health ambulatory visits and prescription drug fills.[7] Because some respondents report very large numbers of visits and fills, while the majority report zero or a handful of visits, we define the dependent variable categories of the model as listed in Table 1. The categorization of larger numbers of visits is designed to correspond to changes in the price schedules of typical insurance plans. For example, many privately administered plans increase cost sharing after 5 visits and impose a coverage limit of 20 mental health visits per year. The expected end-of-year prices also correspond to these segments of the pricing schedule, so that out-of-pocket costs (prior to probability weighting) for categories 7, 8, and 9 are averages of the per visit or per prescription costs faced by consumers over the respective ranges.

Although every respondent has a non-zero probability of facing the end-of-year price associated with each of the categories in Table 1, out-of-pocket costs are only observed for events that actually transpired. Therefore, we impute the out-of-pocket costs respondents would have faced had they consumed ambulatory medical services or prescription drugs at each level of the pricing schedule. This is done separately for the privately insured, uninsured, Medicare recipients, and Medicaid recipients on each segment of the pricing schedule in Table 1 using a two-stage regression-based imputation procedure.

[7] We omit inpatient care because it is quite rare in the community population in the case of mental health, and we suspect that most insurance plans has separate deductibles and cost controls for inpatient services.

In the first stage of the imputation procedure, a probit model is estimated on the sample of consumers with observed out-of-pocket costs to determine the probability of facing positive out-of-pocket costs for the respective visit or prescription fill. The estimates are subsequently used to generate an unbiased estimated of the latent outcome variable underlying the probit model (analogous to $\tilde{r}_k$ in (10)) for the sample of non-consumers. This is done by multiplying the estimated coefficients by each non-consumer's data vector and adding the value of a random draw from the distribution $N(0,1)$. Non-consumers with a predicted latent outcome less than or equal to zero are imputed an out-of-pocket cost of zero for the respective visit, while those with a positive latent outcome are run through a second imputation regression. This regression, also estimated on the sample of consumers, is an OLS model of segment-specific logged out-of-pocket cost on a variety of labor market and socio-demographic variables.[8] In addition, price variables from up to five previous segments of the pricing schedule are included to ensure imputed prices lie along a consistent trajectory. The imputation procedure preserves the distributional characteristics of observed out-of-pocket prices for each category of insurance coverage.

5. Estimation Results

Our principal purpose in estimating the demand models is to provide new estimates of the responsiveness of health care consumption to changes in health care prices so that they may be used in policy analysis. Therefore, we present own and cross-price effects of out-of-pocket prices for the four types of health care included in our empirical demand system: mental health

[8] The probit and OLS imputation regressions include controls for age, race, sex, education level, marital status, family income, urbanization, census region, self-reported physical and mental health status, generosity of employer benefits, unionization, industry and occupation classification, employer size, HMO or managed care enrollee, and dummy variables for year of interview. Since the imputations are insurance- specific, no controls for insurance status are necessary.

visits, mental health drugs, physical health visits, and physical health drugs. For ease of interpretation, we compute two different price elasticity measures. First, arc elasticities between $0 and $5 dollars, $5 and $25, $25 and $75, and $75 and $100, are estimated by simulating the percentage change in the number of visits or prescription fills when out-of-pocket costs are constant over the range of expected demand and change (in percentage terms) by the specified dollar amounts. Second, we compute the average point elasticity, by taking derivatives of the expected quantity demanded with respect to the log of expected end-of-year price and dividing by expected demand. Both elasticity concepts are computed for each individual in the sample and averaged using sample weights to provide unbiased population estimates. Full regression results are reported in Table A3 for the cross-sectional model and in Table A4 for our preferred correlated random effects specification. All standard errors are adjusted for the complex design of the MEPS.

Own price effects

We present estimates of the own (out-of-pocket) price effects from our preferred correlated random effects (CRE) specification in Table 2. The estimated average own-price elasticity for mental health visits is -.06, with arc elasticities changing little across price levels. Ambulatory visits for physical health problems exhibit a slightly higher price elasticity of -.12. The difference in physical and mental health visit price elasticities is statistically significant at the .001 level, but in economic terms they are similar in magnitude.

The demand for prescription drugs is substantially more price responsive. Mental health drugs are 10 times more price responsive than mental health visits, with an average elasticity of -.61. Furthermore, mental health drugs show an increasing arc elasticity of demand as the price level increases. The positive estimated arc elasticity in the range of $0-$5 is likely due to the small number of people facing $0 expected out-of-pocket cost for prescription drugs.[9] Paralleling mental health, drugs for physical health problems have a higher price elasticity than physical health ambulatory visits, at -.29, but this is about half the estimated price elasticity for mental health drugs (difference is statistically significant at the .001 level). Like mental health drugs, however, physical health drugs elasticity of demand is increasing in out-of-pocket price.

We also compare own price effects from our CRE specification with estimates from the cross-sectional model in Table 2. For mental health visits, the own price effects are identical. However, the own price-effects for mental health drugs, physical health visits, and physical health drugs estimated are all smaller in our CRE specification compared to the cross-sectional estimates. Specification tests of whether the random effect term is orthogonal to the regressors strongly reject orthogonality, and the estimated λ parameters in the correlated random effects equation specification are also individually significant (see Table A4). Thus, we prefer the CRE specification.

Own price effect variations by health insurance coverage

While estimates of price effects across the entire population are of clear policy interest, public and private decision-makers also need to know price-responsiveness for particular populations defined by health insurance coverage. We therefore estimate our CRE specification separately for those covered by private insurance, Medicare, and Medicaid, as well as the uninsured, and present price elasticity estimates in Table 3. Depending on the subgroup reported we have made small changes to the set of explanatory variables. For example, the dummy

[9] When we estimate the model on subgroups in some cases there are almost no individuals that report a zero expected price for mental and physical health drugs. In these cases, the $0-$5 forecasts for drugs are outside of the range of the data.

variables indicating a zero expected end-of-year price for mental and physical health drugs have been dropped from all sub-categories except Medicaid.

In general, price responsiveness was greatest among the privately insured population. Average own-price elasticities of demand for mental health and physical health visits were nearly identical at -.17 and -.16, respectively. However, mental health drugs were substantially more price elastic with an average elasticity of -.92, while the average elasticity for physical health drugs is -.26. Arc elasticities increased with price for both physical and mental health drugs.

Average price elasticities were lower among the Medicare population, with the exception of the large own-price elasticity of mental health drugs, -.89. However, physical health drugs did show some price responsiveness at higher out-of-pocket price levels. For example, the arc elasticity between \$75 and \$100 dollars was -.52. Estimated own-price elasticities for the Medicaid population were uniformly small across all four types of health care. This is not particularly surprising given the consistently low levels of cost sharing built into the Medicaid program.

For the uninsured, the own price effects for mental health and physical health visits were similar compared to the privately insured, although the former was not precisely estimated. However, in contrast to the Medicare and privately insured population the demand for mental health drugs (-.28) was less price responsive than the demand for physical health drugs (-.51).

Cross-price elasticities: Substitutes or Complements?

A key question is whether pharmacotherapies serve as complements or substitutes for outpatient treatment. To answer this question, we compute cross-price elasticities across the four types of medical care and present these in Table 4. For the entire population, the percentage change in the demand for physical health visits with respect to a one percent change in physical health drug price is -.07, while the analogous cross price elasticity of drug demand is -.03. Therefore, our estimates suggest that physical health visits and drugs are gross complements, a result that is consistent within each different insured population. For example, the cross-price elasticities between physical health visits and drugs in the privately insured population are also -.07 and -.03. Mental health visits and drugs are also gross complements, although the symmetry is weaker. For the entire population, the percentage change in the demand for mental health visits with respect to a one percent change in mental health drug price is -.17, while the analogous cross price elasticity of drug demand is -.01. The general symmetry with respect to signs is a strong indication of the consistency in our demand estimates.[10]

Did price elasticities change between 1996 and 2003?

The MEPS data we use span an 8 year time period between 1996 and 2003, so it is natural to ask whether price elasticities changed over this period. Our base model includes a deterministic time trend as a regressor, but this cannot fully capture changes in elasticities because it is not interacted with the price variables. Instead, we split our sample into an early period with panels 1-4 (1996-2000) and a later period representing panels 5-7 (2000-2003) and re-estimate the CRE model for each. The results are presented in Table 5. In general, the signs and magnitudes of both the own-price and cross price effects are quite similar in the early and more recent time periods, which increases confidence in the robustness of our approach. For example, the own price effects for physical health visits (-.11 for panels 1-4 vs. -.12 for panels 5-

[10] The symmetry restriction from economic theory implies that the cross price derivatives of the Hicksian demand functions are equivalent. Using the Slutsky equation one can derive an analogous condition for the Marshallian demands. We do not statistically restrict the cross price derivatives in our system of (Marshallian) demands to be symmetric, as many researchers do. However, our finding that symmetry generally holds with respect to sign suggests the model conforms to theory even without such a restriction.

7) and drugs (-.27 vs. -.32) are quite close in the early and more recent periods and not statistically different. The own price effects for mental health treatment, especially mental health drugs were somewhat higher in the more recent time period (-.55 in panels 1-4 vs. -.75 in panels 5-7, t-statistic=2.27).

Robustness

While we find that the price elasticity of demand for physical health visits to be similar in magnitude to estimates from the RAND Health Insurance Experiment, our results also imply that the demand for outpatient mental health visits has become substantially less price elastic since the 1970s/early 1980s when the RAND study was conducted. Because of the potential policy importance of this finding, we want to be sure of its robustness. Obviously, the cost of a new randomized experiment is prohibitive. We also could not properly identify an instrumental variables model, a long-standing problem in health economics research. However, as we noted earlier, observational studies using data from the same time period as the RAND HIE also found substantial price responsiveness. We take advantage of the fact that one of these key studies by Horgan (1986) used data from an earlier predecessor of the MEPS data we use, the 1977 National Medical Care Expenditure Survey (NMCES).

Horgan estimated a standard two-part cross-sectional model of the demand for outpatient specialty mental health visits, predicting the probability of any use with a logit regression and modeling the log of the number of specialty mental health visits using an OLS regression. We are unable to replicate the first (logit) part of the model because we lack an equivalent price variable to the one Horgan used. However, we can estimate the second part of Horgan's cross-sectional model using data from the 2002 MEPS, which collects information on physician specialty. Horgan uses two alternative price concepts: the average percentage paid out-of-pocket of the total cost of outpatient specialty mental health visits and the average per visit out-of-pocket dollar amount. We also estimate the second part of her model with data from the 1987 National Medical Expenditure Survey (NMES), which followed the 1977 NMCES used by Horgan, and the immediate predecessor to the MEPS. Because the three nationally representative surveys are similar in design and content, we are able to replicate Horgan's specification almost exactly; providing consistent estimates of how price-responsiveness changed in her model over the 25 year period from 1977 to 2002.

Table 6 reports Horgan's original findings along with our re-estimation of her model using the 1987 NMES and 2002 MEPS data. In the first column, we see the price-responsiveness that Horgan originally reported using the 1977 data, with own-price elasticities of -.44 for the average out-of-pocket percentage price specification and -.30 for the average out-of-pocket dollar amount. These elasticities diminished somewhat when we re-estimated her model with the 1987 NMES data in the second column, but a clear degree of price responsiveness remains. However, when we re-estimated her model with the 2002 MEPS data we no longer see any significant price effect.

Thus, our re-estimation of Horgan's model with more current data yields similar results to our preferred specification. Namely, the demand for outpatient mental health visits appears to have become substantially less elastic over time. We still note that both our measure of expected price, which is theoretically more consistent than using observed prices, and our CRE specification to correct for potential endogeneity and time-invariant measurement error processes, are improvements over Horgan's model.

We performed a further robustness check on our results by investigating whether the use of expected end-of-year prices produces consistent elasticity estimates throughout the year.

Keeler, Newhouse, and Phelps (1997) have shown that the true shadow price of healthcare varies throughout the year as consumers update their information about how close they are to a discontinuity in their price schedule. Ellis (1986) demonstrates that the expected end-of-year price tracks the true shadow price of healthcare quite closely under fairly realistic assumptions, and shows empirically that estimates of the price responsiveness of demand are similar using expenditures from the first 30, 60, and 90 days of year. In a similar manner to Ellis, we re-estimated our demand system using utilization data from round 1 of the MEPS, corresponding roughly to the first half of the year, and found that our own-price elasticities of demand varied by only 7 percent, on average. Therefore, the expected end-of-year price provides consistent measure of the consumers' perceived health care price.

6. Discussion and Conclusions

Several clear findings emerge from the correlated random effects estimates of our health care demand model. Most importantly, the estimates imply that the demand for outpatient mental health visits has become substantially less price-elastic over the last 25 years. The 1977-1982 RAND Health Insurance Experiment, consistent with observational studies from the same period, found the demand for mental health visits to be substantially more price elastic than for physical health visits. Keeler, Manning and Wells (1988) report an ambulatory mental heath own-price elasticity of -.59 and Manning et al. (1987) report arc own-price elasticities of physical health treatment in the range of -.13 to -.21 from the RAND HIE. Our point estimate of the own-price elasticity for mental health visits during the period 1996-2003 for the full U.S. population is -.06, lower even than our estimate of -.12 for the own-price elasticity for physical health visits. For different insured subpopulations, there were no statistically significant differences in elasticities between physical and mental health visits.

One of the reasons why our elasticity estimates are lower than those found by the RAND investigators may be due to structural and institutional changes to health care markets over the past twenty to thirty years, such as the diffusion of managed care. Although we control for different types of insurance and enrollment in an HMO or managed care plan, all types of health care services are more highly managed than they once were. This is particularly true of mental health services, where the distinction between managed and traditional plans is blurred by the common use of carve-out arrangements to control costs. Therefore, our elasticity estimates should be interpreted as conditional on the current institutional environment, and are more appropriate for forecasting price changes within this environment than wholesale changes to the environment itself.

If it is indeed true that the price responsiveness of mental health ambulatory treatment is less than or equal to physical health treatment, then the justification for higher cost-sharing for mental health based purely on efficiency grounds would no longer hold. This has significant implications for private health insurance plans and Medicare (and to a lesser extent Medicaid), where mental health treatment continues to be covered much less generously on average than other medical services. It also suggests that increasing the generosity of outpatient mental health coverage would not lead to large cost increases, which is consistent with studies of the impact of state legislative mandates for mental health parity, that is, equal coverage for mental health and physical health treatment (Zuvekas et al. 2002; Sturm, 1997; Goldman et al, 2006).

Our results also point to the importance of prescription drug treatment in the overall demand for mental health care. Estimates of the own-price elasticity of demand for mental health drugs are substantially higher than for outpatient mental health visits (with the exception of the Medicaid population). We also note the high, negative cross-price elasticities between mental health drugs and visits. Together, this suggests that many mental health visits are for medication management and that individuals' overall demand for mental health treatment is now more strongly tied to prescription drug than ambulatory costs than it was during the RAND HIE. In other words, the decision to begin and continue mental health treatment is now more heavily influenced by the expected costs of the appropriate course of mental health drugs than the associated ambulatory costs.

Turning to physical health treatment, our estimates of the own-price elasticity of demand for visits are similar in magnitude to those reported from the RAND HIE. That is to say, price elasticities appear to remain small, but they are also not zero as the RAND HIE investigators point out (Manning et al 1987). Because spending on ambulatory visits exceeds $300 billion annually (MEPS Compendia of Tables, 2003), the scope for significant aggregate welfare losses is substantial.

Our findings suggest, however, that concerns about efficiency losses from moral hazard resulting from insurance coverage are better focused on prescription drug coverage rather than coverage for ambulatory care. We found the elasticity of expected out-of-pocket price to be substantially greater for prescription drugs: -.61 for mental health drugs and -.29 for physical health drugs. In contrast, the RAND HIE found little difference in the price elasticity of demand for prescription drugs and other services (Newhouse et al., 1993). Health insurers clearly believe there is substantial consumer price responsiveness for prescription drugs, as they continue to increase consumer out-of-pocket cost-sharing and introduce multi-tiered pricing schedules to encourage substitution of therapeutically equivalent, but cheaper medications, in attempt to restrain rapidly escalating prescription drug costs. Price elasticity estimates from the literature for physical health drugs support this conception, ranging from -.15 up to -.5. While the number of studies that investigate the price responsiveness of mental health drugs is few, estimates range from -.26 and (Goldman et al, 2004; Landsman et al., 2005) -.28 for SSRI antidepressants to -1.15 (Landsman et al. AJMC, 2005) for tricyclic antidepressants. Huskamp et al. (2005) also find substantial price sensitivity for ADHD medications.

In sum, price responsiveness remains heterogeneous in type of health care treatment, although it also appears that price responsiveness for particular treatments changed in the last 25-30 years. We find that there are no longer differences in price effects between ambulatory mental health and physical health visits, but substantially higher price responsiveness in prescription drugs, especially mental health drugs. The theory of optimal second-best insurance coverage suggests that health insurance plans, including those combined with Health Savings Accounts, may need to adjust coverage to reflect changes in the underlying demand for medical services.

Limitations and Future Research

It is quite possible that radical changes in the treatment technology for mental health, such as the move away from outpatient psychotherapy towards pharmacotherapy, explain the observed decrease in the own-price responsiveness of mental health ambulatory treatment. However, we must also consider the impact of managed behavioral healthcare in constraining supply. The price elasticity estimates of 25-30 years ago come largely from a fee-for-service world unconstrained by managed care organizations that may restrict access to or the supply of mental health services. For example, a managed behavioral healthcare organization may authorize and pay for 5 outpatient treatment visits, but no more. In this case, the consumer faces the full marginal cost of any additional treatment visits. We model the resulting nonlinearity in consumers' price schedules by computing expected end-of-year prices. However, the validity of this measure rests in our ability to accurately model the consumer's expectations. If the covariates in our model do not accurately characterize consumer's information set, then our predictions will be biased.

Price schedules for prescription drugs have also become increasingly nonlinear. Prescription drug plans today typically require the lowest consumer cost-sharing for generic medications no longer covered by patents, higher cost-sharing for favored drugs (often as a result of negotiations with pharmaceutical companies), and still higher cost-sharing for non-favored drugs. Further disaggregating prescription drugs to explicitly correspond to these types of tiered pricing schedules that differentiate between generic versus non-generic medications (as well as among non-generics) represents a promising extension of our empirical approach.

The MEPS data make it difficult to fully sort out medication management visits from traditional psychotherapy and from newer forms of behavioral therapy. Data for the 1996 through 2001 period also do not allow us to distinguish whether mental health visits were to primary care physicians or psychiatrists. Beginning in 2002, the MEPS added questions about physician specialty, but we do not yet have enough years of data to apply our panel data estimation techniques. It is quite possible that price elasticities differ for these different forms of mental health treatment, which is something we intend to explore in future work.

Another limitation of our modeling approach is that our method for accounting for endogeneity and meaurment error is not fully general. We assume that the endogeneity of price, health insurance status, and self-reported measures of physical and mental health is generated by correlation with a component of the residual that is time invariant. This is logical given the supposition that unobserved physical and mental health status and propensity of consume treatment are the primary confounders of these variables. However, it is also possible that there exists a correlation between the regressors with time varying error components that we cannot capture. The same is true of measurement error considerations. If the process generating differences between consumers' true expected end-of-year price and our construct is not time invariant, then our parameter estimates will be attenuated.[11] Finally, we identify the correlation between the random effect and included regressors using just two time periods, so that the effect of regressors three periods removed is present in the model's residual. If the included regressors exhibit strong serial correlation then some endogeneity bias may persist despite our attempt to "integrate out" the random effect. However, the lack of suitable instruments for price and insurance makes our approach to correcting for endogeneity and measurement error attractive.

The prospects for another large-scale randomized experiment remain dim given current federal budget forecasts—the RAND HIE cost $136 million to conduct in 1984 dollars (Manning et al., 1987). Thus, more current estimates of price elasticities must come from observational studies. We believe our correlated random effects approach, correcting for the clear endogeneity of prices and health insurance and applied to multiple years of data from the nationally representative MEPS, offers a second-best solution.

[11] Note, however, that one would expect greater measurement error in the physical health price than mental health price given the heterogeneous nature of the former, so it is unlikely that measurement error alone is responsible for "pulling" the ambulatory mental health care elasticity below the physical health care elasticity.

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Table 1. Health Care Consumption and Expected End-of-Year Price Categories

		Percentage of Full Sample			
Category	Visit / Fill No.	MH Visits	MH Drugs	Non-MH Visits	Non-MH Drugs
1	0	93.6	92.0	30.7	39.7
2	1	2.0	1.4	17.4	11.6
3	2	0.9	0.9	11.5	8.1
4	3	0.6	0.7	8.0	5.2
5	4	0.5	0.6	5.7	3.9
6	5	0.3	0.5	4.4	2.8
7	6 – 10	1.0	1.9	11.4	9.5
8	11 – 20	0.7	1.4	7.0	8.8
9	> 20	0.5	0.7	3.8	10.5

Source: Authors' estimates from 1996-2003 Medical Expenditure Panel Survey.

Table 2. Cross-Sectional and Correlated Random Effects Estimates of Own-Price Elasticities: Full Population (N=100,583, T=2)

	Arc Elasticity				Average Elasticity	
	\$0-\$5	\$5-\$25	\$25-\$75	\$75-\$100	estimate	std. err.
Cross-Sectional Estimates						
Mental Health Visits	-.032	-.067	-.063	-.059	-.056	.012
Mental Health Drugs	.413	-.593	-.911	-1.104	-.868	.031
Physical Health Visits	-.053	-.219	-.209	-.197	-.184	.005
Physical Health Drugs	.042	-.395	-.832	-1.186	-.513	.013
Correlated Random Effects Estimates						
Mental Health Visits	-.049	-.076	-.071	-.065	-.063	.010
Mental Health Drugs	.202	-.424	-.676	-.792	-.609	.029
Physical Health Visits	-.071	-.139	-.130	-.122	-.115	.005
Physical Health Drugs	.018	-.213	-.522	-.741	-.288	.016

Source: Authors' estimates from 1996-2003 Medical Expenditure Panel Survey.
Note: Standard errors adjusted for complex survey design of the MEPS.

Table 3. Correlated Random Effects Estimates of Own-Price Elasticities: Privately Insured, Medicare, Medicaid, and Uninsured Populations

	Arc Elasticity				Average Elasticity	
	$0-$5	$5-$25	$25-$75	$75-$100	estimate	std. err.
Privately Insured (N=58,414)						
Mental Health Visits	.018	-.191	-.188	-.178	-.166	.024
Mental Health Drugs	.623	-.767	-1.012	-1.164	-.916	.088
Physical Health Visits	-.123	-.185	-.176	-.165	-.156	.021
Physical Health Drugs	-.083	-.202	-.534	-.762	-.256	.025
Medicare (N=10,930)						
Mental Health Visits	-.011	-.049	-.047	-.043	-.039	.017
Mental Health Drugs	.966	-.559	-.880	-1.044	-.894	.057
Physical Health Visits	-.034	-.062	-.059	-.055	-.051	.007
Physical Health Drugs	-.081	-.040	-.220	-.524	-.129	.025
Medicaid (N=16,837)						
Mental Health Visits	-.052	-.112	-.105	-.098	-.091	.028
Mental Health Drugs	.013	-.013	-.103	-.137	-.042	.020
Physical Health Visits	-.102	-.065	-.060	-.055	-.053	.007
Physical Health Drugs	-.065	-.081	-.089	-.089	-.065	.011
Uninsured (N=14,402)						
Mental Health Visits	-.044	-.082	-.184	-.241	-.154	.208
Mental Health Drugs	.333	-.127	-.246	-.286	-.279	.069
Physical Health Visits	-.112	-.155	-.147	-.137	-.132	.015
Physical Health Drugs	.309	-.103	-.628	-1.034	-.512	.085

Source: Authors' estimates from 1996-2003 Medical Expenditure Panel Survey.
Note: Standard errors adjusted for complex survey design of the MEPS.

Table 4. Correlated Random Effects Estimates of Cross-Price Elasticities (Average)

	MH Visits	MH Drugs	Non-MH Visits	Non-MH Drugs
Full Population (N=100,583)				
Mental Health Visits	-.063	-.165	.028	.026
	(.010)	(.017)	(.011)	(.017)
Mental Health Drugs	-.010	-.609	.014	.085
	(.006)	(.029)	(.008)	(.015)
Physical Health Visits	-.002	.010	-.115	-.070
	(.002)	(.003)	(.005)	(.010)
Physical Health Drugs	-.001	.009	-.029	-.288
	(.003)	(.003)	(.003)	(.016)
Privately Insured (N=58,414)				
Mental Health Visits	-.166	-.344	.065	.097
	(.024)	(.044)	(.018)	(.027)
Mental Health Drugs	.0001	-.916	.003	.099
	(.010)	(.088)	(.012)	(.027)
Physical Health Visits	-.009	-.006	-.156	-.073
	(.004)	(.005)	(.021)	(.032)
Physical Health Drugs	.0004	-.002	-.034	-.256
	(.003)	(.004)	(.005)	(.025)
Medicare (N=10,930)				
Mental Health Visits	-.039	-.634	.103	.147
	(.017)	(.043)	(.028)	(.037)
Mental Health Drugs	.007	-.894	.047	.226
	(.010)	(.057)	(.017)	(.031)
Physical Health Visits	.0006	.0004	-.051	-.022
	(.003)	(.005)	(.007)	(.013)
Physical Health Drugs	-.002	-.0002	-.015	-.129
	(.022)	(.003)	(.004)	(.025)
Medicaid (N=16,837)				
Mental Health Visits	-.091	-.047	.002	.016
	(.028)	(.014)	(.021)	(.020)
Mental Health Drugs	-.061	-.042	-.016	-.024
	(.018)	(.020)	(.021)	(.018)
Physical Health Visits	.015	.027	-.053	-.010
	(.008)	(.005)	(.007)	(.007)
Physical Health Drugs	.004	.020	-.030	-.064
	(.008)	(.005)	(.009)	(.011)
Uninsured (N=14,402)				
Mental Health Visits	-.154	-.077	-.058	.054
	(.208)	(.097)	(.089)	(.141)
Mental Health Drugs	-.010	-.279	.058	-.298
	(.058)	(.069)	(.064)	(.172)
Physical Health Visits	-.004	.022	-.132	-.135
	(.009)	(.016)	(.015)	(.042)
Physical Health Drugs	-.013	.007	-.038	-.512
	(.009)	(.014)	(.012)	(.084)

Source: Authors' estimates from 1996-2003 Medical Expenditure Panel Survey.
Note: Standard errors in parenthesis adjusted for complex design of the MEPS.

Table 5. Correlated Random Effects Estimates of Cross-Price Elasticities (Average): Panels 1-4 vs. Panels 5-7

	MH Visits	MH Drugs	Non-MH Visits	Non-MH Drugs
Panels 1-4 (N=54,131)				
Mental Health Visits	-.046	-.126	.029	.018
	(.014)	(.014)	(.015)	(.021)
Mental Health Drugs	-.001	-.547	.004	.077
	(.009)	(.037)	(.011)	(.020)
Physical Health Visits	-.001	.018	-.113	-.060
	(.003)	(.004)	(.007)	(.013)
Physical Health Drugs	-.002	.014	-.029	-.269
	(.003)	(.004)	(.005)	(.021)
Panels 5-7 (N=46,452)				
Mental Health Visits	-.088	-.346	.025	.072
	(.014)	(.029)	(.013)	(.028)
Mental Health Drugs	-.014	-.745	.014	.077
	(.010)	(.079)	(.014)	(.026)
Physical Health Visits	-.001	.008	-.121	-.090
	(.004)	(.005)	(.008)	(.017)
Physical Health Drugs	.002	.006	-.032	-.318
	(.003)	(.005)	(.005)	(.025)

Source: Authors’ estimates from 1996-2003 Medical Expenditure Panel Survey
Note: Standard errors in parenthesis adjusted for complex design of the MEPS.

Table 6. Results of Re-estimating Horgan's (1986) Model of Demand for Outpatient Specialty Mental Health Visits: Weighted OLS estimates for the Log of Number of Visits for Users with Out-of-Pocket Expenses

OLS Coefficient Estimate	1977[a]	1987[b]	2002[c]
Model 1: Log of the average percent paid out-of-pocket per visit	-.436 (5.22)	-.293 (4.53)	-.034 (.79)
Model 2: Log of the average amount paid out-of-pocket per visit	-.296 (5.55)	-.226 (5.57)	-.049 (1.22)

[a]Source: Horgan (1986), Table 2. Estimate with data from the 1977 National Medical Care Expenditure Survey (NMCES).
[b]Source: Authors' estimates of Horgan's model with data from the 1987 National Medical Expenditure Survey (NMES).
[c]Source: Authors' estimates of Horgan's model with data from the 2002 Medical Expenditure Panel Survey (MEPS).
Note: t-statistics in parenthesis reported for comparability with Horgan (1986), adjusted for complex design of the NMCES, NMES, and MEPS surveys.

Table A1. Sample Descriptive Statistics (N=100,583, T=2)

	Mean	S. D.	Minimum	Maximum
Mental Health Visits	0.234	1.097	0	8
Mental Health Prescription Fills	0.366	1.416	0	8
Physical Health Visits	2.577	2.595	0	8
Physical Health Prescription Fills	2.755	3.015	0	8
Hispanic	0.243	0.429	0	1
Black	0.147	0.354	0	1
Female	0.525	0.499	0	1
Urban	0.781	0.413	0	1
Northeast	0.168	0.374	0	1
Midwest	0.204	0.403	0	1
South	0.369	0.483	0	1
Age	34.667	22.408	0	90
Age Squared (Divided by 100)	17.038	18.086	0	81
Education (Years)	12.461	3.077	0	17
Paid Sick Leave	0.331	0.471	0	1
Paid Vacation	0.454	0.498	0	1
Deterministic Time Trend	4.02	1.96	1	8
Private Insurance*	0.579	0.494	0	1
Medicare*	0.112	0.315	0	1
Medicaid / Other State Program*	0.167	0.373	0	1
HMO / Managed Care*	0.465	0.499	0	1
Log of Disposable Family Income*	9.899	1.599	0	13.023
Poor / Fair Physical Health Status*	0.094	0.292	0	1
Poor / Fair Mental Health Status*	0.060	0.237	0	1
Columbia Impairment Scale*	0.028	0.164	0	1
Log of MH Ambulatory Price*	-0.262	1.796	-11.784	9.307
Log of MH Drug Price*	0.410	1.940	-13.478	6.263
Log of Non-MH Ambulatory Price*	2.076	1.648	-9.007	8.040
Log of Non-MH Drug Price*	2.244	1.129	-7.560	6.724
MH Ambulatory Price is Zero*	0.214	0.410	0	1
MH Drug Price is Zero*	0.045	0.207	0	1
PH Ambulatory Price is Zero*	0.125	0.331	0	1
PH Drug Price is Zero*	0.012	0.111	0	1

Source: Authors' estimates from 1996-2003 Medical Expenditure Panel Survey. Means are unweighted. * Denotes variable is specified as correlated with random effect.

Table A2: Sample Descriptive Statistics for End-of-Year Prices and Associated Probabilities

Category	N	Mean	S.D.	Min	25 Pctl.	50 Pctl.	75 Pctl.	Max
Mental Health Ambulatory Price (Pre-Imputation)								
1	14,819	24.199	96.757	0.000	0.000	3.387	20.000	33,454.21
2	10,227	18.711	46.138	0.000	0.000	0.000	18.000	1,466.25
3	8,094	17.833	40.192	0.000	0.000	0.000	17.913	1,055.70
4	6,759	17.908	59.809	0.000	0.000	0.000	17.104	2,649.60
5	5,702	17.966	54.579	0.000	0.000	0.000	17.190	2,071.59
6	4,961	17.730	36.871	0.000	0.000	1.069	20.780	725.95
7	2,745	17.197	30.544	0.000	0.000	1.782	21.611	300.83
8	1,162	20.628	37.202	0.000	0.000	3.113	25.945	573.00
Mental Health Ambulatory Price Probability								
0	201,166	0.936	0.070	0.265	0.926	0.956	0.976	1.000
1	201,166	0.020	0.018	0.000	0.009	0.015	0.024	0.113
2	201,166	0.009	0.009	0.000	0.004	0.007	0.010	0.061
3	201,166	0.006	0.006	0.000	0.002	0.004	0.007	0.045
4	201,166	0.004	0.005	0.000	0.002	0.003	0.005	0.039
5	201,166	0.003	0.003	0.000	0.001	0.002	0.004	0.031
6	201,166	0.010	0.011	0.000	0.003	0.006	0.011	0.122
7	201,166	0.007	0.009	0.000	0.002	0.004	0.008	0.132
8	201,166	0.005	0.009	0.000	0.001	0.002	0.005	0.207
Mental Health Drug Price (Pre-Imputation)								
1	18,696	27.359	39.828	0.000	4.931	11.460	34.363	884.74
2	15,455	27.183	40.536	0.000	4.584	11.460	32.770	885.00
3	13,459	26.952	39.546	0.000	4.404	11.460	32.112	509.38
4	11,901	26.670	40.468	0.000	3.660	11.460	30.895	659.00
5	10,516	26.784	40.494	0.000	3.519	11.460	31.219	658.10
6	9,378	26.072	36.384	0.000	4.682	12.815	32.818	658.10
7	4,909	24.773	36.897	0.000	3.387	11.688	30.426	509.38
8	1,601	23.485	39.785	0.000	2.342	10.230	27.149	616.42
Mental Health Drug Price Probability								
0	201,166	0.921	0.087	0.226	0.892	0.948	0.979	1.000
1	201,166	0.014	0.011	0.000	0.005	0.011	0.020	0.050
2	201,166	0.009	0.007	0.000	0.003	0.007	0.013	0.035
3	201,166	0.007	0.006	0.000	0.002	0.005	0.010	0.031
4	201,166	0.006	0.005	0.000	0.002	0.004	0.008	0.029
5	201,166	0.005	0.005	0.000	0.001	0.003	0.007	0.027
6	201,166	0.019	0.020	0.000	0.005	0.012	0.026	0.137
7	201,166	0.014	0.020	0.000	0.002	0.007	0.017	0.192
8	201,166	0.007	0.017	0.000	0.001	0.002	0.006	0.353
Physical Health Ambulatory Price (Pre-Imputation)								
1	161,941	28.907	157.197	0.000	0.000	9.520	19.482	16,879.50
2	120,846	26.264	155.597	0.000	0.000	5.645	16.035	14,322.00

Category	N	Mean	S.D.	Min	25 Pctl.	50 Pctl.	75 Pctl.	Max
Physical Health Ambulatory Price (Pre-Imputation)								
3	93,839	23.797	127.504	0.000	0.000	5.115	15.585	9,179.57
4	75,128	22.623	131.674	0.000	0.000	2.854	15.345	8,313.00
5	61,668	22.092	142.429	0.000	0.000	0.000	15.000	16,880.00
6	51,468	19.916	78.025	0.000	0.000	5.645	16.368	6,085.37
7	24,900	16.804	58.350	0.000	0.000	4.874	15.249	2,700.00
8	8,740	13.597	38.681	0.000	0.000	3.680	13.858	1,558.92
Physical Health Ambulatory Price Probability								
0	201,166	0.306	0.171	0.002	0.182	0.279	0.401	0.895
1	201,166	0.175	0.059	0.008	0.136	0.175	0.219	0.314
2	201,166	0.115	0.026	0.017	0.101	0.119	0.132	0.164
3	201,166	0.081	0.020	0.009	0.072	0.086	0.095	0.115
4	201,166	0.058	0.017	0.004	0.048	0.062	0.072	0.087
5	201,166	0.045	0.016	0.003	0.034	0.047	0.059	0.072
6	201,166	0.115	0.057	0.004	0.071	0.108	0.157	0.231
7	201,166	0.068	0.054	0.001	0.028	0.052	0.093	0.250
8	201,166	0.038	0.051	0.000	0.008	0.019	0.044	0.499
Physical Health Drug Price (Pre-Imputation)								
1	140,597	19.943	42.750	0.000	5.000	10.230	21.380	3,244.00
2	113,062	20.990	40.023	0.000	5.115	10.390	23.448	3,243.95
3	94,198	22.183	42.516	0.000	5.163	10.864	25.290	3,244.00
4	82,075	22.799	44.177	0.000	5.195	11.040	25.975	3,244.00
5	72,938	22.819	40.989	0.000	5.195	11.253	26.588	3,243.95
6	66,344	22.991	33.199	0.000	6.720	14.021	28.634	1,958.73
7	4,401	24.048	33.037	0.000	7.574	15.273	30.143	1,665.26
8	24,194	24.113	29.044	0.000	8.175	16.065	31.428	956.91
Physical Health Drug Price Probability								
0	201,166	0.398	0.188	0.002	0.261	0.399	0.528	0.893
1	201,166	0.116	0.058	0.000	0.071	0.116	0.162	0.263
2	201,166	0.078	0.026	0.001	0.061	0.081	0.096	0.145
3	201,166	0.052	0.015	0.001	0.042	0.054	0.063	0.092
4	201,166	0.040	0.012	0.002	0.032	0.041	0.049	0.070
5	201,166	0.029	0.010	0.002	0.022	0.030	0.037	0.052
6	201,166	0.099	0.044	0.003	0.061	0.099	0.139	0.188
7	201,166	0.092	0.067	0.001	0.034	0.071	0.147	0.233
8	201,166	0.098	0.133	0.000	0.013	0.037	0.128	0.909

Source: Authors' estimates from 1996-2003 Medical Expenditure Panel Survey. Means are unweighted

Table A3 Cross Sectional Zero-Inflated Ordered Probit Coefficient Estimates (N·T=201166)

	MH Visits	MH Drugs	Non-MH Visits	Non-MH Drugs
Inflation				
constant	-0.609	-1.212	0.955	1.556
	(0.416)	(0.214)	(0.118)	(0.090)
Hispanic	-0.239	-0.248	-0.220	-0.320
	(0.087)	(0.072)	(0.025)	(0.031)
Black	-0.321	-0.203	-0.310	-0.495
	(0.092)	(0.083)	(0.038)	(0.037)
Female	-0.661	-0.550	0.642	0.659
	(0.080)	(0.052)	(0.030)	(0.021)
Urban	-0.144	-0.064	-0.152	-0.102
	(0.060)	(0.051)	(0.027)	(0.024)
Northeast	0.219	0.180	0.122	0.039
	(0.085)	(0.069)	(0.035)	(0.035)
Midwest	0.249	0.342	0.195	0.160
	(0.100)	(0.073)	(0.030)	(0.036)
South	0.165	0.271	0.209	0.301
	(0.093)	(0.066)	(0.028)	(0.029)
Age	0.075	0.079	-0.043	-0.019
	(0.007)	(0.005)	(0.005)	(0.002)
Age Squared/100	-0.066	-0.068	0.070	0.048
	(0.011)	(0.007)	(0.007)	(0.003)
Education (Years)	-0.012	0.026	0.054	0.049
	(0.014)	(0.008)	(0.004)	(0.004)
Paid Sick Leave	0.046	0.172	0.039	0.008
	(0.109)	(0.090)	(0.023)	(0.026)
Paid Vacation	0.186	0.042	0.046	0.021
	(0.111)	(0.080)	(0.023)	(0.027)
Time Trend	0.011	0.000	0.028	0.037
	(0.012)	(0.009)	(0.004)	(0.004)
Medicare	0.083	0.490	0.414	0.570
	(0.286)	(0.145)	(0.066)	(0.049)
Medicaid / Other State	-0.019	0.124	0.803	0.896
	(0.133)	(0.108)	(0.055)	(0.046)
Private Insurance	0.542	0.691	0.438	0.262
	(0.138)	(0.111)	(0.032)	(0.030)
HMO / Managed Care	0.068	0.055	0.121	0.015
	(0.058)	(0.050)	(0.020)	(0.019)
Log Disp. Family Income	0.003	0.032	0.014	-0.005
	(0.020)	(0.011)	(0.006)	(0.006)
Poor /Fair Physical Health	0.078	0.074	0.429	0.649
	(0.085)	(0.054)	(0.031)	(0.030)
Poor / Fair Mental Health Status	0.222	0.039	0.132	0.216
	(0.113)	(0.068)	(0.041)	(0.040)
Columbia Impairment Scale	0.470	0.267	0.439	0.009
	(0.110)	(0.109)	(0.179)	(0.086)

	MH Visits	MH Drugs	Non-MH Visits	Non-MH Drugs
Log MH Visit Price	-0.064 (0.023)	-0.046 (0.012)	0.017 (0.004)	0.014 (0.004)
Log MH Drug Price	0.326 (0.047)	0.528 (0.015)	0.018 (0.007)	0.027 (0.006)
Log Non-MH Visit Price	-0.016 (0.022)	-0.044 (0.015)	-0.035 (0.007)	-0.049 (0.006)
Log Non-MH Drug Price	-0.052 (0.024)	-0.236 (0.018)	-0.503 (0.021)	-0.907 (0.019)
MH Visit Price is Zero	0.111 (0.109)	0.158 (0.052)	-0.051 (0.021)	-0.068 (0.016)
MH Drug Price is Zero	-0.543 (0.174)	-0.968 (0.111)	0.223 (0.081)	0.272 (0.068)
PH Visit Price is Zero	0.078 (0.073)	0.039 (0.057)	-0.240 (0.032)	-0.154 (0.027)
PH Drug Price is Zero	0.237 (0.165)	0.292 (0.177)	-1.170 (0.120)	-2.395 (0.108)
Ordered Probit				
constant	-2.327 (0.138)	-2.517 (0.153)	0.048 (0.072)	-0.243 (0.066)
Hispanic	-0.381 (0.045)	-0.651 (0.060)	-0.223 (0.021)	-0.237 (0.019)
Black	-0.563 (0.051)	-0.955 (0.063)	-0.479 (0.019)	-0.308 (0.021)
Female	0.395 (0.024)	0.568 (0.026)	0.287 (0.009)	0.283 (0.011)
Urban	0.139 (0.030)	0.065 (0.039)	0.017 (0.016)	-0.081 (0.017)
Northeast	0.047 (0.036)	0.009 (0.056)	0.079 (0.022)	0.048 (0.029)
Midwest	0.022 (0.041)	0.110 (0.060)	0.060 (0.024)	0.191 (0.027)
South	0.085 (0.037)	0.325 (0.050)	0.073 (0.021)	0.275 (0.024)
Age	0.023 (0.004)	0.042 (0.004)	0.005 (0.001)	0.022 (0.001)
Age Squared/100	-0.023 (0.004)	-0.030 (0.005)	0.016 (0.002)	0.013 (0.002)
Education (Years)	0.037 (0.004)	0.005 (0.006)	0.042 (0.002)	0.010 (0.003)
Paid Sick Leave	0.045 (0.033)	-0.018 (0.043)	0.036 (0.013)	0.039 (0.016)
Paid Vacation	-0.184 (0.033)	-0.223 (0.042)	-0.061 (0.015)	-0.052 (0.017)
Time Trend	0.030 (0.006)	0.087 (0.007)	0.020 (0.003)	0.038 (0.003)
Medicare	0.086 (0.066)	0.203 (0.088)	0.210 (0.042)	0.044 (0.034)

	MH Visits	MH Drugs	Non-MH Visits	Non-MH Drugs
Medicaid / Other State	0.755 (0.050)	0.989 (0.070)	0.176 (0.027)	0.217 (0.032)
Private Insurance	0.011 (0.045)	-0.039 (0.067)	0.371 (0.022)	0.292 (0.024)
HMO / Managed Care	-0.048 (0.021)	-0.073 (0.028)	-0.048 (0.012)	0.008 (0.012)
Log Disp. Family Income	-0.023 (0.006)	-0.032 (0.007)	0.010 (0.003)	0.006 (0.004)
Poor /Fair Physical Health	0.245 (0.028)	0.340 (0.034)	0.421 (0.015)	0.455 (0.014)
Poor / Fair Mental Health Status	0.932 (0.035)	1.130 (0.034)	0.130 (0.018)	0.253 (0.018)
Columbia Impairment Scale	1.151 (0.072)	1.572 (0.085)	-0.282 (0.031)	-0.145 (0.041)
Log MH Visit Price	-0.012 (0.006)	0.013 (0.004)	0.006 (0.003)	0.006 (0.003)
Log MH Drug Price	-0.232 (0.019)	-0.502 (0.014)	0.002 (0.003)	-0.004 (0.004)
Log PH Visit Price	-0.021 (0.006)	-0.018 (0.005)	-0.159 (0.005)	-0.062 (0.004)
Log PH Drug Price	-0.030 (0.010)	0.035 (0.009)	-0.051 (0.006)	-0.119 (0.005)
MH Visit Price is Zero	0.047 (0.031)	-0.080 (0.022)	-0.056 (0.011)	-0.037 (0.012)
MH Drug Price is Zero	0.032 (0.083)	0.146 (0.106)	-0.076 (0.024)	-0.140 (0.023)
PH Visit Price is Zero	-0.063 (0.034)	-0.066 (0.028)	-0.033 (0.016)	-0.072 (0.018)
PH Drug Price is Zero	-0.121 (0.103)	-0.319 (0.117)	-0.085 (0.038)	0.169 (0.051)
μ_1	0.226 (0.003)	0.140 (0.002)	0.757 (0.022)	0.622 (0.012)
μ_2	0.353 (0.005)	0.239 (0.004)	1.163 (0.027)	0.980 (0.015)
μ_3	0.450 (0.007)	0.327 (0.005)	1.451 (0.028)	1.210 (0.016)
μ_4	0.534 (0.009)	0.410 (0.006)	1.670 (0.030)	1.390 (0.017)
μ_5	0.602 (0.009)	0.487 (0.007)	1.853 (0.030)	1.523 (0.017)
μ_6	0.883 (0.015)	0.879 (0.012)	2.451 (0.033)	2.020 (0.019)
μ_7	1.248 (0.020)	1.450 (0.021)	3.098 (0.034)	2.628 (0.020)

Source: Author's calculations from 1996-2003 Medical Expenditure Panel Survey (1996-2003)
Standard errors in parentheses adjust for complex design of survey.

Appendix Table A4 Correlated Random Effect Zero-Inflated Ordered Probit Coefficient Estimates

	MH Visits	MH Drugs	Non-MH Visits	Non-MH Drugs
Inflation				
constant	-0.657 (0.374)	-1.218 (0.221)	1.022 (0.126)	1.609 (0.085)
Hispanic	-0.368 (0.098)	-0.288 (0.089)	-0.222 (0.025)	-0.322 (0.028)
Black	-0.274 (0.104)	-0.142 (0.100)	-0.307 (0.038)	-0.500 (0.033)
Female	-0.805 (0.078)	-0.608 (0.058)	0.638 (0.034)	0.662 (0.021)
Urban	-0.102 (0.063)	-0.030 (0.054)	-0.152 (0.028)	-0.104 (0.023)
Northeast	0.154 (0.104)	0.140 (0.087)	0.132 (0.035)	0.038 (0.032)
Midwest	0.120 (0.113)	0.254 (0.084)	0.209 (0.029)	0.163 (0.033)
South	0.192 (0.105)	0.239 (0.079)	0.230 (0.028)	0.305 (0.028)
Age	0.075 (0.007)	0.081 (0.005)	-0.040 (0.005)	-0.019 (0.002)
Age Squared/100	-0.055 (0.011)	-0.067 (0.006)	0.065 (0.008)	0.046 (0.003)
Education (Years)	-0.008 (0.014)	0.024 (0.008)	0.056 (0.004)	0.051 (0.004)
Paid Sick Leave	0.073 (0.114)	0.195 (0.088)	0.037 (0.021)	0.006 (0.023)
Paid Vacation	0.323 (0.120)	0.151 (0.081)	0.040 (0.022)	0.022 (0.024)
Time Trend	0.012 (0.012)	-0.015 (0.010)	0.023 (0.004)	0.029 (0.004)
Medicare	-0.051 (0.303)	0.556 (0.152)	0.432 (0.074)	0.558 (0.053)
Medicaid / Other State	-0.466 (0.134)	-0.182 (0.112)	0.553 (0.065)	0.698 (0.052)
Private Insurance	0.209 (0.140)	0.488 (0.116)	0.252 (0.033)	0.071 (0.027)
HMO / Managed Care	0.109 (0.062)	0.098 (0.054)	0.154 (0.022)	0.057 (0.019)
Log Disp. Family Income	-0.014 (0.020)	0.026 (0.012)	0.014 (0.005)	-0.001 (0.005)
Poor /Fair Physical Health	0.025 (0.087)	-0.134 (0.052)	0.142 (0.030)	0.332 (0.028)
Poor / Fair Mental Health Status	0.073 (0.099)	-0.288 (0.066)	-0.066 (0.037)	0.040 (0.035)

	MH Visits	MH Drugs	Non-MH Visits	Non-MH Drugs
Columbia Impairment Scale	0.141 (0.120)	-0.213 (0.133)	0.492 (0.159)	0.086 (0.084)
Log MH Visit Price	-0.044 (0.024)	-0.040 (0.012)	0.006 (0.004)	0.002 (0.003)
Log MH Drug Price	0.177 (0.034)	0.498 (0.015)	0.014 (0.006)	0.023 (0.005)
Log Non-MH Visit Price	0.024 (0.022)	-0.003 (0.014)	0.002 (0.008)	-0.012 (0.006)
Log Non-MH Drug Price	0.019 (0.023)	-0.168 (0.021)	-0.414 (0.027)	-0.797 (0.024)
MH Visit Price is Zero	0.080 (0.113)	0.180 (0.054)	0.000 (0.021)	-0.018 (0.016)
MH Drug Price is Zero	-0.031 (0.151)	-0.638 (0.132)	0.233 (0.079)	0.314 (0.069)
Non-MH Visit Price is Zero	0.173 (0.076)	0.056 (0.063)	-0.172 (0.034)	-0.087 (0.027)
Non-MH Drug Price is Zero	-0.116 (0.153)	0.139 (0.219)	-1.041 (0.119)	-2.175 (0.115)
Ordered Probit				
constant	-1.727 (0.128)	-1.732 (0.150)	0.090 (0.086)	-0.162 (0.079)
Hispanic	-0.277 (0.044)	-0.570 (0.062)	-0.223 (0.025)	-0.231 (0.021)
Black	-0.445 (0.051)	-0.835 (0.070)	-0.507 (0.022)	-0.336 (0.025)
Female	0.397 (0.024)	0.531 (0.028)	0.303 (0.011)	0.288 (0.014)
Urban	0.104 (0.030)	0.042 (0.038)	0.001 (0.019)	-0.086 (0.019)
Northeast	0.017 (0.039)	-0.023 (0.049)	0.081 (0.025)	0.057 (0.033)
Midwest	0.025 (0.043)	0.096 (0.054)	0.065 (0.027)	0.194 (0.031)
South	0.051 (0.040)	0.299 (0.045)	0.080 (0.024)	0.282 (0.028)
Age	0.004 (0.004)	0.017 (0.005)	0.004 (0.002)	0.021 (0.001)
Age Squared/100	-0.007 (0.004)	-0.007 (0.005)	0.018 (0.003)	0.015 (0.002)
Education (Years)	0.032 (0.005)	-0.001 (0.006)	0.046 (0.003)	0.012 (0.003)
Paid Sick Leave	0.035 (0.033)	-0.042 (0.040)	0.037 (0.014)	0.040 (0.017)
Paid Vacation	-0.210 (0.034)	-0.237 (0.039)	-0.057 (0.016)	-0.050 (0.018)
Time Trend	0.020 (0.006)	0.072 (0.006)	0.014 (0.003)	0.024 (0.003)

	MH Visits	MH Drugs	Non-MH Visits	Non-MH Drugs
Medicare	-0.002 (0.065)	0.043 (0.075)	0.200 (0.060)	0.021 (0.046)
Medicaid / Other State	0.471 (0.050)	0.689 (0.065)	-0.026 (0.033)	-0.026 (0.037)
Private Insurance	-0.101 (0.039)	-0.200 (0.053)	0.202 (0.025)	0.113 (0.026)
HMO / Managed Care	-0.009 (0.020)	-0.047 (0.023)	0.006 (0.015)	0.051 (0.014)
Log Disp. Family Income	-0.010 (0.006)	-0.015 (0.006)	0.007 (0.004)	0.005 (0.004)
Poor /Fair Physical Health	0.014 (0.023)	0.140 (0.024)	0.155 (0.015)	0.139 (0.013)
Poor / Fair Mental Health Status	0.424 (0.029)	0.636 (0.031)	-0.040 (0.018)	0.044 (0.017)
Columbia Impairment Scale	0.676 (0.072)	0.940 (0.089)	-0.333 (0.033)	-0.205 (0.041)
Log MH Visit Price	-0.020 (0.006)	0.004 (0.003)	-0.003 (0.003)	-0.002 (0.003)
Log MH Drug Price	-0.111 (0.012)	-0.422 (0.020)	0.007 (0.003)	0.002 (0.003)
Log Non-MH Visit Price	0.008 (0.006)	0.008 (0.005)	-0.111 (0.006)	-0.024 (0.004)
Log Non-MH Drug Price	0.008 (0.010)	0.082 (0.010)	0.015 (0.006)	-0.038 (0.006)
MH Visit Price is Zero	0.074 (0.030)	-0.042 (0.021)	-0.016 (0.010)	0.004 (0.011)
MH Drug Price is Zero	-0.016 (0.067)	0.168 (0.126)	-0.023 (0.024)	-0.063 (0.024)
Non-MH Visit Price is Zero	-0.034 (0.032)	-0.014 (0.028)	0.048 (0.017)	0.012 (0.018)
Non-MH Drug Price is Zero	0.060 (0.094)	-0.156 (0.138)	0.034 (0.036)	0.211 (0.049)
μ_1	0.227 (0.003)	0.144 (0.002)	0.743 (0.030)	0.588 (0.015)
μ_2	0.358 (0.004)	0.244 (0.004)	1.147 (0.037)	0.937 (0.019)
μ_3	0.456 (0.007)	0.331 (0.005)	1.437 (0.040)	1.167 (0.021)
μ_4	0.537 (0.009)	0.415 (0.006)	1.656 (0.041)	1.346 (0.021)
μ_5	0.604 (0.009)	0.489 (0.008)	1.840 (0.042)	1.478 (0.022)
μ_6	0.877 (0.016)	0.868 (0.014)	2.440 (0.045)	1.976 (0.023)
μ_7	1.229 (0.023)	1.412 (0.028)	3.089 (0.046)	2.584 (0.026)

	MH Visits	MH Drugs	Non-MH Visits	Non-MH Drugs
Correlated Random Effects				
Medicare period 1 λ		-0.102		
		(0.043)		
Medicare period 2 λ		0.129		
		(0.041)		
Medicaid period 1 λ		0.140		
		(0.024)		
Medicaid period 2 λ		0.128		
		(0.024)		
Private insurance period 1 λ		0.106		
		(0.018)		
Private insurance period 2 λ		0.108		
		(0.017)		
HMO period 1 λ		-0.020		
		(0.011)		
HMO period 2 λ		-0.040		
		(0.011)		
Log fam income period 1 λ		0.003		
		(0.003)		
Log fam income period 2 λ		-0.003		
		(0.003)		
Poor/fair health period 1 λ		0.193		
		(0.012)		
Poor/fair health period 2 λ		0.228		
		(0.012)		
Poor/fair MH period 1 λ		0.180		
		(0.017)		
Poor/fair MH period 2 λ		0.205		
		(0.016)		
CIS period 1 λ		0.047		
		(0.029)		
CIS period 2 λ		0.074		
		(0.028)		
Log MH Visit Price period 1 λ		0.010		
		(0.002)		
Log MH Visit Price period 2 λ		0.009		
		(0.002)		
Log MH Drug Price period 1 λ		-0.002		
		(0.003)		
Log MH Drug Price period 2 λ		-0.006		
		(0.003)		
Log Non-MH Visit Price period 1 λ		-0.025		
		(0.003)		
Log Non-MH Visit Price period 2 λ		-0.037		
		(0.003)		
Log Non-MH Drug Price period 1 λ		-0.046		
		(0.004)		

	MH Visits	MH Drugs	Non-MH Visits	Non-MH Drugs
Log Non-MH Drug Price period 2 λ		-0.057 (0.005)		
MH Visit Price=0 period 1 λ		-0.045 (0.010)		
MH Visit Price=0 period 2 λ		-0.043 (0.010)		
MH Drug Price=0 period 1 λ		-0.051 (0.022)		
MH Drug Price=0 period 2 λ		-0.041 (0.023)		
Non-MH Vis Price=0 period 1 λ		-0.070 (0.013)		
Non-MH Vis Price=0 period 2 λ		-0.073 (0.013)		
Non-MH Drug Price=0 period 1 λ		-0.062 (0.035)		
Non-MH Drug Price=0 period 2 λ		-0.102 (0.035)		

Source: Author’s calculations from 1996-2003 Medical Expenditure Panel Survey (1996-2003)
Standard errors in parentheses adjust for complex design of survey.