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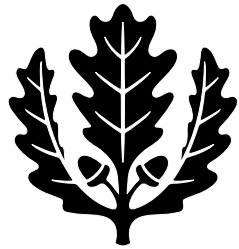
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Abstract

This paper estimates the aggregate demand for private health insurance coverage in the U.S. using an error-correction model and by recognizing that people are without private health insurance for voluntary, structural, frictional, and cyclical reasons and because of public alternatives. Insurance coverage is measured both by the percentage of the population enrolled in private health insurance plans and the completeness of the insurance coverage. Annual data for the period 1966-1999 are used and both short and long run price and income elasticities of demand are estimated. The empirical findings indicate that both private insurance enrollment and completeness are relatively inelastic with respect to changes in price and income in the short and long run. Moreover, private health insurance enrollment is found to be inversely related to the poverty rate, particularly in the short-run. Finally, our results suggest that an increase in the number cyclically uninsured generates less of a welfare loss than an increase in the structurally uninsured.

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I. Introduction

On a yearly basis, about 14 to 16 percent of the U.S. population tends to be uninsured (DeNavas-Walt, Proctor, and Lee, 2005). Many of the involuntarily uninsured face the sharp psychological sting from the financial insecurity that can result from an unexpected medical occurrence. In addition, uninsured individuals are more likely to find themselves in the emergency room of a hospital, sometimes after it is too late for proper medical treatment, with their resulting poorer health and shorter lives causing sizeable social costs. Indeed, Miller et al. (2004) estimate a lower bound dollar value of the health forgone because of uninsurance in the U.S. at $65 to $130 billion per year. Thus, reducing the uninsured population seems a legitimate social goal and identifying why some people are without private health insurance coverage becomes a valuable endeavor for public policy purposes.

Logic suggests that people are without private health insurance for a variety of reasons. First, in a private health insurance system, some people alter their purchasing of health insurance in response to changing economic circumstances such as the price of insurance or their income just like they change their demands for other goods and services. That is, some people may choose to be without private health insurance coverage or may choose only minimal coverage. For example, an individual may decide to self-insure because she expects to gain little from market provided health insurance as a result of its high price relative to expected medical benefits paid out. In this case health insurance is a negative net present value investment, hence it is rational not to buy insurance.

But some people may be without private health insurance coverage for reasons other than its voluntary nature. By borrowing from the different classifications for unemployment offered by labor economists, three categories of uninsurance can be specified, although admittedly these

classifications are not mutually exclusive in the context of uninsurance. First, some people may lack private health insurance coverage during a particular time period because they become frictionally uninsured. Frictional uninsurance considers that some people terminate one job that offered health insurance and are searching for another job. In fact, COBRA of 1985 was developed expressly with frictional uninsurance in mind by requiring employers with more than 20 workers to allow former employees and their dependents the option to retain their health insurance coverage for up to 18 months after terminating employment. However, given that this Act requires the frictionally uninsured to pay the full premiums and an administrative fee of 2 percent, only about 20 percent of those eligible extend their health insurance under COBRA while in-between jobs (Madrian, 1998).

Frictional uninsurance also occurs when people are temporarily without private health insurance because of a mismatch of information. Because of imperfect information, consumers take time to shop around for the right insurers while health insurers search for the right customers. It stands to reason that insurance agents and brokers can impact the number of individuals frictionally uninsured and the duration of frictional uninsurance by providing timely and reliable information (Conwell, 2002). Within the context of frictional uninsurance, Swartz, Marcotte, and McBride (1993) find that monthly family income, educational attainment, and industry of employment in the month prior to losing health insurance are the characteristics with the greatest impact on the duration of a spell without health insurance.

Second, the structurally uninsured comprise another category of those without private health insurance. Included in the structurally uninsured category are those individuals who are without health insurance on a long-run basis because of chronic illnesses, pre-existing conditions, employment that does not offer health insurance coverage, and/or insufficient income. Finally, those

individuals cyclically uninsured make up the last category of uninsurance. Cyclical uninsurance pertains to those individuals (and their families) who change insurance status as they drift in and out of jobs offering group health insurance benefits as the macro-economy normally expands and contracts in the short-term. Cyclically uninsured individuals tend to possess low-skills and may fluctuate between working in small and large firms over the course of the business cycle.

Other than voluntary, frictional, structural, and cyclical uninsurance, the existence of public health insurance alternatives may provide another explanation for the fluctuations in the percentage of the population covered by private health insurance. Both Medicare and Medicaid were enacted in 1965. Since that time, eligibility in both programs has expanded. Thus the creation and expansion of these two public programs may have influenced the number of individuals with private health insurance coverage.

In sum, at any point in time, some people may not be covered by private health insurance because of its voluntary nature, public health insurance alternatives, or their status of being frictionally, structurally, or cyclically uninsured. Obviously, the mix of people lacking private health insurance for these specific reasons will change over time in response to varying market conditions and personal circumstances. Not surprisingly, various studies have attempted empirically to sort out the different reasons why people remain without private health insurance coverage.

Most of the studies focus on the voluntary nature of private health insurance and have estimated the demand for employer-provided health insurance at the micro level to gauge its sensitivity to variations in price and income. These studies tend to agree that the demand for health insurance is relatively inelastic with respect to changes in both price and income (e.g., Taylor and Wilensky, 1983; Marguis and Long, 1995; and Liu and Christianson, 1998). Recently, a couple of

studies have questioned the impact of macroeconomic forces on cyclical uninsurance using micro data sets. Cutler (2002) finds that employer-sponsored health insurance fell during the boom of the 1990s primarily because fewer employees took up coverage when it was offered. His estimates suggest that increased costs to employees explain the entire reduction in take-up rates during the 1990s. Cawley and Simon (2003) find that the probability of any insurance is inversely related to state unemployment and directly related to state GDP. The evidence in their study, however, does not support the prediction of a negative impact of a national recession on health insurance coverage rates. In fact, some of their findings indicate a direct and statistically significant relationship between the existence of a national recession and the insurance rate.

While these studies have provided valuable insights about the forces shaping the demand for private health insurance, the available empirical evidence is incomplete for several reasons. First, the existing empirical literature is mostly based on a static analysis of cross-sectional micro-level data. In some cases, e.g., Cutler (2002) and Cawley and Simon (2003), the panel data include repeated measurements over ten to fifteen years. But the time period is too short to allow a thorough investigation of the economic forces that cause the level of private health insurance to rise and fall over time. Second, in the presence of stochastic non-stationary trends commonly found in variables such as the percent with private health insurance, standard statistics such as *t-statistic*, R^2, and Durbin-Watson may lead to erroneous conclusions. While these statistics are properly specified for cross-sectional data, it is well known that time series require a different econometric methodology for proper inference. For example, it is possible that some observed significant correlations over time may be simply due to the phenomenon of spurious regression (Granger and Newbold, 1974). Third, the empirical models in previous studies implicitly assume that the estimates represent long-

run equilibrium, where people are content with being with or without health insurance or with a certain amount of insurance coverage. However, short run disequilibrium situations are likely to occur as decision-makers balance the cost of being away from their preferred positions and the cost imposed by the adjustment process itself. Consequently, these previous studies may have failed to capture some important information about the short run dynamics characterizing the decision to purchase private health insurance.

To capture both long run and short run dynamics, this paper estimates the aggregate demand for health insurance in the U.S. using an error correction model.[1] The error correction model incorporates a dynamic adjustment process in response to temporary and permanent shocks to private health insurance enrollments. In addition, the model incorporates the cost of being away from a long run aggregate equilibrium level of private insurance. This equilibrium level should be dependent on macroeconomic factors such as GNP, national tax policy, growth of jobs in service sector, etc. Thus, both short run and long run demand elasticity estimates can be derived.

This study exploits a previously overlooked national data series on private health insurance coverage in the U.S. and considers the voluntary nature of private health insurance as well as its frictional, structural, and cyclical aspects. In the next section, the data on private health insurance coverage are described more fully and tracked over time. Section III introduces the basic demand model and discusses the data used in the empirical test while section IV develops an error correction model to explain variations in the private health insurance coverage rate. Section V provides concluding comments and policy implications.

II. *Time Series Data on Private Health Insurance Coverage Rates in the U.S.*

The Health Insurance Association of America (HIAA) independently gathered and issued

information on the health insurance enrollment of the U.S. population since the 1940s but their data collection apparently ended in the mid-1990s. Now HIAA simply reports Census data in their annual guide. The U.S. Census Bureau began systematically collecting and reporting data on the health insurance status of the U.S. population since the mid-1980s. By combining these two series, the percentage of the population enrolled in private health insurance can be viewed over time. Combining the two data series does not seem to be problematic as they are fairly close over eight overlapping years with private health insurance enrollment figures differing by only 0.5 percent, on average.

Since most of our data are from the period 1960 to 1999, we focus exclusively on that period in the ensuing discussion. According to the national data reported by the HIAA and Census Bureau, enrollment in private health insurance has varied considerably over time. For example, Figure 1 illustrates that enrollment in private health insurance plans as a percentage of the population stood at nearly 66 percent in 1960, increasing at about 1 percentage point per year to roughly 76 percent of the population by 1970.[2] From 1970 to 1980, enrollment in private health insurance continued to expand but the rate of growth slowed to less than one-half of a percentage point per year totaling 81 percent of the US population in 1980.

The data further show that enrollment in private health insurance peaked in the late 1970s and early 1980s. After that point, the private health insurance coverage rate continued to fall throughout the rest of the 1980s and most of the 1990s. Only after 1997 did the downtrend in the percentage of the US population covered by private health insurance begin to increase once again. Interestingly, the percentage of the U.S. population covered by private health insurance increased by only a mere 5 percentage points over the entire 40 year period.

The Center for Medicare and Medicaid Services publishes yearly data that can be used to calculate the fraction of consumer expenditures on personal health care items that is reimbursed by private insurance companies. These annual figures track the completeness of health insurance coverage over time and are reported in Figure 2 also for the period from 1960 to 1999. Notice that private health insurance covered less than 30 percent of personal health care in 1960 but rose to nearly 70 percent by 1999. Also notice that the growth in the completeness of health insurance coverage slowed briefly during the mid-1970s, mid-1980s, and late 1990s.

Overall, the time series data on private health insurance enrollment and the completeness of coverage do not display the typical pattern of a stationary process (constant unconditional mean and variance). To our surprise, both series look more like (near) random walks without drift; the enrollment series crossing its mean value (74 percent) only twice: first in 1968 and again in 1988, and the completeness series crossing its mean value (0.51) only once. If private health insurance coverage can be modeled as a nonstationary variable, the implication is rather startling: a shock to the process will not die out -- even in the long run. For example, suppose a negative shock during a recession causes the loss of a certain number of high quality jobs (i.e., jobs with medical coverage), and if these jobs are lost permanently, then the shock to the coverage rate will also be permanent.

It follows that some important information might be gained by modeling both the short run dynamics and long run behavior of the private health insurance coverage rate. Consequently, in this paper, we empirically investigate whether the private health insurance enrollment and completeness rates can be modeled as non-stationary variables and whether these rates are cointegrated with a set of underlying factors such as real per capita income, price of private health insurance, union membership, etc. The empirical analysis is couched in terms of an aggregate demand for private

health insurance.   The cointegration regression models and the concomitant error correction representations allow us to examine empirically both the long run and short-run dynamic properties of the aggregate demand for private health insurance. In the next section, the long run equation for the aggregate demand for private health insurance is specified and the specific variables and data used in the empirical test are discussed.

III.   *Modeling the Aggregate Demand for Private Health Insurance*

Standard utility theory suggests that the quantity demanded of health insurance, *Y*, can be written as a function of the user price of health insurance, *P*, income, *I*, and a vector of other factors, Z or (with time subscripts suppressed):

$$Y = \beta_0 + \beta_1 P + \beta_2 I + \beta_3 Z . \tag{1}$$

Suppose all of the variables are expressed as logarithms, the slope parameters can be treated as elastiticies. Thus, β_1 and β_2 represent, respectively, the price and income elasticities of the demand for private health insurance.

Equation (1) represents a static demand function devoid of a time dimension. It is well known, however, that demand theory offers little guide as to the dynamic adjustment process when the market is temporarily out of equilibrium. In the next two subsections, we discuss a number of econometric issues that arise when we estimate a dynamic version of the demand model (section III.A) and the data specifications (section III.B).

III.A   *Econometric Specification Issues*

First, as mentioned above, equation (1) is a simple representation of a long run steady-state equilibrium aggregate demand function. However, in the short run, user price (*P*) or income (*I*) may not adjust quickly enough to clear the market; hence the equality may not hold exactly. The error

correction model is a formal methodology to characterize the adjustment process that allows deviations from equilibrium in the short run but not the long run.

Second, it is likely that an expected change in current (or future) employment or income level will impose transition costs on individuals. These costs imply that demand for health insurance will depend not only on the current values of P and I but also on rational forecasts of these variables. Hence, lagged variables should be an integral part of equation (1) – to the extent that past values are useful in predicting future values.

Third, microeconomic theory offers little guide as to what factors -- besides price and income, might influence the demand for health insurance. One possible way to select the elements of Z is to consider employment related characteristics of individuals, such as, for example, is the person employed or unemployed? Does he or she belong to a union? Is the person employed in the service industry? If these characteristics are measured as zero-one dummy variables, then the intercept in Equation (1) becomes $\beta+Z_{jt}$ where the subscript applies to the jth economic agent at each point in time t; hence the intercept in the demand equation will vary across individuals. An advantage of this approach is that while price and income elasticities (β_1 and β_2) are still constant, a varying intercept captures how different characteristics might influence health insurance demand.

Ideally, the empirical analysis should be based on a sample of repeated measures of demand for the same group of individuals over a long period of time. While cross-sectional data are readily available, the time-span of these data typically covers only a dozen years or less. One potential solution that will enable us to analyze the demand for health insurance over a much longer period of time is to aggregate data cross-sectionally, and divide by the number of economic agents during each period t to obtain a time series of per-capita demand. Further, employment characteristics are

proxied by percent employed in service industries, union membership rate, unemployment rate, etc.

A related econometric problem is whether the coefficients of the demand equation are likely to remain constant for observations gathered over a long period of time. The inclusion of the control Z variables offers a simple mechanism to account for potential structural shifts.

III.B   Data Specification Issues

In the empirical analysis below, all variables are transformed by taking the natural logarithm so that the estimated parameters measure elasticities. The quantity demanded of health insurance is measured in two ways: the percentage of the population with private health insurance as depicted in Figure 1 (henceforth denoted as *LPRIVATE*), and the completeness of the health insurance coverage (*LCOVERAGE*), measured as the fraction of consumer personal health care spending reimbursed by insurance, as shown in Figure 2. Following the economics of health insurance literature, the user price of private health insurance (*LPRICE*) is specified as $\ln((1 - e*tr)*LF)$. As specified, the user price depends on the marginal tax rate on wage income, tr , the fraction of health insurance premiums exempted from taxation, e , and the loading fee, LF , expressed as premiums divided by medical benefits paid out. Theory suggests that the user price of health insurance falls with a higher marginal tax rate and exempt fraction but rises with a greater loading fee. The user price of health insurance is expected to have an inverse relationship with our two measures of the quantity demanded of health insurance.

For empirical purposes, the marginal tax rate on wage income is measured solely by the annual average marginal federal tax rate. Data for the yearly average social security tax rate and average state income tax rate, which also should be included in the measurement of the marginal tax rate on wage income, are unavailable for the entire period from 1960 to 1999, unfortunately.   The

fraction of premiums exempted from taxation, e, is proxied by one minus the fraction of the workforce that own their own businesses. Up until 2003, the self-employed were unable to take a 100 percent exemption for health insurance premiums.[3]

Per capita real disposable income ($LINCOME$) represents income in the empirical analysis. A direct relation is expected between per capita real disposable income and both $LPRIVATE$ and $LCOVERAGE$, given that most studies have found that private health insurance represents a normal good (Santerre and Neun, 2004). Included among the Z vector of independent variables are the federal poverty rate ($LPOVERTY$), the percentage of national employment in service industries ($LSERVICE$), the national unemployment rate (LU), the labor unionization rate ($LUNION$), the percentage of the population covered by Medicare ($LMCARE$), and the percentage of the population covered by Medicaid ($LMAID$) (only in the $LPRIVATE$ equation).

The federal poverty rate and percentage of national employment in service industries, control for the likelihood of structural uninsurance. In the absence of public programs, poor households lack the wherewithal to purchase health insurance. In addition, shifting employment patterns among industries are beyond the control of individuals in the labor market and can ultimately influence long-term patterns of uninsurance.[4] More precisely, Long and Rodgers (1995) note that employment patterns have shifted from manufacturing where traditionally health insurance has been routinely sponsored by employers to the service industries where employer-sponsored health insurance has not been as widespread. An inverse relation is expected between both the federal poverty rate and the percentage of economy-wide employment in the service sector and the percentage of the population with private health insurance. We also expect that poverty will be inversely related with the

completeness of the health insurance coverage because of the inability to pay but hold no priors for the relationship between service sector employment and insurance completeness.

The percentage of the labor force belonging to a union is intended to capture the degree of frictional uninsurance. Long and Scott (1982) argue that unions provide information about the availability and importance of employer-sponsored health insurance benefits to workers. Alternatively, union jobs are good jobs with rents that take the form of benefits. For these two reasons, the number of individuals with private health insurance should be greater when a larger percentage of the workforce belongs to a union, *ceteris paribus*. The unemployment rate, as a reflection of cyclical uninsurance, is expected to be inversely related to the percentage with private health insurance coverage. We also expect a direct relationship between union membership and the completeness of health insurance coverage but hold no priors for the relationship between the latter variable and the unemployment rate.

The availability of public health insurance may affect the demand for private health insurance coverage so the percentage of individuals covered by the Medicare and Medicaid programs are also specified in the estimation equation. The precise relation between Medicare enrollment and the percent of the population with private health insurance is theoretically unclear. On the one hand, elderly individuals are required to enroll in Part A of Medicare. This requirement tends to reduce the number of individuals with private health insurance. However, Medicare enrollees often purchase Medigap, as a private insurance complement to their public insurance, because it covers medical expenses not reimbursed by Medicare. Also for some individuals, Medicare represents the secondary payer because they are also covered by employer-sponsored health insurance. Thus, the net impact of a growing percentage of the population covered by

Medicare on the percentage of the population with private health insurance and the completeness of health insurance coverage is theoretically unclear.

The theoretical relationship between enrollment in the Medicaid program and private insurance is less ambiguous. The hypothesis is that the Medicaid program crowds-out private health insurance (Cutler and Gruber, 1996). Thus an inverse relationship is anticipated between the percentage of the population enrolled in Medicaid and the percentage of the population with private health insurance. The percentage of the population covered by Medicaid is not expected to have any effect in the insurance completeness equation, however, because the two variables are unrelated since Medicaid substitutes completely for private health care expenditures and no balance billing is allowed. Data for Medicaid enrollment is measured as person-year equivalents as reported in Klemm (2000).

In sum, the quantity demanded of private health insurance, as captured by both enrollment and completeness of insurance coverage, should be found inversely related to price and directly related to income in the empirical analysis. Moreover, an inverse relationship is anticipated between enrollment in private health insurance plans and the federal poverty rate, the national percentage of employment in service industries, the unemployment rate, and the Medicaid coverage rate. Greater unionization should be associated with increased participation in private health insurance plans. The relationship between Medicare and private health insurance coverage rate is unclear theoretically. In addition, the completeness of insurance coverage is expected to be inversely related to the poverty rate, directly related to income and union membership rate, and we have no prior expectation as to its relationship to percentage of employment in the service industries or the unemployment rate.

Appendix A contains the definition of our variable names, their sources, the mean, standard

deviation, minimum and maximum value of each of these variables. Sample data are annual

observation from 1960 to 1999, except for Medicare and Medicaid which did not exist prior to 1966.

Note that because all our variables are found to be non-stationary (see Section IV.A below), the

statistics on the mean and standard deviation are intended only to provide summary description of

the time series variables for the sample period, and do not represent statistical population measures.

Finally, as mentioned earlier, before any actual econometric analysis is carried out, we transform all

the variables by taking the natural logarithm of these variables. This allows us to interpret the

estimated coefficients as elasticities.

IV.   *Empirical Analysis of the Aggregate Demand for Private Health Insurance*

IV.A   *Unit Root Tests*

We begin our empirical analysis by first examining the time series properties of our data.

We first plot and also calculate the autocorrelation and partial autocorrelation functions of the level

and first-difference of the data. Preliminary analysis strongly suggests that the data are non-

stationary. As Granger and Newbold (1974) observed many years ago, nonstationarity may be the

rule rather than the exception for macroeconomic time series data. Moreover, regression with

nonstationary variables may lead to spurious regression results. There are, however, several

empirical methodologies that have been developed for regression with nonstationary variables. The

most popular being the cointegration tests of Engle and Granger (1987) and Johansen (1988).

Cointegration test, however, requires that the time series variables are integrated processes of the

same order. For example, an integrated process of order $d \geq 1$, denote as $I(d)$ contains d unit

roots. Accordingly, we start with the augmented Dickey-Fuller (ADF) test for one unit root.

The ADF regression that we use is: [5]

$$\Delta X_t = a_0 + a_1 \, X_{t-1} + \sum_{i=1}^{k} \phi_i \Delta X_{t-i} + \varepsilon_t \, , \tag{2}$$

where Δ is the first difference operator, and ε_t is a covariance stationary zero mean process. The null hypothesis for the presence of a unit root corresponds to $a_1 = 0$.

We use the BIC method to choose the lag length k, allowing for a maximum of $k = 6$. We also initially include a linear time trend in Equation (2) to allow for the possibility that the nonstationarity may be the result of a deterministic trend. The individual t-statistic on the coefficient of the time trend is never statistically significantly different from zero, however, and a χ^2 test on the joint hypothesis of a unit root and the absence of a linear time trend is not rejected in all cases. For these reasons, we omit a linear time trend from our reported ADF regressions.

Table 1 displays the results of our unit root tests where we report the value of k, the estimated value of a_1 and its corresponding t-statistic, and the Ljung-Box Q-statistic, which is a portmanteau test for serial correlation in the residuals. The Q-statistic is distributed as χ^2, and we calculate the Q-statistic over twelve lags, with the degrees of freedom indicated in parentheses next to the statistic. The critical values for the t-statistic are not standard but may be found in Fuller (1976), and the 5% critical value is –2.94 for our sample size. As can be seen, we cannot reject the null hypothesis of a unit root for any of our ten variables. Moreover, the Q-statistics suggest that the hypothesis of serially uncorrelated residuals is not rejected at the 5% significant level in all cases except for *LSERVICE*, which is not rejected at the 1% significant level. The Q-statistic for *LSERVICE* is dominated by a few relatively large coefficients, especially at lags 2, 7, and 9, and adding additional lags to the ADF regression for this variable did not improve the Q-statistic significantly. Since there is no obvious explanation for the correlations at these lags, we conclude

that they are most likely spurious. Based on these results, we tentatively conclude that all our variables contain at least one unit root.

We test next for a second unit root. The testing procedure follows exactly that of our test for one unit root, except that all variables used in Equation (2) are differenced a second time. The lag length is once again chosen using BIC. As we can see from Table 1, the null hypothesis of a second unit root is uniformly rejected at the 5% significant level. Note, however, the Q-statistic for *LU* is not rejected only at the 1% significant level, and at 0.5% level of significance for *LSERVICE* . Once again, the Q-statistics for these two variables are dominated by a few relatively large coefficients at relatively high order lags, suggesting again that they are most likely spurious. Moreover, an examination of the plots, autocorrelation and partial autocorrelation functions of the first difference of these two variables did not reveal strong evidence of a second unit root. Based on the results in Table 1, we conclude that all our variables could be adequately represented by a first-order integrated process, i.e., $I(1)$ process. Of course, the unit root hypothesis cannot be strictly correct because many or our variables are expressed as percentages, and are bounded between zero and one. In contrast, a stochastic process characterized by a unit root has infinite variability. But as Hall, Anderson and Granger (1992) point out; the unit root hypothesis is a reasonable working assumption for the purpose of model building.

IV.B   Error Correction Representation and Cointegration

The unit root tests of the last section uniformly reject the stationarity hypothesis. It seems natural, therefore, to explore the possibility of a co-integrating relationship between the quantity demanded of private health insurance and its determinants. That is, we may use the Granger Representation Theorem (Engle and Granger, 1987) to establish whether a long-run stationary

equilibrium exists for *LPRIVATE* and *LCOVERAGE* with their economic and control variables. Stationary long run equilibrium may exist as a consequence of economic agents behaving as if they minimize a certain quadratic multiperiod loss function.

Specifically, define $Y_s{}^*$ as the long-run equilibrium demand during period s.[6] We assume that, in the aggregate, economic agents behave as if the actual level of Y_s is set to minimize a weighted average of the adjustment cost (Y_s - Y_{s-1}) over a single period, and the disequilibrium cost (Y_s - $Y_s{}^*$) for all future time periods. We may associate the period-to-period adjustment costs with utility loss incurred by individuals experiencing frictional or cyclical uninsurance. Deviations from long run equilibrium, on the other hand, may reflect utility loss caused by structural uninsurance. The loss function is given by:[7]

$$L_t = E_t \left\{ \sum_{i=0}^{\infty} \rho^i \left[(1-w)\left(Y_{t+i} - Y_{t+i}^*\right)^2 + w\left(Y_{t+i} - Y_{t+i-1}\right)^2 \right] \right\}
\tag{3}$$

where E_t is the expected value operator conditional on information available in the current period t; ρ is a fixed discount factor; *(1 - w)* and *w* are the relative weights associated with their respective adjustment costs.

We hypothesize that the optimal value $Y_s{}^*$ may be represented by a linear function of the X vector, which contains both economic and control variables: $Y_s^* = X_s^{'} \gamma + \varepsilon_s$, where ε_s is a random disturbance term to account for the effect of other market forces. It can be shown that the optimal solution, known as the Euler equation, is given by:

$$Y_t - X_t^{'} \beta = \eta_t
\tag{4}$$

where $\eta_t = \lambda\, Y_{t-1} + (1-\lambda) E_t \left\{ \sum_{i=1}^{\infty} (\rho\lambda)^i \Delta X_{t+i}^{'} \beta \right\} + (1-\lambda)(1-\rho\lambda)\varepsilon_t$, $\beta = (1-\lambda)\gamma$, and λ, one of the

two roots from the Euler equation, is assumed to be less than one to achieve convergence. Thus, the difference between the current level of demand and a linear combination of the variables in X depends on the present value of the first difference of the future values of the variables in X. Moreover, the difference will be stationary if one of the roots to the Euler Equation is close to zero.[8]

It can be shown that the root λ satisfies the quadratic equation $\frac{1}{\rho}\lambda^2 - (\frac{1+\rho w}{\rho w})\lambda + 1 = 0$ (see Nickel, 1985). For values of the discount factor ρ in the neighborhood of 0.95, λ close to zero implies a small weight on the cost of adjustment; in the aggregate, economic agents put more emphasis on the cost associated with being away from the desired level of private insurance. Alternatively, λ close to one implies more concern with short-term adjustment costs.

If the error term η_t is covariance stationary, then Y_t and the vector X_t are cointegrated with cointegrating vector $(1, -\beta)$. The importance of this result is twofold: first, since the variables are cointegrated we can be sure that the estimated results are not due to spurious regression; and second, in the long run the same forces that shape the level of other macro economic variables in the vector X_t also drive the behavior of aggregate demand. Given the relatively large number of variables and the relatively small sample size that we have, we suffer from the "curse of dimensionality" if we use a popular cointegration test such as Johansen's (1988) maximum likelihood approach. That is, as demonstrated in Hansen (1990), there is a dramatic reduction in the power of the test as the size of the system increases, rendering a test such as Johansen's fairly ineffective for our situation. Instead, we use the test developed by Hansen (1990) to test the cointegration hypothesis; its main advantage is that the asymptotic distribution of the t-statistic does not depend on the number of regressors.[9]

To implement Hansen's test, we assume that the error term in the cointegrating regression,

η_t, in Equation (4), follows an autoregressive process with autocorrelation coefficient θ. In the first stage, we use the methods of Cochran-Orcutt to estimate the parameters of Equation (4) including θ. In the second stage, we semi-difference the data: $\hat{Y}_t = Y_t - \hat{\theta} Y_{t-1}$ and $\hat{X}_t = X_t - \hat{\theta} X_{t-1}$ and re-estimate a transformed equation (4), i.e., $\hat{Y}_t - \hat{X}_t'\hat{\beta} = \hat{\eta}_t$. This procedure may be repeated a number of times to insure convergence of $\hat{\theta}$. Because Hansen has shown that there is a size bias in the estimation of θ in finite sample, we use a bias adjustment suggested by Hansen. We first obtain an initial estimate of θ, we next define $\hat{\theta} = \tilde{\theta} + c/T$, where $\tilde{\theta}$ is the initial estimate of θ, T is the sample size, and following Hansen, we use $c = 10$. We then semi-difference the data using $\hat{\theta}$ and follow the procedure as described above until the final iteration where θ is used without the bias adjustment. The estimated residuals $\hat{\eta}_t$ may then be tested for the presence of a unit root using equation (2). For our sample,[10] we found $\hat{\theta} = 0.247$ and the ADF unit-root test statistic on $\hat{\eta}_t$ is -4.49 for the *LPRIVATE* equation. Similarly, for the *LCOVERAGE* equation, $\hat{\theta} = 0.968$ and the ADF unit-root test statistic on $\hat{\eta}_t$ is -3.80. Thus, the evidence leads to a rejection of the unit root hypothesis at better than the 1% level; we conclude that the error term in equation (4) follows a stationary process.

The economic implication of these results is that there exists an equilibrium relationship between aggregate demand (both specifications) and the user price, real income, and the remaining control variables. Moreover, the regression coefficients may be interpreted as long-run demand elasticities. Table 2 reports the estimated coefficients and their standard errors. Note however, although the coefficients are unbiased, consistent and converge quickly, they are not efficient, since the residuals are autocorrelated. Accordingly, we follow the practice in the literature and discuss the results in Table 2 in terms of sign and magnitude, rather than in terms of statistical significance.

According to the results for the *LPRIVATE* equation, user price elasticity is -0.279 whereas income elasticity is 0.151, thus both coefficient estimates have their anticipated signs. Similarly, the results for the *LCOVERAGE* equation indicate that the user price and income elasticities are –0.322 and 0.353, respectively. Despite the use of macro-level data, the estimated elasticities compare very closely to previous estimates ranging between -0.03 and -0.54 for price elasticity and between 0.01 and 0.15 for income elasticity from studies using micro-level data (Santerre and Neun, 2004).

The results for the control variables are equally interesting. The strongest effects, in terms of elasticities, come from *LSERVICE* and *LUNION* : -0.548 and 0.254, for the *LPRIVATE* equation and 0.261 and 0.295 for the *LCOVERAGE* equation, respectively. Variables such as *LU*, *LMCARE* , and *LMAID* do not appear to have important long run effect on the demand for private health insurance, while *LPOVERTY* appears to be marginally important and has the expected sign for the *LPRIVATE* equation only. Interestingly, except for *LPRICE*, *LINCOME* , and *LUNION* , the various coefficients on the same variables in the two equations tend to differ with respect to their signs. Two reasons may account for these observed differences. First, being poor or working in a service industry, for example, may affect the likelihood of someone being uninsured, but once insured these same conditions might have little or an opposite impact on how much insurance the person purchases.[11] For example, unlike workers in the manufacturing industry, service sector workers tend to have less opportunity to purchase health insurance through their employers such that the coefficient estimate on the *LSERVIVCE* variable is likely to be negative in the *LPRIVATE* equation. However, a greater percentage of service sector workers may be female, and females tend to consume more health care services than males. Therefore, once insured, service sector workers may tend to demand more complete health insurance products such that the coefficient estimate on the *LSERVICE* variable is

positive in the *LCOVERAGE* equation.

Second, the two sets of results may differ because possessing insurance may be more about access to medical care than about risk aversion (Nyman, 2003). Nyman argues that health insurance solves an affordability problem and allows financial access to medical care that some people could not otherwise afford because of their low net worth relative to the costs of many medical procedures. If so, the *LPRIVATE* equation may be capturing the access value of possessing health insurance by identifying the number of people with at least catastrophic coverage, whereas, the *LCOVERAGE* equation may reflect the risk aversion feature of health insurance by identifying the extensiveness of the coverage. Thus, the same explanatory variables may have different impacts on the dependent variables in the two regression equations.

IV.C   Long Run Equilibrium Relationship and the Error Correction Model

The analysis of the previous section shows that both the *LPRIVATE* and the *LCOVERAGE* equations are cointegrated. Engle and Granger (1987) show that a set of cointegrated variables has an error correction model (ECM) representation. The ECM follows directly from Equation (4), assuming that each of the independent variables follows a random walk:

$$\Delta Y_t = (\lambda - 1)\hat{\eta}_{t-1} + \Delta X_t' \alpha + \zeta_t, \tag{5}$$

where $\hat{\eta}_{t-1}$ is the error correction term.

The empirical results associated with the ECM are displayed in Table 3. Before discussing the results, we note that checks for serial correlation, heteroscedasticity (against an ARCH alternative), and parameter constancy (with a breakpoint in 1985 -- the year COBRA was passed into law), all turn out to be statistically insignificant for both demand equations. Also, we note that the adjusted R^2 is fairly large for a growth rate model: 50% and 72%, respectively, for the *LPRIVATE*

and *LCOVERAGE* equations.

The estimated coefficient for $\hat{\eta}_{t-1}$ is -0.883 with a t-statistic of -3.558 (p-value $= 0.002$) for the *LPRIVATE* equation, and -0.491 with a t-statistic of -4.628 (p-value $= 0.000$) for the *LCOVERAGE* equation. Hence, the estimated coefficients satisfy both theoretical requirements: less than one in absolute value, negative and statistically different from zero. Moreover, the magnitude implies a sizable feedback effect. For example, for the *LPRIVATE* equation, 88 percent of a unit equilibrium error in the previous period is reversed in the current period. Hence, the percent of individuals with private insurance adapts fairly quickly to variations in its long run equilibrium. In some sense this is good news for policy makers who wish to impact the equilibrium level of the structurally uninsured, especially if some variables such as the poverty rate are highly sensitive to policy adjustments.

The implied value of λ, the root from the Euler equation, is 0.117 for the *LPRIVATE* equation, and 0.509 for the *LCOVERAGE* equation. The implication is that, in the aggregate, people consciously consider more the cost of disequilibrium than the period-to-period adjustment cost. In other words, transitioning between short spells with or without private health insurance generates less disutility than long periods without insurance. Alternatively stated, the welfare loss created by a drop in the percent of private health insurance caused by changes in the number of frictionally or cyclically uninsured is smaller than the welfare loss due a change in the number of structurally uninsured.

Table 3 shows short-run elasticity estimates for the various determinants of the aggregate demand for private health insurance.[12] According to the estimates, the aggregate demand for private health insurance, both in terms of enrollment and completeness of coverage, is relatively inelastic in

the short run with respect to user price. Specifically, the elasticity estimate on user price implies that a 10 percent increase in price is associated with a 2.3 percent decrease in the percentage of the population with private health insurance and a 1.8 percent reduction in the completeness of health insurance coverage in the short-run.

The income elasticity of demand for private health insurance enrollment is positive, as expected, and statistically significant at better than the 5 percent level for a one-tailed test. According to its estimate, a ten percent increase in income is associated with a 3.6 percent increase in the percentage of the population covered by private health insurance. The only surprising result obtained is the negative income elasticity of demand estimate in the completeness equation. Recall that a positive income elasticity estimate was anticipated. However, this expectation of a direct relationship was based on prior research focusing on the impact that income has on the purchasing of health insurance with little regard to the completeness of the coverage. Thus, from a theoretical perspective, we cannot rule out an inverse relationship between income and the completeness of health insurance. For example, the degree of insurance completeness may decline with income, at least after some point, because higher income households can avoid some of the expense load behind insurance by self-insuring to a greater extent and paying a greater amount as out-of-pocket expenses when an illness takes place. However, given that the coefficient estimate on income is only marginally statistically significant, it would be imprudent of us to generalize our findings beyond this particular sample.

Results for the other variables also merit some discussion. First, as anticipated, the empirical results suggest that the private health insurance coverage rate and poverty rate move in opposite directions in the short-run. More specifically, the elasticity estimate suggests that a 10 percent

decline in the poverty rate is associated with a 1.2 percent increase in the percent enrolled in private health insurance plans. Similarly, a 10 percent decline in the poverty rate is associated with a 1.1 percent increase in the completeness of health insurance coverage. Second, the results indicate that variables other than price, level of income, and the distribution of income, represented by the poverty rate, have no short-run impact on the demand for health insurance or the completeness of coverage. This finding is not too surprising given that most of these variables, like the percentage of workers in the service sector and union membership rate, tend to change very slowly over time and therefore have more of a long-term than short run impact on health insurance coverage status.

V.   *Conclusion*

In this paper we examine the long run behavior and short run dynamics of the aggregate demand for private health insurance within a cointegration and an error correction model framework. The error correction model considers that people incrementally balance the benefits of an adjustment towards their desired objective with the costs of making the adjustment. Just like the demand for other goods and services, the empirical findings in this paper indicate that the aggregate demand for private health insurance is related to price, income, and other factors in a fairly predictable manner. Individuals weight the cost of adjusting their health insurance purchase relative to the disequilibrium cost of being away from their preferred quantity of health insurance at a point in time. At the margin, it appears that disequilibrium costs impose greater disutility than short-run spells in-between insured and uninsured status.

In this paper we also advance the argument that people are uninsured for voluntary reasons as well as for involuntary reasons reflecting structural, frictional, and cyclical circumstances. In fact, the original Medicare Act, and especially Medicare's expansion in 1973 to individuals with certain

disabilities, may have been enacted with structural uninsurance in mind. As mentioned previously, COBRA of 1985 was directed at frictional uninsurance. In addition, many analysts believe that individual health insurance plans may grow in the future as information on the Internet reduces the time involved in searching out a health insurance company. It follows that any serious public or private initiatives to increase private health insurance coverage through voluntary means, both in terms of enrollment and completeness, should consider the various reasons why people remain uninsured. That is, we cannot expect one remedy to cure all of the causes for uninsurance. Thus, a variety of public and private approaches may be necessary to reduce uninsurance in a primarily voluntary health insurance system.

Our empirical findings strongly confirm results from prior micro-level studies regarding the price and income elasticities of the demand for health insurance. Despite the aggregate nature of our data and the error correction modeling, we find that the demand for private health insurance appears to be relatively insensitive to changes in user price and consumer income in both the short and long run and with respect to both enrollment in private health plans and the completeness of health insurance coverage. The relative insensitivity of demand to changes in user price may mean that incremental subsidization programs may have little impact on the purchasing and completeness of private health insurance coverage at the aggregate level. Moreover, unlike many other types of social problems like infant mortality, environmental conditions, and workplace safety, the relatively small income elasticities of demand may imply that we cannot expect private health insurance coverage to naturally improve with a higher standard of living in the U.S. Thus, just like social security and automobile liability insurance are required for most workers and drivers, it may be necessary to

mandate health insurance coverage if society one day reaches the conclusion that the benefits of universal health insurance coverage outweighs its costs.

Finally, although we obtain reasonable results with our empirical procedures, we are unable to estimate our equations within a system framework because of our limited sample size and the relatively large number of variables involved. Thus, we are unable to address the question of multiple cointegration. This is a shortcoming of this study, which hopefully will be addressed in future studies.

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Table 1: Augmented Dickey-Fuller (ADF) Unit Root Tests

Variable	One Unit Root			Two Unit Roots		
	k	a_1	Q-statistic (d.f.)	k	a_1	Q-statistic (d.f)
LPRIVATE	2	-0.062	12.542 (8)	0	-0.421	17.200 (10)
		(1.927)			(2.934)*	
LCOVERAGE	1	-0.010	11.486 (9)	0	-0.512	9.964 (10)
		(1.092)			(3.680)*	
LPRICE	2	-0.008	10.269 (8)	1	-0.519	9.401 (9)
		(0.979)			(3.818)*	
LINCOME	1	-0.027	8.825 (9)	0	-0.657	11.067 (10)
		(1.799)			(4.143)*	
LPOVERTY	1	-0.111	8.740 (9)	0	-0.565	8.011 (10)
		(2.481)			(3.710)*	
LSERVICE	0	0.003	23.123* (10)	0	-0.908	23.781* (10)
		(0.400)			(5.518)*	
LUNION	2	-0.003	12.545 (8)	1	-0.578	12.662 (9)
		(0.184)			(3.623)*	
LU	3	-0.008	12.577 (7)	1	-0.918	18.026* (9)
		(0.505)			(4.624)*	
LMCARE	2	-0.050	3.847 (8)	0	-0.819	1.643 (10)
		(2.209)			(4.500)*	
LMAID	1	-0.074	11.587 (9)	0	-0.504	10.773 (10)
		(1.560)			(7.646)*	

Notes: Absolute values of the t-statistics are in parentheses below the estimates. * denotes the rejection of the null hypothesis at the 5% level of significance. (d.f.) denotes the degrees of freedom.

Table 2: Cointegrating Regression and Long-Run Elasticities

The cointegrating regression (Equation (4)) is $\hat{Y}_t = \hat{X}_t^{'} \hat{\beta} + \hat{\eta}_t$.

|	Panel A		Panel B	
	LPRIVATE		LCOVERAGE	
Variable	**β estimate**	**St. Error**	**β estimate**	**St. Error**
Constant	3.581	1.004	-6.201	1.547
LPRICE	-0.279	0.044	-0.322	0.068
LINCOME	0.151	0.206	0.353	0.320
LPOVERTY	-0.147	0.074	0.104	0.106
LSERVICE	-0.548	0.103	0.261	0.125
LUNION	0.254	0.108	0.295	0.165
LU	0.038	0.020	-0.001	0.027
LMCARE	-0.098	0.155	0.193	0.237
LMAID	-0.013	0.020		
R^2	0.97		0.99	
Adjusted R^2	0.96		0.99	
S.E. of regression	0.012		0.019	
D.W.	1.65		0.95	

Table 3: Error Correction Model (ECM) and short run elasticities

The ECM is from Equation (5): $\Delta Y_t = (\lambda - 1)\hat{\eta}_{t-1} + \Delta X_t' \alpha + \zeta_t$.

| Variable | Panel A | | | Panel B | | |
	LPRIVATE			LCOVERAGE		
	Coefficient estimate	t-statistic	P-value	Coefficient estimate	t-statistic	P-value
Constant	-0.012	-1.409	0.172	0.005	0.655	0.519
$\hat{\eta}_{t-1}$	-0.883	-3.558	0.002	-0.491	-4.628	0.000
LPRICE	-0.231	-3.460	0.002	-0.181	-3.452	0.002
LINCOME	0.361	1.901	0.070	-0.284	-1.737	0.096
LPOVERTY	-0.121	-4.437	0.042	-0.109	-2.372	0.027
LSERVICE	-0.133	-0.462	0.649	-0.088	-0.356	0.725
LUNION	0.142	1.294	0.209	0.011	0.126	0.901
LU	0.028	1.072	0.295	0.000	0.002	0.999
LMCARE	-0.108	-0.672	0.508	0.009	0.071	0.943
LMAID	-0.001	-0.066	0.948			
R^2	0.63			0.80		
Adjusted R^2	0.50			0.72		
S.E. of regression	0.0105			0.009		

Note: All variables are in logarithm first-difference form, and are thus percentage changes, except $\hat{\eta}_{t-1}$, which is the disequilibrium error (lagged once) from Equation (4).

Figure 1: Percent of US Population with Private Health Insurance
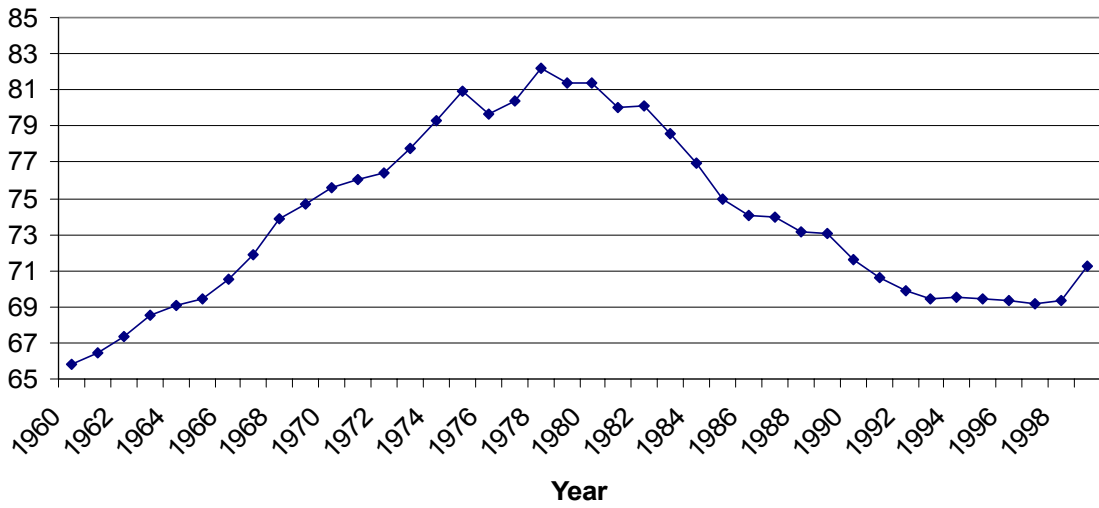
Figure 2: Completeness of Health insurance Coverage
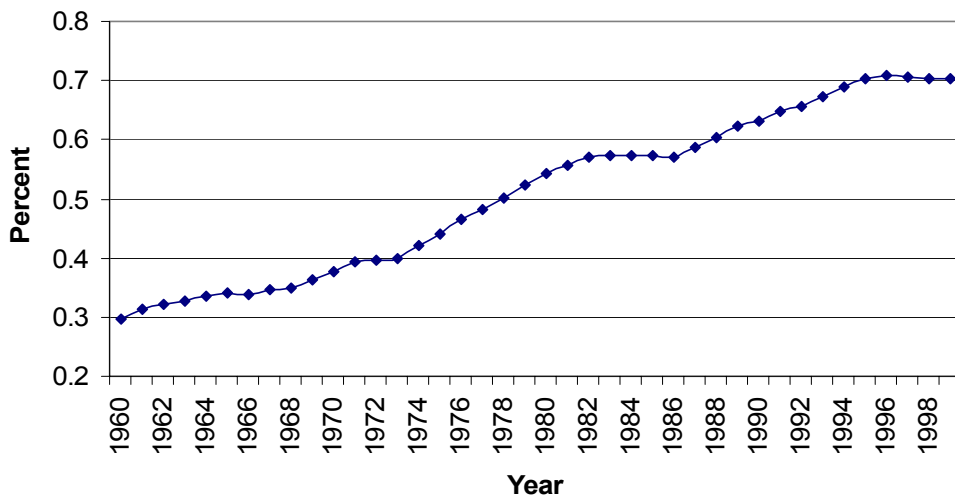
Appendix A: Definition of Variable, Summary Statistics, and Data Sources

Variable	Definition	Mean	Standard Deviation	Minimum Value	Maximum Value	Data Source
LPRIVATE	The natural logarithm of percent with private health insurance	73.82	4.77	65.79	82.20	HIAA (1999) and Mills (2002)
LCOVERAGE	The natural logarithm of completeness of coverage	0.508	0.138	0.296	0.708	http://www.cms.gov
LPRICE	The natural logarithm of user price of private health insurance	0.0037	0.0022	0.0012	0.0077	See note
Tr	Average marginal tax rate	0.234	0.027	0.202	0.309	Feenberg and Coutts (1993), and http://www.nber.org/~taxsim/
	Percent with own business	7.655	0.996	6.70	10.40	http://www.bls.gov
LF	The natural logarithm of real loading fee	0.019	0.012	0.007	0.041	http://www.cms.gov
LINCOME	The natural logarithm of per capita real disposable personal income	29.86	6.17	18.53	40.33	http://www.bea.gov
LPOVERTY	The natural logarithm of federal poverty rate	11.61	2.641	8.80	18.50	http://census.gov
LSERVICE	Percent of national employment in service industry	20.72	5.232	13.66	30.31	http://www.bls.gov
LUNION	The natural logarithm of union membership rate	22.90	6.243	13.90	30.40	http://www.laborresearch.org
LU	The natural logarithm of national unemployment rate	6.00	1.483	3.50	9.70	http://www.bls.gov
LMCARE	The natural logarithm of percent of population covered by Medicare	12.46	1.59	9.72	14.37	http://www.cms.hhs.gov
LMAID	The natural logarithm of perent of population covered by Medicaid	8.96	2.44	2.03	12.71	Klemm (200)

Notes: All variables are annual observation and have been transformed by taking natural logarithm. LPRICE is computed as ln((1-e*tr)*LF) as defined in the text. The summary statistics are computed without taking the natural logarithm of the data.

Endnotes

[1] Previous studies using the same methodology but different estimation technique include the study by Kuo, Tsai, and Chen (2003) on insurance lapse rate.

[2] Private insurance plans are defined as all supplemental, comprehensive, and catastrophic insurance policies, including those individually purchased, both by the non-elderly and elderly (e.g., Medigap) and group policies sponsored by employers or trade associations.

[3] The loading fee is treated as being exogenously determined. Empirical studies have shown that health insurance is produced with constant returns to scale (Blair and Vogel, 1978 and Wholey et al., 1996).

[4] However, we cannot rule out the possibility that the poverty rate is also cyclical.

[5] Equation (2) is appropriate for our study because most of our variables have bounded variation. We also use the longest possible sample period in our unit root test.

[6] As in Granger (1986), we use the term "equilibrium" to describe the dynamic behavior of an economic system and its tendency to move in a particular direction.

[7] The loss function described by equation (3) is standard in the econometrics literature, see e.g., Gregory (1994) and references therein.

[8] This also requires that the changes in the X variables are stationary.

[9] The trade-off is that we are unable to investigate the possibility of multiple cointegrating vectors within Hansen's framework. We did, however, attempt to model the cointegrating relationships using Johansen's maximum likelihood approach. Unfortunately, we are unable to obtain a satisfactory model for both the $LPRIVATE$ and the $LCOVERAGE$ equations. Thus, we are unable to address the issue of multiple cointegrating vectors. An appendix detailing our attempt at using Johansen's approach is available upon request.

[10] The sample period for cointegration tests is 1966-1999 since both $LMCARE$ and $LMAID$ do not exit prior to 1966.

[11] Recall that we have no prior expectation as to the relationship between $LCOVERAGE$ and $LSERVICE$.

[12] Note that a lagged value of the dependent variable was specified in the completeness equation to correct for serial correlation.

Appendix

In this appendix, we present an analysis of co-integration using Johansen's (1988) maximum likelihood approach. The main purpose here is to attempt to determine whether or not there is more than one cointegrating vector, and it is not intended to be a full analysis of the model, which is provided in the paper. Thus, this should be viewed as a supplement to the analysis provided in the paper.

We have a model of fairly large dimension and relatively modest sample data size. Thus, unfortunately, we suffer both from the "curse of dimensionality" and small sample bias with Johansen's approach.

We start with the basic vector autoregressive model (VAR):

$$z_t = \sum_{i=1}^{k} A_i z_{t-i} + \xi_t,$$ (A.1)

where z_t is a $n\,x\,1$ vector of stochastic variables, $A_i, i = 1, 2, \ldots k$ is a $n\,x\,n$ matrix of coefficients, and ξ_t is a $n\,x\,1$ vector of normally, independently, and identically distributed errors with mean zero and constant variances/covariances. Without loss of generality, and letting $k = 1$, we rewrite equation (A.1) in its vector error-correction form (VECM):

$$\Delta z_t = A_0 + \Gamma \Delta z_{t-1} + \Pi z_{t-1} + \xi_t$$ (A.2)

where A_0 is a vector of intercepts, and Δ is the first difference operator. The hypothesis of cointegration is now formulated as

$$H_0 : \text{rank}(\Pi) \le r, \ r \le n, \text{ or } \Pi = \alpha\beta',$$

where α and β are $n\,x\,r$ matrices of full rank.

In Johansen's approach, all stochastic variables are initially treated as "endogenous" variables. Since we have a large system, $n = 9$, and small data sample, $T = 36$, it is desirable to reduce the dimensionality of the model, especially since some of our variables may reasonably be classified as weakly exogenous variables. Doing so would allow us to obtain more efficient estimates of the "structural" parameters. Accordingly, we follow Pesaran, Shin, and Smith (2000) and consider only a partial system, where some variables are classified as weakly exogenous. The partial system that we estimate is

$$\Delta y_t = \widetilde{A}_0 + \Gamma_0 \Delta x_t + \Gamma_1 \Delta z_{t-1} + \Pi_y z_{t-1} + \widetilde{\xi}_t,$$ (A.3)

where $z_t = (y_t, x_t)$, where y_t is a $p\,x\,1$ vector of "endogenous" variables, and x_t is a $m\,x\,1$ vector of weakly "exogenous" variables, where $m = n - p$. The difficulty is in deciding which variables should be treated as "endogenous" and which should be considered as "exogenous". One, and perhaps not an entirely unreasonable, classification scheme is to treat all "economic" variables as endogenous, and all other "control" variables as exogenous. This implies that for our purpose,

$$y_t = (LPRIVATE, (OR\ LCOVERAGE), LPRICE, LINCOME, LU), \text{ and}$$

$$x_t = (LPOVERTY, LSERVICE, LUNION, LMCARE, LMAID).$$

In what follows, we report our results using this classification scheme. We should note, however, that we have tried other classification schemes, but the results do not differ significantly from what we report here in this appendix. Note also that *LMAID* is not included with the model with *LCOVERAGE* . We start our empirical analysis by first determining the number of cointegrating vector. We report our results in Table A.1. We include also an unrestricted constant, i.e., the constant is not restricted to the cointegration space, and because of degrees of freedom consideration, we can only use one lag in our model, i.e., $k = 1$. There are two test statistics for cointegration, the Lambda-max and the trace statistics. The Lambda-max test statistic tests the null hypothesis of r cointegrating vector(s) against the specific alternative of $r + 1$ cointegrating vector(s). The trace statistic tests the null hypothesis of no cointegrating vector ($r = 0$) against the general alternative of one or more cointegrating vectors, i.e., $r > 0$. We only report the trace-statistic since both statistics give similar results, and we are mainly interested in whether or not there is more than one cointegrating vector. We also apply a finite-sample adjustment factor to our trace statistics suggested by Reinsel and Ahn (1992). The adjustment factor is $(T - pk)/T$, where T is the effective sample size, and p, k are as defined before. The adjustment factor may be thought of as measuring the bias in using the asymptotic critical values. Thus, the bias increases with increases in p and k , but decreases with increase in T , and no bias as $T \rightarrow \infty$. The critical values at the 5% significance level are taken from Pesaran, Shin, and Smith (2000), Table 6(c).

Table A.1

	Model with *LPRIVATE*	Model with *LCOVERAGE*	Critical Value at the 5% significance level
$r = 0$	172.90*	188.65*	95.14
1	91.87*	101.88*	66.94
2	42.39	51.65*	42.73
3	14.99	20.68	22.19
LB(8)	229.44* (96)	229.08* (96)	
LM(1)	30.70* (16)	28.39* (16)	
LM(4)	28.91* (16)	23.78 (16)	

Notes: LM(8) is a multivariate Ljung-Box test based on the first 8 lags of the estimated auto- and cross-correlations. The test statistic is distributed as chi-squared with degrees of freedom given in the parentheses. LM(1) and LM(4) are LM-type tests for first and fourth order autocorrelations. Both test statistics are distributed as chi-squared with degrees of freedom given in parentheses. "*" denotes the rejection of the null hypothesis at the 5% level of significance.

Table A.1 suggests that there are two cointegrating vectors for the model with *LPRIVATE* , and three for the model with *LCOVERAGE* . The finding of more than one cointegrating vector means that the model is only uniquely identified up to the cointegration space, and not identified by an unique cointegration vector. Before concluding on the number of cointegrating vectors, we check several diagnostic statistics for model adequacy. First, we check the system residuals for serial correlations. As the multivariate Ljung-Box statistic indicates, the null hypothesis of no serial correlations is rejected for both models at the 5% level of significance. Moreover, also at the 5% level of significance, the Lagrange-Multiplier tests for no first and fourth order serial correlations are rejected in both cases for the model with *LPRIVATE* , and rejected for no first order serial correlations for the model with *LCOVERAGE* . Thus, the lag structure of the VECM is inadequate in producing serial uncorrelated residuals. The most obvious solution is to increase the lags in the VECM, but unfortunately, we are unable to do this because of insufficient sample data (increasing the lag by one gives us a negative number of degrees of freedom!).

We next calculate the estimated eigenvalues of the A matrix (the companion matrix) in Equation (A.1). Under the assumption of cointegration, the eigenvalues should be inside the unit circle. The number of eigenvalues close to unity gives the number of common stochastic trends in the model [see Stock and Watson (1988)]. Figure A.1 and Figure A.2 show graphically the eigenvalues of the model with
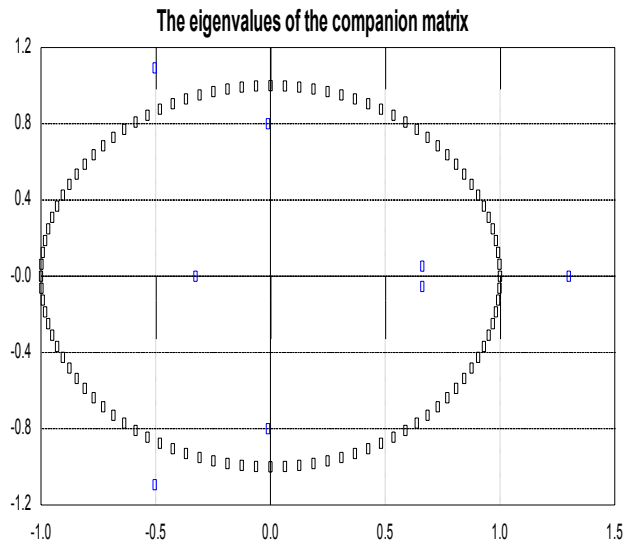
LPRIVATE and the model with *LCOVERAGE* , respectively. As can be seen, in both cases, the largest root lies outside the unit circle, suggesting nonstationarity, and thus the model is not an adequate description of the data.

Figure A.1: Model with *LPRIVATE*
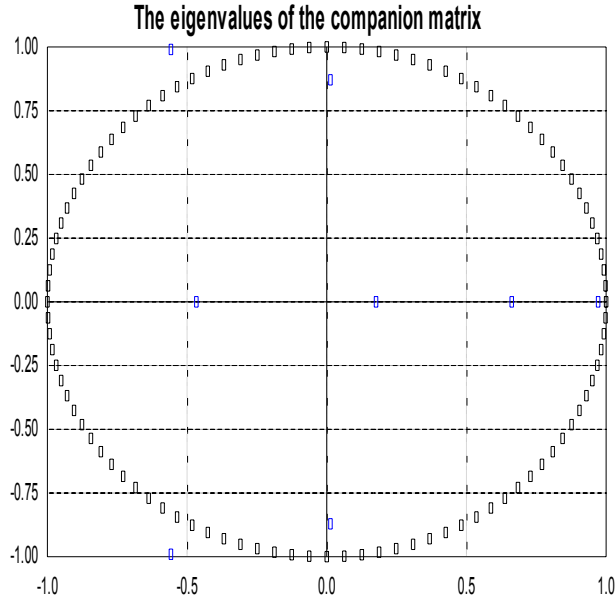
Figure A.2: Model with *LCOVERAGE*

Based on these diagnostic statistics, we are unable to obtain a satisfactory model for both *LPRIVATE* and *LCOVERAGE* . Hence, we are unable to conclude that there is more than one cointegrating vector for the models using Johansen's approach. However, we cannot, at the same time, rule out the possibility of multiple cointegrating vectors.

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