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Forecasting Medical Net Discount Rates

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Abstract

Determining the present value of future medical costs is an important issue for a variety of public and private entities. This article examines the time-series properties of medical net discount rates and considers the implications for forecasting. The article provides evidence that the standard autoregressive moving average forecasting model may be improved by modeling the time-varying volatility characteristics of the medical net discount rates.

Introduction

While rising medical costs are a topic of much political and academic discussion, little research has been conducted as to the time-series properties of medical cost inflation. A great deal of the literature has focused on the determinants of medical costs as well as cross-country comparisons of health care expenditures (e.g., Gerdtham and Lothgren, 2000;[1] Santere and Neun, 2000), on medical cost-effectiveness (Meltzer, 1997), and on measurement issues (Berndt et al., 1998). Time-series-based studies that provide reliable estimates of future medical costs, appropriately discounted, would be of wide use to economists and health care policymakers. For example, knowledge of the time-series behavior of medical costs can be used to improve the planning and decision making of governmental agencies, pension plan administrators, hospital administrators, provider groups, insurance companies, pharmaceutical companies, and other health care–related entities.[2] In particular, the present value of future medical costs is an important determinant in many decisions made over time, such as the financing of long-term health care, investment in plant and equipment, project

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[1] Examining a number of countries, Gerdtham and Lothgren (2000) found that health care expenditures and GDP share a long-run equilibrium relationship.

[2] A recent *Wall Street Journal* article (Work Week, 12/5/00) reported that current methods used to forecast health care costs often perform poorly.

evaluation, and any other task that involves the use of present-value analysis of future medical costs.[3]

This article examines the growth rates of five medical cost indexes, including the composite Consumer Price Index (CPI) medical care index, in relation to the discount rate. We construct medical cost net discount rates (MNDRs) using monthly data over the period of January 1980 through December 1999. The time-series properties of these MNDRs are examined by conducting stationarity tests.[4] Thus, the first task of this article is to examine each MNDR to determine if it can be characterized as a stationary or a nonstationary process. If the MNDR is nonstationary, due to deterministic trend or a unit root, then the use of historical averages for forecasting purposes is inappropriate. But if the MNDR is stationary around its mean, then the use of historical averages of the MNDR may be used for forecasting. However, because medical cost inflation exhibits periods of high volatility, often appearing in clusters, we examine the possibility that the conditional variance of the MNDR may contain useful information that may improve the forecast of MNDRs.

Data, Methodology, and Results

We collected monthly data covering the period January 1980 to December 1999 for five CPI medical cost indexes: medical care (MCARE), medical care services (MSERV), medical care commodities (MCOM), physician's services (PHYS), and prescription drugs and medical supplies (RX). The indexes were constructed by the Bureau of Labor Statistics using a three-year base period.[5] MCARE is a major item group in the CPI that consists of MSERV and MCOM. MSERV are the dominant component of medical care and are computed using 6,306 unique price observations (quotes) on professional medical services, hospital services, nursing home services, and health insurance imputation. PHYS, the largest subcategory of professional medical services, is composed of 1,050 quotes and includes services by physicians in private practice that are billed by the physician. MCOM have 1,369 unique price observations on such items as prescription drugs, nonprescription over-the-counter drugs, and other medical supplies and equipment. RX, which include 694 quotes on all drugs and medical supplies dispensed by prescription, are the largest component within MCOM. The weights for the indexes are designed to reflect household expenditures for health insurance premiums and out-of-pocket expenses.

We computed the annual growth rate in each cost index (g) on a year-over-year basis, which provides a usable starting point of 1981:01.[6] We also obtained the constant-maturity one-year Treasury bill rate and converted it to a bond-yield basis (r). We com-

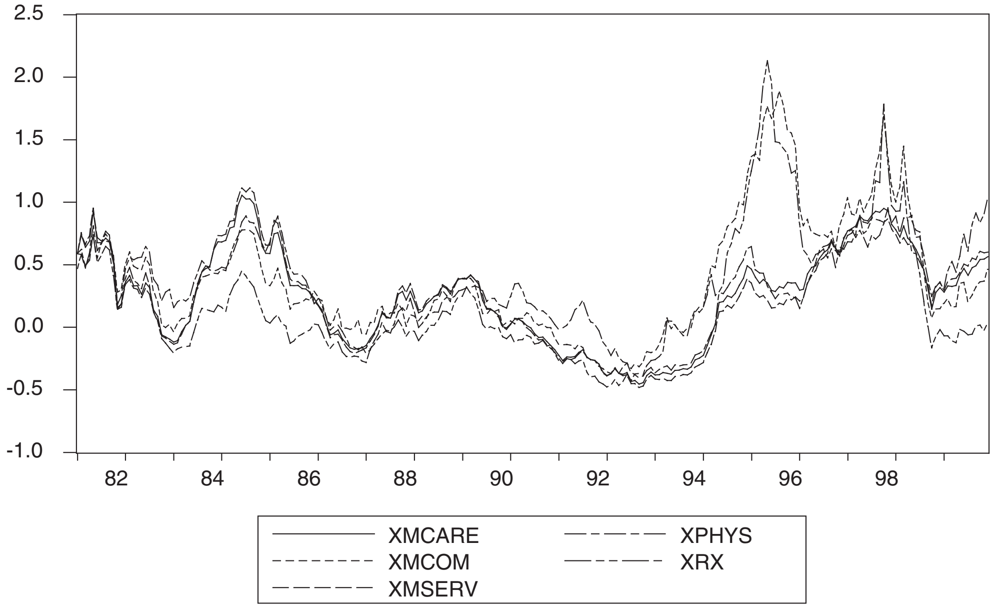
[3] The *Wall Street Journal* (11/10/00) reported that PacifiCare Health Systems, Inc., the largest operator of Medicare health maintenance plans in the United States, attributed its recent (incorrect) earnings forecast to higher-than-expected medical costs and that this may be a factor in their decision to eliminate certain health care plans and product lines.

[4] The stationarity of net discount rates and ratios for earnings growth has received considerable attention in the literature. For examples, see Haslag et al. (1994), Pelaez (1996), Payne et al. (1999), and Hays et al. (2000).

[5] Detailed information is available on the BLS Web site.

[6] While we determined the starting period by the availability of a comparable set of observations available on all series, beginning the study after 1980 also has the advantage of eliminating the period in which the Federal Reserve conducted its well-known "monetary

FIGURE 1
Medical Net Discount Rates



Notes: XMCARE ≡ MNDR for medical care, XMCOM ≡ MNDR for medical care commodities, XMSERV ≡ MNDR for medical care service, XPHYS ≡ MNDR for physician's services, and XRX ≡ MNDR for prescription drugs and supplies. The MNDRs represent percents and are measured on the vertical axis. Years are on the horizontal axis.

puted the net discount rate (measured in percent terms) for each index as follows:[7]

$$X^j = (r - g^j)/(1 + g^j), \tag{1}$$

where the superscript j denotes the medical cost index. Figure 1 presents plots of the MNDRs in levels. Note that the MNDRs follow similar patterns. Figure 2 shows the first-difference of each MNDR. The changes in MNDRs exhibited substantial volatility, and the conditional variance of these series may not be constant (but may instead be time-varying). Thus, it may be that one can improve upon forecasts of MNDRs by incorporating information about time-varying (or nonconstant) variance. In this case, one should model the series using time-series techniques that can take this violation of the classical regression model into account. One can use the class of models described by Engle (1982) and known as autoregressive conditional heteroscedasticity (ARCH) models in these situations.

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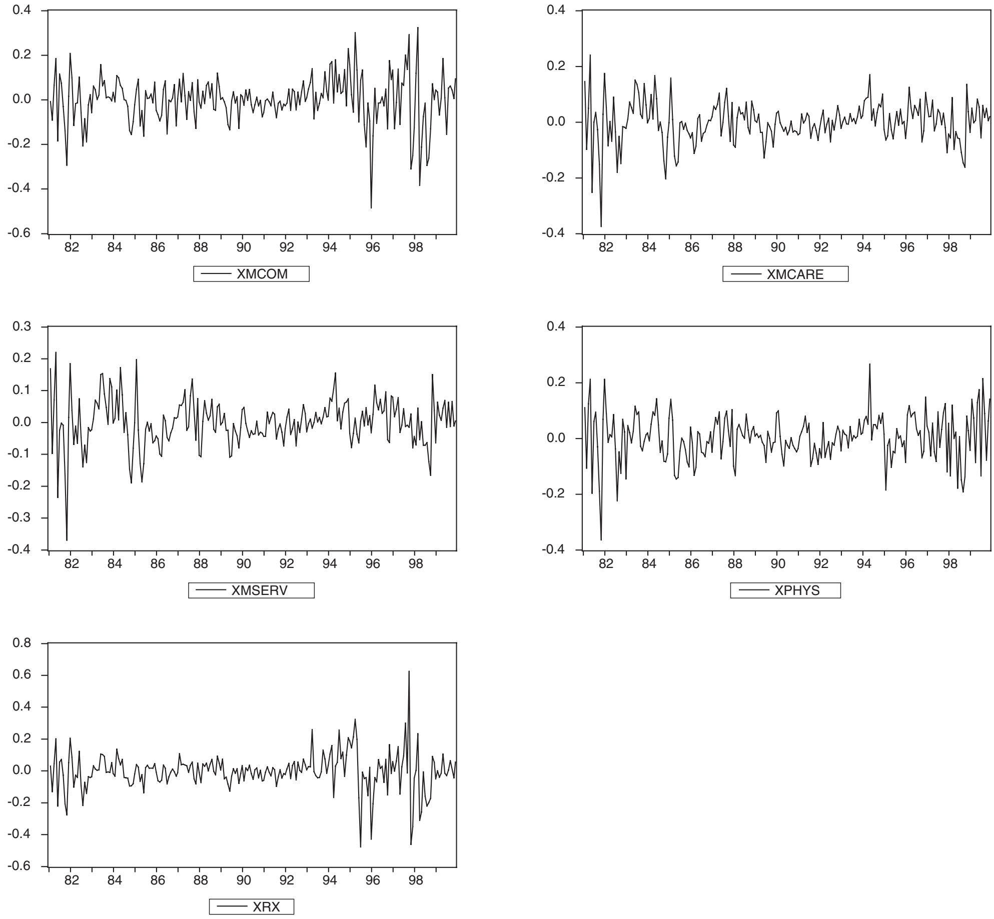
experiment." Payne et al. (1999) discussed this issue and showed that net discount rates by earnings sector were affected by this change in interest rate regime.

[7] See Gamber and Sorenson (1994) for more on the computation of the net discount rate. Note that the medical cost indexes measure the cost of a fixed bundle of goods or services over time, while the medical expenditures of an individual constitute a changing mix of goods and services over time.

Figure 2
Changes in MNDRs



All variables are in first-differences. XMCARE ≡ MNDR for medical care, XMCOM ≡ MNDR for medical care commodities, XMSERV ≡ MNDR for medical care service, XPHYS ≡ MNDR for physician's services, and XRX ≡ MNDR for prescription drugs and supplies. The MNDRs represent percents and are measured as differences on the vertical axis. Years are on the horizontal axis.

Tables 1 and 2 show descriptive statistics for each of the MNDRs in levels and their first-differences, respectively. We found the highest mean net discount rate in MCOM, followed by PHYS, MCARE, MSERV, and RX. Standard deviations ranged from a low of 0.35 in PHYS to a high of 0.50 in RX. The range in MNDRs was from a minimum of −0.48 (XRX) to a maximum of 1.89 (XMCOM). The mean change in each MNDR was not significantly different from zero. The standard deviation of change in MNDR was highest in RX, and the lowest standard deviation was for MCARE. Each of the differenced MNDRs exhibited excess kurtosis (i.e., fat tails), a property that is often associated with time-varying volatility. Based on a review of the descriptive statistics, it appears that it may not be appropriate to assume that the time-series behavior of

TABLE 1
Descriptive Statistics for MNDRs

	XMCARE	XMCOM	XMSERV	XPHYS	XRX
Mean	0.2488	0.3842	0.2361	0.3051	0.2148
Median	0.2871	0.2521	0.2439	0.2913	0.0411
Max.	1.0560	1.8901	1.1139	1.0389	2.1301
Min.	−0.4545	−0.3706	−0.4805	−0.4031	−0.4772
Std. Dev.	0.3795	0.4851	0.3919	0.3451	0.4977
Kurtosis	2.1588	3.5973	2.1929	2.2311	4.8401

Notes: XMCARE ≡ MNDR for medical care, XMCOM ≡ MNDR for medical care commodities, XMSERV ≡ MNDR for medical care service, XPHYS ≡ MNDR for physician's services, and XRX ≡ MNDR for prescription drugs and supplies. The number of usable observations equals 228.

TABLE 2
Descriptive Statistics for Changes in MNDRs

	△XMCARE	△XMCOM	△XMSERV	△XPHYS	△XRX
Mean	−0.0001	−0.0006	0.0001	0.0025	−0.0025
Median	0.0024	0.0027	−0.0010	0.0077	0.0008
Max.	0.2403	0.3245	0.2204	0.2665	0.6254
Min.	−0.3747	−0.4846	−0.3695	−0.3638	−0.4766
Std. Dev.	0.0735	0.1077	0.0737	0.0837	0.1176
Kurtosis	6.4163	5.6178	6.0713	4.5471	8.8959

Notes: △ denotes the first-difference operator, XMCARE ≡ MNDR for medical care, XMCOM ≡ MNDR for medical care commodities, XMSERV ≡ MNDR for medical care service, XPHYS ≡ MNDR for physician's services, and XRX ≡ MNDR for prescription drugs and supplies. The number of usable observations equals 227.

each medical cost index, and its corresponding MNDR, is identical. This warrants a more formal examination of the time-series properties of each MNDR.

To determine whether or not each of the MNDRs is stationary, we performed unit root tests based on the method of Dickey and Fuller (1981).[8] We used the augmented Dickey-Fuller test (ADF) to check for the presence of unit roots and base it on the ordinary least-squares regression of Equation (2).

[8] This article focuses on the MNDR and does not specifically examine the time-series behavior of the underlying components of the net discount rate. However, preliminary evidence suggests that both the interest rate and the growth rates in the medical cost indexes are nonstationary (results available upon request). It is possible for two nonstationary series to form a stationary series. For example, if the two underlying series were cointegrated, a simple bivariate error correction model would provide information as to how the two series returned to an equilibrium relationship following a shock. However, for the case in which the two underlying series do not form a stationary series and are not cointegrated, examination of the constructed series (i.e., the MNDR) is appropriate and informative.

$$\triangle X_t^j = \rho_0 + (\rho_1 - 1)X_{t-1}^j + \rho_2 t + \sum_{k=1}^{m} \alpha_k \triangle X_{t-k}^j + e_t, \tag{2}$$

where X^j is the individual MNDR series under investigation, $\triangle$ is the first-difference operator; t is a linear time trend, e_t is a covariance stationary random error, and m is determined by Akaike's information criterion to ensure serially uncorrelated residuals. The null hypothesis is that the MNDR is a nonstationary time series and is rejected if $(\rho_1 - 1) < 0$ and is statistically significant. We used the finite sample critical values for the ADF test developed by MacKinnon (1991) to determine statistical significance.

The results of the unit root tests are presented in Table 3 and suggest that each series is nonstationary. Note that while we included a constant in the ADF tests, we determined that none of the MNDRs exhibited a deterministic time trend. A shock to any one of these series is permanent, as the MNDR will not return to its long-run mean value over time. However, we found the first-difference of each MNDR to be stationary. Thus, the first-difference of each MNDR is stationary around its mean and, therefore, historical averages of changes in MNDRs may be useful approximations for future changes in MNDRs. Moreover, this finding suggests that forecasting models of MNDRs should be specified using the first-difference of the MNDR as opposed to the level. While a shock to a change in MNDR is transitory, it may not fully dissipate within one month. An autoregressive moving average (ARMA) model in first-differences is capable of handling this type of behavior and is often used when forecasting variables with similar properties as these MNDRs.

Equation (3) gives an ARMA model of the MNDR in first-differences. For ease of exposition, we now drop the superscript.

$$\phi(L)\triangle X_t = \theta(L)\varepsilon_t + \mu, \tag{3}$$

where $\triangle$ is the first-difference operator, ϕ and θ are polynomials in the lag operator L, ε is an error term, and μ is a constant term. Examination of the autocorrelation

TABLE 3
ADF Tests of Stationarity

MNDR	Level	First-Difference
XMCARE	−2.56	−4.80[a]
XMCOM	−2.41	−4.94[a]
XMSERV	−2.59	−4.79[a]
XPHYS	−1.95	−6.04[a]
XRX	−2.45	−5.15[a]

Notes: Superscripts a and b denote significance at the 1 and 5 percent levels, based on critical values in MacKinnon (1991). We used four lags on the augmenting term, as suggested by Akaike's information criterion, which were sufficient to ensure the absence of autocorrelation in the residuals. Note that $\triangle$ denotes the first-difference operator, XMCARE ≡ MNDR for medical care, XMCOM ≡ MNDR for medical care commodities, XMSERV ≡ MNDR for medical care service, XPHYS ≡ MNDR for physician's services, and XRX ≡ MNDR for prescription drugs and supplies.

TABLE 4
MA Estimation of MNDRs

	$\triangle$XMCARE	$\triangle$XMCOM	$\triangle$XMSERV	$\triangle$XPHYS	$\triangle$XRX
μ	5.69×10^{-5}	−0.0004	0.0002	0.0027	−0.002
θ_1	0.3353[a]	0.2384[a]	0.4169[a]	0.2177[a]	0.1619
BG	1.93	1.19	2.92	1.81	0.38
ARCH-LM	20.53[a]	8.54[a]	25.06[a]	15.95[a]	39.29[a]
Adj. R^2	0.08	0.04	0.12	0.03	0.02

Notes: θ denotes the estimated coefficients on the MA(1) component of the model, and μ is a constant term. The superscripts a and b denote significance at the 1 and 5 percent levels. Note that *BG* is the Breusch-Godfrey test statistic for serial correlation (null hypothesis is no serial correlation), *ARCH-LM* is the chi-square statistic to test for autoregressive conditional heteroscedasticity (null hypothesis is no ARCH effects), and $\triangle$ denotes the first-difference operator. XMCARE ≡ MNDR for medical care, XMCOM ≡ MNDR for medical care commodities, XMSERV ≡ MNDR for medical care service, XPHYS ≡ MNDR for physician's services, and XRX ≡ MNDR for prescription drugs and supplies. The number of included observations is 227.

functions and standard Box-Jenkins techniques indicated that the best-fitting model for each $\triangle$MNDR was ARMA(0,1), that is, MA(1). Table 4 presents the results of estimating Equation (3) for the $\triangle$MNDRs. In each case, the MA term was significantly different from zero at less than the 1 percent level. The MA(1) terms varied from a low of 0.16 to a high of 0.42.[9] In addition, each of the models was free of serial correlation as evidenced by Breusch-Godfrey tests. The results of the MA(1) models suggest that shocks to changes in MNDRs affect the series in the current period and in the period immediately following the shock. Thus, while each $\triangle$MNDR is stationary, shocks do not immediately dissipate, and this information can be used to construct viable forecasting models of the $\triangle$MNDRs.

The conventional (linear) ARMA model assumes that the variance of the error process is constant (i.e., the unconditional variance and the conditional variance exist and are greater than zero, and the current volatility is independent of past volatilities). We tested each MA(1) model for the presence of ARCH using the Lagrange multiplier test described in Engle (1982, p. 1000). The models all exhibited ARCH effects, suggesting that the variance of the equations varies over time in a way that depends on how large the errors were in the past. This confirms the casual observation of volatility clustering, as seen in Figure 2.

Engle (1982) has shown that in the presence of ARCH, modeling both the mean and the variance of the process under investigation improves the efficiency of the parameter estimates. The ARCH technique models the variance of the series as a function of past volatility. The ARCH model allows for nonlinearity in the second moment in that the variance changes over time in a predictable way.

In order to examine the MNDR with time-varying volatility, we estimated the following two equations simultaneously via the method of maximum likelihood.

[9] The necessary and sufficient conditions for the models to be stationary were met. For a discussion of these conditions and their derivation, see Harvey (1994).

TABLE 5
MA–ARCH Estimation of MNDRs

	△XMCARE	△XMCOM	△XMSERV	△XPHYS	△XRX
Mean					
μ	0.0038	0.0091	0.0034	−0.0008	−0.0020
θ_1	0.4149[a]	0.2096[b]	0.4084[a]	0.3046[a]	0.4073[a]
Variance					
α_0	0.0027[a]	0.0065[a]	0.0026[a]	0.0040[a]	0.0052[a]
α_1	0.4402[a]	0.5029[a]	0.4248[a]	0.4292[a]	0.8781[b]

Notes: The superscripts a and b denote significance at the 1 and 5 percent levels. Note that △ denotes the first-difference operator, XMCARE ≡ MNDR for medical care, XMCOM ≡ MNDR for medical care commodities, XMSERV ≡ MNDR for medical care service, XPHYS ≡ MNDR for physician's services, and XRX ≡ MNDR for prescription drugs and supplies.

$$\phi(L)\triangle X_t = \theta(L)\varepsilon_t + \mu, \quad \varepsilon_t \sim N(O,h_t^2) \tag{4}$$

$$h_t^2 = \alpha_0 + \sum_{a=1}^{q} \alpha_a \varepsilon_{t-a}^2 \tag{5}$$

Equation (4) gives the mean equation of the change in MNDR and includes a constant term (μ) in the estimation, while Equation (5) is the (conditional) variance equation.[10] $V(\varepsilon_t|\Omega_{t-1}) = h_t^2$ is the conditional variance of ε_t with respect to the information set Ω_{t-1}.[11]

Table 5 presents the results. The mean equation results are similar to those presented in Table 4 and are discussed above, so we do not discuss them here. Note, however, that the ARCH terms are all statistically significant. This suggests that the volatility of each △MNDR is predictable and depends on how large the error was in the past. Thus, one would expect the effect of unexpected changes in discount rates or medical costs to increase the volatility of the △MNDR in the short term, as well as increase/decrease the value of the △MNDR in accordance with whether it was a positive or negative shock.

In particular, we found that each △MNDR can be modeled as an ARCH(1) process. The estimated ARCH terms are 0.88 (XRX), 0.50 (XMCOM), 0.44 (XMCARE), 0.43 (XPHYS), and 0.42 (XMSERV). Thus, a shock to the △MNDR increases volatility in the next (future) period, with the effect being largest in XRX and smallest in XMSERV. In each case, we found that conditional volatility of the series can be predicted. Taking

[10] We computed the quasi–maximum likelihood covariances and standard errors as described in Bollerslev and Wooldridge (1992). We estimated the model under the assumption that the errors are conditionally normally distributed.

[11] The necessary condition for Equation (4) to be covariance-stationary, $\alpha_1 < 1$, was satisfied in each case. And q-statistics suggested that the mean equation was free of serial correlation. Correlograms of the squared standardized residuals indicated that the variance equation was correctly specified, with no evidence of remaining ARCH effects. Jarque-Bera tests indicated that the standardized residuals may not have been normally distributed. However, the estimates were still consistent under quasi–maximum likelihood assumptions (see Bollerslev and Wooldridge, 1992).

this information into account improves our understanding of the time-series behavior of MNDRs. As an example of the improvement in forecasting that can be expected by taking into account the time-series behavior of the MNDR, we compared several (out-of-sample) forecast estimates of the medical care net discount rate (XMCARE). A standard moving average model (i.e., MA[1]) provided a point estimate for May 2000 equal to 0.25, while the moving average model (in first-differences) augmented with the ARCH equation provided a point estimate of 0.59. The actual value of XMCARE in May 2000 was 0.57. We performed this exercise for the other MNDRs, as well as for various forecast horizons, and we obtained similar results.

Concluding Remarks

This article has examined the time-series properties of MNDRs. Unit root tests indicated that each MNDR was nonstationary, while the first-difference of each series was stationary. We constructed ARMAs for the first-difference of each MNDR; however, they appeared to suffer from ARCH. To address the problem of time-varying volatility, we estimated ARCH models and found that the conditional variance of each $\triangle$MNDR was predictable and that current shocks to a series increased the volatility of the series in the next period.

The results can be summarized as follows. The mean MNDRs are between 0.21 and 0.38 percent. Unexpected changes in the value of a MNDR are permanent, as the levels of the MNDRs are nonstationary. This is a particularly interesting finding as a number of articles have identified the earnings net discount rate as a trend-stationary process (e.g., Payne et al., 1999; Hays et al., 2000). Thus, for example, the assumptions commonly made in applied work that is directed toward computing the value of economic damages in lost earnings do not necessarily carry over to the computation of medical damages. However, shocks to changes in the MNDRs are temporary and do not persist indefinitely. At first glance, this suggests that, in applied work, it is not appropriate to use the historical mean of the MNDR. Further analysis suggests that changes in MNDRs can be forecast using a standard ARMA model. In our case, we found the MA(1) specification to work fairly well. Based on differences in the time-series behavior of the changes in MNDRs, in particular the moving average components, it may be misleading to generalize the behavior of all MNDRs by focusing attention solely on the MNDR computed using the composite medical cost index. However, regardless of the MNDR of interest, we found that unexpected changes in the first-differences of MNDR also have a significant effect on the volatility of the series. This confirms the commonly held belief that MNDRs and inflation are characterized by distinct periods of high volatility and low volatility. We used the ARCH model of Engle (1982) to model the time-varying volatility of the changes in MNDRs and found that the estimation of ARCH models improves parameter estimates over the standard MA model by increasing efficiency.[12]

We found differences in the degree of persistence of volatility depending on which MNDR was used, which provides additional evidence against using just the compos-

[12] In applied work, the future level of the MNDR is often of interest. However, most statistical packages will provide the forecast of the level based on a model that is estimated in first-differences (e.g., Eviews, MicroTSP, Win RATS). Modeling the time-varying volatility characteristic of the MNDRs (i.e., ARCH effects) in conjunction with the MA model of the mean change in the MNDR improves this forecast.

ite index in applied work. Moreover, our findings suggest the need to examine the MNDR series under investigation in some detail before making forecasts or conducting present-value analysis. For example, if one is interested in using the PHYS MNDR to compute the present value of future medical needs over the next few years, then one can place more confidence in the point estimates if the period immediately preceding the forecast (1 to 2 months) is characterized by relatively low volatility as compared to high volatility. However, if the computation is to be made for a much longer horizon, the effects of any shock on volatility should dissipate and it is appropriate to use the current MNDR as the forecast; or if one is interested in changes in MNDR, then use of the historical average is appropriate. This research suggests that one can obtain improved forecasts by taking into account the time-varying nature inherent in the volatility of MNDRs. Thus, our results complement the work of others, such as Krueger (2001), who have shown the usefulness of the medical net discount, computed as in Equation (1), in litigation economics, where the present value of medical damages is an important issue. The findings presented here may aid the analyst or researcher in the computation of MNDRs to be used in applied work.

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