The Dynamic Relationship between Health and Health Insurance in the U.S.

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August 14, 2013

Abstract

This paper revisits the link between health insurance and health by estimating a model that allows for insurance and health to be linked through both dynamic and contemporaneous channels, each with different policy implications. The model produces two main findings. First, while insurance and health appear to be negatively related dynamically, they are positively related contemporaneously, with positive contemporaneous associations outweighing the negative dynamic links, resulting in a net positive relationship between insurance and health. Second, good health appears to be self-sustaining regardless of insurance status, implying that public policies should target health, directly, rather than indirectly via insurance reforms.

JEL Codes: I11, C33, C51
Keywords: dynamics, MEPS

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1 Introduction

In February 2010, President Obama signed into law landmark health care legislation that, for the first time, promised near universal health insurance coverage to every American. A key motivation behind passage of the law was the widely-held belief that when uninsured individuals acquire coverage, health status subsequently improves. Policy makers on both sides of the aisle rarely question the presumed links between insurance and health, but academic literature, both in economics and health services research, indicates that the links are much murkier. In the wake of the signing of the Affordable Care Act, a better understanding of these links has become an urgent concern if the expected impacts of the law are to be properly understood. This paper returns to this issue with particular emphasis on the dynamic links between insurance and subsequent health.

Existing studies on the impact of insurance on health fall into two categories. The first set, based on observational data, generally find small but significant positive correlations between insurance and health (see Hadley, 2003, for a review). However, studies based on observational data suffer from several empirical complications. First, individuals with health coverage surely differ from those without coverage across numerous dimensions. Some of these factors are recorded in household surveys, such as age, gender, race, and employment activity. However, other factors, such as risk aversion and genetic composition are, at best, only partially measured. Second, causality might point in the opposite direction, with health status influencing insurance coverage. For example, individuals, possessing knowledge of their own health states, might seek insurance policies tailored to their specific health needs. Furthermore, as widely reported in the popular press, insurance companies might seek to deny coverage to individuals with certain, presumably costly-to-insure, health problems.

To address these concerns, a second strand of literature attempts to exploit quasi-experimental settings in which health insurance is exogenously introduced to a particular population. The majority of evidence from these studies suggests that any positive effects of insurance on health are concentrated among certain groups, specifically infants, the elderly, and the poor, with less evidence of positive effects among the broader population (see Levy and Meltzer, 2003, for a review). These studies provide important information, as they approximate the "true" causal effect of insurance. On a more aggregate level, such studies provide insights into what could be expected if insurance coverage were extended to those currently lacking coverage.[1]

However, aside from Medicare Part A, which assigned a large population to one homogenous insurance plan, few health insurance reforms that have been implemented, or will be implemented, mimic these experimental settings (Hadley, 2003). To the contrary, health insurance reforms enacted in the U.S., beginning with Medicare Part B, have not simply re-assigned uninsured people to insurance. Rather, these reforms have typically allowed individuals to choose not only their type of insurance, but also whether to participate at all. Even the recently passed Affordable Care Act, with its mandate that everyone have insurance by 2014, leaves insurance choice, as

[1] Some noteworthy studies in this area include Lurie et al. (1996); Fihn and Wicher (1988); Haas, Udvarhelyi, and Epstein (1993); Currie and Gruber (1996); Goldman et al. (2001); Perry and Rosen (2001); Lee-Feldstein, Feldstein, Buchmueller, and Katterhagan (2003).

well as the decision to comply with the mandate, up to individuals. The implication is that when insurance reforms introduce elements of individual choice, the predicted impacts on health might depart from what is suggested by quasi-experimental studies.

An additional concern is that little evidence exists regarding the *dynamic* links between insurance and health. Lack of dynamic information in observational studies stems, largely, from a lack of data sources that track individuals' insurance coverage and health over time. In the case of quasi-experimental studies, inference often derives from one-time changes in policy, and, therefore, conclusions necessarily focus on short-run impacts. However, a more detailed dynamic investigation is warranted, as health responses to some medical interventions may require longer periods to materialize (Deb, Trivedi, and Zimmer, 2010).

This paper revisits the link between health insurance and health. However, rather than try to identify true causality via a quasi-experiment, this paper incorporates the dynamic concept of Granger causality (1969), which, despite its name, has less to do with true causality, and more to do with the extent to which insurance and health help predict each other. Results are based on two large longitudinal household surveys, each with different lengths and frequencies, which permits conclusions about both short-run and long-run links between insurance and health. The results, while of limited applicability to compulsory, blanket insurance expansions, should help assess the expected impacts of policies in which choice of compliance is, to some extent, left to individuals.

The model, based on a variant of Mosconi and Seri (2006), allows for insurance and health to be linked through both dynamic and contemporaneous channels, each with different policy implications. The model produces two main findings. First, while insurance and health appear to be negatively related dynamically, they are positively related contemporaneously. Most importantly, the positive contemporaneous associations outweigh the negative dynamic links, resulting in a net positive relationship between insurance and health. Second, good health appears to be self-sustaining regardless of insurance status, implying that public policies should focus less on insurance reform, and more on improving health. This conclusion coincides with extra-welfarist views of health economics (Brouwer and Koopmanschap, 2000).

2 Data

Estimates in this paper rely on two large household surveys, each with different lengths and frequencies. First, the Medical Expenditure Panel Survey (MEPS) records information at approximately six-month intervals but contains only five time periods per person. Second, the 1979 National Longitudinal Survey of Youth (NLSY) provides a longer panel − eight records per person in this study − but at only biennial frequency. Using two surveys with different frequencies allows an investigation of short-run versus long-run relationships. During the periods under consideration, these two surveys recorded information on the two measures of interest in this study: health insurance and health status.

The Medical Expenditures Panel Survey (MEPS) is a nationally representative household survey conducted by the Agency for Healthcare Research and Quality. The MEPS Household Component contains information on individuals' demographics, labor market attachment, health status, and insurance status. The present study focuses on respondents between ages 18 and 64, as insurance options for individuals outside this age range differ markedly. Data are drawn from the 2000-2006 waves, resulting in a sample of 5,518 unique individuals, after eliminating respondents with missing information for key variables. Each MEPS respondent is interviewed for five rounds over two and a half years. Although MEPS records some information at higher frequencies, health status is measured only for the five rounds. Consequently, a panel of five rounds was created for each respondent; although lengths vary somewhat, each round corresponds to a reference period of approximately six months. The final sample includes a balanced panel of 27,590 person/round observations.

The 1979 National Longitudinal Survey of Youth (NLSY) originally consisted of 12,686 individuals who were between ages 14 and 21 in 1979. This cohort has been interviewed annually since 1979 (biennially since 1994). The survey contains detailed information about labor market attachment, employment traits, demographic characteristics, and, beginning in the early 1990s, health insurance coverage. The estimation sample is drawn from the 1990, 1992, 1994, 1996, 1998, 2000, 2002, and 2004 waves of the survey. The sample includes only individuals observed in all waves. The final sample size consists of 5,013 subjects, for a balanced panel of 40,104 person/biennial observations.[2]

[2]In a study of state dependence in health status, Contoyannis, Jones, and Rice (2004) find that sample attrition does not substantially influence their main findings. However, it is difficult to determine whether their finding also applies to the analysis in this paper. In a short panel, such as MEPS, concerns of attrition are somewhat reduced. For NLSY, approximately 26 percent of subjects present in the 1990 wave attrited before the 2004 wave. Sample averages did not reveal any statistically significant year-to-year differences in insurance or health between those who remain in the survey and those who attrited. However, this is only an informal check. More formally

The two most important variables in this study are insurance coverage and health status. For both MEPS and NLSY, insurance is defined as having coverage from any source, public or private, at the time of interview. In MEPS, the main health indicator measures whether the respondent's self-reported health was "excellent", "very good", or "good". In NLSY, the main health variable relates specifically to employment prospects: It captures whether the individual's health status *does not* limit current work activity. For the remainder of the paper, these two health measures are referred to, collectively, as "good health". It is important to note that both health measures rely on self-reported information. MEPS does record more objective health measures, but not for all rounds, and NLSY records objective health measures only for the over-40 population. However, self-reported health measures, even coarsely defined binary measures such as the ones used in this paper, have been shown to strongly correlate with more objective health measures (Bound, 1991).

Based on these variable definitions, the unconditional correlations between insurance and health are 0.02 in MEPS and 0.04 in NLSY; both are statistically larger than zero at the 0.01 level. The numbers indicate positive, albeit weak, positive contemporaneous associations between insurance and health.

Tables 1 and 2 provides information about dynamic links. Taking the first row of Table 1 as an example, 895 person/round observations in MEPS begin with no insurance and bad health. 410 of these observations remain in that state in the subsequent round. The remaining observations experience transitions in the subsequent

addressing attrition would add another layer of complexity to an already-large model. However, the similarity between results obtained from the two surveys should, at least to some extent, offer evidence that attrition probably has minimal effect on the main findings.

round: 346 switch to good health, 94 acquire insurance, and 45 switch to good health and acquire insurance. Overall, Tables 1 and 2 highlight several points. First, subjects appear highly likely to remain in their previous-period state, which is consistent with evidence of state dependence in insurance and health (Zimmer, 2010). Second, anticipating one of the main findings of this paper, good health appears to exhibit high persistence regardless of insurance status. Third, bad health appears to exhibit relatively lower persistence, again regardless of insurance state, indicating a sort of gravitational pull toward good health, at least among the non-elderly populations considered in this paper.

Table 3 provides sample means separated by income level.[3] Most of the control variables in MEPS were recorded in the first round, and therefore, do not vary across time. In NLSY, these measures are recorded every two years, and thus do vary across time. For sake of comparison, however, all sample averages refer to the initial wave/year. Not surprisingly, subjects in the low income group are less likely to have insurance and report good health. Other socioeconomic variables also appear to vary by income status. For example, in both surveys, the high income group is slightly older, more educated, and more likely to be married. The low income group has larger families and consists of a higher percentage of females and minorities.

[3] Because income measures vary over time in NLYS, but not in MEPS, each sample relies on a different definition for "low income." In MEPS, low income refers to subjects with family incomes below 200 percent of the federal poverty line upon entry in the survey. In NLSY, low income refers to subjects who report being in poverty at any point in the survey.

3 Dynamic Bivariate Probit

This section presents a bivariate model of insurance and health, allowing for both contemporaneous and dynamic links between the two. The specification also accounts for unmeasured heterogeneity, both time-varying and time-invariant. Most importantly, the models permits specific tests of these various links between insurance and health, and, as outlined in more detail below, it provides a laboratory through which to assess the impacts of health insurance expansions. The model is a variant of an approach developed by Mosconi and Seri (2006). To keep the present paper relatively self-contained, key details of the model are outlined here, but the interested reader is referred to Mosconi and Seri for a more detailed exposition.

3.1 The model

Let y_{it} be a dichotomous indicator equaling 1 if subject i has insurance in period t, and 0 otherwise. Similarly, let h_{it} equal 1 if subject i is in good health in period t, and 0 otherwise. Subject i's insurance state and health status follow

$$y_{it} = \mathbf{1}\left(\gamma_{11} y_{i,t-1} + \gamma_{12} h_{i,t-1} + \gamma_{13} y_{i,t-1} h_{i,t-1} + \mathbf{X}_{it} \boldsymbol{\beta}_1 + c_{1i} + \epsilon_{1it} > 0\right) \tag{1}$$

$$h_{it} = \mathbf{1}\left(\gamma_{21} y_{i,t-1} + \gamma_{22} h_{i,t-1} + \gamma_{23} y_{i,t-1} h_{i,t-1} + \mathbf{X}_{it} \boldsymbol{\beta}_2 + c_{2i} + \epsilon_{2it} > 0\right) \tag{2}$$

where $\mathbf{1}(\cdot)$ denotes the indicator function. These formulations specify insurance and health as dependent on the following components: (1) previous-period insurance and health, as well as their interaction; (2) exogenous explanatory variables, $\mathbf{X}_{it}$, some of which vary over time; (3) time-invariate unobserved heterogeneity, c_{1i} and c_{2i}, that affect insurance and health, respectively, and are possibly related; (4) random time-varying disturbances, ϵ_{1it} and ϵ_{2it}. The disturbances follow a bivariate normal distribution,

$$\begin{bmatrix} \epsilon_{1it} \\ \epsilon_{2it} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \cdot \\ \rho_{it} & 1 \end{bmatrix}\right) \tag{3}$$

where the correlation depends on previous-period insurance and health,

$$\rho_{it} = \arctan\left(\delta_0 + \delta_1 y_{i,t-1} + \delta_2 h_{i,t-1} + \delta_3 y_{i,t-1} y h_{i,t-1}\right). \tag{4}$$

The arctan operator ensures correlations bound on $(-1, 1)$.

The unobserved heterogeneity terms, c_{1i} and c_{2i}, are treated as random effects, which introduces two complications. First, a respondent's initial insurance and health states, y_{i1} and h_{i1}, are likely correlated with c_{1i} and c_{2i}, a situation referred to as the "initial conditions" problem. Following Wooldridge (2005), this problem is addressed by parameterizing c_{1i} and c_{2i} as functions of y_{i1} and h_{i1}, which treats initial conditions as deterministic and allows them to correlate with the random effects. The second complication is that random effects models require c_{1i} and c_{2i} to be uncorrelated with conditioning variables. This is almost certainly violated in the current context, as socioeconomic information, such as martial status, cannot be assumed to be independent of insurance and health. This concern is addressed by further parameterizing c_{1i} and c_{2i} as functions of time-averaged time-varying controls, denoted $\overline{\mathbf{X}}_i$, a modification that permits correlation between explanatory variables and random effects (Mundlak, 1978; Chamberlain, 1984). Thus, the unobserved heterogeneity terms are specified as

$$c_{1i} = \alpha_{11} y_{i1} + \alpha_{12} h_{i1} + \overline{\mathbf{X}}_i' \boldsymbol{\alpha}_1 + \xi_{1i}, \tag{5}$$

$$c_{2i} = \alpha_{21} y_{i1} + \alpha_{22} h_{i1} + \overline{\mathbf{X}}_i^{'} \boldsymbol{\alpha}_2 + \xi_{2i}, \tag{6}$$

where ξ_{1i} and ξ_{2i} denote time-invariant heterogeneity. Note that in the MEPS sample, marital status is the only time-varying control variable. In contrast, other than racial and gender indicators, all control measures vary over time in the NLSY sample.

Substituting (5) and (6) into (1) and (2), the right-hand side information can be summarized as

$$\mu_{yit} = \gamma_{11} y_{i,t-1} + \gamma_{12} h_{i,t-1} + \gamma_{13} y_{i,t-1} h_{i,t-1} + \mathbf{X}_{it} \boldsymbol{\beta}_1 + \alpha_{11} y_{i1} + \alpha_{12} h_{i1} + \overline{\mathbf{X}}_i^{'} \boldsymbol{\alpha}_1 + \xi_{1i}$$

$$\mu_{hit} = \gamma_{21} y_{i,t-1} + \gamma_{22} h_{i,t-1} + \gamma_{23} y_{i,t-1} h_{i,t-1} + \mathbf{X}_{it} \boldsymbol{\beta}_2 + \alpha_{21} y_{i1} + \alpha_{22} h_{i1} + \overline{\mathbf{X}}_i^{'} \boldsymbol{\alpha}_2 + \xi_{2i}.$$

Together with the distribution specified in (3), the model follows a bivariate probit formulation. Defining $q_{yit} = 2y_{it} - 1$ and $q_{hit} = 2h_{it} - 1$, the (unlogged) likelihood contribution of subject i is expressed as

$$L = \prod_{t=3}^{T} \Phi_2 \left(q_{yit} \mu_{yit}, q_{hit} \mu_{hit}, q_{yit} q_{hit} \rho_{it} \right) \tag{7}$$

where $\Phi_2 (\cdot)$ represents the cumulative bivariate standard normal distribution.[4]

Note that the likelihood equation (7) depends on time-invariant heterogeneity (ξ_{1i}, ξ_{2i}), which is not observed. Estimation proceeds by assuming that (ξ_{1i}, ξ_{2i}) follow a joint standard normal distribution with correlation θ. The heterogeneity terms are then numerically integrated out of equation (7), and the resulting expression is maximized with respect to the estimable parameters.[5]

[4]Periods $t = 1, 2$ are omitted from this calculation to accommodate the inclusion of lagged values and initial conditions. Thus, the MEPS likelihood is formed from the remaining 3 time periods, whereas the NLSY likelihood is formed from the remaining 6 periods.

[5]Estimation proceeds by Maximum Simulated Likelihood (Train, 2003) with 25 quasi random halton draws. Results were robust to larger numbers of draws, but covergence slowed considerably.

All models consider AR(1) dynamics, partly because of the relatively short MEPS sample. To be sure, the vector-autoregression literature suggests that higher order systems might provide better approximations with high-frequency data, such as daily or monthly, and when there are no conditioning variables to absorb variation in the dependent variable (Lutkepohl, 1991). On the other hand, with relatively low-frequency data and a suitable list of regressors, the case for a higher order model is less compelling.

3.2 Links between insurance and health

The model introduces three channels through with insurance and health are linked. One of these channels describes dynamic links while the other two capture contemporaneous associations. First, lagged values of insurance and health, as well as their interaction, enter directly into expressions (1) and (2). Second, the correlation term, ρ_{it}, captures the influence of time-varying factors that affect both insurance and health. Although this term reflects contemporaneous correlations, its magnitude does include dynamic elements, as it depends, in part, on lagged insurance and health, as specified in expression (4). Third, time-invariant heterogeneity that affects insurance (ξ_{1i}) and heterogeneity that affects health (ξ_{2i}) are linked through the estimable correlation term θ.

The model's numerous links between insurance and health, although thorough, also cloud interpretation. While the following section introduces formal tests of these links, this section presents an estimated conditional probability that distills all of the various links into one measure to assist policy discussions.

Because health, rather than insurance itself, should be the main focus on policy discussions (Brouwer and Koopmanschap, 2000), the probability of interest is $\widehat{\Pr}(h_t = 1|y_t = 1)$. This probability can be calculated, post estimation, as

$$\widehat{\Pr}(h_t = 1|y_t = 1) = \frac{\widehat{\Phi}_2\left(\widehat{\mu}_{yit}, \widehat{\mu}_{hit}, \widehat{\rho}_{it}\right)}{\widehat{\Phi}\left(\widehat{\mu}_{yit}\right)} \tag{8}$$

where the circumflex notation indicates that estimated parameter values have been substituted, and Φ denotes the univariate normal distribution. Note that this probability incorporates contemporaneous links between insurance and health, via the bivariate distribution Φ_2, as well as dynamic relationships, as $\widehat{\mu}_{yit}$, $\widehat{\mu}_{hit}$, and $\widehat{\rho}_{it}$ all depend on lagged insurance and health.

Conditioning on $y_t = 1$ serves two purposes. First, it preserves the explicit contemporaneous links between insurance and health, which would only be indirectly present if one calculated the marginal probability $\widehat{\Pr}(h_t = 1)$. Second, it allows for the construction of a policy experiment where subjects acquire insurance in period $t-1$, and then retain coverage in the subsequent period. Such a policy experiment, which seems consistent with real life policy initiatives, particularly the recently-passed Affordable Care Act, is discussed below in more detail. However, to explore the implications of conditioning on insurance status, and to assess the impact of contemporaneous links, Section 6 presents estimates of $\widehat{\Pr}(h_t = 1)$, without conditioning on y_t, from a simpler specification that does not incorporate contemporaneous links.

4 Tests of Links between Insurance and Health

Much of the time series literature emphasizes the concept of "non-causality", which, in the event that non-causality is rejected, allows the researcher to remain agnostic about the channels through which different variables are linked. In the same spirit, the model presented above permits formal tests of non-causality between insurance and health, but the model does not capture "true" causality in the experimental sense of the concept. That is, the model cannot, nor does it seek to, mimic random assignment into insurance. Rather, the causality definitions conform with the Granger notion of the term, which, as noted by Hamilton (1994, p. 308), has more to do with prediction than true causality. These definitions of causality, while of limited applicability to compulsory, blanket insurance expansions, should help assess the expected impacts of policies, such as the recently-passed Affordable Care Act, in which insurance assignment is not random, but rather insurance states are, to some extent, left to individuals.

Using terminology introduced by Florens and Fougere (1996), the definition of non-causality employed in this paper is *one-step ahead*, which describes the time horizon, and *strong*, implying that the focus is on the entire distribution (Chamberlain, 1982; Florens and Mouchart, 1982). Then, following Mosconi and Seri (2006), the non-causality definitions are:

- **Definition 1−One-step ahead strong non-causality:** h does not one-step ahead strongly cause y if, conditional on $\mathbf{X}$,

$$\Pr\left(y_{it}|y_{i,t-1},h_{i,t-1},\mathbf{X}_{it},c_{1i}\right)=\Pr\left(y_{it}|y_{i,t-1},\mathbf{X}_{it},c_{1i}\right).$$

Similarly, y does not one-step ahead strongly cause h if, conditional on X

$$\Pr\left(h_{it}|y_{i,t-1},h_{i,t-1},\mathbf{X}_{it},c_{2i}\right)=\Pr\left(h_{it}|h_{i,t-1},\mathbf{X}_{it},,c_{2i}\right).$$

In words, if lagged insurance offers no assistance in predicting current health, then insurance does not one-step ahead cause health (and the same for the effect of lagged health on current insurance).

- **Definition 2−Strong contemporaneous non-causality:** y and h are strongly contemporaneously non-causal if

$$\Pr\left(y_{it}|h_{it},y_{i,t-1},h_{i,t-1},\mathbf{X}_{it},c_{1i}\right)=\Pr\left(y_{it}|y_{i,t-1},h_{i,t-1},\mathbf{X}_{it},c_{1i}\right)$$

and

$$\Pr\left(h_{it}|y_{it},y_{i,t-1},h_{i,t-1},\mathbf{X}_{it},c_{2i}\right)=\Pr\left(h_{it}|y_{i,t-1},h_{i,t-1},\mathbf{X}_{it},c_{2i}\right)$$

This definition implies that current health (insurance) offers no assistance in predicting current insurance (health).

- **Definition 3−Strong contemporaneous spurious non-causality:** y and h are strongly spuriously non-causal if

$$\Pr\left(y_{it}|h_{it},y_{i,t-1},h_{i,t-1},\mathbf{X}_{it},c_{1i},c_{2i}\right)=\Pr\left(y_{it}|y_{i,t-1},h_{i,t-1},\mathbf{X}_{it},c_{1i}\right)$$

and

$$\Pr\left(h_{it}|y_{it},y_{i,t-1},h_{i,t-1},\mathbf{X}_{it},c_{1i},c_{2i}\right)=\Pr\left(h_{it}|y_{i,t-1},h_{i,t-1},\mathbf{X}_{it},c_{2i}\right)$$

In words, insurance and health are spuriously non-causal if time-invariant factors that affect health (insurance) do not help predict insurance (health).

Following Mosconi and Seri (2006), tests of these three definitions proceed as follows:

- **Test of definition 1:** h does not strongly one step ahead cause y if $\gamma_{12} = \gamma_{13} = 0$, or, stated differently, if $h_{i,t-1}$ can be excluded from equation (1). Similarly, y does not strongly one step ahead cause h if $\gamma_{21} = \gamma_{23} = 0$, or, stated differently, if $y_{i,t-1}$ can be excluded from equation (2).

- **Test of definition 2:** y and h are contemporaneously non-causal if $\delta_0 = \delta_1 = \delta_2 = \delta_3 = 0$, or, stated differently, if $\rho_{it} = 0$ in equation (3).

- **Test of definition 3:** y and h are contemporaneously spuriously non-causal if $\theta = 0$, or, stated differently, if the two time-invariant heterogeneity factors (ξ_{1i}, ξ_{2i}) do not exhibit correlation.

Standard Wald tests are used to calculate these three tests.

The differences between these three definitions are subtle, particularly the latter two. Yet, each holds different policy implications. If insurance and health are found to be dynamically related, as determined by Definition 1, then policies that aim to expand insurance coverage might yield significant improvements in future health, but cost-benefit analyses must account for the delayed benefits. Similar policy prescriptions would apply if insurance and health exhibit contemporaneous links, as in the case of Definition 2, but under this scenario, benefits would be sooner realized. On the other hand, if contemporaneous links between insurance and health derive primarily from spurious correlation based on unobserved heterogeneity, as in the case of

Definition 3, then public funds might be more efficiently employed to identify which traits drive these relationships.

5 Results

This section emphasizes dynamic and contemporaneous links between insurance and health, with brief mention given to estimates of control variables. Full tables of results appear in Appendix Tables A1−A4. Aside from some variation in precision, coefficients of the control variables reveal consistent patterns, both for low- and high-income respondents, and in both MEPS and NLSY. Females appear to be in worse health. Hispanics have lower insurance rates, while high-income NLSY blacks also have lower insurance rates. Both black and Hispanics have worse health in the low-income MEPS sample. Age negatively correlates with health, and is also positively associated with insurance in MEPS. Married subjects have higher insurance rates, but worse health in the high-income NLSY group. Family size correlates with better health in MEPS and more insurance among low-income NLSY respondents. Education shows positive associations with insurance and health, although some of these estimates lack statistical significance.

5.1 Dynamic links between insurance and health

Focusing first on own-state dependence, in both MEPS and NLSY, subjects who have insurance during the survey's initial period are, not surprisingly, more likely to have insurance in future periods. Likewise, subjects who enter in good health tend to remain in good health in future periods. Similar patterns emerge with respect to lagged insurance and health, with these lagged measures positively related to their current-period values.

Turning attention to the cross dynamic links between insurance and health, for high-income respondents, initial-period good health correlates with higher probabilities of having insurance in subsequent periods. The reverse is also true, with initial insurance correlating with better health in future periods. But the lagged measures reveal a different pattern. For low-income MEPS respondents, lagged insurance does not appear to influence current health, and lagged health does not appear to alter current insurance status. But for high-income MEPS subjects, the lagged health measure is negatively related to current insurance status, and, likewise, lagged insurance is negatively related to current health. Negative dynamic links between health and insurance have previously been reported by Zimmer (2010). This finding might reflect that health problems are more likely to be diagnosed when someone has access to health care. This finding is also consistent adverse selection into insurance; if prices of insurance policies do not completely reflect individual characteristics associated with anticipated health care spending, then individuals who expect to consume health care select into insurance (Chiappori and Salanie, 2000).

5.2 Contemporaneous links between insurance and health

The model incorporates contemporaneous links through two separate channels. First, the term ρ_{it} measures the extent to which time-varying factors influence insurance *and* health at time t. This contemporaneous measure does, however, include a dynamic dimension, as its magnitude depends on lagged insurance and health. The constant term for low-income subjects, both in MEPS and NLSY, is negative and significant.

For low-income respondents, lagged insurance and good health appears to strengthen current-period links between insurance and health, although this result lacks statistical significance in the NLSY sample. For high-income respondents, however, lagged insurance and good health appear to reduce contemporaneous links, although these findings are only marginally significant in both surveys.

The other contemporaneous measure, θ, captures the influence of time-invariant factors that affect both insurance and health at time t. For both MEPS and NLSY, this terms is negative and significant for low-income respondents, and positive and significant for high-income subjects.

Unfortunately, these numerous estimates make it difficult to determine the actual direction of contemporaneous links, let along their magnitudes, in part due to the role that previous-period insurance and health play in affecting these links. Section 5.4 presents estimated probabilities to help distill this information into a more interpretable form.

5.3 Wald tests of non-causality

Table 4 presents Wald statistics for the three tests outlined in Section 4. The first two rows show results for dynamic links. For low income subjects in both MEPS and NLSY, health does not appear to affect next-period insurance. On the other hand, among high income subjects, health does appear to help predict future insurance states. The second row shows that insurance does appear to be linked to next-period health status, with the exception of the low-income MEPS group, for which the estimate is not significant.

The third row shows that, aside from the high-income NLSY sample, insurance and health exhibit strong contemporaneous links, in the sense that current insurance (health) states have predictive value in determining current health (insurance) states. The fourth row indicates that health and insurance also exhibit spurious links, meaning that unobserved heterogeneity correlated with current health also correlates with current insurance.

5.4 Estimated probabilities

To help distill the various dynamic and contemporaneous links between insurance and health into more useful measures, Tables 5 report estimated probabilities of good health, calculated according to equation (8). These probabilities consider a policy experiment in which everyone has insurance in period t, but not everyone has insurance in period $t-1$. This hypothetical scenario roughly approximates the periods leading up to the Affordable Care Act's individual mandate, which requires everyone to acquire coverage by 2014. The goal is to assess the impact of acquiring insurance in period $t-1$ on health in period t.

The first two rows of each table show that when the subject was in good health in period $t-1$, the subject is also highly likely to remain in good health in period t regardless of previous-period insurance status. Thus, good health appears to be largely self-sustaining.

The next two rows consider subjects who lack good health in period $t-1$. In the relatively high-frequency MEPS survey, acquiring insurance in the previous period leads to larger probabilities of good health in the current period, 17 and 10 percentage points higher, respectively, for low- and high-income subjects. Although estimates from the full models indicate that lagged insurance *negatively* correlates with current-period health, this relationship is dwarfed by the *positive* current-period contemporaneous links, including the finding that previous-period insurance appears to strengthen positive current-period contemporaneous links.

In the NLSY survey, a similar pattern emerges for the high-income sample: previous-period insurance correlates with a 13 percentage point increase in the probability of current-period good health (evidenced by the increase in probability from 0.39 to 0.52). On the other hand, low-income subjects exhibit the opposite, with previous-period insurance associated with a 10 percentage point decrease in the probability of current-period good health. This disparate finding for the low-income NLSY group probably stems from the finding (shown in Table 4) that this group is the only one for which insurance strongly correlates with future health, but without a subsequent feedback effect to subsequent insurance states, thus reducing any potential synergistic effects between insurance and health.

6 A Simpler Specification without Contemporaneous Links

To compare the results from the previous section, with all its contemporaneous and dynamic channels, this section presents results from a simpler model that does not allow contemporaneous links. By comparing estimates of a simpler model to those from the full baseline specification, one can determine the relative impacts of dynamic versus contemporaneous links between insurance and health. The simpler model is based on a version of equation (2), repeated here,

$$h_{it} = \mathbf{1}\left(\gamma_{21} y_{i,t-1} + \gamma_{22} h_{i,t-1} + \gamma_{23} y_{i,t-1} h_{i,t-1} + \mathbf{X}_{it}\boldsymbol{\beta}_2 + c_{2i} + \epsilon_{2it} > 0\right) \tag{9}$$

where, in contrast to equation (2), the terms ρ_{it} and θ are restricted to zero. (That is, c_{2i} and ϵ_{2it} in the health equation are not linked to c_{1i} and ϵ_{1it} in the insurance equation.) Without contemporaneous links, equation (9) is estimated as a univariate dynamic probit, where

$$c_{2i} = \alpha_{21} y_{i1} + \alpha_{22} h_{i1} + \overline{\mathbf{X}}_i^{\prime} \boldsymbol{\alpha}_2 + \xi_{2i}, \tag{10}$$

and ξ_{2i} is treated as a univariate random effect.

Results from this restricted model, presented in Table 6, point to two important results. The first result, which confirms findings from the baseline model, is that, with only dynamic channels linking insurance and health, insurance is negatively dynamically related to good health, especially among low-income respondents.

Second, after removing the influence of contemporaneous effects, good health still appears to be self-sustaining irrespective of insurance status, as was the case in the more complete models. However, magnitudes shrink in the absence of contemporaneous effects: Previous-period good health correlates with probabilities of current-period good health between approximately 0.60−0.70 in MEPS and 0.80 in NLSY, reductions of 20 to 40 percent compared to the baseline models. The implication is that a sizable portion of persistence in good health stems from its ability to strengthen contemporaneous links between insurance and health.

7 Conclusion

It is important to highlight that, although improvements in health are certainly a focus of insurance expansions, they are not the only concern. Uncertainty in a utility-maximizing model introduces potential welfare losses. Pooling risks through insurance has the potential to reduce these welfare losses by mitigating the utility consequences of adverse health shocks. These potential welfare gains do not, at least to a first order, depend on the linkages between health and insurance.

This paper does not address these larger welfare issues. Rather it zeros in on relationships between health and insurance, with particular emphasis on the numerous dynamic and contemporaneous links between the two. The results of the model lead to several important policy implications. First, with the exception of low-income NLSY respondents, acquiring insurance does appear to correlate with future improvements in health. Although this presents an argument in favor of insurance expansions, these positive links derive, primarily, from *contemporaneous* associations between insurance and health. Indeed, consistent with previous research, dynamic links between insurance and health are negative, but the positive contemporaneous links more than outweigh the negative dynamic effects. These results appear to support insurance expansion as a means to improve health.

On the other hand, results also indicate that good health appears to be self-sustaining, both in short- and longer-run horizons. More importantly, this finding, as well as its magnitude, appears to be independent of previous-period insurance status. This finding suggests that public policies would be more efficiently implemented by targeting health, directly, rather than indirectly via insurance reforms.

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Table 1 – Transitions in insurance and health (MEPS)
$y = 1$ denotes insurance
$h = 1$ denotes good health

		Next period states			
		$y_{t+1}= 0$ $h_{t+1}= 0$	$y_{t+1}= 0$ $h_{t+1}= 1$	$y_{t+1}= 1$ $h_{t+1}= 0$	$y_{t+1}= 1$ $h_{t+1}= 1$
Previous period states					
$y_t= 0$ $h_t= 0$	N = 895	410	346	94	45
$y_t= 0$ $h_t= 1$	N = 5,097	314	4,069	49	665
$y_t= 1$ $h_t= 0$	N = 2,267	69	73	1,343	782
$y_t= 1$ $h_t= 1$	N = 13,813	38	646	731	12,398

Table 2 – Transitions in insurance and health (NLSY)
$y = 1$ denotes insurance
$h = 1$ denotes good health

		Next period states			
		$y_{t+1}= 0$ $h_{t+1}= 0$	$y_{t+1}= 0$ $h_{t+1}= 1$	$y_{t+1}= 1$ $h_{t+1}= 0$	$y_{t+1}= 1$ $h_{t+1}= 1$
Previous period states					
$y_t= 0$ $h_t= 0$	N = 615	178	147	182	108
$y_t= 0$ $h_t= 1$	N = 4,796	203	2,417	200	1,976
$y_t= 1$ $h_t= 0$	N = 2,500	171	131	1,450	748
$y_t= 1$ $h_t= 1$	N = 27,180	148	1,967	1,051	24,014

Table 3 – Sample mean upon entry into survey

	MEPS		NLSY	
	Low income	High income	Low income	High income
	N = 1,956	N = 3,562	N = 1,714	N = 3,299
Insurance	0.55	0.82	0.69	0.91
Good health	0.74	0.90	0.94	0.97
Age	37.0	40.5	28.9	29.1
Married	0.44	0.62	0.33	0.62
MSA	0.77	0.83	0.51	0.43
Family size	3.58	3.07	3.62	2.93
Education	10.9	13.3	11.8	13.5
Black	0.22	0.11	0.46	0.23
Hispanic	0.37	0.17	0.07	0.05
Female	0.57	0.51	0.63	0.50
Nonwage income	$96	$117	$214	$621

Table 4 – Wald tests of causality

Null hypothesis	MEPS Low income	MEPS High income	NLSY Low income	NLSY High income
Health does not one-step ahead cause insurance χ^2 (2)	1.31	17.28*	0.04	20.77*
Insurance does not one-step ahead cause health χ^2 (2)	1.52	10.03*	30.42*	7.48*
Insurance and health are not contemporenously causal χ^2 (4)	9.08†	15.14*	12.29*	6.77
Insurance and health are not spuriously linked χ^2 (1)	14.56*	10.85*	62.63*	74.56*

* p < .05; † p < .10

Table 5 – Estimated probabilities from full model

$\Pr(\text{good health}_t = 1 | \text{insurance}_t = 1)$ - MEPS

Previous period states		Low income	High income
$\text{insurance}_{t-1} = 0$	$\text{good health}_{t-1} = 1$	0.99	0.96
$\text{insurance}_{t-1} = 1$	$\text{good health}_{t-1} = 1$	0.97	0.99
$\text{insurance}_{t-1} = 0$	$\text{good health}_{t-1} = 0$	0.13	0.44
$\text{insurance}_{t-1} = 1$	$\text{good health}_{t-1} = 0$	0.30	0.54

$\Pr(\text{good health}_t = 1 | \text{insurance}_t = 1)$ - NLSY

Previous period states		Low income	High income
$\text{insurance}_{t-1} = 0$	$\text{good health}_{t-1} = 1$	0.93	0.99
$\text{insurance}_{t-1} = 1$	$\text{good health}_{t-1} = 1$	0.96	0.99
$\text{insurance}_{t-1} = 0$	$\text{good health}_{t-1} = 0$	0.44	0.39
$\text{insurance}_{t-1} = 1$	$\text{good health}_{t-1} = 0$	0.34	0.52

Table 6 – Estimated probabilities from model with no contemporaneous links

Pr(good $\text{health}_t = 1$) - MEPS

Previous period states		Low income	High income
$\text{insurance}_{t-1} = 0$	good $\text{health}_{t-1} = 1$	0.65	0.70
$\text{insurance}_{t-1} = 1$	good $\text{health}_{t-1} = 1$	0.60	0.73
$\text{insurance}_{t-1} = 0$	good $\text{health}_{t-1} = 0$	0.37	0.48
$\text{insurance}_{t-1} = 1$	good $\text{health}_{t-1} = 0$	0.31	0.47

Pr(good $\text{health}_t = 1$) - NLSY

Previous period states		Low income	High income
$\text{insurance}_{t-1} = 0$	good $\text{health}_{t-1} = 1$	0.82	0.78
$\text{insurance}_{t-1} = 1$	good $\text{health}_{t-1} = 1$	0.83	0.82
$\text{insurance}_{t-1} = 0$	good $\text{health}_{t-1} = 0$	0.55	0.30
$\text{insurance}_{t-1} = 1$	good $\text{health}_{t-1} = 0$	0.38	0.44

Appendix Table A1 – MEPS - Low income (* p < .05; † p < .10)

	Insurance equation		Good health equation	
	Coeff.	St. Err.	Coeff.	St. Err.
Insurance_{t-1}	2.099*	0.134	−0.069	0.139
Good health_{t-1}	0.154	0.140	0.705*	0.098
$\text{Insurance}_{t-1} \times \text{Goodhealth}_{t-1}$	−0.124	0.145	0.152	0.124
Age	0.145*	0.032	−0.244*	0.030
Married	0.315	0.217	−0.104	0.213
MSA	0.022	0.088	0.184*	0.083
Family size	−0.002	0.021	0.055*	0.022
Education	0.018	0.012	0.018	0.012
Black	−0.032	0.098	−0.054	0.093
Hispanic	−0.196*	0.094	−0.0002	0.093
Female	0.180	0.073	−0.042	0.071
Nonwage income	0.019	0.034	−0.069*	0.033
Constant	−2.150*	0.259	0.084	0.247
Initial insurance	1.148*	0.082	−0.106	0.105
Initial good health	−0.150	0.098	1.526*	0.080
Time-average married	−0.403†	0.239	0.162	0.234
ρ_{it}				
Insurance_{t-1}	0.445*	0.210		
Good health_{t-1}	0.582*	0.197		
$\text{Insurance}_{t-1} \times \text{Goodhealth}_{t-1}$	−0.574*	0.253		
Constant	−0.409*	0.176		
θ	−0.394*	0.103		

Appendix Table A2 – MEPS - High income (* p < .05; † p < .10)

	Insurance equation		Good health equation	
	Coeff.	St. Err.	Coeff.	St. Err.
Insurance_{t-1}	1.744^*	0.174	-0.525^*	0.189
Good health_{t-1}	-0.778^*	0.189	0.548^*	0.140
$\text{Insurance}_{t-1} \times \text{Goodhealth}_{t-1}$	0.482^*	0.180	0.066	0.155
Age	0.126^*	0.029	-0.166^*	0.030
Married	0.568^*	0.218	-0.189	0.236
MSA	0.011	0.087	0.118	0.084
Family size	-0.002	0.023	0.057^*	0.025
Education	0.057^*	0.012	$0.024^\dagger$	0.013
Black	-0.100	0.099	-0.358^*	0.095
Hispanic	-0.220^*	0.088	-0.235^*	0.092
Female	0.023	0.065	-0.169^*	0.064
Nonwage income	0.003	0.007	0.007	0.006
Constant	-2.211^*	0.284	0.362	0.271
Initial insurance	1.366^*	0.088	0.497^*	0.131
Initial good health	0.389^*	0.124	1.719^*	0.089
Time-average married	-0.188	0.238	0.196	0.254
ρ_{it}				
Insurance_{t-1}	-0.083	0.224		
Good health_{t-1}	-0.289	0.234		
$\text{Insurance}_{t-1} \times \text{Goodhealth}_{t-1}$	0.342	0.287		
Constant	-0.213	0.180		
θ	0.629^*	0.191		

Appendix Table A3 – NLSY - Low income (* p < .05; † p < .10)

	Insurance equation		Good health equation	
	Coeff.	St. Err.	Coeff.	St. Err.
Insurance$_{t-1}$	0.545*	0.085	−0.321*	0.089
Good health$_{t-1}$	0.055	0.089	0.874*	0.081
Insurance$_{t-1}$ × Goodhealth$_{t-1}$	−0.023	0.093	0.518*	0.095
Age	−0.033	0.050	−0.290*	0.060
Married	0.450*	0.063	−0.058	0.076
MSA	0.132*	0.050	0.045	0.059
Family size	0.052*	0.015	0.002	0.018
Education	0.182*	0.043	0.004	0.049
Black	−0.013	0.065	0.058	0.064
Hispanic	0.146	0.117	0.011	0.117
Female	0.187*	0.061	−0.156*	0.061
Nonwage income	−0.005	0.004	0.001	0.003
Constant	−1.691*	0.542	−0.089	0.525
Initial insurance	0.664*	0.061	−0.064	0.063
Initial good health	−0.176	0.122	0.678*	0.114
Time-average married	−0.196†	0.107	0.386*	0.117
Time-average nonwage	0.001	0.007	−0.010	0.009
Time-average family size	−0.028	0.027	0.062*	0.029
Time-average education	−0.087	0.046	0.067	0.052
Time-average age	0.109	0.140	−0.027	0.142
Time-average MSA	−0.026	0.094	0.029	0.099
ρ_{it}				
Insurance$_{t-1}$	0.023	0.119		
Good health$_{t-1}$	0.132	0.111		
Insurance$_{t-1}$ × Goodhealth$_{t-1}$	0.057	0.139		
Constant	−0.203*	0.097		
θ	−0.459*	0.058		

Appendix Table A4 – NLSY - High income (* p < .05; † p < .10)

	Insurance equation		Good health equation	
	Coeff.	St. Err.	Coeff.	St. Err.
Insurance_{t-1}	0.608^{*}	0.163	0.107	0.159
Good health_{t-1}	-0.494^{*}	0.153	1.421^{*}	0.165
$\text{Insurance}_{t-1} \times \text{Goodhealth}_{t-1}$	0.142	0.169	-0.346^{*}	0.173
Age	-0.054	0.060	-0.384^{*}	0.070
Married	0.460^{*}	0.075	-0.198^{*}	0.091
MSA	0.057	0.053	0.118^{*}	0.059
Family size	0.010	0.024	0.046	0.030
Education	0.016	0.050	0.102^{*}	0.051
Black	-0.164^{*}	0.065	-0.059	0.073
Hispanic	$-0.218^{\dagger}$	0.119	0.111	0.134
Female	-0.052	0.055	-0.471^{*}	0.060
Nonwage income	-0.003	0.003	-0.001	0.003
Constant	-1.843^{*}	0.517	0.280	0.553
Initial insurance	0.881^{*}	0.075	0.290^{*}	0.093
Initial good health	0.394^{*}	0.156	1.579^{*}	0.131
Time-average married	0.252^{*}	0.117	$0.244^{\dagger}$	0.137
Time-average nonwage	0.007	0.008	0.002	0.007
Time-average family size	-0.036	0.037	$-0.072^{\dagger}$	0.043
Time-average education	0.143^{*}	0.052	-0.008	0.054
Time-average age	0.101	0.135	-0.065	0.151
Time-average MSA	0.032	0.103	-0.253^{*}	0.112
ρ_{it}				
Insurance_{t-1}	$-0.401^{\dagger}$	0.213		
Good health_{t-1}	-0.272	0.210		
$\text{Insurance}_{t-1} \times \text{Goodhealth}_{t-1}$	$0.469^{\dagger}$	0.241		
Constant	0.174	0.184		
θ	0.544^{*}	0.063		