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RESEARCH ARTICLE

The Relationship between Local Economic Conditions and Acute Myocardial Infarction Hospital Utilization by Adults and Seniors in the United States, 1995–2011

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Objective. To assess the association between aggregate unemployment and hospital discharges for acute myocardial infarction (AMI) among adults and seniors, 1995–2011.

Data Sources/Study Setting. Community hospital discharge data from states collected for the Healthcare Cost and Utilization Project (HCUP) State Inpatient Databases (SID) and economic data from the Bureau of Labor Statistics, 1995–2011.

Study Design. Quarterly time series study of unemployment and aggregate hospital discharges in local areas using fixed effects to control for differences between local areas.

Data Collection/Extraction Methods. Secondary data on inpatient stays and unemployment rates aggregated to micropolitan and metropolitan areas.

Principal Findings. For both adults and seniors, a 1 percentage point increase in the contemporaneous unemployment rate was associated with a statistically significant 0.80 percent (adults) to 0.96 percent (seniors) decline in AMI hospitalization during the first half of the study but was unrelated to the economic cycle in the second half of the study period.

Conclusions. The study found evidence that the aggregate relationship between health and the economy may be shifting for cardiovascular events, paralleling recent research that has shown a similar shift for some types of mortality (Ruhm 2013), self-reported health, and inpatient use among seniors (McInerney and Mellor 2012).

Key Words. Acute myocardial infarction, economic cycles, hospital utilization, determinants of health, Medicare

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Although life expectancy in the United States has been increasing at a fairly constant rate, population health appears to fluctuate with the economic cycle. In particular, a significant body of research in both developed and developing

countries has found that aggregate mortality increases during economic expansions and declines in economic contractions (Ruhm 2000, 2003, 2005a, b, 2007; Tapia Granados 2005; Stevens et al. 2011; Ionides, Wang, and Tapia Granados 2012). However, research using more recent data has found that Medicare beneficiaries report worse health and more inpatient care during economic downturns (McInerney and Mellor 2012, 1994–2008 data). Using 1976–2009 data, Ruhm (2013) found evidence that the aggregate relationship between mortality (all ages) and employment switched in the United States during the mid-1990s—from increasing mortality during expansions to declining mortality during economic expansions.

Explanations for why economic conditions may be related to health can be broadly categorized as behavioral (e.g., impacts of one's own decisions on health) or structural (e.g., indirect impacts of unemployment not related to an individual's own behavior). The two main behavioral explanations are changes in the value of time and economic stress. The change in the value of time associated with the economic cycle would lead to better health during a recession because healthy behaviors typically require an investment of time to pursue, such as cooking healthy meals at home, exercise, and getting adequate sleep. Some studies have provided evidence of this behavior, finding that during recessions many health behaviors (better diet, more physician activity) increase and unhealthy behaviors such as alcohol use and smoking decrease (Ruhm 2003, 2005a; Xu 2013). But other studies have found the opposite—that when unemployment rises, fruit and vegetable consumption decreases and fast food and snack consumption increases (Dave and Kelly 2012). Recent evidence has also found that use of dental care, routine nonemergency care, and certain screening services (which require an investment of time) declined during the recession of the late 2000s (Lusardi, Schneider, and Tufano 2010; Dorn et al. 2012; Wall, Vujicic, and Nasseh 2012). Although changes in the value of time may broadly affect all workers because of exposure to the economic climate, those directly affected by job loss may experience worse health due to economic stress. Charles and DeCicca (2008) found worse weight-related health and mental health for men with low unemployment

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probabilities. Using individual data on people age 51–75 years from 1992 to 2010, Dupre et al. (2012) found that the risk of heart attack increased significantly after job loss and that risk increased more the more job losses the person experienced and the longer the cumulative duration of time unemployed.

There is a range of indirect or structural ways that economic conditions may affect health. For example, Stevens et al. (2011) provided evidence that tightness in the labor market for low-paid nursing home staff may lead to increased mortality among the institutional older adults during economic expansions. Health may also be a factor of production during economic growth periods. Increased construction and other economic activity lead to more on the job accidents, more traffic accidents, more pollution, and poorer health. Providers may also be more willing to accept public insurance during economic downturns, leading to better care among Medicare beneficiaries (McInerney and Mellor 2012).

Burgard, Ailshire, and Kalousova (2013) provided a discussion and review of the contradictory evidence on the relationship between health and the economic cycle. They concluded that aggregate-level studies have found that health tends to improve during recessions, but individual-level studies on those most severely affected by a poor economy (e.g., those who experience a job loss) have found that these individuals tend to experience poorer health. Aggregate studies examine the reduced form relationship, which includes mechanisms that may be working in opposite directions. For example, aggregate studies can show that health increases during a recession if the effect of more time to invest in health (perhaps a small amount of time per person but broadly experienced) is larger than the negative impact on the subset of people who lose their jobs. This aggregate relationship could change over time if some mechanisms change in importance because of how broadly they affect the population (e.g., affects everyone or just those who lose their jobs).

The purpose of this paper was to estimate the relationship between the economic cycle and hospitalizations for acute myocardial infarctions (AMIs), commonly known as heart attacks or infarctions. We focused on AMIs because they are well-defined by coding procedures and determinants of AMIs are relatively well understood. Because AMI is a life-threatening event, the decision to be admitted to the hospital is not discretionary, although about half of deaths occur before hospital arrival. AMI occurs when the blood supply to the heart is interrupted. Risk factors include sex (male), age (older), family history, tobacco use, diabetes, hypertension,

dyslipidemia, high cholesterol, obesity, sedentary lifestyle, exposure to air pollution, and possibly poor oral health (Brook et al. 2004; Yusuf et al. 2004; American Heart Association 2012; Lockhart et al. 2012). For AMI, the ability of the patient (or bystanders) to recognize symptoms and quickly obtain care is a matter of life or death. Over half of AMI deaths occur within the first hour of symptom onset or before admission to a hospital (Moser et al. 2006). Previous research has found that the following factors were associated with delays in receiving care for the broader category of acute coronary syndrome, which includes AMI: older, female, lower education, black, Latino, lower socioeconomic status, history of angina, diabetes, hypertension, heart failure, smoking, hyperlipidemia, being alone when symptoms occur, fearing consequences of seeking help, and being embarrassed about seeking help (Moser et al. 2006).

Unemployment may affect both underlying health (e.g., the probability of having a heart attack) as well as the probability of getting to the hospital in time. Higher local unemployment could decrease the likelihood of having a heart attack among insured workers who have more time available for health-promoting activities. Among people who lose their jobs, higher local unemployment may lead to more heart attacks (Dupre et al. 2012). Employment could affect getting to the hospital in time in a variety of ways. If people are more likely to be alone when unemployment increases (e.g., if the unemployed are at home by themselves), then the probability of making it to the hospital in time may decline because being alone is a risk factor for delays in heart attack care (Moser et al. 2006). If people do not have insurance because of job loss or have inadequate insurance, they may delay a trip to the hospital. Budget cuts for ambulance services during a poor economy are another way that care could be delayed during a recession. To the extent that traffic delays increase during a strong economy, this can also delay people obtaining timely heart attack care.

Previous research on hospitalizations and AMI mortality suggests that we would expect AMI hospitalizations to decrease during a recession. Ruhm (2003) found that all-cause hospitalizations increase during economic expansions based on individual-level survey data (1972–1981 National Health Interview Surveys) and analyses that controlled for the individual's age, sex, income, education, race, marital status, and veteran status. Ruhm (2007) and Stevens et al. (2011) found that AMI mortality increases during expansions, although the two studies disagreed on what age groups were most affected, leading to different conclusions about causality. Ruhm (2007) found a larger impact for younger age groups than seniors, suggesting that the increased

value of time during an expansion led to less investment in health among younger adults compared with seniors who may not experience as large a change in the value of time because many are retired. Stevens et al. (2011) reanalyzed the same data and found a larger impact for seniors than for younger age groups and provided suggestive evidence of a structural mechanism. Shortages of health care workers (particularly low-wage workers in nursing homes) during economic expansions may lead to increased mortality in older adults during economic expansions. In a recent working paper, Ruhm (2013) reported that although total mortality has shifted from procyclical (increasing during an expansion) to essentially acyclical, cardiovascular mortality remains procyclical.

Summary of Approach

This study uses the census of community hospital discharges in the United States, 1995–2011, to relate quarterly fluctuations in economic conditions (measured by the local unemployment rate) to the AMI discharges rate. Although this is an aggregate study, we examined this relationship at a granular geographic level (metropolitan and micropolitan areas) so that local changes in economic conditions identify the relationship. Previous U.S. research has mostly related state unemployment rates with state-level measures of health (Ruhm 2007, 2013; Ionides, Wang, and Tapia Granados 2012) or individual-level data with state unemployment rates (Ruhm 2003; McInerney and Mellor 2012). Charles and DeCicca (2008) used 1997–2001 individual data and metropolitan statistical area unemployment rates to examine the impact of unemployment on obesity and mental health measures.

We examined adults and seniors separately because the mechanism of how unemployment may affect health and AMI hospitalizations may differ for adults under 65 and seniors. Adults under 65 are more likely to be directly negatively affected through job losses because they are more attached to the labor force. This attachment to the labor force also leads to more adults experiencing changes in the value of time because of the economic cycle than seniors, who are less likely to work. Seniors may be affected through the economic stress of a negative wealth shock in a bad economy, but they are protected from losing their health insurance through Medicare (although gaps in Medicare coverage can result in significant expenses). For adults under 65, losing a job is likely to mean losing income and also health insurance.

METHODS

Data

The key outcomes, AMI discharge rates for working-age adults (aged 20–64 years) and seniors (age 65 years and older) were measured using quarterly hospital discharges, 1995–2011, in each core based statistical area (CBSA), divided by the population of adults or seniors in that CBSA. CBSAs are defined by the U.S. Census Bureau, include one or more counties, and are classified as metropolitan (urban core population of 50,000 or more plus surrounding areas) or micropolitan areas (urban core population of 10,000 to 50,000 plus surrounding areas). Because definitions of the CBSAs changed during the study period due to population inflows and outflows, both the numerator (count of AMI hospitalizations) and denominator (population) were first constructed at the county level and then aggregated up to the CBSA. We aggregated data at the CBSA level because economic conditions can vary greatly within a state, particularly during the recent recession.

We obtained quarterly AMI discharges from states that contributed 1995–2011 data to the Healthcare Cost and Utilization Project (HCUP) State Inpatient Databases (SID) (Agency for Healthcare Research and Quality 2013). The SID contain the universe of the inpatient discharge abstracts from participating states that are translated into a uniform format to facilitate multi-state comparisons and analyses. Together, the SID encompass almost 90 percent of all U.S. hospital discharges. Some states include discharges from specialty hospitals, such as acute psychiatric hospitals. The SID contain a core set of clinical and nonclinical information on all patients, regardless of payer, including those covered by Medicare, Medicaid, private insurance, and the uninsured. Data were available back to 1988, but the analysis was limited to 17 years because a smaller subset of states contributed in early years. A majority of states contributed data from 1995–2011, but some contributed some, but not all years (see Appendix S1). This analysis was limited to discharges from community, nonrehabilitation hospitals, and patients who resided in the CBSA. Discharges with incomplete data on CBSA of residence, age, and missing diagnosis were excluded, which led to the omission of less than 1 percent of hospitalizations. AMI hospitalizations were defined as discharges with ICD-9-CM codes 410.XX in the primary diagnosis field. Discharges included live discharges (to home, other facilities) as well as deaths in the hospital.

The denominator for hospitalization rates was constructed from the U.S. Census Annual Population Estimates Program, which provides annual esti-

mates for each county by age, race, Hispanic origin, and sex since 1940 (U.S. Populations Estimates Program 2013). Quarterly population estimates were linearly extrapolated from each year's annual estimate, using the fact that the annual estimates are based on July 1 of each year. To conform to HCUP data use agreement requirements, quarterly observations with 10 or fewer discharges were set to missing.

The key independent variable was the quarterly unemployment rates in each CBSA, calculated from seasonally adjusted monthly rates obtained from the Bureau of Labor Statistics Local Area Unemployment Statistics (Bureau of Labor Statistics 2013). We constructed variables to measure changes in the demographic characteristics of each CBSA during the study period and included the percentage of the CBSA's population that was female, white, black, and Hispanic, and the percentage in each age group using annual Census estimates and linearly extrapolating to quarterly estimates.

Analytic Approach

The first set of analyses replicated the methods used in previous analyses using a semilog model with local-area fixed effects. The second set of models continued to use local-area fixed effects but examined a functional form that may be less sensitive to small numbers of AMI hospitalizations in some local areas. These models were then used to estimate a lagged relationship and investigated whether the relationship between AMI hospitalizations and unemployment may have changed during the study period.

Hospitalizations rates are likely to differ between CBSAs because of a range of reasons that we do not observe in these data, such as the underlying health, culture of health, poverty, and medical infrastructure. Local-area (CBSA) fixed effects were included to control for these factors. We also included year fixed effects to control for nationwide changes in treatment in cardiovascular disease. We included fixed effects for calendar quarters to control for seasonality in AMI discharges, and a linear time trend was included to control for the nationwide decline in AMI hospitalizations.

The first set of models is based on equation (1):

$$\ln(Y_{cqt}) = \alpha_0 + \alpha_1 E_{cqt} + \alpha_2 X_{cqt} + \alpha_3 T_{trend} + \lambda_c + \lambda_q + \lambda_t + \lambda_{qt} + \epsilon_{cqt}, \quad (1)$$

where Y_{cqt} is the natural log of AMI hospitalizations per 1,000 in CBSA c , quarter q (0–3), and year t (1995–2011), and the unit of analysis is defined by the CBSA, year, and quarter. E is the unemployment rate, X is a vector of demographics (age, gender, race), and T_{trend} is a linear trend in quarters 1–68

(17 years*4 quarters). A set of indicators for each CBSA (λ_c), year (λ_y), and quarter (λ_q) were included, and the interaction of year and quarter (λ_{qt}) was included in some specifications. The interaction of year and quarter indicators allowed seasonality to vary from year to year. This approach closely follows the analytic approach used by Ruhm (2007) in a study of AMI mortality that used aggregate annual state data 1979–1998 and other studies (Ruhm 2000; Ionides, Wang, and Tapia Granados 2012). Ruhm (2007) included indicators for year, state, and state-specific linear time trends to control for unchanging differences in mortality between states, national time trend, and slow-moving (linear) changes within states, respectively.

One way of controlling for area-specific trends is to use a linear trend or quadratic with separate trends for each local area. However, there is a potential for overfitting the data when using a parametric approach. An alternative approach is to use a technique from the macroeconomic literature to filter out nonlinear trends from each local area. Ionides, Wang, and Tapia Granados (2012) applied this approach and also argued that some of the inconsistent results for age subgroups reported in the literature may be due to misspecified state-specific trends. These authors argued that this misspecification introduces a small amount of bias that does not significantly affect inference for total mortality, but the bias becomes more important for estimates of subgroup mortality. To implement this approach, we filtered unemployment using the Hodrick–Prescott filter (Hodrick and Prescott 1997) (HP filter), as suggested by Ionides, Wang, and Tapia Granados (2012), as well as other applied techniques suggested as alternatives. Ionides et al. filtered all of the variables in the model. We filtered only unemployment after determining that the other measures do not appear to have as strong cyclical components that require filtering.

The HP filter decomposes the series for each CBSA into two components: a smooth growth or trend component and a cyclical component (with mean zero). The cyclical component replaces the unemployment variable in the model. The parameter λ is set to control the degree of smoothing; as λ approaches infinity, the filtered series approaches a linear local-area trend. We used $\lambda = 1,600$, which previous research has suggested is appropriate for quarterly economic data (Ravn and Uhlig 2002). We also examined specifications using other parameter values ($\lambda = 400$ and $\lambda = 100$), and results were similar to the specifications with $\lambda = 1,600$ presented here. The advantage of the HP filter is that it is a data-driven approach to removing smooth, nonlinear trends in each state to reveal any cycles in AMI hospitalizations.

The HP filter can lead to spurious findings of cyclicalities if the detrending parameters are misidentified. It can also result in high-end sample bias. There-

fore, we applied two other types of filtering techniques, the Beveridge–Nelson (BN) decomposition and Christian–Fitzgerald (CF) asymmetric band-pass filters to assess the robustness of our empirical results (Beveridge and Nelson 1981; Christiano and Fitzgerald 1999, 2003; Nelson 2008). BN decomposition is a detrending method using unobserved components in which unemployment is assumed to contain unobserved permanent components consisting of a random walk with drift and temporary components driven by a stationary autoregressive process. The CF asymmetric band-pass filters is a band-pass filter that formulates the detrending and smoothing problem in the frequency domain. The key advantage of the CF filter is that it is designed to work well on a larger class of time series and converges in the long run to the optimal filter.

The first set of models use a semilog specification (hospitalization rates are logged, unemployment is not) in a linear model (implemented using *areg* in *STATA*); thus, the coefficient on unemployment is the impact of a 1 percentage point increase in the state unemployment rate on the percentage change in hospitalizations. This semilog approach with fixed effects has been widely used in state-level aggregate studies (e.g., Ruhm 2007, 2013). The second set of models use a GLM with log link, Poisson family, and fixed effects with robust standard errors (Huber/White/Sandwich estimator of variance) where the dependent variable is the count of the number of AMI hospitalizations in that quarter-CBSA and the population is included as the exposure variable, shown in equation (2), and implemented using *STATA*'s *xtpoisson* command (*STATA* 2013):

$$Y_{cqt} = \exp(\alpha_0 + \alpha_1 E_{cqt} + \alpha_2 X_{cqt} + \alpha_3 T_{trend} + \alpha_4 \ln(P_{cqt}) + \lambda_c + \lambda_q + \lambda_t + \lambda_{qt} + \epsilon_{cqt}), \quad (2)$$

where P_{cqt} is the population of adults or seniors in CBSA c , quarter q , and year t , and the coefficient on population (α_4) is constrained to equal 1. This approach is also known as Poisson quasi-maximum likelihood (QLME). There are several advantages to this approach over the semilog linear model, and interpretation of coefficients is identical to the log-transformed linear model (Cameron and Trivedi 2010; Wooldridge 2010). Small nonzero values can be influential in log-transformed linear models (e.g., in small CBSAs), and the smearing estimate is not required to transform $\ln(y)$ to y . Log of population is included in the regression with the coefficient constrained to 1 to account for the fact that when the population size doubles, the number of AMI hospitalizations should also double.

The next set of models include up to two lags of unemployment, shown in equation (3):

$$Y_{cqt} = \exp(\alpha_0 + \alpha_1 E_{cqt} + \alpha_2 E_{cqt-1} + \alpha_3 E_{cqt-2} + \alpha_4 X_{cqt} + \alpha_5 T_{trend} + \alpha_6 \ln(P_{cqt}) + \lambda_c + \lambda_q + \lambda_t + \lambda_{qt} + \epsilon_{cqt}) \quad (3)$$

The sum of the coefficients on unemployment ($\alpha_1 + \alpha_2 + \alpha_3$ in equation 3) provides the cumulative impact of increased unemployment over three quarters (contemporaneous quarter plus previous two quarters). We used the delta method, implemented with *STATA*'s nlcom command, to calculate confidence intervals and *z*-statistics for this cumulative effect of unemployment. The final set of models split the time period in half to assess whether the aggregate impact of unemployment was the same in the first and second halves of the study period. The time period was split in half for convenience to preserve sample size in each interval and also grouped the Great Recession, which started in 2008, into the later time period.

RESULTS

The study sample included 48 states and 897 CBSAs. A subset of states contributed all years. There were a total of 42,759 CBSA-year-quarter observations with an average of 47.67 quarters per CBSA. Table S1 (see Appendix) provides a complete list of states and CBSA-quarters for each state. We excluded observations based on 10 or fewer discharges to conform to HCUP data use-agreement requirements, yielding 34,678 observations for adults under 65 and 38,972 observations for seniors. For adults, this suppression led to the exclusion of 50 CBSAs. For seniors, this suppression led to the exclusion of 19 CBSAs.

Table 1 shows the distribution of the covariates included in the models. AMI discharges were much higher for seniors (rate of 2.90 per 1,000) compared with adults under 65 years (0.53 per 1,000). Because all of our models included CBSA indicators, the impact of unemployment on AMI hospitalizations was identified using local variation within each CBSA over time. This variation was summarized by the "within-CBSA" standard deviation in the unemployment rate, calculated by subtracting the CBSA-specific mean from each observation and adding the global mean $\bar{E}$ for comparability ($E_{ct} - \bar{E}_c + \bar{E}$), implemented using xtsum in *STATA 12.1* (Stata Corp., College Station, TX, USA). The average unemployment rate across CBSA-year-quarters

Table 1: Description of AMI Discharges, Unemployment, and Demographic Variables

	Number of CBSA- Year-Quarters	Mean	Standard Deviation		
			Overall	Between CBSA	Within CBSA
AMI discharges per 1,000, adults	34,678	0.53	0.23	0.21	0.13
AMI discharges per 1,000, seniors	38,972	2.90	0.73	0.83	0.48
AMI discharges per 1,000, adults and seniors	42,759	0.98	0.37	0.29	0.23
Unemployment rate, %	42,759	6.5	3.0	2.2	2.2
Female, % of population	42,759	50.6	1.6	1.6	0.4
White, % of population	42,759	79.0	17.7	18.7	2.3
Black, % of the population	42,759	8.5	11.2	12.7	0.8
Hispanic, % of the population	42,759	8.7	13.7	14.6	1.7
Age 20–44, % of the population	42,759	31.0	4.1	3.0	2.9
Age 45–64, % of the population	42,759	24.0	3.0	2.5	1.8
Age 65–74, % of the population	42,759	7.4	1.8	1.6	0.5
Age 75–older, % of the population	42,759	6.9	1.9	1.8	0.4

Notes: Overall standard deviation is the standard deviation of the original variable (x_{it}). Between-CBSA, SD is the standard deviation of the CBSA-level means ($\bar{x}_c$). Within-CBSA, SD is the standard deviation of a variable created by subtracting the CBSA-level mean from each observation ($x_{it} - \bar{x}_c + \bar{x}$), where the global mean $\bar{x}$ is added to make the scale comparable.

was 6.5 percent with substantial variation over time within each CBSA (within-CBSA SD = 2.2 percent).

Table S2 (see Appendix) presents model results using various filtering techniques. We used these results to evaluate the most effective approach. All models specify AMI as the natural log of the AMI hospitalization rate in thousands. Models 1–2 (adults) and 9–10 (seniors) do not include any filtering. Models 3–4 and 11–12 filter unemployment with the HP filter; Models 5–6, 13, and 14 apply the BN decomposition filter; and Models 7–8, 15, and 16 apply the CF asymmetric band-pass filter to unemployment. These filters are all nonlinear, detrending methods at the CBSA level. The odd-numbered models do not include the interaction between year and quarter, whereas the even-numbered models do include these interaction terms.

We found that AMI hospitalizations declined 0.20 percent (Model 5) to 0.58 percent (Model 4) with each percentage point increase in the unemployment rate for adults (Models 1–8). This decline was significant in all models. For seniors, AMI hospitalizations declined within the same range as adults (0.25 percent [Model 12] to 0.42 percent [Model 1]), although the difference was not statistically significant in three of the models (both CP- filtered models

and the HP-filtered model that included year-quarter interactions). Confidence intervals for each of the models for seniors and adults overlapped, indicating that findings were not significantly different for the two age groups.

Our final set of models split the 17-year time period in half (1995–2003 and 2004–2011) and also introduced additional lags of unemployment along with the contemporaneous unemployment rate for adults (Table 2) and seniors (Table 3). To facilitate comparison of results and because the use of filtering did not significantly affect model findings, all final models were unfiltered. Models in Tables 2 and 3 use the log-link GLM models (equation 2). Table 2 shows that the relationship between unemployment and AMI hospitalizations appears to be acyclical between 1995 and 2011 (models 1–2) in the log-link GLM models that are less vulnerable to influential observations from small CBSAs. The cumulative impact of unemployment was also acyclical, although the first lag was positive and significant.

However, once the study period was split into two time intervals using a convenient break point, the relationship switched from negative (more unemployment was associated with fewer AMI hospitalizations) to acyclical from the first to second time period. During 1995–2003, a 1 percentage point increase in unemployment was associated with a 0.72 percent to 0.80 percent ($Z = 2.63$ and 2.90) decrease in contemporaneous AMI hospitalizations (Models 3–4). When two lags were included, the cumulative effect of unemployment was a 1.05 percent to 1.31 percent decline in AMI hospitalizations for every 1 percentage point increase in unemployment that was sustained over three quarters ($Z = 3.01$ and 3.58 , models 15–16). The coefficients on unemployment and its lags were negative, except for the first lag in the two-lag model (Models 15–16), and this was statistically significant in the model with the year-quarter flags (Model 16). During the second half of the time period (2004–2011), the relationship between AMI hospitalizations and unemployment was not statistically significant except for the first lag in models 11–12, and the coefficient was positive (procyclical). The coefficients on contemporaneous unemployment (Models 5–6) and the cumulative effect in the lag models were all positive but not statistically significant.

A similar finding emerged for seniors, with evidence from the lag models that the countercyclical relationship observed in the first half of the study period may have switched to procyclical in the second half (Table 3). The models without lags found a negative but insignificant relationship during the entire study period (Models 1–2), a negative significant relationship during the first half of the study period (Models 3–4), and a positive but insignificant relationship in the second half of the study period (Models 5–6). Using data

Table 2: Estimates of the Effect of Unemployment on Adults (20–64 years) 1995–2011, 1995–2003, 2004–2011, GLM Log-Link Model

	1995–2011		1995–2003		2004–2011	
	Models 1–6: Contemporaneous Unemployment (No Lags)					
Unemployment rate (lag = 0)	(1)	(2)	(3)	(4)	(5)	(6)
	0.0013 [–0.0031, 0.0056] (0.57)	0.0011 [–0.0034, 0.0057] (0.48)	–0.0072 [–0.1195, –0.0025] (2.99)	–0.0080 (3.19)	0.0024 [–0.0016, 0.0064] (1.19)	0.0021 (0.89)
Observations	34,666	34,666	15,231	15,231	19,417	19,417
	Models 7–12: Contemporaneous and Previous Quarter Unemployment (One Lag)					
Unemployment rate lag = 0	(7)	(8)	(9)	(10)	(11)	(12)
	–0.0022 [–0.0051, 0.0008] (1.45)	–0.0020 [–0.0050, 0.0010] (1.30)	–0.0062 [–0.0102, –0.0023] (3.11)	–0.0068 [–0.0110, –0.0027] (3.23)	–0.0030 [–0.0068, 0.0009] (1.5)	–0.0033 [–0.0075, 0.0009] (1.55)
Unemployment rate, lag = 1	0.0042 [0.0009, 0.0045] (2.50)	0.0040 [0.0002, 0.0076] (2.06)	0.0022 [0.80)	–0.0020 [–0.0058, –0.0017] (1.07)	0.0065 [0.0028, 0.0102] (3.44)	0.0066 [0.0019, 0.0114] (2.74)
Cumulative effect of unemployment	0.0020 [–0.0028, 0.0069] (0.82)	0.0019 [–0.0034, 0.0071] (0.69)	–0.0078 [–0.0135, –0.0020] (2.63)	–0.0088 [–0.0148, –0.0029] (2.90)	0.0035 [–0.0008, 0.0079] (1.59)	0.0033 [–0.0020, 0.0086] (1.23)
Observations	31,040	31,040	13,312	13,312	17,699	17,699
	Models 13–18: Contemporaneous and Previous Two Quarters Unemployment (Two Lags)					
Unemployment rate lag = 0	(13)	(14)	(15)	(16)	(17)	(18)
	–0.0023 [–0.0021, 0.0041] (1.45)	–0.0022 [–0.0053, 0.0010] (1.36)	–0.0071 [–0.0113, –0.0029] (3.29)	–0.0081 [–0.0126, 0.0036] (3.51)	–0.0027 [–0.0066, 0.0013] (1.32)	–0.0032 [–0.0075, 0.0022] (1.46)
Unemployment rate lag = 1	0.0035 [0.0007, 0.0063] (2.47)	0.0049 [0.0016, 0.0081] (2.95)	0.0026 [–0.0010, 0.0061] (1.41)	0.0040 [0.0000, 0.0080] (1.97)	0.0033 [–0.0011, 0.0076] (1.45)	0.0046 [–0.0003, 0.0094] (1.83)
Unemployment rate lag = 2	0.0010 [–0.0021, 0.0041] (0.63)	–0.0010 [–0.0045, 0.0024] (0.58)	–0.0060 [–0.0097, –0.0023] (3.15)	–0.0090 [–0.0131, –0.0049] (4.32)	0.0037 [–0.0002, 0.0075] (1.87)	0.0026 [–0.0018, 0.0071] (1.15)
Cumulative effect of unemployment	0.0022 [–0.0031, 0.0075] (0.83)	0.0017 [–0.0041, 0.0074] (0.57)	–0.0105 [–0.0174, –0.0037] (3.01)	–0.0131 [–0.0202, –0.0059] (3.58)	0.0043 [–0.0003, 0.0089] (1.82)	0.0040 [–0.0018, 0.0098] (1.35)
Observations	29,226	29,226	12,489	12,489	16,722	16,722

Continued

Table 2 *Continued*

	1995–2011		1995–2003		2004–2011	
Demographics in	YES	YES	YES	YES	YES	YES
CBSA	YES	YES	YES	YES	YES	YES
CBSA	YES	YES	YES	YES	YES	YES
Linear time trend,	YES	YES	YES	YES	YES	YES
quarters 1–36						
Year	YES	YES	YES	YES	YES	YES
Quarter	YES	YES	YES	YES	YES	YES
Year-quarter	NO	YES	NO	YES	NO	YES

Notes: Each cell lists coefficient, 95% confidence interval in brackets, and *t*-values in parenthesis. Coefficients that are significantly different from zero at 95% confidence levels are in bold. Demographics describe characteristics of the CBSA: % white, % black, % Hispanic, % age 65–74 years, and % age 75 years and older.

Table 3: Estimates of the Effect of Unemployment on Seniors (65 Years and Older) 1995–2011, 1995–2003, 2004–2011, GLM Log-Link Model

	1995–2011			1995–2003			2004–2011		
	Models 1–6: Contemporaneous Unemployment (No Lags)								
	(1)	(2)	(3)	(4)	(5)	(6)			
Unemployment rate (lag = 0)	0.0036 [–0.0079, 0.0008] (1.61)	–0.0023 [–0.0071, 0.0025] (0.95)	–0.0110 [–0.0161, –0.0059] (4.22)	–0.0096 [–0.0151, –0.0040] (3.4)	0.0014 [–0.0033, 0.0061] (0.60)	0.0028 [–0.0027, 0.0083] (0.99)			
Observations	38,961	38,961	17,127	17,127	21,824	21,824			
	Models 7–12: Contemporaneous and Previous Quarter Unemployment (One Lag)								
	(7)	(8)	(9)	(10)	(11)	(12)			
Unemployment rate lag = 0	–0.0155 [–0.0209, –0.0100] (5.57)	–0.0142 [–0.0201, –0.0083] (4.70)	–0.0183 [–0.0243, –0.0124] (6.03)	–0.0167 (5.21)	–0.0130 [–0.0190, –0.0071] (4.33)	–0.0126 [–0.0195, –0.0058] (3.64)			
Unemployment rate, lag = 1	0.0146 [0.0090, 0.0203] (5.11)	0.0148 [0.0087, 0.0208] (4.75)	0.0110 [0.0045, 0.0174] (3.33)	0.0110 [0.0046, 0.0174] (3.36)	0.0178 [0.0125, 0.0231] (6.58)	0.0198 [0.0130, 0.0265] (5.75)			
Cumulative impact of unemployment	–0.0008 [–0.0056, 0.0040] (0.73)	0.0006 [–0.0047, 0.0058] (0.21)	–0.0073 [–0.0136, –0.0010] (2.28)	–0.0057 [–0.0124, 0.0010] (0.097)	0.0048 [0.0000, 0.0095] (1.97)	0.0071 [0.0014, 0.0129] (2.43)			
Observations	35,999	35,999	15,505	15,505	20,482	20,482			
	Models 13–18: Contemporaneous and Previous Two Quarters Unemployment (Two Lags)								
	(13)	(14)	(15)	(16)	(17)	(18)			
Unemployment rate lag = 0	–0.0153 [–0.0207, –0.0099] (5.55)	–0.0141 [–0.0199, –0.0083] (4.74)	–0.0184 [–0.0245, –0.0123] (5.93)	–0.0165 [–0.0229, –0.0101] (5.07)	–0.0122 [–0.0181, –0.0063] (4.030)	–0.0119 [–0.0187, –0.0052] (3.46)			
Unemployment rate lag = 1	0.0117 [0.0067, 0.0168] (4.61)	0.0110 [0.0061, 0.0159] (4.44)	0.0107 [0.0055, 0.0159] (4.06)	0.0096 [0.0047, 0.0144] (3.89)	0.0130 [0.0069, 0.0190] (4.19)	0.0136 [0.0071, 0.0202] (4.06)			
Unemployment rate lag = 2	0.0036 [–0.0005, 0.0077] (1.71)	0.0048 [0.0002, 0.0094] (2.05)	0.0006 [–0.0052, 0.0064] (0.21)	0.0025 [–0.0033, 0.0082] (0.85)	0.0051 [0.0005, 0.0097] (2.17)	0.0072 [0.0018, 0.0126] (2.60)			
Cumulative impact of unemployment	0.000 [–0.0053, 0.0053] (0.00)	0.0017 [–0.0042, 0.0076] (0.57)	–0.0071 [–0.0155, 0.0013] (1.65)	–0.0044 [–0.0133, 0.0045] (0.98)	0.0059 [0.0008, 0.0109] (2.29)	0.0089 [0.0026, 0.0152] (2.76)			
Observations	34,462	34,462	14,837	14,837	19,612	19,612			

Continued

Table 3 *Continued*

	1995–2011		1995–2003		2004–2011	
Demographics in	YES	YES	YES	YES	YES	YES
CBSA						
CBSA	YES	YES	YES	YES	YES	YES
Linear time trend,	YES	YES	YES	YES	YES	YES
quarters 1–36						
Year	YES	YES	YES	YES	YES	YES
Quarter	YES	YES	YES	YES	YES	YES
Year-quarter	NO	YES	NO	YES	NO	YES

Notes: Each cell lists coefficient, 95% confidence interval in brackets, and *t*-values in parenthesis. Coefficients that are significantly different from zero at 95% confidence levels are in bold. Demographics describe characteristics of the CBSA: % female, % white, % black, % Hispanic, % age 65–74 years, and % age 75 years and older.

from the entire study period suggests negative to no relationship between unemployment and hospitalizations for seniors. In the first half of the study period, the cumulative effect was negative but not significant in some specifications (model) because of a large and positive coefficient on the first lag of unemployment. In the second half of the study period, the inclusion of additional lags resulted in a positive and significant relationship between AMI hospitalizations and cumulative increases in unemployment sustained over two or three quarters. A 1 percentage point increase in unemployment for three quarters was associated with a 0.59 percent to 0.89 percent increase in AMI hospitalizations in these models.

DISCUSSION

This study found evidence that the aggregate relationship between local unemployment and AMI hospitalizations may have switched at some point during the study period from a negative relationship to no relationship or a positive relationship. For adults under 65 years old, a 1 percentage point increase in unemployment was associated with a statistically significant 0.80 percent decline in AMI hospitalizations during the first half of the study period, but a positive and nonsignificant relationship in the second half of the study period. Similar results were found for seniors. A 1 percentage point increase in unemployment was associated with a statistically significant 0.96 percent decline in AMI hospitalizations by seniors in the first half of the study period and a positive but insignificant relationship in the second time period.

The magnitude of the relationship between AMI hospitalizations and unemployment in the first half of the study period was similar to the magnitude of the relationship found by Ruhm (2013), who used aggregate annual state data, 1976–2009. Ruhm (2013) found that a 1 percentage point increase in unemployment was associated with a statistically significant 0.26 percent decline in cardiovascular deaths. The results do support a cumulative effect of unemployment, although the cumulative effect of unemployment over three quarters was not significantly larger (95 percent confidence intervals overlap) than the contemporaneous effect.

The results were sensitive to the choice of model. The semilog linear model (equation 1) appeared to be susceptible to influence by small numbers of hospitalizations. When this was corrected using the log-link GLM model, the results were directionally similar but no longer statistically significant. The

changing nature of the relationship between AMI hospitalizations and unemployment may explain why different specifications of the CBSA-level trend (alternative, nonlinear filtering methods) yielded different results. Although we broke the data into two time periods, 1997–2003 and 2004–2012, we did not expect that the shift away from procyclicality would happen at a specific point in time. We split the data using this convenient break point to improve the fit of our models. The Ruhm (2013) study used mortality and unemployment data from 1979 to 2009 to investigate the timing of the shift. Results from that study suggested the shift was gradual, given that there was little sensitivity to the choice of end-years when using various cut points. It is likely that the shift from procyclical to acyclical or countercyclical occurred at different times in different local areas, so the choice of trend may alter findings. Because local areas (CBSAs) have varying number of data points, any method to handle local trends may be limited by a small number of data points from which to measure the trend.

This study contributes to the recent literature on the aggregate relationship between unemployment and health, which has shown a shift from recessions associated with better health to being unrelated to mortality (Ruhm 2013) or recessions being associated with worse health and more inpatient care (McInerney and Mellor 2012) among Medicare beneficiaries. Ruhm found that this shift (which appears to have started in the 1990s) may be attributable to cancer mortality, which increasingly can be treated using expensive medical care, thus making the unemployed, who are more likely to be uninsured, particularly vulnerable to cancer death. The evidence present here indicates that this switch is also occurring for cardiovascular disease and among both adults under 65 and seniors over age 65 who are relatively well-insured for cardiovascular care through Medicare.

It may be speculated that the shift away from a procyclical relationship is driven by the same factors that have led to the observed moderation in health care costs in the last decade (Blumenthal, Stremikis, and Cutler 2013). For example, broader economic factors such as the Great Recession that began in 2007 may have instigated both the observed moderation in health care costs and a changing relationship between unemployment and AMI hospitalizations. Alternatively, structural changes in the health system such as the rise in consumer-driven health plans, cost containment efforts, and the slowdown of technology diffusion could have affected both outcomes. One important consideration when exploring this issue is that the shift away from procyclicality may have occurred as early as the 1990s (Ruhm 2013), which would have proceeded many of these health system

changes. Other potential explanations that should be explored that may be more consistent with the timing of the shift include an increased cost of housing, which adds burden to the unemployed, and the emerging focus on healthy workplaces, which may enhance the health and well-being of the employed.

The main limitation of this study is its aggregate nature, which is not suited to disentangling the mechanisms behind the relationship between unemployment and AMI. However, aggregate studies are valuable because they provide information about the net effect of changes in economic conditions.

The main contribution of this study was to examine very recent data (through 2011), include lags, and consider the possibility that the relationship between health and aggregate unemployment may have shifted over time. We extended the literature on cardiovascular health using AMI hospitalizations; previous literature has studied only cardiovascular or AMI mortality (Ruhm 2007, 2013; Stevens et al. 2011). Future research should continue to investigate the mechanisms behind the relationship between unemployment and health by using individual-level data but take the next step to link the microlevel findings to aggregate findings based on how broadly the population is affected.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix SA1: Author Matrix.

Table S1. Description of Number of Observations, CBSAs, Quarters, and Unemployment Rate in States Included in the Study.

Table S2. Estimates of the Effect of Unemployment 1995–2011, Logged AMI Hospitalization Rate.