Flu and Finances: Influenza Outbreaks and Loan Defaults in US Cities, 2004–2012

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Objectives. We examined the association between influenza outbreaks in 83 metropolitan areas and credit card and mortgage defaults, as measured in quarterly zip code–level credit data over the period of 2004 to 2012.

Methods. We used ordinary least squares, fixed effects, and 2-stage least squares instrumental variables regression strategies to examine the relationship between influenza-related Google searches and 30-, 60-, and 90-day credit card and mortgage delinquency rates.

Results. We found that a proxy for influenza outbreaks is associated with a small but statistically significant increase in credit card and mortgage default rates, net of other factors. These effects are largest for 90-day defaults, suggesting that influenza outbreaks have a disproportionate impact on vulnerable borrowers who are already behind on their payments.

Conclusions. Overall, it appears there is a relationship between exogenous health shocks (such as influenza) and credit default. The results suggest that consumer finances could benefit from policies that aim to reduce the financial shocks of illness, particularly for vulnerable borrowers. (*Am J Public Health*. Published online ahead of print July 16, 2015: e1–e6. doi:10.2105/AJPH.2015.302671)

Seasonal influenza is a viral airborne disease that generally spreads each fall and winter, causing an estimated 1.5 million people to get sick and 200 000 to be hospitalized in a typical year in the United States.[1,2] Symptoms can range from mild and hardly distinguishable from a common cold to severe and life-threatening. Influenza accounts for at least 500 000 deaths in the United States in the past 3 decades.[3]

For employed individuals, influenza can make attending work difficult, because of either personal illness or caring for sick household members. This generates significant costs to employers and employees. Estimates from 2007 suggest that annual influenza outbreaks lead to $16.3 billion in lost productivity and wages, and $10.4 billion in medical costs,[4] although these costs vary considerably across place.[5]

Although there is a robust literature on the economic costs of influenza, we know little about how such unexpected health shocks are associated with other aspects of the economy, such as loan defaults. We built on existing knowledge of the economic costs of influenza by examining how influenza outbreaks influence credit card and mortgage default rates in US cities.

In the wake of the Great Recession, loan defaults have increased, with negative financial consequences for families.[6] For loans due on a monthly basis, such as mortgages and credit cards, past-due balances and late fees accumulate each month. Three missed payments (90-day delinquent) is a signal of a loan at high risk for failure and in most states triggers legal collections processes.[7]

In the microeconomic literature, illness is seen as a shock—an unexpected event—that can affect household income and expenses. If the shock results in a disruption to income, households will respond with shifts in consumption and expenditure patterns.[8] We contend that influenza, as a health shock, has the potential to trigger loan default by constraining a family's budget because of personal illness or caretaking burdens. Influenza may also trigger inattention to household financial management and a lack of planning for future bill payments.[9–11] This may be especially problematic for borrowers who are already behind on their payments, whom we define as vulnerable borrowers. For these borrowers, who also tend to be economically vulnerable and disadvantaged in other ways,[12,13] an influenza outbreak could increase the likelihood of further missed payments. A recent study supports this notion, and shows that economically vulnerable households are more likely to borrow and borrow more in the event of a health shock than less vulnerable households.[14] However, this study did not examine credit default.

A growing literature examines the complex and potentially multidirectional relationship between health and default.[15–19] Most research examines whether defaults influence health,[15,19,20] and less examines how health may have an impact on default risk.[21] However, a key problem inherent in this literature is that health status is endogenous, and it is difficult if not impossible to disentangle processes of causation, selection, and reverse causation with survey data.

Our interest in influenza provides us with a unique opportunity to improve causal estimates of health shocks on default. Influenza occurs to varying degrees in every city and year in the United States, and the intensity of the outbreak is an ostensibly exogenous health shock for communities. Thus, influenza outbreaks provide a natural experiment in which we use variation in influenza severity across time and place to identify the effects of a particular health shock on default. Specifically, we ask whether influenza outbreaks in US metropolitan statistical areas (MSAs) are associated with defaults from the first quarter (March) of 2004 (Q1 2004) to the second quarter (June) of 2012 (Q2 2012).

We make 3 contributions with this study. First, we extended the literature on the economic costs of influenza. Second, we contributed to the literature on health shocks and default by providing a stronger test of the potential causal impacts of health shocks on loan default. Third, we considered whether effects vary across types of default, including 30-, 60-, and 90-day defaults. We predicted that influenza may have the greatest effect on borrowers who are already in default, such that the association between influenza and default should be stronger for borrowers who are farther behind.

METHODS

We drew data from several sources. We drew MSA-level influenza data from Google Flu Trends,[22] a publically available source that proxies for influenza severity. Monthly MSA-level estimates were available for 82 cities in the United States from 2004 to 2012. Although researchers question the validity of the 2013 Google data because it overestimated Centers for Disease Control and Prevention reports,[23] the 2004–2012 data are a valid measure of influenza and highly correlated with official estimates.[24–28] Any bias is likely to be systematic across geographies, and should not be correlated with our identification strategy.

We drew credit defaults from the Federal Reserve Bank of New York and Equifax Consumer Credit Panel. The Consumer Credit Panel is a 5% random sample of all credit files for US persons with Social Security numbers drawn from Equifax administrative credit bureau records. The 5% random sample is then supplemented with the credit report data for all persons who reside at the same address as the primary individual, yielding a total sample of approximately 40 million credit files each quarter. The panel begins in the first quarter of 1999 and data are collected each quarter on an ongoing basis, providing a snapshot of the individual's credit file as it stands on the last day of the quarter.[29] We aggregated these individual-level credit data to generate zip code–level averages for each quarter.

We drew additional annual data at the MSA level from the American Community Survey, 5-year moving averages from the American Community Survey small area surveys aggregated at the zip-code level, the Behavioral Risk Factor Surveillance System at the state level, and Small Area Health Insurance Estimates at the county level. The American Community Survey is an annual nationally representative survey of conducted by the US Census Bureau to create estimates of social and economic characteristics of the population.[30] The Behavioral Risk Factor Surveillance System is a state-based annual, nationally representative repeated cross-section of the health and health behaviors of US residents.[31] Small Area Health Insurance Estimates data are produced by the US Census Bureau, and provide detailed estimates of health insurance coverage for US counties.[32] For our instrumental variables analysis, we also drew data from the National Climatic Data Center.[33] We structured the final data set as a zip code–level panel by quarter, covering about 9401 zip codes in 83 MSAs from first quarter 2004 through second quarter 2012, a total of 34 periods.

Influenza Severity and Loan Defaults

We drew our measure of influenza severity from Google Flu Trend data, based on weekly Google searches related to influenza-like illnesses. It is constructed by taking the natural log of the sum of all Google influenza-like illness–related Internet searches in a particular MSA and quarter.[25]

We examined 2 types of default: mortgage delinquency and credit card delinquency. For each of these variables, we examined the link between influenza and logged (1) 30-day delinquency, (2) 60-day delinquency, (3) 90-day delinquency, and (4) all delinquencies. We calculated the default rates for the various periods as the percentage of credit files in a given zip code and quarter that are 30, 60, 90, or any days delinquent. We considered time since delinquency as an important indicator of the vulnerability of borrowers. Borrowers who are behind by more than 1 payment (60-day or 90-day) may be particularly at risk for falling behind in the wake of an unexpected health shock. Vulnerable borrowers who are multiple payments behind are also more likely to be lower income, have less than a college degree, have unstable employment, and be a minority race.[12]

Metropolitan Statistical Area and Zip Code–Level Confounders

We included an array of MSA and zip code–level sociodemographic characteristics that may confound the association of interest. These included logged population size, percentage of the population aged 65 years and older (zip code), median income (zip code), percentage of adults with a college degree (zip code), and the unemployment rate (MSA). We also controlled for annual influenza vaccination rates (MSA) and the health insurance rate (MSA). To ensure that the results were not driven by differences in borrowing practices across cities, we controlled for the average credit card balance in each zip code from the Equifax data. Because data were missing for some zip codes in some quarters or years, models with a full array of controls will have smaller sample sizes than models drawn only from credit reports and influenza search data.

Finally, in the event that influenza severity is not fully exogenous to default, we used weather patterns data from the National Climatic Data Center in a 2-stage least squares (2SLS) instrumental variables analyses to estimate the effect of influenza on default. These are daily weather observations at the MSA level (by weather station) aggregated quarterly. We used 2 instruments in the first stage, average temperature and average relative humidity for the MSA–quarter, both of which are associated with influenza,[34,35] but which we have no reason to suspect are independently correlated with credit outcomes.

Analytic Strategy

We used 3 regression-based modeling strategies to assess the association of interest. We first estimated ordinary least squares (OLS) regression models predicting logged default rates, net of MSA and zip code–level confounders. However, this approach is subject to omitted variable bias, as cities and zip codes that differ in influenza and default also differ on a range of other factors. Thus, we estimated quarter-year fixed-effects models to assess how within-MSA changes in influenza severity are associated with within–zip code changes in defaults, net of all observed and unobserved confounders that are stable across zip codes and time. A key strength of this approach is that we can treat each zip code as its own control when estimating the influenza–default association.

Finally, we employed a 2SLS instrumental variables model, in which we used weather patterns by quarter and MSA to instrument for the effect of influenza on default, by generating variation in influenza severity that is exogenous to default. This estimate is the local average treatment effect of weather-induced influenza severity on credit defaults.[36] We based all analyses on built-in routines in Stata version 13 (StataCorp LP, College Station, TX), in which the error term was corrected with Huber–White corrections for heteroscedasticity, and clustered at the MSA level. Summary statistics for all variables are shown in Table 1.

RESULTS

Table 1 shows the bivariate association between influenza searches and defaults. We classified low influenza severity as being less than half the overall MSA mean rate for influenza trends, mid influenza severity as half to 1.5 times the overall MSA mean, and high influenza severity as greater than 1.5 times the MSA mean. On the whole, we found a statistically significant positive association between influenza searches and default rates, with the exception of 30- and 60-day credit card default. However, this pattern could be driven by a number of other time or geographic-based factors, prompting a more detailed specification by using regression analysis.

Table 2 shows OLS regression models in which we regressed logged credit card default rates on influenza and all controls. Net of confounders, we found no significant association between influenza and 30-day credit card defaults. However, we did find a significant association between influenza severity and 60-day defaults, 90-day defaults, and all defaults. The log–log estimates suggest about a 0.5% increase in 60-day default rates with a 1% increase in influenza severity ($b = 0.00546$; $P < .001$). The association was stronger for 90-day default, suggesting nearly a 1% increase in 90-day defaults with a 1% increase in influenza severity. These estimates suggest a positive association between influenza and credit card defaults that increases with the number of days delinquent. As such, influenza outbreaks appear to disproportionately affect the finances of financially fragile borrowers who are already behind on their payments. Similar models that used nonlogged dependent and independent variables, as well as population rates, produced similar results.

In Table 2, we also present estimates from quarter-year fixed-effects models that allowed us to use each zip code as its own control, and assess whether within-MSA changes in influenza severity are associated with within–zip code changes in credit card default, net of all stable between–zip code observed and unobserved characteristics and national time trends. Here the estimates were similar in significance and direction, but smaller in magnitude. For example, a 1% increase in influenza severity was associated with a 0.3% increase in 90-day defaults. The magnitude of this association was similar across all default outcomes.

In Table 3 we turned to mortgage default. Estimates from OLS regression models revealed a statistically significant, but small positive association between influenza and 60- and 90-day default, but not 30-day default or all defaults. These estimates were substantially smaller than the estimates for credit card default. Here, a 1% increase in influenza was associated with only a 0.3% increase in 90-day mortgage defaults. We found similar results in the quarter-year fixed-effects models, though the coefficients are slightly smaller in magnitude.

Finally, Table 4 shows the 2SLS estimate of the effect of influenza on credit card and mortgage defaults. The first-stage F-test statistic was 23.09, above the 10% Stock–Yogo suggested maximal cutoff of 19.93. Other weak-identification tests were also consistent with MSA–quarter mean temperatures being a valid predictor of influenza severity. The second-stage estimates were mostly consistent with these estimates. For example, a 1% increase in influenza severity was associated with a 0.7% increase in 90-day credit card defaults, and a 0.1% increase in 90-day mortgage defaults. One anomalous finding from the 2SLS estimates was that influenza severity was actually

TABLE 1—Descriptive Statistics and Bivariate Association Between Influenza-Related Google Searches and 30-, 60-, and 90-Day Credit Card and Mortgage Delinquency Rates: United States, 2004–2012

	Univariate Statistics			Bivariate Statistics: Influenza Searches			
Variable	Mean (SD)	Min	Max	Low	Mid	High	F-test[a]
Logged influenza searches	10.07 (1.362)	0	12.90				
Logged credit card default rates							
30-day defaults	0.413 (0.878)	0	16	0.220	0.211	0.197	44.75***
60-day defaults	0.262 (0.694)	0	18	0.225	0.218	0.217	3.85*
90-day defaults	0.201 (0.605)	0	18	0.169	0.170	0.177	3.94*
Logged mortgage default rates							
30-day defaults	0.199 (0.528)	0	34	0.211	0.219	0.221	4.96**
60-day defaults	0.080 (0.317)	0	9	0.076	0.089	0.095	43.55***
90-day defaults	0.042 (0.228)	0	12	0.366	0.467	0.535	59.95***
Control variables							
% vaccinated	27.26 (20.89)	0	62.89				
Unemployment rate	6.116 (2.582)	0	18.37				
% some college	39.99 (27.44)	0	90.82				
% older than 65 y	22.55 (15.18)	0	46.44				
Median income, $	42 243.1 (28 579.6)	0	94 267				
Health uninsurance rate	3.231 (5.055)	0	24.08				
Logged population size	14.84 (1.042)	11.93	16.74				
Average credit card balance, logged	4.827 (2.774)	0	12.38				
Average temperature, °F	58.14 (15.11)	14.10	94.80				

Note. The sample size was n = 205 352 (9128 unique zip codes). Influenza search data source: Google Flu Trends.[22] Default data provided by Equifax Consumer Credit Panel.[29] All other measures obtained from American Community Survey,[30] Behavioral Risk Factor Surveillance System,[31] Small Area Health Insurance Estimates,[32] and National Climatic Data Center.[37]
[a]F-test from 1-way analysis of variance test.
*$P < .05$; **$P < .01$; ***$P < .001$.

TABLE 2—Ordinary Least Squares and Fixed-Effects Regressions of Logged Zip Code–Level Credit Card Default Rates on Logged Metropolitan Statistical Area–Level Influenza Severity: United States, 2004–2012

Search/Delinquency Rate	Ordinary Least Squares Regression Models,[a] b (95% CI)	Zip Code–Quarter Fixed-Effects Models,[b] b (95% CI)
Logged influenza searches		
30-d	0.002 (-0.001, 0.005)	0.003*** (0.002, 0.005)
60-d	0.006*** (0.003, 0.007)	0.004*** (0.002, 0.005)
90-d	0.010*** (0.007, 0.012)	0.003*** (0.002, 0.004)
Any	0.011*** (0.008, 0.015)	0.003*** (0.001, 0.005)
Constant		
30-d	−0.608*** (−0.672, −0.545)	0.199*** (0.184, 0.215)
60-d	−0.460*** (−0.506, −0.414)	0.121*** (0.108, 0.133)
90-d	−0.426*** (−0.466, −0.386)	0.089*** (0.078, 0.100)
Any	−1.12 (−1.22, −1.01)	0.386*** (0.364, 0.408)

Note. CI = confidence interval. Standard errors are corrected for clustering.
[a]205 352 observations (9128 unique zip codes), with metropolitan statistical area and zip code level control variables.
[b]291 488 observations (9197 unique zip codes), without metropolitan statistical area and zip code level control variables.
*P < .05; **P < .01; ***P < .001.

negatively associated with 30-day defaults. The negative effect of influenza severity on 30-day defaults likely results from the local average treatment effect we are estimating here by using weather patterns as instruments. The 30-day delinquency was only a risk for those who were current on their credit card and mortgage payments. Thus, it is possible that weather-induced influenza severity was associated with people staying indoors, less likely to use credit cards and more likely to remember to pay their bills. In general, the results from the 2SLS analysis were similar to the OLS and fixed-effects models, and support the contention that health shocks are more likely to affect the financial well-being of vulnerable borrowers.

TABLE 3—Ordinary Least Squares and Fixed-Effects Regressions of Logged Zip Code–Level Mortgage Default Rates on Logged Metropolitan Statistical Area–Level Influenza Severity: United States, 2004–2012

Search/Delinquency Rate	Ordinary Least Squares Regression Models,[a] b (95% CI)	Zip Code–Quarter Fixed-Effects Models,[b] b (95% CI)
Logged influenza searches		
30-d	−0.000 (−0.002, 0.002)	0.001 (-0.001, 0.003)
60-d	0.003*** (0.001, 0.005)	0.001* (0.001, 0.001)
90-d	0.003*** (0.001, 0.005)	0.001*** (0.001, 0.001)
Any	0.002 (0.000, 0.003)	−0.000 (−0.002, 0.002)
Constant		
30-d	−0.148*** (−0.207, −0.089)	0.105*** (0.091, 0.119)
60-d	−0.167*** (−0.198, −0.136)	0.026*** (0.018, 0.034)
90-d	−0.129*** (−0.149, −0.109)	0.007*** (0.001, 0.012)
Any	−0.351*** (−0.433, −0.269)	0.157*** (0.139, 0.175)

Note. CI = confidence interval. Standard errors are corrected for clustering.
[a]205 352 observations (9128 unique zip codes), with metropolitan statistical area and zip code level control variables.
[b]291 488 observations (9197 unique zip codes), without metropolitan statistical area and zip code level control variables.
*P < .05; **P < .01; ***P < .001.

In sum, we generally found a statistically significant positive association between influenza severity and credit default. Influenza severity appears to more substantially increase credit card default (vs mortgage default) and 90-day default (vs less-severe defaults). The fact that the 2SLS estimates largely matched the OLS estimates in magnitude and significance suggests that influenza is largely an exogenous health shock.

DISCUSSION

The surge in mortgage and credit card default that was precipitated by the Great Recession raised important questions about the link between public health, default, and debt. In this article we bring together 2 separate literatures on the economic consequences of influenza[4] and the growing research on debt and health,[15–18] and show that influenza severity is positively associated with credit card and mortgage default rates. Importantly, our findings suggest that influenza outbreaks have a disproportionate impact on the finances of borrowers who are behind on their payments.

Although our findings revealed a somewhat small association between influenza and default, this is perhaps unsurprising: influenza outbreaks may have an impact on household finances, but are unlikely to have as large and long-lasting of an impact on household finances that other major health shocks might have.[21] However, we did find that the impact of influenza is larger for borrowers who are behind on payments, which dovetails with research that shows that vulnerable populations have a greater need for borrowing in the wake of a health shock.[14] Our study builds on this research by showing that this lack of resource to absorb a financial shock comes with consequences for default. It is also intuitive that we find larger effects for credit card than mortgage default. Homeowners are, on average, more financially stable than the credit card user population. Moreover, the size of the mortgage payment relative to other bills makes it unlikely that borrowers would forget about their mortgages as a result of influenza, and in times of financial distress mortgages are likely the last payment a borrower will neglect.

This is the first study to examine the link between influenza outbreaks and credit

TABLE 4—Two-Stage Least Square Instrumental Variable Regressions of Logged Zip Code–Level Mortgage Default Rates on Logged Metropolitan Statistical Area–Level Influenza Severity (Instrumented With Weather Patterns): United States, 2004–2012

Search/Delinquency Rate	Credit Card Defaults, b (95% CI)	Mortgage Defaults, b (95% CI)
Logged influenza searches		
30-d	–0.007*** (–0.010, –0.004)	–0.005*** (–0.007, –0.003)
60-d	0.000 (0.000, 0.001)	0.000 (–0.002, 0.001)
90-d	0.007*** (0.005, 0.010)	0.001* (0.001, 0.002)
Any	–0.001 (–0.004, 0.003)	–0.003 (–0.007, 0.001)
Constant		
30-d	0.278*** (0.249, 0.308)	0.184*** (0.159, 0.209)
60-d	0.131*** (0.105, 0.156)	0.058*** (0.040, 0.077)
90-d	0.032*** (0.009, 0.056)	0.018*** (0.004, 0.032)
Any	0.387*** (0.347, 0.426)	0.241*** (0.212, 0.270)

Note. CI = confidence interval. Standard errors are corrected for clustering. First-stage 2-stage least square instrumental variable results show F test of 23.68. The 10% Stock-Yogo maximal cutoff instrumental variable was 19.93.
*P < .05; **P < .01; ***P < .001.

default, and makes several contributions. First, we built on previous research on the economic impact of influenza outbreaks, and showed that influenza may affect other aspects of the US economy, particularly loan default. Second, our interest in influenza provides us with a unique opportunity to contribute to the broader literature on health shocks and credit default. Previous research is limited because health shocks are often endogenous, and most studies are unable to assess causation. Our focus on influenza, an exogenous (though relatively minor) health shock, as well as our use of a range of methodological strategies, provides greater (though not absolute) confidence for a link between this health shock and default. However, we acknowledge that our study has limitations that restrict our ability to make causal claims and that omitted variable bias may be a concern.

Importantly, this study presents a classic internal–external validity trade-off. Although our study has relatively high internal validity (exogenous health shock), it has lower external validity: influenza outbreaks tell us little about how families in the United States struggle to balance the onset and progression of chronic illnesses and household finances.[21] Another limitation of this study is that we were unable to test for heterogeneity in the effect of influenza on default with our aggregate-level data. It is likely that the effects presented in this article underestimate the impact of influenza on default for economically vulnerable populations because our estimates represent an average effect across a range of borrowers, some of whom will be more socially and economically advantaged and have a lower risk of influenza and default. Relatedly, we are unable to draw inferences about individual-level processes with our data. With these aggregate-level data, we are unable to know whether individuals who defaulted were struck with influenza, and the ecological fallacy is a concern.

However, using aggregated data has some advantages. Our ability to demonstrate a relationship between MSA-level influenza severity and zip code–level rates of credit delinquency across multiple econometric specifications represents a potentially substantive contribution to this otherwise scant literature. Future research that combines individual- and contextual-level data would be well positioned to address the ecological fallacy.

The strong link between health and debt suggests a need to reexamine the social safety nets that protect families when illness strikes.[21] In the case of influenza, recent legislation on paid sick leave could alleviate the financial burden of illness, particularly among low-income populations who have a high risk of default.[38] Future research should continue to investigate this question, perhaps by examining the link between health shocks and default in countries with strong social safety nets (e.g., paid sick leave, high minimum wage) and countries with weaker social safety nets. Researchers should also consider how recent policy changes in the United States, such as the expansion of paid sick leave and the expansion of Medicare and Medicaid under the Affordable Care Act, may modify the link between health shocks and household finances. Future research should continue to investigate the link between health and default, as well as the policies that can reduce the financial devastation of illness in the United States, particularly for vulnerable populations that have high risk of both health shocks and default. ■

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***Note.** The analysis and conclusions set forth in this article are those of the authors and do not indicate concurrence by other members of the research staff or the Board of Governors of the Federal Reserve System.*

Contributors

J. N. Houle and J. M. Collins originated the study. J. N. Houle drafted the introduction and conclusion of the study and conducted the early analyses. J. M. Collins completed the analyses and was responsible for data and methods. M. D. Schmeiser provided the default data and assisted with data interpretation and writing. All authors interpreted the findings and edited multiple drafts of the article.

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Human Participant Protection

This study used de-identified aggregated data and did not use human participants. However, study analyses were conducted while the corresponding author and the author primarily responsible for data analysis (J. M. C.) were at the University of Wisconsin–Madison, and this study was approved by the University of Wisconsin institutional review board ("Owner Occupied Housing and Wellbeing" 2012-0095).

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