Panic! Social Learning and the Response to SARS in Taiwan*

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Abstract

When SARS struck Taiwan in 2003, people avoided the health care system en masse, perceiving greater disease risk in hospitals and clinics. Outpatient medical visits declined by 30 percent over a few weeks, and only recovered several months after the disease passed. Since prevalence evolves rapidly and varies by location, objective risk information is scarce during an emerging epidemic. In the absence of objective data, people may rely on the subjective risk assessments of their peers. This form of social learning leads to herd behavior, which may cause people to overreact in an emergency. This paper argues that herding is partially responsible for the exaggerated response to SARS in Taiwan. We develop and test a mode of peer interaction during SARS using a rich data set of health care claims from Taiwan. According to the model, the change in peer visits from an earlier period is an indicator for the group's subjective risk perception. We regress individual medical visits on the change in peer visits in a difference-in-difference specification that uses recent migrants and the pre-SARS period as control groups. We also address common unobservables directly by controlling for the level of peer visits. According to our estimates, an increase in the change in peer visits of one standard deviation increases visits by 15 percent.

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1 Introduction

Disease outbreaks such as SARS and the swine flu pose a critical and continuing threat to public health. Novel epidemics have occurred throughout history, but these phenomena have become a global concern with the ubiquity of international air travel. In the past 10 years, the world has experienced global epidemics of SARS, avian flu (H5N1), swine flu (H1N1), as well as outbreaks of meningitis and Ebola in Africa and Foot and Mouth Disease in Europe. The National Institutes of Health catalogues several dozen pathogens that have either emerged or reemerged during the past two decades, as well as several other potential bioterrorist pathogens (NIAID 2010). Both SARS and avian flu outbreaks were limited by moderately difficult interpersonal transmission, while swine flu manifested with mild symptoms. Epidemiologists remain on alert for an emerging pathogen that is both highly lethal and easily transmitted from person to person.

The private "prevalence response" to disease risk endogenously limits the spread of infection. Heightened disease prevalence creates an incentive for people to protect themselves through actions such as social isolation, condom use, or vaccination (Philipson 2000, Gersovitz and Hammer 2003). For communicable diseases, self protection has the positive externality of reducing the likelihood of secondary infection, which reduces the steady state prevalence (Philipson and Posner 1993). Existing studies of the prevalence response assume that people adopt rational expectations about key epidemiological parameters (Ahituv et al. 1996). This assumption is sensible for a slow-moving epidemic, in which a person can reasonably forecast the future disease risk, but is ill-suited to a novel outbreak. During an outbreak, public information about the disease's prevalence and severity is typically limited, out of date, and unrepresentative of a person's idiosyncratic risk. AIDS first appeared in the United States in 1981, but the government did not begin publishing data on HIV prevalence until 1985, by which time thousands of cases had appeared (Osmond 2003). The earliest published estimates of prevalence varied widely and did not separately report prevalence among high-risk populations. During an outbreak or other emergency, it is unclear how people evaluate or respond to risk.

The scarcity of information may foster a sense of "panic" during an emergency. Although panic lacks a unified economic meaning, a common definition is a "sudden mass fear and anxiety over anticipated events." Herd behavior is one possible cause panic. Lacking objective risk information, people rationally respond to the signal contained in the actions of their peers and create an "information cascade" that leads to a herd response (Bikchandani et al. 1992, Banerjee 1992, Welch 1992). As the authors show, it may be rational to incorporate peers' beliefs even when those beliefs result from herding. By causing people to over-respond to a small risk, herding may exaggerate the prevalence response to a disease. In the context of SARS, people had little objective data about disease risk in the health care system. We argue that, by learning from the beliefs and actions of their peers, people formed a herd reaction that accentuated the prevalence response to SARS. In this view, people panic during an emergency because suddenly higher uncertainty causes them to follow their peers.

The SARS Epidemic struck Taiwan from March through July of 2003, having already caused thousands of infections elsewhere in Asia. SARS, a respiratory illness resembling severe pneumonia, caused 312 infections and 82 deaths in Taiwan during this period. SARS is transmitted when an infected person coughs or sneezes near susceptible person. Therefore, many people responded to the epidemic by avoiding restaurants, trains, shopping centers, and otherwise distancing themselves from others (Chou et al. 2004, Siu and Wong 2004). People perceived a heightened risk from the health care setting, which was the source of 73 percent of SARS infections (Hsieh et al. 2004). As a result, outpatient medical visits fell by 31 percent from March through June of 2003. Health care utilization did not return to normal until October, nearly four months after the epidemic had passed. The magnitude and duration of this decline suggests that this phenomenon may be more complicated than a fully informed and rational prevalence response.

This paper argues that social learning about disease risk contributed to the suppression of visits during SARS. We use a comprehensive and nationally representative panel of outpatient claims to track health care utilization before, during, and after the SARS epidemic. In our analysis, a peer group is the set of people who visit a common physician. As elaborated below, the change in utilization of the peer group from an earlier period is a proxy for the group's subjective assessment of the SARS risk. In regressions of individual visits on the change in peer visits, the differential effect during the SARS period may be interpreted as social learning about disease risk. Regressions show a lagged effect of 2-4 weeks, which is consistent with a process of intermittent belief revision within the peer group. This lagged response generates intertemporal feedback between individual and group visits, which leads to herding.

The influence of common unobservables is a serious concern in this regression. Common omitted factors may jointly determine both individual and group visits, causing a spurious positive correlation between individual and group variables (Manski 2000). This paper relies on two independent strategies to identify social learning. First, we compare recent migrants, who are less socially connected, to long-term residents in a difference-in-difference specification. To interfere with this regression, common unobservables must differentially affect non-migrants during the SARS period. Secondly, we control for the level of peer visits directly in the regression. Many common unobservables cause a spurious correlation because they affect the contemporaneous level of visits for both the individual and the group. By controlling for current visits, this approach exploits variation in peer visits from a year earlier to identify social learning. Estimates are similar under both approaches, which suggests that either strategy sufficiently addresses this issue.

The paper proceeds as follows. Section 2 provides additional motivation for the study of panic, social learning, and emerging infectious disease. Section 3 develops a simple model of social learning that illustrates how herding may accentuate the prevalence response to an unfamiliar disease. Section 4 describes the data and context and Section 5 presents regressions of visits on the change in peer visits under various specifications. Section 6 concludes.

2 Social Learning During an Emergency

Humans have suffered through emerging disease outbreaks throughout history. Outbreaks of the bubonic plague occurred periodically throughout the middle ages in Europe. The Black Death, which was the most notorious episode, took place from 1348-50 and killed more than 30 percent of the population of Europe (Monecke et al. 2009). Influenza has also emerged periodically throughout history, such as in 1485 with a "sweating sickness" swept across Britain (Walsh 2009). The Spanish flu pandemic of 1918 killed between 50 and 100 million people throughout out the world and had implications for a generation thereafter (Almond 2006).

The frequency and severity of pandemic infections will likely increase in the future. The organisms responsible for most recent outbreaks have been zoonotic pathogens that evolved the ability to survive in humans. Population growth continues to push civilization into previously uninhabited areas an increase the intensity of contact between humans and native species. This process increases the probability that a zoonotic organism will evolve into a human pathogen (Abraham 2007). In Greenfeld's (2006, p. 28) view, the SARS epidemic typifies the risk of emerging infectious disease. He comments that, "When another pandemic emerges, it will likely also come from southern China. Hong Kong, pressed as it is against the guts of China will be among the first afflicted. And because Hong Kong is a global transportation hub–more than 240 international flights a day originate in Chek Lap Kok airport–the virus will reach your hometown just twenty-four hours after it reaches Hong Kong." Although SARS has not returned since 2003, the epidemic is a relevant case study for future global outbreaks.

The SARS case study also presents and opportunity to analyze the economic significance of "panic." Although economics does not provide a unified definition of the term, panic may be interpreted in many contexts as an overreaction to unfamiliar risk. In general, a person may exhibit an extreme response to risk either because he perceives a high probability or a high disutility of the adverse event. Experimental studies have found that people tend to overestimate the probability of unlikely events. Sunstein and Zeckhauser (2008) conjecture that people further exaggerate the probability of "fearsome risks" with greater emotional valence. In their view, people overreact to threats such as terrorism and new diseases because these risks are less familiar and therefore convey a greater sense of fear.

Alternatively, people may exhibit an extreme response to unfamiliar risk because they are highly risk averse over these gambles. Authors have shown that risk aversion is situationally dependent and varies according to the magnitude of the potential gain or loss. Extreme risk aversion during an emergency may explain the overreaction that is associated with a panic. Finally, the panic response may arise because an unfamiliar risk accentuates ambiguity, or uncertainty regarding the underlying risk of a gamble (Ellsberg 1961, Kunreuther et al. 1995). If a risk is unfamiliar, it is difficult for the person to discern the probability associated with the gamble, which introduces additional uncertainty (over the true probability distribution) into expected utility. Heightened ambiguity creates an incentive for the decision maker to search for information about the probability distribution in order to attenuate the ambiguity. Therefore it is not surprising that social learning increases during an emergency, particularly when objective risk data are incomplete.

While this study is the first examination of panic in an infectious disease context, contagion is familiar in asset markets (Scharfstein and Stein 1990, Froot et al. 1992). A panic response may lead to herding in both cases, however the behavioral response has a different externality in an asset market than with a disease. A herd response to sell a distressed asset reduces the price of the asset. At a high initial price, this response accentuates the incentive for others to sell the asset as well. Therefore the herd response reinforces the reason to panic in an asset market. In contrast, social distancing during an epidemic imposes a positive externality on others by reducing the risk of infection. For a communicable disease, the risk of infection depends upon the probability of contact between a susceptible and an infected person. By avoiding public spaces, people reduced the chance of passing SARS to others. This mechanism limits the incentive to panic.

A large literature shows evidence of peer effects and social learning in everyday contexts. Many studies focus on how peer effects influence the academic achievements of students (Graham 2008, Sojourner 2009). Several papers have argued that social learning is an important factor in the adoption of new technologies (Foster and Rosenzweig 1995, Conley and Udry 2010, Bandiera and Rasul 2006). Studies have found peer effects in decisions about health care utilization (Aizer and Curry 2004, Rao et al. 2007, Deri 2005). The identification problems associated with peer effects are well known and difficult to address convincingly (Manski 2000). Where possible, this literature has relied upon randomization such as the Tennessee STAR experiment to identify peer effects. In contexts where randomization is not available, authors have relied on structural predictions to identify correlations that are consistent with peer effects. This study of peer effects during the SARS epidemic extends this literature by examining social learning in the unexplored context of infectious disease. Although social learning is likely to be quite salient in this setting, randomization is not feasible as a research method. We develop empirical tests from theory and validate these tests in the data.

Social learning during a disease outbreak has important epidemiological implications. In general, people under-respond privately to disease prevalence because they do not internalize the positive externality associated with their protection (Geoffard and Philipson 1996). By accentuating the prevalence response, herd behavior may improve welfare and limit disease transmission. Herding also increases the heterogeneity in risk exposure within the community since it allows groups to diverge to distinct equilibria. As Kremer (1996) demonstrates in the context of HIV, risk heterogeneity facilitates disease transmission by increasing the effective prevalence among the at-risk population. By enhancing the variance in risk exposure across groups, social learning may help to create "reservoirs" of infection.

3 Theory

This section provides a theoretical motivation for the empirical analysis. First, we show that the change in peer behavior during SARS is a proxy for the group's subjective risk perception. This step is necessary because subjective peer beliefs are unobservable in the data. Next we argue that incorporating peer beliefs may be rational, even when those beliefs reflect a herd response. Although the government of Taiwan released public information about SARS transmission, peer beliefs may contain more specific information about transmission risk in a particular location. Herding decreases the precision of this information source but does not cause it to be biased.

3.1 Peer Behavior and Subjective Peer Beliefs

People receive utility from wealth, w and health, h. Suppose for simplicity that the consumption of these two goods is additive toward utility. Thus, a person's utility when sick is $u(w, h-s) = u(w+h-s)$ where $s < h$ is the level of sickness, and $u' > 0$ and $u'' < 0$.

If medical care perfectly cures sickness (other than SARS), then the patient's utility from care is $u(w+h-c)$, where c is the co-pay for a medical visit. SARS risk complicates the decision to seek care by introducing the probability, q, that a medical visit may lead to the patient's death.[1] Under the assumption that utility at death is zero ($u(w,0)=0$), the patient's expected utility from visiting the doctor during SARS is:

$$qu(w-c,0)+(1-q)u(w-c,h)=(1-q)u(w+h-c) \tag{1}$$

Absent the SARS risk, a patient visits the doctor if his copayment is less than the cost of his sickness: $u(w+h-c)>u(w+h-s)$, or $c<s$. If patients differ in the severity of their sickness, the aggregate demand for medical care is given by $D(c)=N\int_{s>c}f(s)ds$, where $f(s)$ is the distribution of sickness in the population and N is the population of patients.

An increase in the expected SARS risk suppresses the level health care utilization. Because SARS lowers the utility of visiting the doctor by $(1-q)$, a person must be sicker in order to seek care during epidemic: $(1-q)u(w+h-c)>u(w+h-s)$. This reduction in the demand for medical care has the same effect as an increase in the copayment. A first-order Taylor approximation around $(w+h)$ of the logged visit condition yields the requirement that $\ln(1-q)-R(w+h)c>-R(w+h)s$, where $R(w+h)=u'(w+h)/u(w+h)>0$. Solving for s leads to an expression for the threshold of sickness for visiting the doctor: $s>c+T(q)$, where:

$$T(q)=-\ln(1-q)/R(w+h)>0 \tag{2}$$

and $T'(q)>0$. Aggregate demand for visits is given by $D(c+T)=N\int_{s>c+T}f(s)ds$. Therefore, SARS functions like a visit tax by increasing the possibility that the patient may die as a result of seeking care.

This measure of SARS risk is more sensible when aggregated within a peer group. For any individual, idiosyncratic factors may dominate in his decision of whether to seek care either before or during SARS. However this noise averages out within a group and improves the quality of the signal.

An observer can infer someone's perception of the SARS risk from the decline his medical consumption. This inference is more sensible when observations are aggregated across a large number of people since idiosyncratic factors average out. Figure 4 illustrates that, under the assumptions of linear demand and perfectly elastic supply, the change in quantity is proportional to the perceived SARS risk. The assumption of perfectly elastic supply may be unrealistic in practice since the SARS epidemic may have also induced physicians to

[1]For simplicity, we ignore SARS morbidity.

reduce labor supply. However it is also likely in practice that patients could distinguish between supply and demand shifts by observing, for instance, whether a particular physician was still accepting appointments. Our empirical analysis addresses the potential for supply shocks directly.

3.2 Is Social Learning Rational?

Social learning in the context of an epidemic may be rational, even if people realize that they are following a herd. We restate this point, which also appears in the original herding models of Bikchandani et al. (1992) and Banerjee (1992). Let $q \in [0,1]$ be the true risk from SARS. People receive a public signal, g, about the SARS risk from news reports, which has mean q and variance σ_g^2. People also receive a signal from peers that has mean 0 and variance σ_p^2. The distribution of the average of the two signals has mean 0 and variance $(\sigma_g^2 + \sigma_p^2)/4 + \sigma_{gp}/2 \leq \sigma_g^2$, where σ_{gp} is the covariance of the two signals. Unless the two signals are perfectly correlated, the average of the two signals is more precise than the the government signal on its own.

It is rational to incorporate the peer signal as long as it contains any independent information. The optimal weight to place on the peer signal rises with its information content. If α is the fractional weight placed on the signal from peers, then the weight that minimizes variance is:

$$\alpha = \frac{\sigma_g^2 - \sigma_{gp}}{\sigma_g^2 + \sigma_p^2 - 2\sigma_{gp}} < 1 \tag{3}$$

which is positive as long as the signals covary positively. The weight on the peer signal increases as the σ_{gp} falls, but declines as σ_g^2 increases. Subjective peer beliefs are most valuable when they are independent of the public signal and exhibit low variance.

The risk assessments of peers may be highly informative in the context of SARS despite the potential for herding. The public signal of SARS risk arrives in the form of daily reports on the number of SARS cases by county. This information is useful but does not speak directly to the risk of contracting SARS in a particular location, which is the relevant parameter for the patient. Herding reduces the information content in the subjective peer belief but does not bias that belief. Instead, people observing a herd learn about the beliefs of the initial movers, rather than the whole group(Bikchandani et al. 1998). Even if an information cascade introduces bias, it may still be rational to incorporate the information. A person who has a defined expectation of the bias can subtract the bias from the peer beliefs.

4 Context and Data

4.1 The SARS Epidemic in Taiwan

Taiwan is a a densely-populated island located off of the coast of mainland China. The country has a population of 22 million and per capita GDP of around $31,000. Modern infrastructure such as highways and high-speed railways facilitates travel within the country. Taiwan consists of 25 cities and counties, which further subdivide into 368 townships and districts (hereafter referred to as townships). In 1996, Taiwan implemented a public fee-for-service health care system, which is administered through the Bureau of National Health Insurance (BNHI) (Cheng 2003). Through the program, the government reimburses physicians for most health care expenses. Patients contribute modest copayments of under $5 for visits, tests, and medicines. People may seek care from either hospital outpatient departments, or from small storefront clinics, which are ubiquitous in cities and serve around 70 percent of the market. Patients in Taiwan utilize the health care system intensively, visiting providers a median of 10 times per hear. Frequent visits for minor conditions such as sore throats and colds are responsible for the elevated utilization.

The SARS Epidemic reached Taiwan on March 14 of 2003, when a person who had recently traveled to China became the first suspected case. Isolated SARS cases occurred for the next several weeks as the epidemic flared in other parts of Asia. On April 22, 2003, an indigenous outbreak occurred at the Ho-Ping Hospital in Taipei, which led to the infection of dozens of hospital staff. This outbreak led to multiple secondary outbreaks across the country. The epidemic lasted through the end of June, by which time 312 people had become infected and 82 people had died. At its height, SARS infected 60 people per day and had a case fatality rate of 9.6 percent. Nevertheless the overall prevalence was only 3.7 cases per 100,000 people. Figure 1 plots the number of reported and probable SARS cases by two-week period during 2003. Probable cases are a subset of reported cases, and require stricter criteria for diagnosis, which is described further below.

The Ho-Ping outbreak occurs in Period 9 of the figure, which marks the escalation of the outbreak. This event sparked a "panic" in the population. According to Ko et al. (2006), "The Taiwanese people suffered intense anxiety due to the uncertainty and insecurity they experienced during the first several weeks. People started to hoard all possible protective equipment, and reject people or materials with any risk of infection, including infected patients, the families of patients, subjects quarantined, and even health providers." Economic activity fell precipitously. For instance, domestic airline traffic fell by 30.3 percent, while international traffic dropped by 58 percent compared to 2002 (National Policy Foundation 2003). Figure 2, which plots the nationwide number of outpatient visits during 2003, shows that people also avoided the health care system. The figure shows a precipitous decline in visits that begins in March and accelerates along with the epidemic. Aggregate visits reach a minimum in Period 12, which coincides with the end of SARS incidence. The figure also plots the time series for 2001 and 2002. These years do not show the same pattern, discounting seasonality as an explanation for the 2003 decline. Some of the people who eschewed the western health care system turned toward Chinese medicine. According to the Taiwanese newspaper Star News, the price of Isatidis Radix, which was said to counteract viruses, increased by 800 percent.

After the decline in visits during SARS, it several months for visits to return to normal. Figure 2 demonstrates that, although SARS disappeared around Period 12, visits did not return to normal until around Period 20, roughly four months later. This finding is inconsistent with the simplest model of risk-neutral and fully-informed prevalence response, under which visits would immediately return to normal after the disease threat abated. Instead it is reasonable to conjecture that people were not fully informed about the true SARS risk, particularly after SARS incidence fell to zero. In the absence of full information, this paper argues that people responded to the subjective risk perceptions of their peers. A well-known prediction of peer effect models is "excess variance" in outcomes across groups (Glaeser et al. 1996, Graham 2008). Health care utilization during the SARS period features this pattern, which points to social learning as a potential explanation. Figure 3 plots the coefficient of variation across patients in outpatient visits by two-week period from 2001-2003.[2] The 2003 series shows a large increase during the SARS period that does not appear in either 2001 or 2002. This evidence motivates the search for additional evidence of social learning in this context.

4.2 Data

This study uses a comprehensive data set of health care claims in order to track health care utilization in Taiwan. Taiwan's national health insurance system generates data on the claims of all program participants, including the visits, prescriptions, and diagnoses. The BNHI furnishes a panel data set to researchers, which includes all of the claims from 1997 to the present of one million nationally-representative patients (4.3 percent of Taiwan's population). We utilize a subset of these data in order to calculate visits by two-week period for all of 2001 to 2003. This approach incorporates an extended "pre" period before SARS occurred in the spring and summer of 2003.

[2]Since visits are bounded below at zero, the decline in visits mechanically suppresses the variance in visits. The coefficient of variation, which normalizes by the mean level of visits, partially addresses this issue.

A demonstration of social learning hinges upon the definition of a peer group. Unfortunately, the data do not naturally delineate peer groups by listing each person's social connections. As an alternative, we treat the set of people who attend a common physician from 2001 to 2003 as a peer group. Word of mouth is the most common way that people search for a new physician: according to Hoerger and Howard (1995), 75 percent of patients in the US used a friend's referral to select a primary care physician. Because of the role of social networks in physician selection, many people who visit the same doctor are likely to know each other either directly or indirectly (Harris 2003, Tu and Lauer 2008). Patients belong to a median of 7 peer groups since they visit this man physicians over the period. Peer groups contain a median of 61 people.

The distinction between migrants and non-migrants is central to the identification strategy below. We define a migrant anyone who has arrived in their 2003 township prior to 2002, so that he or she has been present for less than two years when SARS arrives. The data do not identify patients' residential townships, but do provide the townships of medical facilities. For each year from 1999 to 2003, we infer the residential township of each patient based on his or her modal township for health care visits. For each pairwise combination of townships, we also calculate the overlap in patient traffic, which measures the distance between the townships. This metric directly captures the likelihood that a person who changes modal townships has not actually moved. We classify a change in the modal township as a move if the overlap between the townships is less than 1 percent. In selecting a low threshold of overlap, our approach minimizes the risk of misclassifying non-migrants as migrants. According to this definition, around 6 percent of the population moves each year.

The data furnished by the BNHI, which contains all of the claims of one million people, is unmanageably large for our context. To construct a regression dataset, we select a 2 percent subsample of this group. Half of the regression sample is selected at random from the population, while the other half consists entirely of migrants. This oversampling strategy increases the statistical power to detect significant migrant interactions. Our regressions rely on probability weights to restore the original proportion of migrants to the data.

The estimates in the next section evaluate the effect of social learning on health care utilization during SARS. The SARS Period, which is the basis for this interaction, begins in the 10th week and ends in the 38th week of 2003. This definition encapsulates both the actual SARS epidemic and the extended period afterward while visits remained suppressed. The change in peer visits from one year earlier is a proxy for the peer group's subjective risk perception. For each peer group, $\overline{v}$ is the average number of visits by peers, excluding the index person. Then change in peer visits, $\Delta\overline{v}$ is the change in $\overline{v}$ from one year earlier.

Although the length of the difference is arbitrary, a one year difference is appealing because it removes any seasonal variation in health care utilization. The results are robust to using a six-month lag instead.

Data on SARS prevalence are available from the Taiwan Centers for Disease Control (Taiwan CDC). For each SARS case, the agency provides the date of diagnosis, location, and classification. SARS cases may be either "reported," "suspected," or "probable." A reported case is any case that is referred to the Taiwan CDC for investigation as possible SARS. A suspected case is a reported case that also (1) exhibits high fever and difficulty breathing and (2) an epidemiological link to other SARS cases. A probable case is a suspected case for which there is also radiographic evidence of pneumonia or respiratory distress syndrome or a positive assay for the SARS coronavirus (WHO 2003). We measure SARS prevalence as the number of reported cases per 100 people in the township. Although reported cases are the least likely to materialize as confirmed cases, these cases were the most salient for people at the time as a SARS risk indicator. A normalization by population scales the SARS incidence so that it more closely reflects the risk that a person faces when entering the health care system.

Summary statistics for visits and SARS cases appear in Table 1. The table shows individual visits to specific physicians for both migrants and non-migrants, as well as total peer visits, average peer visits, and the change in average peer visits. The table reports means of each variable for 2001, 2002, and 2003, which is divided between SARS and non-SARS periods. Overall, patients visited each physician an average of 0.037-0.040 times per two-week period during 2001 and 2002. This rate of utilization fell to 0.032 during the SARS period, mirroring the decline in Figure 2. The table shows a similar decline for both migrants and non-migrants, although the migrants have lower overall utilization. Other patients in the peer group have 22-24 total visits per two-week period, which falls to 20.28 during the SARS period. Since the peer group consists of only people from the panel of one million patients, actual patient volume is roughly 22 times this amount. Averages for the change in peer visits show a large positive change from 2000 to 2001, followed by small declines that become sharper during SARS. SARS prevalence (which is zero by definition outside of the SARS period) is remarkably low relative to Taiwan's population. Throughout the course of the epidemic, only a few hundred people were ever infected.

5 Estimation

5.1 Specification

In this section, we estimate a model of social learning from peers about SARS risk. The model in Section 3 illustrates how the change in visits of peers from a baseline period, $\Delta\overline{v}$ is a proxy for the group's perception of SARS risk. In regressions of individual visits, v, on $\Delta\overline{v}$, the coefficient on $\Delta\overline{v}$ measures the effect of social learning on health care utilization. Our regressions elaborate on the following specification:

$$v_{ijkt} = \alpha_j + \delta_t + \gamma_1 \Delta\overline{v}_{ijkt} + \gamma_2 s_{kt} + \epsilon_{ijkt} \tag{4}$$

In this specification, i indexes the patient, j indexes the physician (which is equivalent to the peer group), k indexes the township or district, and t indexes the two-week period. v_{ijkt} is the patient's number of visits to a particular physician during a two-week period, and $\Delta\overline{v}$ is the year-on change in the average number of peer visits, which is calculated excluding the index person. s_{kt} is the number of reported SARS cases per 100 people, which is the public signal of SARS risk. All independent variables are calculated over the current period and the two prior periods, so that they cover a total of six weeks.

The specification includes a peer group fixed effect, α_j, which allows the regression to compare similar peer groups by absorbing the physician's time-constant level of activity. Regressions also include a complete set of time dummies, δ_t, which absorb generalized trends in medical utilization. Standard errors are clustered by the patient's modal township (calculated for all visits from 2001 to 2003), which allows an arbitrary error correlation across people in a common township. Regressions, which are estimated by OLS, also use probability weights to place equal emphasis on each person in the data.

Any regression of individual behavior on group behavior is complicated by the reflection problem, which is the joint determination of the individual and group variables (Manski 2000). In our context, a positive effect of $\Delta\overline{v}$ may arise because common unobservables affect both v and $\Delta\overline{v}$. Since $\overline{v}_{ijkt}$ is one component of $\Delta\overline{v}_{ijkt}$, any factor that causes heterogeneity in both v and $\Delta\overline{v}$ may spuriously induce a positive estimate of γ_1. Two particular sources of heterogeneity threaten the identification of (4). First, unobservable supply shocks may affect the attendance of both the index person and the peer group. For instance some physicians may respond to SARS by curtailing hours or closing entirely while others remain open. Secondly, patients may sort into peer groups based on common unobservable characteristics such as risk aversion, which affect how they respond to an emergency. Either of these channels could generate a spurious positive relationship between

v and $\Delta\overline{v}$.

We overcome these concerns through two complementary empirical strategies. The first approach is a difference-in-difference specification based on an interaction with the SARS period and an indicator for the patient's migrant status. As discussed above, a migrant is defined as a person who has lived in his or her 2003 township for less than three years. Having recently arrived, migrants are less socially connected than longer-term residents. In a framework of social learning, migrants should exhibit a weaker response to $\Delta\overline{v}$ than non-migrants. Difference-in-difference regressions adhere to the following specification:

$$\begin{aligned} v_{ijkt} =& \alpha_j + \delta_t + \gamma_1 N_i + \gamma_2 S_t N_i + \gamma_3 \Delta\overline{v}_{ijkt} + \\ & \gamma_4 S_t \Delta\overline{v}_{ijkt} + \gamma_5 N_i \Delta\overline{v}_{ijkt} + \gamma_6 S_t N_i \Delta\overline{v}_{ijkt} + +\gamma_7 s_{kt} + \epsilon_{ijkt} \end{aligned} \tag{5}$$

In this specification, N_i is an indicator that the person is a non-migrant and S_t is an indicator for the SARS period (weeks 10-38 of 2003). The coefficient of interest in this specification is γ_7, which measures the differential effect of $\Delta\overline{v}$ during the SARS period relative to the non-SARS period, and for non-migrants relative to migrants.

To interfere with this regression, any omitted variable must apply differentially to non-migrants during the SARS period. For instance, there must be greater heterogeneity in the supply restriction by physicians for non-migrants than for migrants. Alternatively, migrants must exhibit different preferences or other characteristics that affect their response to an emergency. Summary statistics from Table 1 show that migrants and non-migrants have almost identical percentage declines in visits during the SARS period, which suggests that common unobservables did not differ in a meaningful way across these groups.

The second approach controls for $\overline{v}$ directly in the regression. Without this control, $\Delta\overline{v}$, which is defined as $\overline{v}_{ijkt} - \overline{v}_{ijkt-26}$, may vary either through the contemporaneous or lagged peer visits. The primary threat to identification comes from a spurious correlation between contemporaneous values of v and $\overline{v}$. Controlling for $\overline{v}_{ijkt}$ in the regression absorbs the component of $\Delta\overline{v}$ that is correlated with v through common unobservables. These regressions take the form:

$$v_{ijkt} = \alpha_j + \delta_t + \beta_1 \Delta\overline{v}_{ijkt} + \beta_2 \overline{v}_{ijkt} + \beta_3 S_t \Delta\overline{v}_{ijkt} + \beta_4 S_t \overline{v}_{ijkt} + \beta_5 s_{kt} + \epsilon_{ijkt} \tag{6}$$

Regressions with this control identify a social learning effect through variation in $\overline{v}_{ijkt-26}$. The informational content of a decline in visits is stronger in peer groups that have high past visits because visits are bounded below at zero. Put another way, someone's lack of medical utilization during SARS does not signal his perceived risk if he had no prior utilization. For unobserved supply or demand shocks to cause a spurious correlation in this specification, they must induce a *negative* correlation between v and $\overline{v}$.

5.2 Results

Results based on the difference-in-difference specification from equation (5) appear in table 2. The first column shows the single difference based on the interaction between S_t and $\Delta\overline{v}$. This regression shows a particularly strong correlation between v and $\Delta\overline{v}$ during the SARS Period and suggests that social learning may be important during this period.

Columns 2 and 3 of the table show the double interaction between non-migrants and the SARS period. In Column 2, the differential effect of $\Delta\overline{v}$ for non-migrants during SARS is 0.067, which is statistically significant. This estimate implies that the elasticity of v with respect to $\Delta\overline{v}$ is 0.035. An increase in $\Delta\overline{v}$ of one standard deviation increases utilization by 15 percent over the mean level. Column 3 includes controls for the number of local SARS cases per 100 people, s_{kt}, and lagged individual visits, $v_{ijkt-26}$. The number of local SARS cases has the expected negative sign but is insignificant, which is not surprising since the time dummies in the regression capture the nationwide response to SARS. The control for $v_{ijkt-26}$ absorbs the autocorrelation in v that could otherwise cause a correlation between v_{ijkt} and $\overline{v}_{ijkt-26}$. A comparison of Columns 2 and 3 shows that the result is not sensitive to the inclusion of these controls.

Results based on specification (6), which control for $\overline{v}$ directly, appear in Table 3. Column 1 replicates the first column of Table 2 by showing the differentially strong correlation between visits and the change in peer visits during the SARS period. Column 2 controls for $\overline{v}_{ijkt}$ and $S_t\overline{v}_{ijkt}$, which attenuates but not eliminate the effect of $\Delta\overline{v}$. Once we include these controls, the social learning effect has a similar magnitude to the difference-in-difference estimate in Table 2. The regression also shows a negative but insignificant effect of $S_t\overline{v}$. The sign of this coefficient is consistent with a role for crowding in health care facilities, which exacerbates disease risk. Column 3 of Table 2 includes additional controls for local SARS cases (s_{kt}) and lagged individual visits ($v_{ijkt-26}$). As before, SARS cases have a negative but insignificant effect on utilization. While autocorrelation in visits may cause induce a direct correlation between v_{ijkt} and $\overline{v}_{ijkt-26}$, this correlation is likely to be positive, which biases the coefficient on $\Delta\overline{v}$ downward. Including both of these controls does not appreciably change the coefficient estimate for $\Delta\overline{v}$.

A comparison of Tables 2 and 3 shows that both approaches yield similar estimates of the effect of social learning. Column 4 of Table 2 combines both approaches by interacting $\Delta\overline{v}$ with S_t and N_i while also controlling for $\overline{v}$. If both approaches are adequate in controlling for common unobservables, then there should be no differential effect of of $S_t\Delta\overline{v}$ for non-migrants after conditioning on $\overline{v}$. The results in Column 4, which find an insignificant effect of $S_t N_i \Delta\overline{v}$ of 0.004, validate this hypothesis and support the empirical validity of these approaches.

5.3 Falsification Using Chinese New Year

The results in the previous section show that an increase in social learning coincides with the steep decline in visits during the SARS period. We investigate the possibility that the decline in visits could mechanically generate this pattern through a falsification test using Chinese New Year. Chinese New Year is a major holiday in Taiwan that occurs during late January or early February according to the lunar calendar. The holiday lasts for two weeks, although most of the activity is concentrated in the first few days. During Chinese New Year, many people, including both doctors and patients, travel in order to visit their families, which reduces both the supply and demand for medical care. This pattern is evident in Figure 2, which shows the number of visits per period from 2001 to 2003. In each year, there is a large dip in visits during the first few weeks of the year. The decline during 2003 is around two thirds of the magnitude of the drop due to SARS. The drop in visits during Chinese New Year is plainly unrelated to social learning. A positive "peer effect" during Chinese New Year suggests that the main results for the SARS period may be spurious. In contrast, a result of no peer effect during Chinese New Year gives confidence in the main SARS findings.

To investigate this possibility, we replace S_t and all related interactions with C_t, an indicator for Chinese New Year in our main specifications. To avoid interference from the SARS episode, these regressions use 2001 and 2002 data only, excluding 2003. Results for the Chinese New Year regressions appear in Table 4. The first column shows the single interaction between $\Delta\overline{v}$ and C_t, which is negative and significant and the opposite result from the SARS interaction above. Column 2 applies the difference-in-difference specification to Chinese New Year, and with a point estimate of -0.007, finds no significant differential effect of $\Delta\overline{v}$ for non-migrants during Chinese New Year. Column 3 controls for $\overline{v}$ and $C_t\overline{v}$, and also finds a small and insignificant effect of $\Delta\overline{v}$. Column 4 incorporates both approaches simultaneously and shows a positive but insignificant effect, which is an order of magnitude larger than the "zero" effect in Column 4 of Table 3. On the whole, these results show no evidence of social learning during Chinese New Year, providing support for our methodology in general.

6 Conclusion

This paper argues that the 2003 SARS epidemic accentuated social learning in Taiwan. The epidemic led to an extreme decline in health care utilization that lingered long after authorities brought SARS under control. Since people formulate beliefs about disease risk through iterative observation, social learning may induce a herd response in which people respond in a similar way to their peers. This phenomenon has important but unexplored implications for the epidemiology of emerging diseases. By encouraging a large reaction to disease prevalence, herding may attenuate an epidemic and improve welfare. However herding also generates heterogeneity in the prevalence response, which could exacerbate disease prevalence by fostering reservoirs of infection. Although SARS may or may not return, other emergencies are likely to have comparable dynamics. Policymakers should understand how social learning and herding mediate the community's response to risk in specific contexts.

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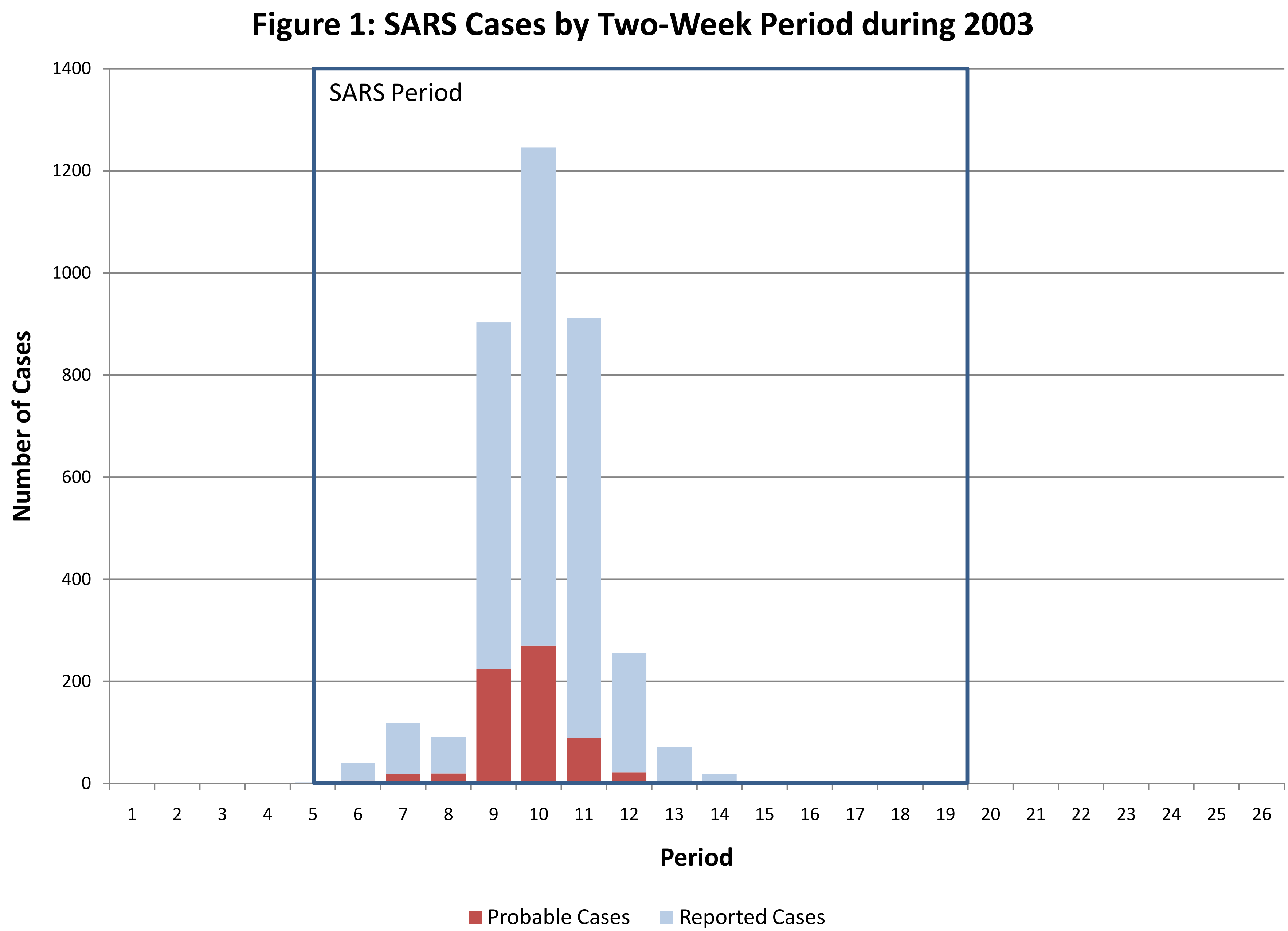
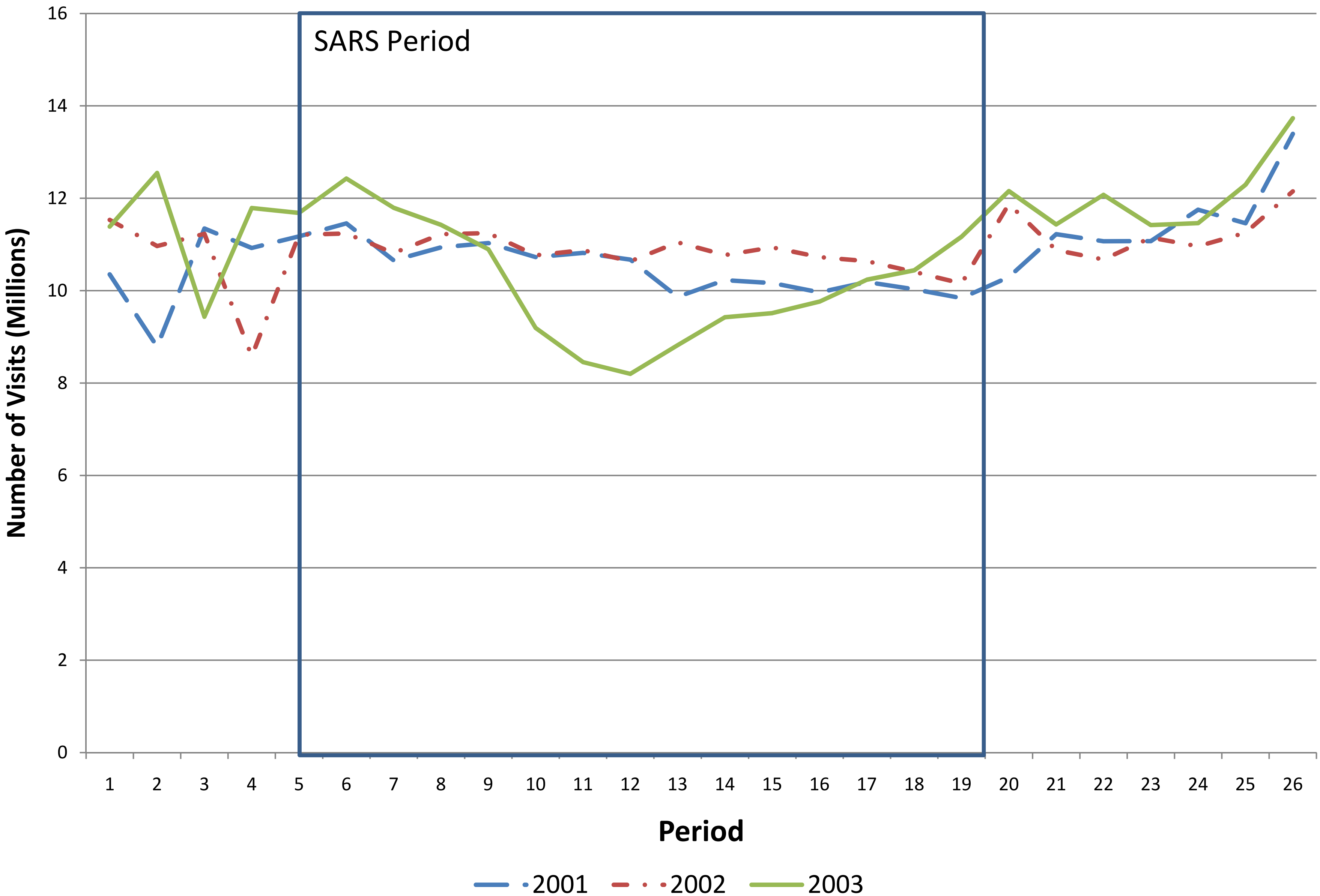


Figure 1: SARS Cases by Two-Week Period during 2003
SARS Period
Number of Cases
0
200
400
600
800
1000
1200
1400
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26
Period
Probable Cases
Reported Cases

Figure 2: Aggregate Outpatient Visits by Two-Week Period: 2001-2003



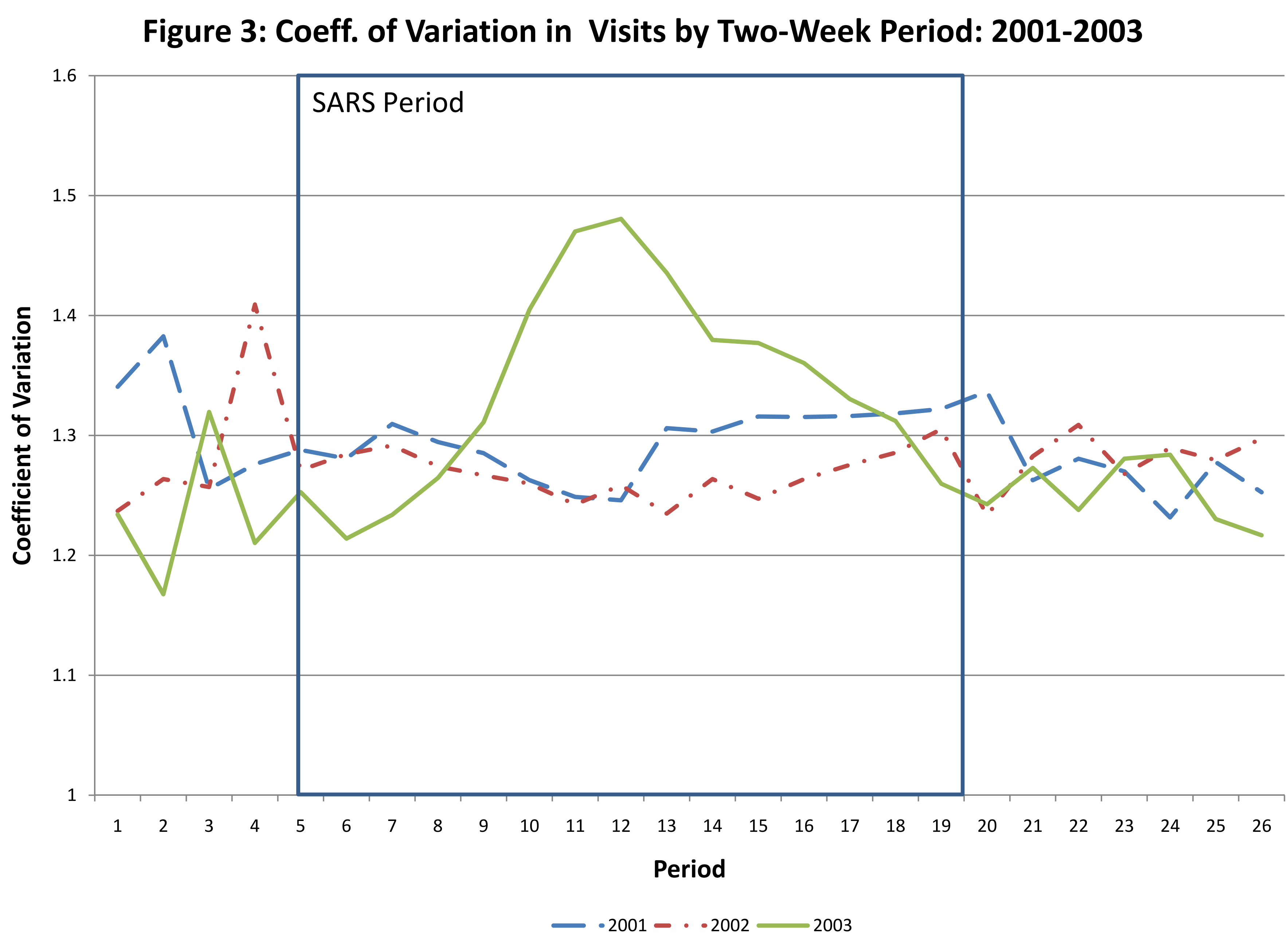


Figure 3: Coeff. of Variation in Visits by Two-Week Period: 2001-2003
SARS Period
Coefficient of Variation
1.6
1.5
1.4
1.3
1.2
1.1
1
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
Period
2001
2002
2003

Figure 4. Effect of SARS on equilibrium quantity is equivalent to an increase in copay (by T) proportional to the probability q of catching SARS.

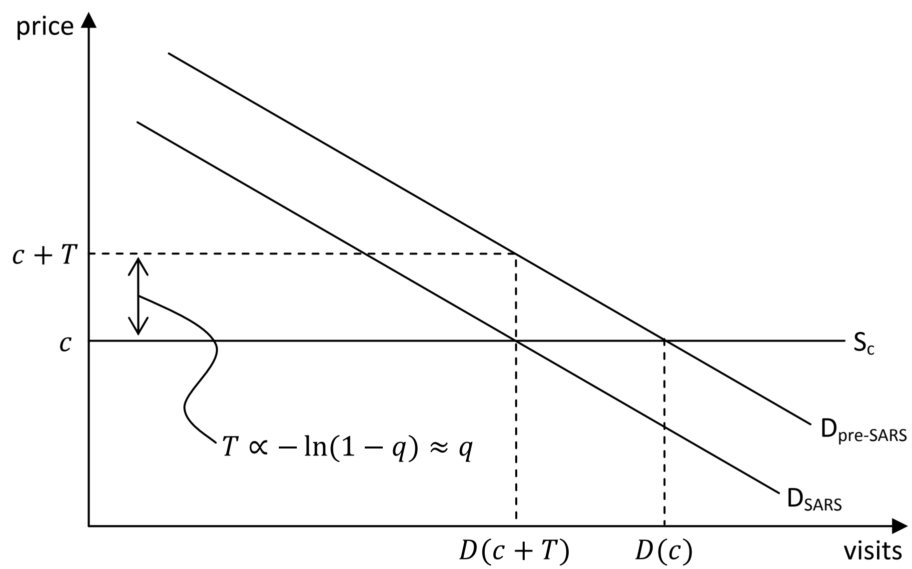


Table 1: Individual and Group Visits by Time Period

Period	2001	2002	2003 (no SARS)	2003 (SARS)
	(1)	(2)	(3)	(4)
Individual Visits				
Overall	0.040	0.037	0.037	0.032
	(0.000)	(0.000)	(0.000)	(0.000)
Non-migrants	0.048	0.044	0.043	0.038
	(0.000)	(0.000)	(0.000)	(0.000)
Migrants	0.033	0.031	0.031	0.027
	(0.000)	(0.000)	(0.000)	(0.000)
Peer Visits				
Total	24.95	23.65	22.66	20.28
	(0.01)	(0.01)	(0.02)	(0.02)
Average	0.047	0.044	0.043	0.038
	(0.000)	(0.000)	(0.000)	(0.000)
Change in average	0.017	-0.003	-0.001	-0.007
	(0.000)	(0.000)	(0.000)	(0.000)
Reported SARS cases	0	0	0	0.002
	--	--	--	(0.000)
Observations	3,689,920	3,689,920	1,561,120	2,128,800

Note: standard errors appear in parentheses

Table 2: Difference-in-Difference Regressions

Dependent variable:	Individual visits (t)		
	(1)	(2)	(3)
Change in peer visits (t to t-2)	0.172	0.172	0.183
	(0.008)	(0.007)	(0.007)
Non-migrant x change in peer visits (t to t-2)		-0.00002	0.006
		(0.00958)	(0.010)
SARS x change in peer visits (t to t-2)	0.114	0.054	0.049
	(0.018)	(0.013)	(0.013)
Non-migrant x SARS x change in peer visits (t to t-2)		0.067	0.064
		(0.022)	(0.022)
SARS cases per 100 people (t to t-2)			-1.085
			(5.169)
Individual visits (t-26)			0.102
			(0.007)
Non-migrant and SARS x non-migrant dummies	No	Yes	Yes
Year-of-move and SARS x year-of-move dummies	No	Yes	Yes
Peer group fixed effects	Yes	Yes	Yes
Time period fixed effects	Yes	Yes	Yes
Sample size	10,785,920	10,785,920	10,785,920
R-squared	0.118	0.119	0.128

Note: standard error appear in parentheses and are clustered by the patient's modal township.

Table 3: Regressions Controlling for Peer Visits

Dependent variable:	Individual visits (t)			
	(1)	(2)	(3)	(4)
Change in peer visits (t to t-2)	0.172	-0.011	0.022	0.086
	(0.008)	(0.010)	(0.011)	(0.011)
Non-migrant x change in peer visits (t to t-2)				-0.072
				(0.011)
SARS x change in peer visits (t to t-2)	0.114	0.064	0.061	0.057
	(0.018)	(0.024)	(0.025)	(0.015)
Non-migrant x SARS x change in peer visits (t to t-2)				0.004
				(0.030)
Peer visits (t to t-2)		0.356	0.323	0.152
		(0.016)	(0.016)	(0.019)
Non-migrant x peer visits (t to t-2)				0.192
				(0.016)
SARS x peer visits (t to t-2)		-0.017	-0.016	-0.048
		(0.031)	(0.031)	(0.016)
SARS x non-migrant x peer visits (t to t-2)				0.037
				(0.037)
SARS cases per 100 people (t to t-2)			-2.99	-2.77
			(4.74)	(4.74)
Individual visits (t-26)			0.101	0.100
			(0.007)	(0.007)
Non-migrant and SARS x non-migrant dummies	No	No	No	Yes
Year-of-move and SARS x year-of-move dummies	No	No	No	Yes
Peer group fixed effects	Yes	Yes	Yes	Yes
Time period fixed effects	Yes	Yes	Yes	Yes
Sample size	10,785,920	10,785,920	10,785,920	10,785,920
R-squared	0.118	0.120	0.129	0.129

Note: standard errors appear in parentheses and are clustered by the patient's modal township.

Table 4: A Falsification Test Using Chinese New Year

Dependent variable:	Individual visits (t)			
	(1)	(2)	(3)	(4)
Change in peer visits (t to t-2)	0.181	0.187	0.012	0.096
	(0.009)	(0.008)	(0.011)	(0.013)
CNY x change in peer visits (t to t-2)	-0.056	-0.050	0.010	-0.014
	(0.021)	(0.015)	(0.022)	(0.017)
Non-migrant x change in peer visits (t to t-2)		-0.006		-0.093
		(0.011)		(0.012)
CNY x non-migrant x change in peer visits (t to t-2)		-0.007		0.026
		(0.027)		(0.030)
Peer visits (t to t-2)			0.307	0.110
			(0.018)	(0.024)
CNY x peer visits (t to t-2)			-0.142	-0.104
			(0.025)	(0.019)
Non-migrant x peer visits (t to t-2)				0.219
				(0.019)
CNY x non-migrant x peer visits (t to t-2)				-0.041
				(0.036)
Non-migrant and CNY x non migrant dummies	No	Yes	No	Yes
Peer group fixed effects	Yes	Yes	Yes	Yes
Time period fixed effects	Yes	Yes	Yes	Yes
Sample size	7,096,000	7,096,000	7,096,000	7,096,000
R-squared	0.127	0.128	0.128	0.129

Note: standard errors appear in parentheses and are clustered by the patient's modal township.