I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 12066

The Effect of Superstition on Health: Evidence from the Taiwanese Ghost Month

Martin Halla
Chia-Lun Liu
Jin-Tan Liu

JANUARY 2019

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 12066

The Effect of Superstition on Health: Evidence from the Taiwanese Ghost Month

Martin Halla
Johannes Kepler University Linz, CDECON, IZA and Austrian Public Health Institute

Chia-Lun Liu
Lehigh University

Jin-Tan Liu
National Taiwan University and NBER

JANUARY 2019

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

The Effect of Superstition on Health: Evidence from the Taiwanese Ghost Month*

Superstition is a widespread phenomenon. We empirically examine its impact on health-related behavior and health outcomes. We study the case of the Taiwanese Ghost month. During this period, which is believed to increase the likelihood of bad outcomes, we observe substantial adaptions in health-related behavior. Our identification exploits idiosyncratic variation in the timing of the Ghost Month across Gregorian calendar years. Using high-quality administrative data, we document for the period of the Ghost Months reductions in mortality, hospital admissions, and births. While the effect on mortality is a quantum effect, the latter two effects reflect changes in the timing of events. Efficient public health policy should account for emotional and cultural factors.

JEL Classification: I12, D83, D91, Z12

Keywords: superstition, false beliefs, health, risky activities, health-care utilization, mortality, fertility, birth outcomes

Corresponding author:
Martin Halla
Johannes Kepler University of Linz
Department of Economics
Altenbergerstraße 69
4040 Linz
Austria

E-mail: martin.halla@jku.at

* For helpful discussions and comments we would like to thank seminar participants at the Hungarian Academy of Sciences (Centre for Social Sciences, RECENS) and the University of Hohenheim. The usual disclaimer applies. A Web Appendix available on the corresponding author's website provides further results referenced in the paper.

1 Introduction

Historically, medicine was closely associated with superstitions, magic and religion. The Greek physician Hippocrates laid the foundation for a rational approach to medicine. While modern scientific medicine rejects any supernatural origin of disease, many patients still believe in supernatural powers and superstition, or have severe misconceptions about the origin of certain diseases and the effectiveness of treatments. For instance, the believe that witchcraft can cause and heal diseases is widespread within developing countries in general, and in Africa in particular (Tenkorang et al., 2011). One recent phenomenon in high-income countries is the surge in the opposition to vaccines. The so-called "anti-vaccine movement" is fueled by misconceptions and myths about immunizations (Chang, 2018; Hussain et al., 2018; Oster, 2018). Despite the pervasiveness of such wrong beliefs, empirical evidence quantifying its impact on health is scarce.

In this paper, we estimate the impact of superstition on health-related behavior and health outcomes. Our research design is based on the so-called *Ghost Month*. In Taiwanese culture, the seventh lunar month is Ghost Month. According to legend, during this month, the gates of the afterlife are opened, and ghosts roam the living world. The presence of the ghosts is believed to increase the risks of accidents and cause a higher likelihood of bad outcomes in general. Therefore, believers of this legend try to avoid a number of activities, such as traveling, swimming, leaving the house after sunset, major social events, major purchases, and supposedly even elective surgeries. According to survey data, about 72 percent of all Taiwanese participate in the Ghost Month festival, and about 66 percent believe that ghosts that are not offered any worship will wander around.[1]

There are several potential channels through which the Ghost Month may affect health. All channels are linked to the adaption of health-related behavior. The most effective adaption would be a self-enforced restraint from (or avoidance of) certain social or economic activities. Depending on the nature of these activities the effects on health can be either positive of negative. The avoidance of activities involving risks or causing stress may improve health. In contrast, adaptions in the domain of health-care utilization may be detrimental. If followers avoid or postpone health-care services (such as surgeries or births), they may jeopardize their health. The followers' adaptions may also generate spillover effects on others including non-followers. Other patients could be affected by variation in hospital occupancy rates caused by followers. Or, on a macro-level, a reduction in the overall volume of traffic (and in related pollution) may have positive effects on the population at a large.

We have access to high-quality administrative data, which allows us to test the effect of the Ghost Month in different domains. First, we have access to cause-specific mortality

[1]About 20 percent believe in the latter statement "yes, very much", and about 46 percent believe "yes, somewhat". All figures are based on data from the *Taiwan Social Change Survey*. Details are provided in Section 2.

data. These allow us to infer on changes in activities associated with certain risks (such as driving). Second, we can utilize information on hospital admissions to study health-care utilization. Third, we use birth certificates to examine a potential effect on fertility and children's health at birth. We aim to identify an *intention-to-treat* (ITT) effect of the Ghost Month, without relying on the actual behavioral adaption due to superstitious beliefs. To identify this causal effect, we exploit the idiosyncratic timing of the Ghost Month. The exact date of the Ghost Month is determined by the lunar calendar, which is based on cycles of the lunar phases. Since the lunar and the Gregorian calendar are not fully synchronized, the exact date of the Ghost Month varies in the Gregorian calendar over years. For official and business purposes, Taiwan has adopted the Gregorian calendar for the longest time. The traditional lunar calendar is only used to define the dates of such festivals. Our estimation strategy is to identify the behavioral consequences of the Ghost Month (in daily data), while controlling for Gregorian calendar day and year fixed-effects. Thus, our identifying assumption is that the variation in timing of the Ghost Month across Gregorian calendar years is not correlated with unobserved determinants of our outcomes.[2]

Our analysis provides evidence that the Ghost Month affects mortality, the timing of health-care utilization, and fertility. During the Ghost Month, mortality drops by about 4 percent. Since there is no evidence that deaths were shifted to the period before or after the event, we conclude that the Ghost Month saves (yearly about 316) lives. Our analysis of cause-specific mortalities highlights two causal mechanism. First, there is a drop in accidental deaths by about 8 percent. This effect is stronger among younger people, who are less likely to die from drowning or traffic accidents. Second, there is a reduction in non-accidental deaths by about 3 percent. This effect comes from people above 60, who are less likely to die from cerebro-cardiovascular diseases. This can be explained with a reduction in overall activity and lower levels of stress. With respect to health-care utilization, we estimate a reduction in hospital admission during the Ghost Month by about 4 percent. This reduction comes exclusively from admission with surgeries (minus 9 percent) and is substantially larger for "deferrable" conditions (up to minus 20 percent). This effect is (at least to large extent) a tempo effect, since we observe more admissions shortly before and after the Ghost Month. Further analysis provides some evidence for negative health effects due to this re-scheduling of surgeries. Finally, we find an effect on fertility. Births are significantly less likely during the Ghost month (minus 4 percent), but peak shortly before and after. This tempo effect is mainly driven by an adaption in conception and to a much smaller degree by a manipulation in the date of birth. There

[2] A comparable estimation strategy has been used in the economic literature before to identify the effect of diurnal fasting during pregnancy on later child outcomes, which exploits that the fasting month of Ramadan follows the lunar calendar (Almond and Mazumder, 2011; Almond, Mazumder and Van Ewijk, 2015). These papers assume that pregnancies are not timed relative to Ramadan along unobserved determinants of health.

are no adverse effects on birth outcomes.

Our findings contribute to two strands of literature. *First*, we add to the literature on superstition. Superstition is a widespread phenomenon. Data from the *World Values Survey* (WVS), covering respondents from 33 countries, shows that about 19 percent cary a lucky charm (such as a mascot or a talisman), and about 49 percent believe that a lucky charm can protect or help them. About two-thirds of all respondents consult a horoscope to know about their future, and about one-third takes this into account in their daily life. While these beliefs and behavior are negatively correlated with education, they are present in every strata of the population (see Appendix Tables A.1 and A.2 for descriptive statistics and a regression analysis, respectively.) These figures make clear that superstition should not be treated as a cognitive deficit found in small parts of the population.[3]

Despite the high prevalence of superstition, little is known how these false beliefs affect market outcomes and overall welfare. The existing empirical evidence in the economics and finance literature comes predominantly from stock markets, housing markets, and license-plate auction markets.[4] While these settings provide excellent environments to study the effects of superstition on market outcomes, the negative welfare-consequences are in these cases probably limited. We consider any effects on health as more relevant. Here the analytical evidence is sparse. In the medical literature, there are a couple of mostly descriptive papers showing that superstition affects the *timing* of health-care utilization.[5] Economics scholars have so far focused on the effect of superstition on the

[3]Recent theoretical literature in economics and psychology considers choices influenced by superstition as the result from wrong beliefs. These modelling approaches face the challenge to explain how wrong beliefs (= superstition) can persist. Economic models are sparse. Most prominently, Fudenberg and Levine (2006) show in a game-theoretic model that (some but not all) superstition can persist, even when agents are rational. The model's key insight is, loosely speaking, that persistence tends to arise if superstition is about something that happens very infrequently. Psychologists suggest to use dual process models — such as the corrective model advocated by Kahneman and Shane (2002, 2005) — to understand why superstitious thinking is widespread. These models suggest that individuals derive their choices using two systems: "*System 1 quickly proposes intuitive answers to judgment problems as they arise, and System 2 monitors the quality of these proposals, which it may endorse, correct or override*" (Kahneman and Shane, 2005, page. 51). If individuals explicitly recognize that their intuitive judgment was wrong, but nevertheless maintain it, they are said to acquiesce to their intuition (Risen, 2016).

[4]In the finance literature, a note by Kolb and Rodriguez (1987) started a debate, whether stock market returns on Friday the thirteenth are different from the returns of other Fridays (Dyl and Maberly, 1988; Chamberlain et al., 1991; Coutts, 1999; Lucey, 2001). There is evidence for an impact of numbers considered 'lucky' in Chinese numerology on financial decision in the Chinese initial public offering market (Hirshleifer et al., 2018), in the Chinese real estate markets (Shum et al., 2014), as well as in the North American market (Fortin et al., 2014). Similar findings are documented on the Russian market (Pokryshevskaya and Antipov, 2015). There is also a small literature on the law and economics of superstition (summarized in Leeson (2017)), which uses rational choice theory to explain seemingly bizarre practices.

[5]The outcomes under consideration are the timing of hospital discharge in Japan (Hira et al., 1998) and Norther-Ireland (O'Reilly and Stevenson, 2000), of orthopedic surgeries in Taiwan (Chiu et al., 2018), and the timing of death in several countries (Panesar and Goggins, 2009; Anson and Anson, 2001; Wilches-Gutiérrez et al., 2012). With respect to accidents there is best to our knowledge only one paper. Yang et al. (2008) present descriptive evidence that drowning deaths decrease in Taiwan during the Ghost Month.

timing and mode of birth. Almond, Chee, Sviatschi and Zhong (2015) provide evidence that Chinese-American mothers manipulate the timing of birth to achieve a "lucky" or to avoid an "unlucky" birthdate, which include the number "8" and "4", respectively. This skewed pattern in the timing of Chinese birth is driven by sons only. The authors provide further evidence that the change in timing is accompanied with an increase in the incidence of C-sections. A comparable pattern was pointed out in two papers in the medical literature, both of which study Taiwan.[6] Whether or not the change in the timing and/or mode of birth has consequences for the children's health remains is not analyzed in these studies.[7] We add to this literature by studying the consequences of superstition in high-quality administrative data and providing the first comprehensive analysis of superstition and health. In terms of outcomes, our analysis (goes beyond the timing and mode of birth and) studies a wide array of outcomes allowing us to infer on the effect of superstition on activities involving certain risks and all types of inpatient health care-utilization. In contrast to the mostly descriptive studies in the medical literature, our evidence is derived from an econometric estimation strategy that exploits only idiosyncratic variation in the timing of superstitious behavior.

Second, we contribute more broadly to the literature on the demand for health-care that incorporates non-rational factors (Rice, 2013; Matjasko et al., 2016). Our findings show that false believes (driven by superstition) are an important case of bounded rationality in the domain of health. We show that superstition has far-reaching consequences not only for health-care utilization, but also for health outcomes and even for mortality. While our evidence is based on a specific case, we conclude more generally to pay more attention to emotional and cultural factors in the demand for health-care. There are several public health concerns which should be addressed with a more holistic approach. For instance, policymakers in high-income countries have to resolve the underutilization of vaccinations and the overutilization of antibiotics. Low-income countries face problems such as non-pathogenic disease theories (Bennett et al., 2018), harmful belief in witchcraft or female genital mutilation (Vogt et al., 2016).

The remainder of the paper is organized as follows. The next section describes the legend of the Ghost Month in more detail and provides survey-based evidence on the number and characteristics of followers. Section 3 presents our research design and discusses our data sources, our estimation strategy and some descriptive statistics of our estimation samples. Section 4 discusses our main findings. Section 5 concludes the paper.

[6] Lo (2003) shows in data from the year 1988 that C-sections are significantly higher (lower) on auspicious (inauspicious) days. Closer related to our work is Lin et al. (2006), who also study the Ghost Month. They provide evidence that C-section rates are significantly lower during the Ghost Month.

[7] A related strand of literature examines how incentives created by taxes and subsidies affect the timing of births (see, for instance, Dickert-Conlin and Chandra, 1999; Gans and Leigh, 2009; Schulkind and Shapiro, 2014; LaLumia et al., 2015; Borra et al., forthcoming). This behavior can — in contrast to adaptions due to superstition — in principle be reconciled with rational behavior. However, this literature points to negative health effects due to birth date manipulations.

2 Ghost Month

In Taiwanese culture, the seventh lunar month is called Ghost Month. According to legend, during this period, the gates of the afterlife are opened, and ghosts roam the living world. The presence of the ghosts is believed to increase the risks of accidents and elevate the likelihood of bad outcomes in general. Therefore, believers of this legend try to avoid several activities. For instance, swimming during the Ghost Month is considered as dangerous since people believe ghosts are looking for victims of drowned to be reborn. Hospitals are regarded as the places where life and death are connected. Thus, believers avoid visiting hospitals and supposedly even doing surgeries during the Ghost Month. Other activities believers try to avoid include, but not limited to, traveling, leaving the house after sunset, whistling at night, major social events such as funerals and weddings, and major purchases.

The period of the Ghost Month is defined by the lunar calendar. Since the lunar calendar has intercalary months and days, it changes in relation to the Gregorian calendar every year. Thus, the timing of the Ghost Month changes across years defined by the Gregorian calendar. Figure 1 shows the variation in the starting and end date of the Ghost Month (according to the Gregorian calendar) across the years 1980 to 2000. The 27$^{\text{th}}$ of July, for instance, was only in the year 1995 in the Ghost Month. In all other years, the 27$^{\text{th}}$ of July was before the Ghost month. The dates of the lunar calendar are always published in the printed Gregorian calendar and Taiwanese people are well aware of the start and end-date of the Ghost Month.

How widespread is the belief in the Ghost Month? During the Ghost Festival, which is on the 15$^{\text{th}}$ day of the Ghost Month, people prepare food, burn incense, and burn joss paper to the spirits of ancestors and lost ghosts. It is widely believed that worshiping to the supernatural power can protect people. According to the data from the *Taiwan Social Change Survey* (TSCS), about 72% of Taiwanese take part in the Ghost Festival.[8] Of course, participating in this festival could simply reflect cultivation of customs and traditions, and does not necessarily imply that participants actually believe in the legend. To assess the prevalence of the latter phenomenon, we use the following survey question: "*Do you believe that, ghosts that are not offered any worship will wander around?*". According to data from several waves of the TSCS, about 66 percent of Taiwanese believe either "*very much*" or "*somewhat*" in this statements on ghosts. Table 1 shows the full distribution of answers by survey years from 1994 to 2014. The share of believers is remarkably stable over this 20 years time period. Since the responses to this question reveal how strong respondents believe in the existence of ghosts, it should be a good proxy for whether they also believe in the Ghost Month. In fact, the share of Taiwanese believing

[8]Similar to the WVS, the TSCS tracks the long-term trends of various values in Taiwanese society. The survey is carried out at 5-year cycles for each topic of questionnaires and provides pooled cross-sectional data. The 72 percent stated in the main text are based on data from 1990.

in ghosts is almost as high as the participation rate in the Ghost Festival.

Who are the believers of the Ghost Month? Having established that about two-thirds of all Taiwanese believe in the Ghost month, we want to explore whether believers differ systematically from non-believers in their socioeconomic characteristics. To provide evidence we estimate a linear probability model. We define a binary variable equal to one if people respond either "*very much*" or "*somewhat*" to the ghost question from above and regress this on several demographic characteristics. The estimation results are summarized in Table 2. It turns out that females and employed individuals are more likely to be superstitious. The estimated effects are about plus 10 and 3 percentage points, respectively. We see that superstition is decreasing with age, however the magnitude is quite small. Most importantly, we learn that the belief is negatively associated with educational attainment. For instance, respondents with a college degree are about 23 percentage points less likely to believe as compared to the base group with primary education only. A comparison of the second and the third column reveals that conditioning on educational attainment, household income is not correlated with believing.[9]

Are believers of the Ghost Month indeed adapting their behavior? So far, we have evidence that roughly two-thirds of Taiwanese believe in the Ghost Month, with believers being more likely young, female and having a lower level of education. This evidence based on stated preferences suggests that the Ghost Month may have pronounced effects on actual behavioral. In our main analysis, we will test whether this translates into health effects. At this point we are able to present some evidence on the avoidance of major social events. We have access to data from *Marriage Certificates*, which covers the universe of marriages from 1998 to 2006. Figure 2 depicts the aggregated average number of daily marriages around the Ghost Month. This figure clearly shows that people avoid getting married during the entire period of the Ghost Month. The average number of daily marriages sixty days before and after the Ghost Month is 283, while the corresponding number during the Ghost Month is only 29. This is equivalent to a reduction of about 90 percent. While these behavioral adaption — most likely affecting only the timing, but not the incidence of marriages — bears no welfare consequences, it nicely demonstrates that the Ghost Month affects behavior.[10]

In summary, stated and revealed preferences provide compelling evidence for widespread behavioral adaptions due to superstitious beliefs in the Ghost Month.

[9]The correlations with sex, age and education are remarkably similar to those found in the analysis of the determinants of other aspects of superstition in international survey data discussed in the introduction (see Appendix Table A.2). A more comprehensive analysis of the determinants of superstition based on WVS data is provided by Torgler (2007). Mocan and Pogorelova (2017) exploit compulsory schooling reforms in 11 European countries to show that education causally decreases these superstitious beliefs.

[10]An alternative strategy to provide evidence for behavioral adaption during the Ghost Month, would have been the analysis of time-use survey data. Unfortunately, all three waves of the *Time Utilization Survey* have been conducted outside the Ghost Month.

3 Research Design

In this section, we first introduce our administrative data sources and define our outcome variables. Then we present our estimation strategy and discuss the resulting identifying assumption. In the final step, we present some descriptive statistics for our estimation samples.

3.1 Data Sources

For our empirical analysis, we have access to several high-quality administrative data sources from Taiwan. We use three different individual-level data sets: (1) *Death Certificates*; (2) *Inpatient Hospitalization Records*; and (3) *Birth Certificates*. The first data set covers the universe of all deaths in the period between 1980 and 2001. It includes information on the exact date of death and the cause of death according to the *International Classification of Diseases* (ICD). The second data set comprises information on all hospital admissions in the period between 1982 and February 1995 for the sample of people, who had been covered by Labor Insurance.[11] It includes information on the exact dates of admission and discharge, diagnosis, medical treatment, and fees. The third data set includes information on live births in the period between 1978 and 2006. It comprises information on the date and location of birth, gestational length, birth weight, and some socioeconomic information on parents.

3.2 Outcome Variables

To study the effect of the Ghost Month on accidents, the demand of health-care utilization and fertility, we compile different panel data sets with daily observations across all 25 counties in Taiwan. The outcome variables are the daily number of deaths (by type), daily number of hospital admissions (by type), and the daily number of births. We also consider sub-samples defined by characteristics such as sex, age, educational attainment to explore potential heterogeneity of treatment effects.

To estimate the health consequence of avoiding having appropriate medical treatments due to false beliefs, we use individual-level data on mortality, morbidity and birth outcomes. We use the national identification number received by each citizen in Taiwan to merge inpatient data and *Death Certificates* to track death records of patients after their hospitalization. This allows us to test whether shifting a surgery to avoid the Ghost Month affects the probability of death within a certain period of time. To assess any

[11] The individuals are only observed until February 1995 since the National Health Insurance (NHI) was introduced in Taiwan after March 1995. In this study, we only obtain hospital admissions data before the NHI. For more details on the NHI of Taiwan, see Chou et al. (2014). According to official statistics, the number of workers who are covered by Labor Insurance before the introduction of NHI is 8,496,883, which comprises 55.3% of the population aged over 15.

effects on morbidity, we use the longitudinal component of the *Inpatient Hospitalization Records*. This allows us to estimate any effect on the likelihood of a hospital re-admission. In the case of births, we use the information on gestational length and birth weight in birth certificates. This data allows us to define binary outcomes of being preterm, low birth weight, and very low birth weight.

3.3 Estimation Strategy

To identify causal effects, we exploit that the exact timing of the Ghost Month varies across years defined by the Gregorian calendar. Figure 1 depicts the variation in the starting and end dates across the years 1980 to 2000. To define our estimation sample we use the earliest start date (27$^{\text{th}}$ of July) and latest end date (22$^{\text{nd}}$ of September). We further exclude 24$^{\text{th}}$ and 25$^{\text{th}}$ of August, which belong to the Ghost Month in every year. This way we have in our estimation sample for each calendar day *at least* one year, in which this day was during the Ghost Month, as well as, *at least* one year, in which this particular day was outside the Ghost Month. This variation allows us to estimate the effect of the Ghost month, while controlling for Gregorian calendar day fixed-effects. To be more specific, this idea can be translated into the following type of estimation model,

$$O_{rdy} = \alpha + \tau \cdot gm_{dy} + \sum_{d} \kappa_d + \sum_{y} \delta_y + \sum_{r} \gamma_r + nb_{dy} + \epsilon_{it} \tag{1}$$

where O_{rdy} is the absolute number of incidences in outcome O on Gregorian calendar-day d in year y in region r. The coefficients capturing the Gregorian calendar-days fixed-effects are denoted by κ_d. We also control for Gregorian calendar year fixed-effects (δ_y) to capture unobserved secular trends in the respective outcome variable, and for regional fixed-effects (γ_r) accounting for time-invariant heterogeneity across regions. Finally, we control for two types of non-business days (nb_{dy}). First, we include a binary variable equal to one if the day is either a Saturday or a Sunday.[12] Second, we control for official public holidays and so-called “unofficial holidays”. This requires the inclusion of two binary control variables for the *Mid-Autumn Festival* and *Qixi Festival*, respectively.[13]

[12]It is important to control for weekends. First, there is typically a substantially lower volume of health-care utilization on weekends. For instance, we expect a significantly lower number of hospital admissions. Second, different strands of literature have documented a weekday pattern also in mortality. For instance, the so-called *weekend effect* describes the robust finding that the risk of mortality after admission to a hospital is significantly higher on weekends as compared to weekdays (Pauls et al., 2017).

[13]In Taiwan, there are (official) public holidays and so-called “unofficial holidays”. In both categories, some holidays are determined by the Gregorian calendar, while others follow the lunar calendar. The holidays determined by the Gregorian calendar are in our estimation models automatically covered by the Gregorian calendar-days fixed-effects κ_r. Notably, in the relevant time period (i.e., between the 27$^{\text{th}}$of July and the 27$^{\text{th}}$of September) there are only 3 holidays, all of which are unofficial ones (*Father’s Day* on the 8$^{\text{th}}$ of August, the *Journalist’ Day* on the 1$^{\text{th}}$ of September, and the *Armed Forces Day* on 3$^{\text{rd}}$of September). The holidays determined by the lunar calendar require additional control variables in our model. During the relevant time period there is one official public holiday and one unofficial holiday.

The variable of primary interest is gm_{dy}, which is equal to one if the day d is within the Ghost Month in the given year y, and zero otherwise. The coefficient τ measures the effect of the Ghost Month on the respective outcome. Thus, we aim to identify an *intention-to-treat* (ITT) effect, without relying on the actual behavioral adaption due to superstitious beliefs. We have to assume that the timing of the Ghost Month is exogenous, but the unobserved behavioral adaption can be endogenous. Using the language of RCTs, we could compare the timing of the Ghost Month with the assignment to treatment (which has to be random), and the actual behavioral adaption is equivalent to the compliance (which can be endogenous). This exogeneity assumption is equivalent to assuming that the variation in timing of the Ghost Month across Gregorian calendar years is not correlated with unobserved determinants of the respective health outcome. We see no obvious reason why the idiosyncratic timing of the Ghost month should be correlated with unobserved determinants of the daily number of deaths, hospital admissions, or births.

We estimate a version of eq. (1) that allows for a more flexible behavioral adaption with respect to the timing. If individuals adjust their health relevant behavior in response to the Ghost Month, they may also pre- or postpone certain activities to the period before or after the Ghost Month. To test this specific adaption, we include binary variables gm_{dy}^{-5} and gm_{dy}^{+5}, which are equal to one if the day d is within a 5 days period before and after the start of the Ghost Month in the given year y, respectively.

$$O_{rdy} = \alpha + \tau^{pre} gm_{dy}^{-5} + \tau^{1} gm_{dy}^{1-10} + \tau^{2} gm_{dy}^{11-20} + \tau^{3} gm_{dy}^{21-last} + \tau^{post} gm_{dy}^{+5} + \sum_{d} \kappa_d + \sum_{y} \delta_y + \sum_{r} \gamma_r + \epsilon_{it} \tag{2}$$

Further, we allow the effect of the Ghost Month on the respective health outcome to vary across the duration of the Ghost month. We distinguish between the first ten days (gm_{dy}^{1-10}), the second ten days (gm_{dy}^{11-20}), and the remaining nine or ten days ($gm_{dy}^{21-last}$). Thus, the parameters τ^1, τ^2 and τ^3 show to which degree the incidences change during the Ghost Month, while τ^{pre} and τ^{post}, inform us about related pre- and or postponment.

3.4 Estimation Samples and Descriptive Statistics

Table 3 provides descriptive statistics for our estimation samples drawn from three different data sources. First, we use data from *Death Certificates* (see Panel A). These data are available in the period between 1980 and 2001. We compile a daily county-level data set with 30,750 observations. Here we focus on calendar days for which with have variation in the Ghost Month status over the years (see notes to Table 3 for details). The average daily incidence of death is 10.78 cases, including 1.32 cases of accidental deaths and 9.26

The former is the *Mid-Autumn Festival* (on 15$^{\text{th}}$ day of the 8$^{\text{th}}$ lunar month) and the latter is the *Qixi Festival* (on the 7$^{\text{th}}$ day of 7$^{\text{th}}$ lunar month).

cases of non-accidental deaths. For a small fraction of cases, the cause is unknown. Second, we use data from *Inpatient Hospitalization Records*, which are available in the period between 1982 and 1995 (see Panel B). Our unit of observation is again county-day. The average number of admissions is 66.15, including about 41% of admissions with surgeries and 59% without surgeries. Finally, we use *Birth Certificates*, which are available in the period between 1978 and 2006 (see Panel C). We compile a daily county-level data set on number of live births. We further use individual-level data to study birth outcomes. Here we focus on births to mothers aged between 16 and 45. This sample comprises 1,537,170 births, where the average gestation is 39.2 weeks and the average birth weight is around 3,200 grams.

4 Estimation Results

We present our estimation results in three steps. First, we discuss our evidence on the effect on (cause-specific) mortality. Second, we present our estimates on adaptions in the domain of health-care utilizations using information on different types of hospital admissions. We also explore consequences of the latter behavior on subsequent health outcomes. Third, we turn to our evidence on the effect on fertility and birth outcomes.

4.1 Mortality

Table 4 summarizes our results of the estimation model described by eq. (2). The dependent variable is the daily number of deaths (of a certain type) at county-level divided by its sample mean. Thus, our estimates are semi-elasticities and can be interpreted as percent changes. We find robust evidence for a reduction in mortality during the Ghost Month. The overall number of deaths decreases by around 3.9 percent. The estimates suggest that the effect is somewhat stronger during the first 10-day interval (almost minus 5 percent) and decreases thereafter to 3 to 4 percent (see column (1)). All three coefficients are precisely estimated and statistically significant at the 1-percent level. In contrast, there are no significant changes in mortality just before or after the Ghost Month. This suggests that the reduction in mortality is not a tempo, but a quantum effect. Put differently, behavioral adaptions to the Ghost month save lives. Each year about 316 lives are saved due to behavioral adaptions in response to the Ghost Month.[14]

In columns (2) and (3) of Table 4, we distinguish between the two broad categories of accidental and non-accidental deaths, which are defined by the ICD-9 code available in our data. We find comparably stronger effects for accidental as compared to non-accidental deaths. In the former case, we see reductions between 7 to almost 10 percent. This effect is quantitatively very comparable to the weekday-weekend gradient in this estimation,

[14]This estimate is calculated as follows: $10.782 \times 3.9\%$ estimated reduction$\times 30$ days$\times 25$ counties $= 316$.

which suggests that there are 9 percent more accidental deaths on weekends. In contrast, non-accidental deaths go down by only 3 to 4 percent. Notably, the baseline level of non-accidental deaths is, however, much larger, such that the effect is more important in absolute terms.[15]

The drop in accidental deaths can unambiguously be explained by a reduction in activities with certain risks. Since we do not see any significant effects just before or after the Ghost Month, we conclude that individuals not only pre- or postpone risky activities, but completely forgo these during the Ghost Month. To gain more insights, we re-run our analysis for cause-specific mortalities summarized in Table 5. Columns (1) to (5) report the results for the top five leading causes of accidental deaths; daily averages are reported in the lower panel. We find the strongest effects on deaths caused by traffic accidents (about minus 7 percent) and drowning (about minus 23 percent). This evidence is in line with the widespread Ghost Month beliefs, that strongly emphasize to avoid swimming, traveling, and leaving the house after sunset. For other accidental causes of death (i.e., falling, poisoning, and electric) we only find weak evidence.

In the case of non-accidental deaths, the interpretation of the results is not so straightforward. There are two plausible causal mechanism. First, the reduction of overall activity during the Ghost Month may lead to lower levels of stress; reducing the mortality among high-risk groups. Second, the negative effect on mortality may be related to adaptions in health-care utilizations. We come back to the latter channel in Section 4.2.2, and examine cause-specific mortalities to explore the former mechanism. We focus on the top five leading underlying cause of non-accidental deaths in our data: Diabetes mellitus; Malignant neoplasm of liver and intrahepatic bile ducts; Malignant neoplasm of trachea, bronchus, and lung; Acute but ill-defined cerebrovascular disease; and Chronic liver disease and cirrhosis. We suggest to interpret deaths by diabetes mellitus predominantly as caused by cerebro-cardiovascular diseases.[16] Our estimations results are summarized in columns (6) to (10) of Table 5. We find a significant effect of the Ghost Month for two (out of five) cause-specific deaths: cerebrovascular disease and diabetes mellitus. Both categories can

[15]In the *Death Certificates*, there are about 1.9 percent of cases with an unknown cause of death (i.e., the ICD-9 code is missing, see Table 3). We also examine the effects of the Ghost Month on the incidence of these cases. We find no statistically significant coefficients.

[16]First, one has to acknowledge that the reporting practice of *one* cause does not capture the reality of many deaths having multiple causes. Our data follows ICD-9, which defines the underlying cause of death (UCD) as "*the disease [...] which initiated the train of morbid events leading directly to death*". In the case of diabetes, it is generally difficult to unambiguously determine one UCD, since most diabetic patients suffer from multiple conditions. Importantly, patients with diabetes are almost twice as likely to have a heart attack or a stroke as people who do not have diabetes. Second, it is documented that Taiwanese physicians tend to choose diabetes as the UCD if multiple diseases coexist. The latter fact is discussed in a report published (in Mandarin) by the *Department of Health, Executive Yuan* (Chen, 2005), which has access to *Death Certificates* with richer information. This report compares Taiwanese physicians with their peers from Sweden and the US. It offers three explanations why Taiwanese physicians "favor" diabetes as UCD if multiple diseases coexist: (i) it is a habit of local physicians, (ii) it is due to medical training in filing the death certificates, or (iii) it is the location of filling diabetes on the Taiwanese certificates paperwork. Third, we have checked our suggested interpretation with a physician.

be associated with a decreased number of deaths due to strokes and heart attacks. We suggest that the negative effect on non-accidental deaths, can be explained by a reduced risk-exposure due to the avoidance of activities such as traveling, going-out at night and major events.[17]

4.1.1 Treatment Effect Heterogeneity

Our survey data analysis suggests that female, younger and less educated individuals tend to be more superstitious (see Table 2). Given that the *Death Certificates* include individual-level information on sex, age and educational attainment, we can test whether these differences in stated preferences translate into differences in revealed preferences. Put differently, we check whether behavioral adjustment due to superstitious beliefs and the resulting effects on mortality vary significantly across different sub-samples defined by these socio-demographic characteristics. Figure 3 depicts the estimation results using our main model described by eq. (2) by these group and place of occurrence. We find no significant differences between the sexes or educational groups. The same holds true for residents in urban and rural areas. With respect to age, we find (in line with the stated preferences) stronger effects for younger individuals. Teenagers, a group which is prone to risky behavior, seem to benefit the most from behavioral adjustments during the Ghost Month. If we distinguish between accidental and non-accidental deaths and apply our heterogeneity analysis on these two sub-sample (not shown), we learn that the effects for teenagers indeed exclusively comes from accidental deaths. In contrast, the reduction in non-accidental deaths is driven by individuals above 60.

Overall, our analysis of mortality provides evidence that behavioral adaptions to the Ghost Month — such as a reduction in risky activities and overall activity — save lives by reducing accidental and non-accidental deaths.

4.2 Health-care Utilization: Hospital Admissions

We now turn to the effect of the Ghost Month on health-care utilization. There are four potential causal channels: (i) the reduction in risky activities may not only reduce mortality, but also lead to a decline in hospital admissions; (ii) the reduction in overall activity may reduce related admissions, such as strokes or heart attacks; (iii) superstitious patients may want to avoid hospital admissions during the Ghost Month and schedule

[17] One potential causal pathway is reduced exposure to pollution. We have tried to test the hypothesis that pollution levels are lower during the Ghost Month. Our analysis was based on a data-set on different pollutants in the period between 1982 and 2001 covering up to 71 monitoring stations operated by the *Environmental Protection Administration, Executive Yuan.* While we found mostly negative effects of the Ghost Month on pollution levels, we consider these findings not robust. Detailed estimation output is available upon request.

their appointments accordingly; (iv) superstitious doctors may reduce their labor supply during the Ghost Month. While all mechanism would lead to a reduction of health-care utilization during the Ghost Month, we expect for the former two channels a quantum effect, and for the latter two channels a tempo effect.

Our first outcome variable is the daily number of hospital admissions. Column (1) of Table 6 shows that hospital admissions are significantly lower during the Ghost Month. The effect size varies somewhat over the course of the period with an average of about minus 3.8 percent. However, unlike the quantum effect we observed in the case of mortality, the evidence for health-care utilization points to a tempo effect. We find significant effects for an increased number of admissions in the period just after the Ghost Month of about 6 percent. Since the time span for postponing surgeries is unknown, it is hard to assess whether the total effect is mere tempo or also some quantum. Thus while we cannot rule out the presence of the causal channels iii. and iv, we can conclude that channel i. and/or ii. are in place.

This results suggest that the main causal driver of this effect is a lower demand (or supply) for medical services. It seems plausible that believers of the Ghost Month only try to avoid potentially risky health-care services. To test this hypothesis, we distinguish in columns (2) and (3), between patients who undergo surgery during the hospital stay, and those who do not. As expected, the effect is driven by the more risky admissions with surgery. We find a significant reduction in this category, during the Ghost Month of about 9 percent and important increases just before and after of about 3 and 8 percent, respectively. This result confirms the interpretation of a *tempo effect*, with believers pre- and postponing surgeries. Since the effect of the postponement is comparably larger, we conclude that it is easier for patients to defer a hospital visit rather than schedule an earlier one. In the case of admission without surgeries, there is only some evidence for an increased number right after the Ghost Month.

Given this clear evidence that patients distinguish between different types of health-care utilization, we provide further tests exploiting the degree of "deferability" of admissions. To approximate the deferability of an admission, we follow a procedure suggested by Card et al. (2009). They exploit the fact that hospitals typically schedule planned admissions for "deferrable" conditions on weekdays, when more staff is available. In contrast, unplanned admissions for "non-deferrable" conditions should have very similar weekend and weekday admission rates. Following this logic, the fraction of weekend admissions in the case of absolutely "non-deferrable" conditions should be close to 2/7. We compute the fraction of weekend admissions at the diagnosis-level using data in the period between 1982 and 1992.[18] This gives us a distribution of fractions of weekend admissions rates

[18]We do not use data from the years 1993 and 1994, since many observations have missing diagnosis codes. This is probably related to the introduction of the *National Health Insurance* in March 1995 (see footnote11. In the course of this, Taiwan has changed its classification system of diagnostic codes (from so-called 'A-codes') to ICD-9. We speculate that in the two years prior to NHI some hospitals already

across all diagnosis, reflecting a decreasing degree of "deferability" as one moves from the left to the right tail. We then compute quartiles for fraction of weekend admissions and split the diagnosis codes into four groups.

In Table 7 we present results on the effect of the Ghost Month on the daily number of hospital admissions with surgeries in these four sub-samples of diagnosis with varying degree of "deferability". A comparison of estimated coefficients across columns, clearly shows that the effect of the Ghost Month increases with the "deferability" of conditions. In the case of the "most-deferrable" conditions, the number of admissions decreases during the Ghost Month on average by almost 20 percent. This highlights how widespread the adaptions due to superstitious beliefs are. In contrast, for the category of the "least-deferrable" conditions, we observe a comparable small reduction of 4 percent. Coefficient estimates on the period before and after the Ghost Month illustrate that the patients defer surgeries, but do not have them early.

4.2.1 Treatment Effect Heterogeneity

We check again for heterogenous effects across different parts of the population. The *Inpatient Hospitalization Records* allow us to split the sample by sex, age and location. We focus here on the number of admissions with surgery (see Figure 4). We do not find any statistically significant differences across age groups or regions. In contrast, our analysis reveals a significant differences across sexes. Women are much more likely (about 12 percent) to postpone surgeries as compared to men (about 4 percent). This gradient is in line with our survey-based evidence suggesting that women are on average more superstitious and are more likely to believe in ghosts (plus 10 percentage points).

4.2.2 Health Consequences due to Adaptions in Health-care Utilization

So far, we have evidence that a significant number of patients — in particular among those with "deferrable" conditions — avoid surgeries during the Ghost Month. We now test the hypothesis whether this adaption due to superstitious beliefs has consequences for health. There are two potential causal mechanism. First, the post-ponement *per se* may have a negative impact on health. Second, the higher level of hospital occupancy right before or after the Ghost Month may decrease the quality of health-care services.

Our estimation strategy to gauge health consequences is examining subsequent morbidity and mortality of pre- and post-Ghost Month hospital admissions. Our measure for morbidity is the 30-day re-admission rate. We estimate again a model as described by eq. (2), but mainly focus on the parameters τ^{pre} and τ^{post}. Methodologically, we face here the challenge that we cannot identify the patients, who defer their surgery due to the Ghost Month, on an individual-level. We only know that a certain share of patients, who

switched to the ICD-9 codes, which resulted in missing information on A-codes.

are admitted to the hospital just before, and in particular, just after the Ghost Month adapted the timing of their surgery. Put differently, our sample comprises two types of patients in this period. First, those who have a surgery in this period, because they re-scheduled it in order to avoid a surgery during the Ghost Month. Second, there are patients who have their surgery in this period according to a regular (supposedly optimal) timing. Thus, if we test whether patients admitted during this period have different subsequent morbidity and mortality outcomes, we have a measurement error in our treatment of interest "adapted timing of surgery". This leads to an attenuation bias and we have a higher risk of making a Type-II error.

Morbidity To examine morbidity, we construct an individual-level dataset tracking the full hospitalization records of all patients, who were admitted to a hospital between 1982 and 1992. This dataset comprises 861,591 admissions. For each admission we define a binary variable equal to one if the patient readmits to hospital within 30 days after hospitalization. We obtain an average readmission rate of 0.085. Based on findings in the previous section, we are particularly interested in the morbidity of patients, who either pre- or postpone their hospital admissions due to the Ghost Month. We here follow our previous estimation strategy, but include control variables for patients' sex, age, and diagnosis at the initial admission. Our results provide no evidence for significant changes in the probability of readmission of post-Ghost Month admissions (i.e., the coefficient on gm^{+5}). This holds for cases with and without surgery during their initial admission, as well as in sub-samples of initial diagnosis with a varying degree of "deferability" (see Appendix Table A.3). In contrast, we find evidence for a higher likelihood of readmission for pre-Ghost Month admissions (i.e., the coefficient on gm^{-5}). The estimated effect of 0.3 percentage points is equivalent to an increase by 6 percent.

Mortality In a final step, we consider an effect from shifting hospital admissions due to Ghost Month on subsequent mortality. Therefore, we use a match between the *Inpatient Hospitalization Records* of all admissions with surgeries in the period between 1982 and 1992 and *Death Certificates.* For each admission we define a binary variable equal to one if a patient dies within 30 days after hospitalization. The estimation strategy is equivalent to the case of readmissions. Our results show no discernible evidence of a different 30-day mortality rate for pre- or post-Ghost Month admissions (see Appendix Table A.4). This holds for all cases with surgery (during their initial admission), as well as for initial admissions with different degrees of "deferability".

In sum, we find some evidence for adverse health consequences due to preponing surgeries. In contrast, there is no discernible evidence in the case of postponing surgeries. The coefficients on post-Ghost Month admissions are all precisely estimated zero effects.

However, since this set of results likely suffers from attenuation bias, the latter finding has to be interpreted with caution.

4.3 Fertility

Our results on the effect on fertility are summarized in Table 8. In column (1) the outcome variable is the number of daily live births. We find that the number of newborns decreases significantly during the Ghost Month. The effect varies somewhat over the course of the Ghost Month with reductions between 2.4 and 4.7 percent. In contrast, shortly before and after the Ghost Month the number of newborns increases by about 5 percent. This U-shaped pattern suggests that a significant number parents adjust the timing of birth in order to avoid a delivery during the Ghost Month.

There are two potential adjustment mechanism: parents could either manipulate the date of birth or the date of conception. The former mechanism would mean that women with an expected due date during the Ghost Month decide to deliver either early or late. The latter mechanism requires forward looking parents, who create a particular seasonality in conception; with a lower rate of conceptions in the period corresponding with expected due dates during the Ghost Month, and with higher conception rates in periods with expected due dates shortly before and after the Ghost Month.

There are several ways to assess the relative importance of the two adjustment mechanism. First, we contrast the scope of planning births with the U-shaped pattern. Responsible obstetricians would not plan a delivery in the absence of medical reasons that is very far away from the due date. By contrast we observe reductions in live births also in the middle of the Ghost Month, which would require a shift of up to 14 days. Second, postponing birth is harder than inducing it. Therefore, we should see a larger peak before as compared to after the Ghost Month. Our estimates, however, show equally sized peaks. Third, the manipulation of the date of birth, would alter gestational length. In column (2), we use individual-level data and examine gestational length. This estimation indeed shows a statistically significant shorter (longer) gestational length for children born right before (after) the Ghost Month; however the estimates are quantitatively very small. The observed changes of about 0.2 days ($\approx 0.0007 \times 39.2 \times 7$), remain small even if we take into account that only about 5 percent of births in this period have manipulated date of births. In a final step, we provide direct evidence on the manipulation of conception dates. Therefore, we use individual-level information on the date of birth and gestational length to approximate the date of conception. We then calculate for each case the expected due date assuming a regular gestational length of 40 weeks. We then generate a data set on the daily number of births, which would have been observed in case all newborns, would have been born on their expected due date. The estimates summarized in column (3) show a comparable U-shaped pattern albeit with a lower magnitude. This is direct evidence for a manipulation in conception dates. In sum, this evidence suggest that both types of manipulation take place. The dominant form are forward looking parents avoiding a delivery during the Ghost Month by timing the conception right.

4.3.1 Treatment Effect Heterogeneity

The individual-level information included in the *Birth Certificates* allows us to check for several dimensions of heterogeneity. In Figure 5, we summarize estimation results by selected mother (age, educational attainment, place of birth) and child (sex and parity) characteristics. For most sub-groups we find very comparable effects. Maternal age is the exception. While we see the same qualitative pattern across all age-groups, the magnitude increases significantly with age. The sample-splits by other characteristics, which are correlated with age (parity and education) do not show an equivalent pattern. We conclude that this heterogeneity reflects a "true" age effect. One possible explanation is that older women are more forward looking in their conception behavior.

4.3.2 Birth outcomes

Lastly, we consider an effect on children's health at birth.[19] Manipulations of the date of birth may have direct consequences for birth outcomes; however, given our evidence that this type of manipulation is less prevalent and rather mild, we expect this channel to be of minor importance. In contrast, manipulations of the date of conception should have no health consequences. Children may also be affected by fluctuations in the number of admissions to maternity units or to the hospital in general. Children delivered shortly before or after the Ghost Month could be negatively affected by the higher number of hospital admission during these periods. Conversely, children delivered during the Ghost Month could benefit from the hospitals' reduced work-load. A final channel could be the maternal behavior. Children born towards the end of the Ghost Month (or shortly thereafeter) could benefit, from a reduction in maternal activity related to stress. Thus, for deliveries shortly before the Ghost Month we expect (either due to a manipulation of birth dates or high levels of hospital occupancy) negative effects. For deliveries shortly after the Ghost Month the effect is unclear. Both, behavioral adaptions by mothers during the Ghost Month and the post-ponement of births (such as later scheduled caesarean sections) may be positive. In contrast, the hospital occupancy should be negative if at all.

Our results are summarized in Table 9. We use the available information on gestational age and birthweight to define binary variables capturing a preterm birth (below 37 weeks),

[19]A recent paper using Taiwanese data is interested in the causal effects of shortened gestation on birth outcomes. Chiang et al. (2017) aim to exploit manipulations in the date of birth due to the Ghost month within an instrumental variable (IV) approach. Their binary IV is defined as an expected due date during the Ghost Month, which increases the likelihood of an induced birth with a shortened gestation. For this IV to be valid, the authors have to assume that parents do *not* account for the Ghost Month in their conception behavior. Our estimation results challenge this identifying assumption.

a low birth weight birth (LBW; below 2,500 grams), and a very low birth weight birth (VLBW; below 1,500 grams). For children born right before the Ghost Month, we do not find any robust evidence. For children delivered right after the Ghost Month, we find on average better birth outcomes. The children have a longer gestation and a higher birth weight. Both effects are also presented a medically critical margins, with a reduced likelihood of a preterm birth and a (very) low birth weight. These positive effects could result from lower levels of prenatal stress maternal activity during the Ghost Month.[20]

5 Conclusions

In this paper, we empirically examine the impact of superstition on health-related behavior and health outcomes. We study the case of the Taiwanese Ghost Month. During this period, which is believed to increase the likelihood of bad outcomes, we observe substantial adaptions in health-related behavior. These lead to reductions mortality, lower levels of health-care utilization, and a lower number of births. While the impact on mortality is a quantum effect, the latter two adaptions represent mere tempo effects. The re-scheduling of health-care utilization is stronger among deferrable conditions and increases 30-day readmission rates. The adaption in fertility is mainly achieved by adaptions in conception behavior and to a smaller extent by manipulations of the time of birth.

Our findings show that superstition is an important case of bounded rationality of economic agents. This type of false believes has far-reaching consequences not only for health-related behavior, but also for health outcomes and even for mortality. While our evidence is based on the specific case of superstition, we suggest more generally that efficient public health policy should to account for emotional and cultural factors.

[20] The estimated effects are not driven by the compositional changes in mother's age, which we observe around the Ghost Month (see Figure 5). The inclusion of control variables for age does not alter the estimated effects and the effects are very comparable across age groups (results not shown).

References

Almond, Douglas and Bhashkar Mazumder (2011), 'Health Capital and the Prenatal Environment: The Effect of Ramadan Observance during Pregnancy', *American Economic Journal: Applied Economics* **3**(4), 56–85.

Almond, Douglas, Bhashkar Mazumder and Reyn Van Ewijk (2015), 'In Utero Ramadan Exposure and Children's Academic Performance', *Economic Journal* **125**(589), 1501–1533.

Almond, Douglas, Christine P. Chee, Maria M. Sviatschi and Nan Zhong (2015), 'Auspicious Birth Dates among Chinese in California', *Economics & Human Biology* **18**, 153–159.

Anson, Jon and Ofra Anson (2001), 'Death Rests a While: Holy Day and Sabbath Effects on Jewish Mortality in Israel', *Social Science & Medicine* **52**(1), 83–97.

Bennett, Daniel, Asjad Naqvi and Wolf-Peter Schmidt (2018), 'Learning, Hygiene and Traditional Medicine', *Economic Journal* **128**(612), F545–F574.

Borra, Cristina, Libertad González and Almudena Sevilla (forthcoming), 'The Impact of Scheduling Birth Early on Infant Health', *Journal of the European Economic Association* .

Card, David, Carlos Dobkin and Nicole Maestas (2009), 'Does Medicare Save Lives?', *Quarterly Journal of Economics* **124**(2), 597–636.

Chamberlain, Trevor W., C. Sherman Cheung and Clarence C.Y. Kwan (1991), 'The Friday the Thirteenth Effect: Myth or Reality?', *Quarterly Journal of Business and Economics* **30**(2), 111–117.

Chang, Lenias V. (2018), 'Information, Education, and Health Behaviors: Evidence from the MMR Vaccine Autism Controversy', *Health Economics* **27**(7), 1043–1062.

Chen, Li-Hua (2005), ICD-10 and Multiple Causes of Death: An Example of Diabetes (in Chinese), Research report, Department of Health, Executive Yuan, Taiwan.

Chiang, Chun-Fang, Elliott Fan and Chen-Yu Hsiao (2017), Chased by Ghosts: Exploring the Economic Factors and Health Consequences of Shortened Gestational Age, Unpublished manuscript, National Taiwan University, Taipei, Taiwan.

Chiu, Shin-Lin, Mei-Jih Gee, Chih-Hsin Muo, Chiao-Lee Chu, Shou-Jen Lan and Chiu-Liang Chen (2018), 'The Sociocultural Effects on Orthopedic Surgeries in Taiwan', *PloS one* **13**(3), e0195183.

Chou, Shin-Yi, Michael Grossman and Jin-Tan Liu (2014), ‘‘The Impact of National Health Insurance on Birth Outcomes: A Natural Experiment in Taiwan’’, *Journal of Development Economics* **111**, 75–91.

Coutts, Andrew (1999), ‘Friday the Thirteenth and the Financial Times Industry Ordinary Shares Index 1935–94’, *Applied Economics Letters* **6**(1), 35–37.

Dickert-Conlin, Stacy and Amitabh Chandra (1999), ‘Taxes and the Timing of Births’, *Journal of Political Economy* **107**(1), 161–177.

Dyl, Edward A. and Edwin D. Maberly (1988), ‘The Anomaly That Isn’t There: A Comment on Friday the Thirteenth’, *Journal of Finance* **43**(5), 1285–1286.

Fortin, Nicole M., Andrew J. Hill and Jeff Huang (2014), ‘Superstition in the Housing Market’, *Econmic Inquiry* **52**(3), 974–993.

Fudenberg, Drew and David K. Levine (2006), ‘Superstition and Rational Learning’, *American Economic Review* **96**(3), 630–651.

Gans, Joshua S. and Andrew Leigh (2009), ‘Born on the First of July: An (Un)natural Experiment in Birth Tming’, *Journal of Public Economics* **93**, 246–263.

Hira, Kenji, Tsuguya Fukui, Akira Endoh, Mahbubur Rahman and Munetaka Maekawa (1998), ‘Influence of Superstition on the Date of Hospital Discharge and Medical Cost in Japan: Retrospective and Descriptive Study’, *British Medical Journal* **317**(7174), 1680–1683.

Hirshleifer, David, Ming Jian and Huai Zhang (2018), ‘Superstition and Financial Decision Making’, *Management Science* **64**(1), 232–252.

Hussain, Azhar, Syed Ali, Madiha Ahmed and Sheharyar Hussain (2018), ‘The Anti-vaccination Movement: A Regression in Modern Medicine’, *Cureus* **10**(7), e2919.

Kahneman, Daniel and Frederick Shane (2002), Representativeness Revisited: Attribute Substitution in Intuitive Judgment, *in* T.Gilovich, D.Griffin and D.Kahneman, eds, ‘Heuristics and Biases: The Psychology of Intuitive Judgment’, Cambridge University Press, New York, NY, pp. 49–81.

Kahneman, Daniel and Frederick Shane (2005), A Model of Heuristic Judgment, *in* K. J.Holyoak and R. G.Morrison, eds, ‘The Cambridge Handbook of Thinking and Reasoning’, Cambridge University Press, New York, NY, pp. 267–293.

Kolb, Robert W. and Ricardo J. Rodriguez (1987), ‘Friday the Thirteenth: ‘Part VII’ – A Note’, *Journal of Finance* **42**(5), 1385–1387.

LaLumia, Sara, James M. Sallee and Nicholas Turner (2015), 'New Evidence on Taxes and the Timing of Birth', *American Economic Journal: Economic Policy* **7**(2), 258–293.

Leeson, Peter T. (2017), *WTFI? An Economic Tour of the Weird*, Stanford University Press, Stanford, CA.

Lin, Herng-Ching, Sudha Xirasagar and Yu-Chi Tung (2006), 'Impact of a Cultural Belief about Ghost Month on Delivery Mode in Taiwan', *Journal of Epidemiology & Community Health* **60**(6), 522–526.

Lo, Joan C. (2003), 'Patients' Attitudes vs. Physicians' Determination: Implications for Cesarean Sections', *Social Science & Medicine* **57**(1), 91–96.

Lucey, Brian M. (2001), 'Friday the 13th: International Evidence', *Applied Economics Letters* **8**(9), 577–579.

Matjasko, Jennifer L., John H. Cawley, Madeleine M. Baker-Goering and David V. Yokum (2016), 'Applying Behavioral Economics to Public Health Policy: Illustrative Examples and Promising Directions', *American Journal of Preventive Medicine* **50**(5S1), S13–S19.

Mocan, Naci and Luiza Pogorelova (2017), 'Compulsory Schooling Laws and Formation of Beliefs: Education, Religion and Superstition', *Journal of Economic Behavior & Organization* **142**, 509–539.

O'Reilly, D. and M. Stevenson (2000), 'The Effect of Superstition on the Day of Discharge from Maternity Units in Northern Ireland: 'A Saturday Flit is a short sit'', *Journal Journal of Obstetrics and Gynaecology* **20**(2), 139–142.

Oster, Emily (2018), 'Does Disease Cause Vaccination? Disease Outbreaks and Vaccination Response', *Journal of Health Economics* **57**, 90–101.

Panesar, Nirmal S. and William B. Goggins (2009), 'Postponement of Death around Chinese Holidays: A Hong Kong Perspective', *Singapore Medical Journal* **50**(10), 990–996.

Pauls, Lynn A., Rebecca Johnson-Paben, John McGready, Jamie D. Murphy, Peter J. Pronovost and Christopher L. Wu (2017), 'The Weekend Effect in Hospitalized Patients: A Meta-Analysis', *Journal of Hospital Medicine* **12**(9), 760–766.

Pokryshevskaya, Elena B. and Evgeny A. Antipov (2015), 'A Study of Numerological Superstitions in the Apartments Market', *Economics Bulletin* **35**(1), 83–88.

Rice, Thomas (2013), 'The Behavioral Economics of Health and Health Care', *Annual Review of Public Health* **34**, 431–447.

Risen, Jane L. (2016), ‘Believing What We Do Not Believe: Acquiescence to Superstitious Beliefs and Other Powerful Intuitions’, *Psychological Review* **123**, 182–207.

Schulkind, Lisa and Teny Maghakian Shapiro (2014), ‘What a Difference a Day makes: Quantifying the Effects of Birth Timing Manipulation on Infant Health’, *Journal of Health Economics* **33**, 139–158.

Shum, Matthew, Wei Sun and Guangliang Ye (2014), ‘Superstition and ‘Lucky’ Apartments: Evidence from Transaction-Level Data’, *Journal of Comparative Economics* **42**(1), 109–117.

Tenkorang, Eric Y., Stephen O. Gyimah, Eleanor Maticka-Tyndale and Jones Adjei (2011), ‘Superstition, Witchcraft and HIV prevention in Sub-Saharan Africa: The Case of Ghana’, *Culture, Health & Sexuality* **13**(9), 1001–1014.

Torgler, Benno (2007), ‘Determinants of Superstition’, *Journal of Socio-Economics* **36**, 713–733.

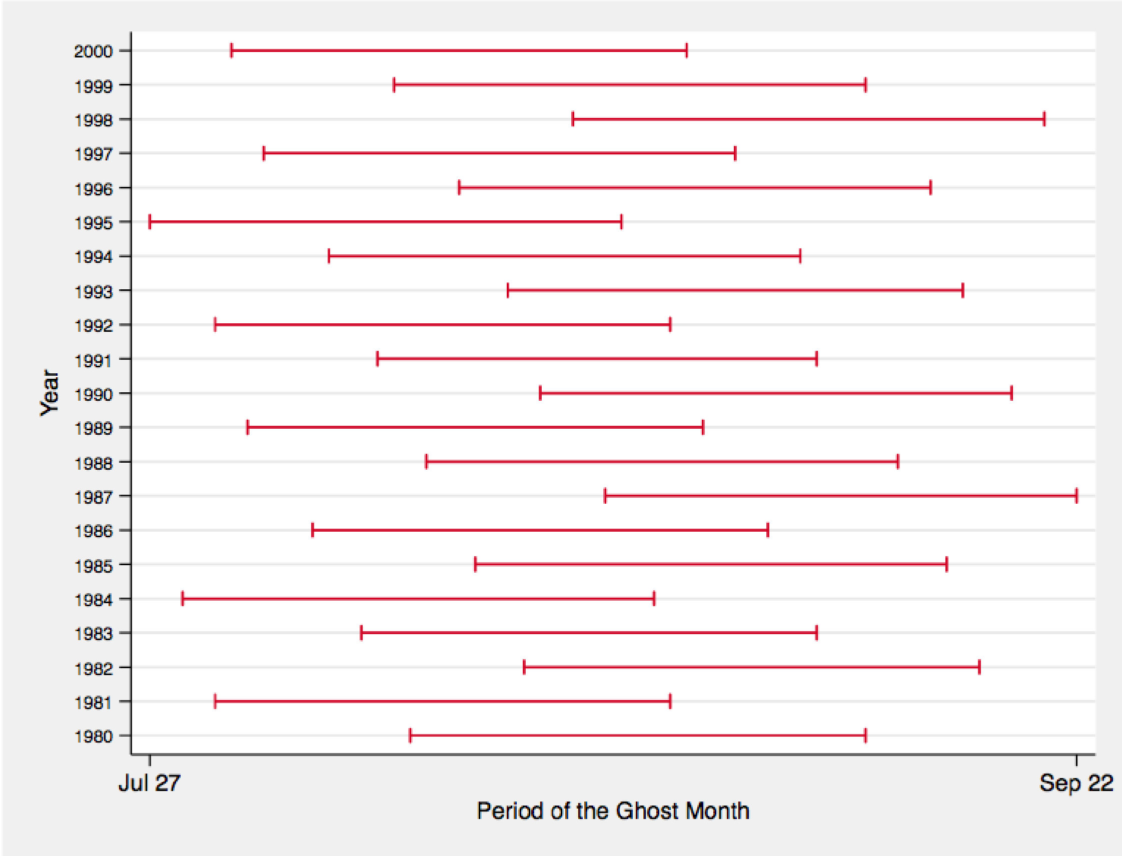
Vogt, Sonja, Nadia Ahmed Mohmmed Zaid, Hilal El Fadil Ahmed, Ernst Fehr and Charles Efferson (2016), ‘Changing Cultural Attitudes towards Female Genital Cutting’, *Nature* **538**, 506–509.

Wilches-Gutiérrez, José L., Luz Arenas-Monreal, Alfredo Paulo-Maya, Ingris Peláez-Ballestas and Alvaro J. Idrovo (2012), ‘A ‘Beautiful Death’: Mortality, Death, and Holidays in a Mexican Municipality’, *Social Science & Medicine* **74**(5), 775–782.

Yang, Chiang-Hsing, Yu-Tung Huang, Craig Janes, Kuan-Chia Lin and Tsung-Hsueh Lu (2008), ‘Belief in Ghost Month Can Help Prevent Drowning Deaths: A Natural Experiment on the Effects of Cultural Beliefs on Risky Behaviours’, *Social Science & Medicine* **66**(9), 1990–1998.

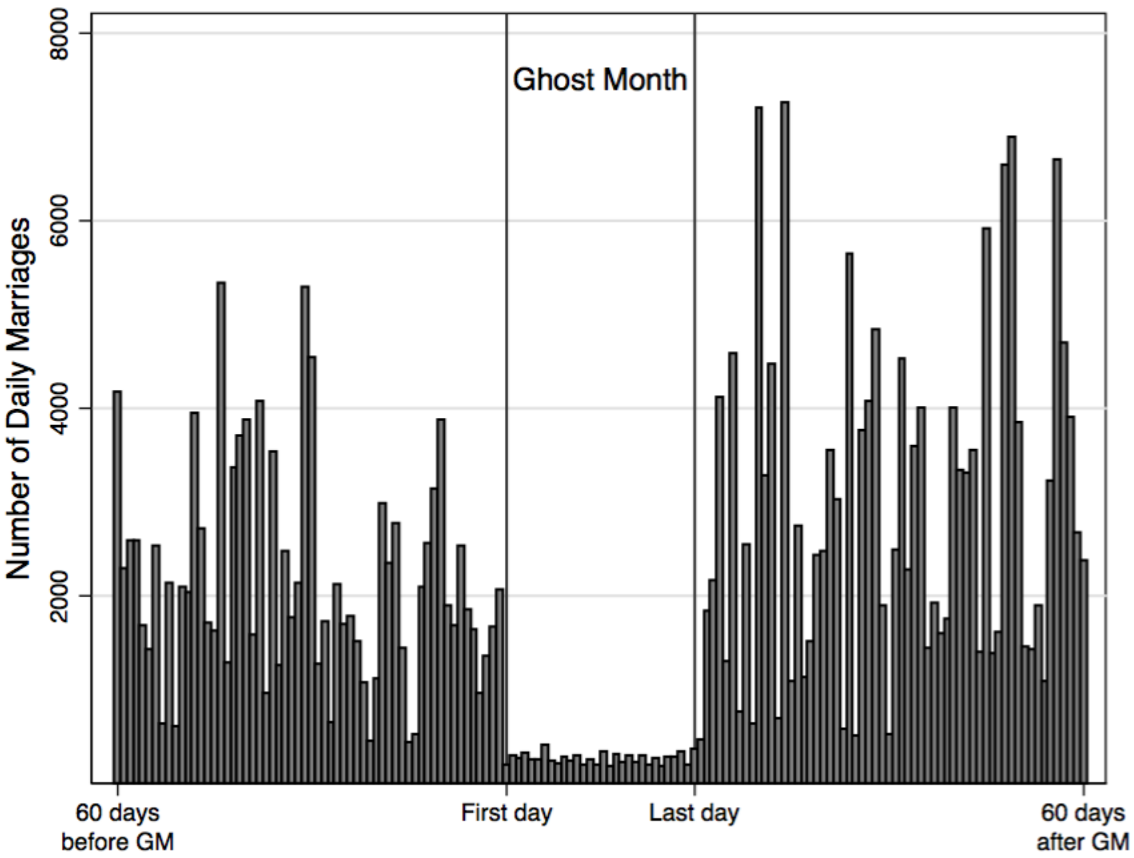
6 Figures (to be placed in paper)

Figure 1: Period of the Ghost Month according to Gregorian calendar, 1980-2000



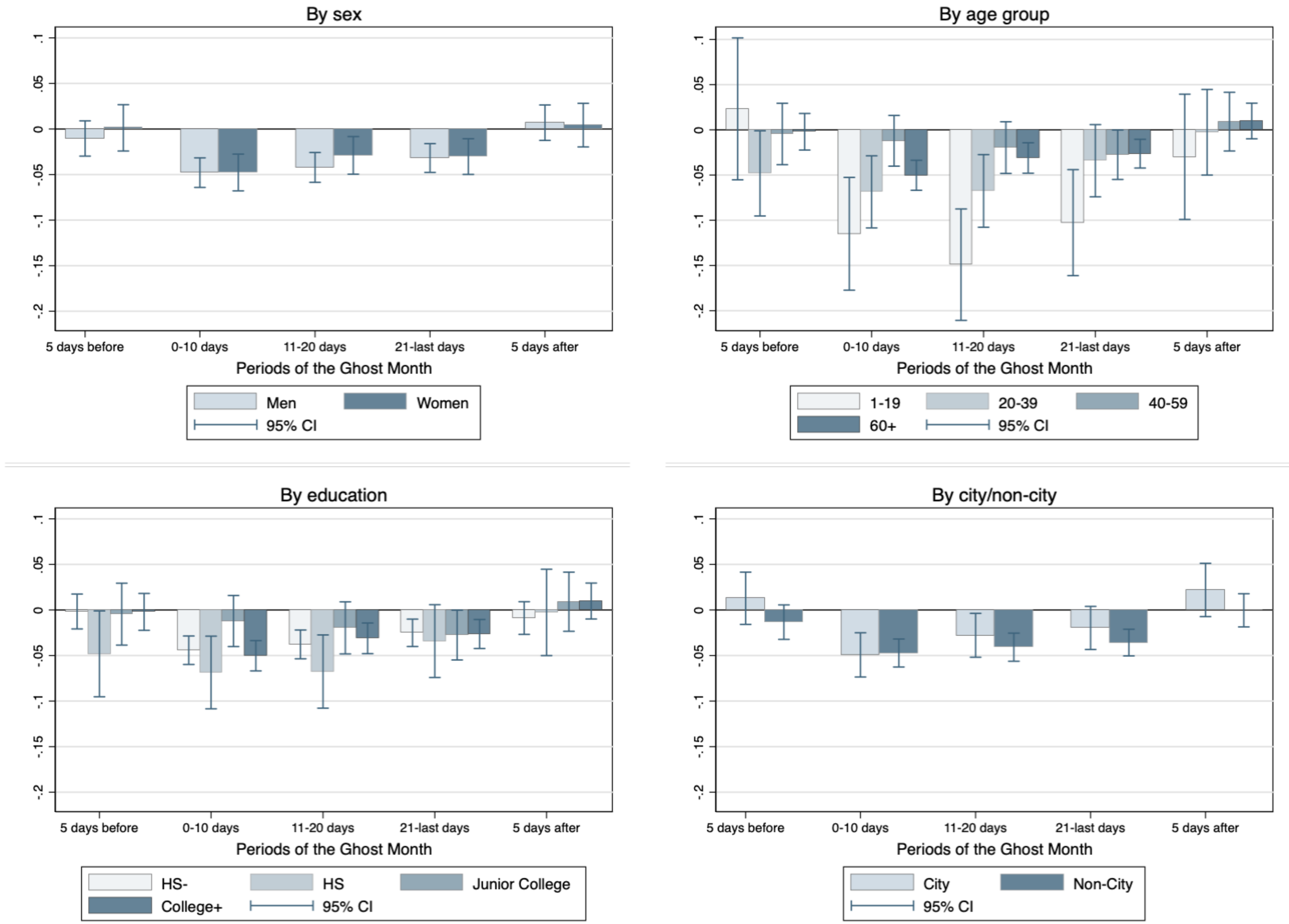
Notes: The period of the Ghost Month varies across years defined by the Gregorian calendar. This figure depicts the respective starting and end date across the years 1980 to 2000. The earliest start date is the 27^{th} of July. The latest end date is the 22^{nd} of September. All calendar days within the interval defined by these two dates have, with the exception of 24^{th} and 25^{th} of August, variation in their Ghost Month status across years.

Figure 2: Number of Daily Marriages Before, During, and After the Ghost Month in Taiwan, 1998-2006



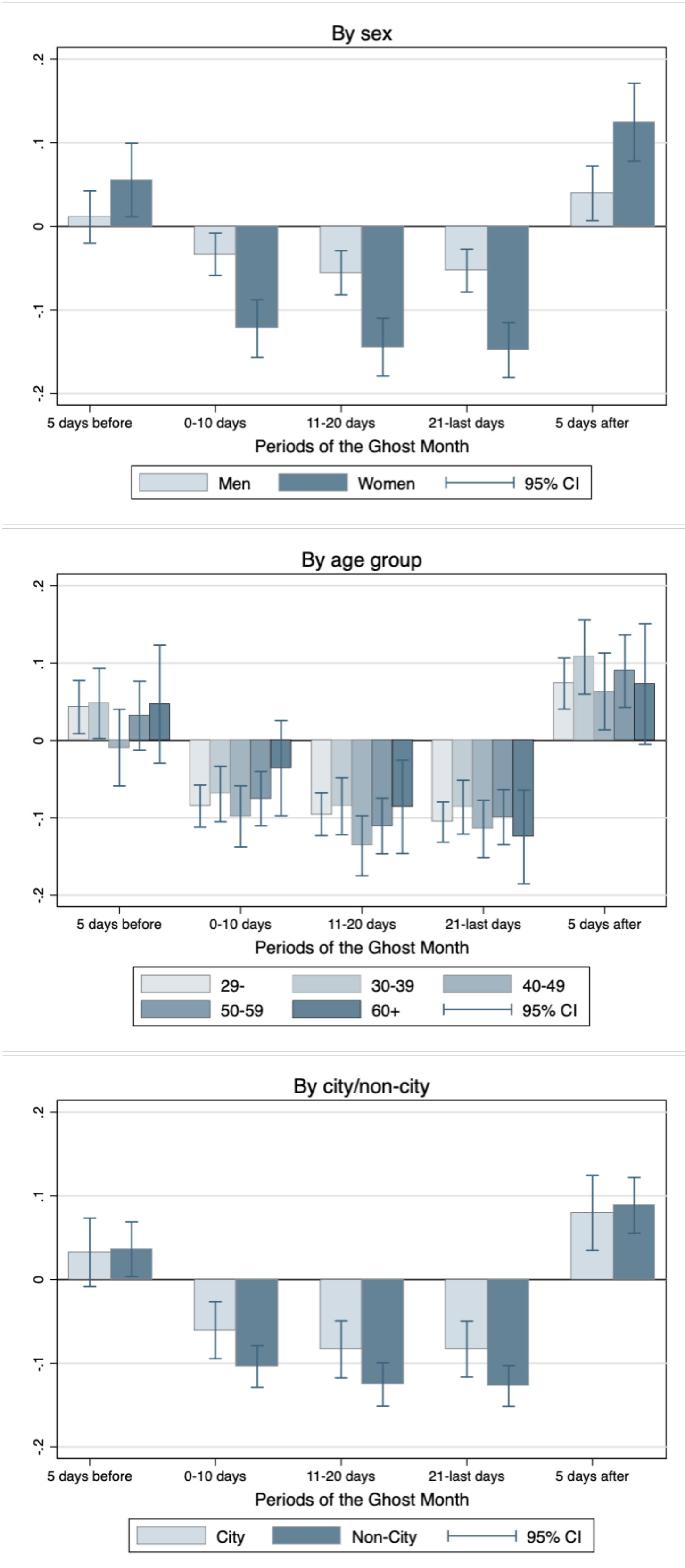
Notes: This figure depicts the aggregated number of daily marriages around the Ghost Month (GM) in Taiwan from 1998 to 2006. The data comes from *Marriage Certificates*, which covers the universe of marriages. Sixty days before and after the GM, the average number of daily marriages is 283, while the corresponding number during the GM is only 29. This is equivalent to a reduction of 90 percent.

Figure 3: The Effects of the Ghost Month on the Number of Deaths by Sex, Age, Education and Residence



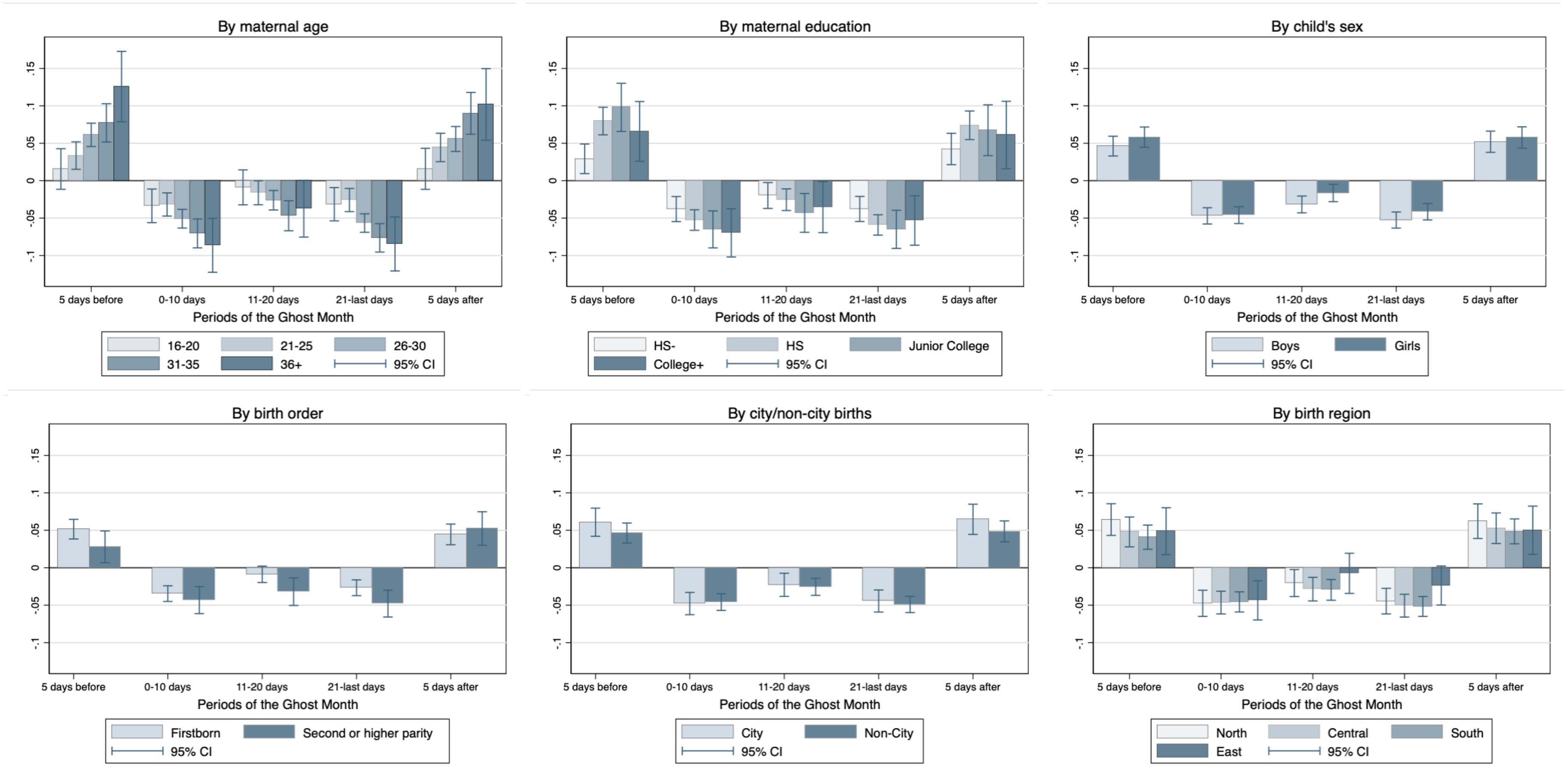
Notes: These figures depict sub-group analyses of the effect of the Ghost Month on the daily number of deaths summarized in column (1) of Table 4. Estimated coefficients can be interpreted as semi-elasticities.

Figure 4: The Effects of the Ghost Month on the Number of Surgeries by Sex, Age and Location



Notes: These figures depict sub-group analyses of the effect of the Ghost Month on the daily number of hospital admission summarized in column (2) of Table 6. Estimated coefficients can be interpreted as semi-elasticities.

Figure 5: The Effects of the Ghost Month on the Number of Births by Selected Mother and Child Characteristics



Notes: These figures depict sub-group analyses of the effect of the Ghost Month on the daily number of births summarized in column (1) of Table 8. Estimated coefficients can be interpreted as semi-elasticities.

7 Tables(to be placed in paper)

Table 1: Percentage of Taiwanese who believe in ghosts

	Year					
	1994	1999	2004	2009	2014	Overall
Yes, very much	21.88	19.10	20.38	16.39	21.05	19.65
Yes, somewhat	47.34	43.13	43.55	48.10	47.55	45.97
No, not really	20.69	25.73	27.91	28.87	22.62	25.37
Not at all	10.10	12.04	8.16	6.64	8.78	9.02
Observations	1,426	1,586	1,752	1,867	1,777	8,408

Notes: The exact survey question asked in the *Taiwan Social Change Survey* reads as follows "Do you believe that, spirits that are not offered any worship will wander around?".

Table 2: **Socio-economic correlates of believing in ghosts**

	Believing in ghosts Do you believe that, spirits that are not offered any worship will wander around?		
Female	0.093***	0.107***	0.093***
	(0.011)	(0.011)	(0.011)
Age (in years)	−0.007***	−0.005**	−0.007***
	(0.002)	(0.002)	(0.002)
Married	0.026	0.040**	0.027
	(0.017)	(0.017)	(0.017)
Employed	0.033***	0.036***	0.033***
	(0.013)	(0.013)	(0.013)
Educational attainment (Base group: less than elementary school)			
Junior high	−0.070***		−0.068***
	(0.019)		(0.019)
Senior high	−0.107***		−0.104***
	(0.017)		(0.018)
Some college	−0.133***		−0.129***
	(0.020)		(0.020)
College or above	−0.229***		−0.224***
	(0.020)		(0.021)
Household income (Base group: less than 30k)			
30-70k		−0.032**	−0.009
		(0.016)	(0.016)
70-100k		−0.052***	−0.002
		(0.019)	(0.020)
100k+		−0.078***	−0.010
		(0.019)	(0.020)
Refuse to answer/don't know		−0.018	0.003
		(0.019)	(0.019)
Year fixed-effects	Yes	Yes	Yes
County fixed-effects	Yes	Yes	Yes
Adjusted R-squared	0.041	0.027	0.040
Number of observations	8,224	8,366	8,210
Mean of dependent variable	0.656	0.656	0.656

Notes: The data come from the *Taiwan Social Change Survey*. The survey years are 1994, 1999, 2004, 2009, and 2014. The dependent variable is based on the survey question "Do you believe that, spirits that are not offered any worship will wander around?". It is a binary variable equal to one if people respond 'Very much' or 'Somewhat believe'; and zero 0 if people respond 'Not at all' or 'Not really'. Robust standard errors are reported in parentheses, where stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Descriptive Statistics

	Mean	S.D.	Min	Max	Obs.
Panel A: Death Certificates, 1980-2001 [a]					
County-level data	Mean	S.D.	Min	Max	Obs.
Daily number of deaths	10.78	8.05	0	57	30,750
Accidental death	1.32	1.51	0	34	30,750
Non-accidental death	9.26	7.19	0	54	30,750
Unknown cause	0.20	0.54	0	8	30,750
Panel B: Inpatient Hospitalization Records, 1982-1995 [b]					
County-level data	Mean	S.D.	Min	Max	Obs.
Daily number of admissions	66.15	84.21	0	720	17,550
With surgery	27.32	37.44	0	327	17,550
Without surgery	38.82	48.29	0	393	17,550
Panel C: Birth Certificates, 1978-2006 [c]					
County-level data	Mean	S.D.	Min	Max	Obs.
Daily number of births	36.09	32.78	0	210	43,500
Individual-level data					
Gestation length	39.22	1.61	24	44	1.537,170
Premature birth	0.049	–	0	1	1.537,170
Birth weight	3195.4	470.7	500	6000	1.537,170
Low birth weight	0.054	–	0	1	1.537,170
Very low birth weight	0.004	–	0	1	1.537,170

Notes: Taiwan is divided in 25 counties (to be precise, 18 counties and 7 city districts). To derive our estimation samples, we use in each year the period from the earliest starting date of the Ghost month to the latest end date (see Figure 1). These dates vary across Panels, since the years with available data differ. [a] County refers to the county of birth. To derive our estimation sample, we use in each year the period between the 27th of July and the 22nd of September. We exclude the 24th and 25th of August, since these two calendar days were always within the Ghost Month in the years 1980 to 2001. We further exclude two days with an extraordinarily high number of deaths due to earthquakes (September 21 and 22, 1999). Thus, we have 30,750 ($=$ 22 years $\times$ $(58-2)$ calendar days $\times$ 25 counties $-$ 2 days $\times$ 25 counties) observations. [b] County refers to the location of the hospital. To derive our estimation sample, we use in each year the period between the 28th of July and the 22nd of September. We exclude 24th, 25th, and 26th of August, since these three calendar days were always within the Ghost Month in the years 1982 to 1995. Thus, we have 17,550 ($=$ 13 years $\times$ $(57-3)$ calendar days $\times$ 25 counties) observations. [c] County refers to the county of birth. To derive our estimation sample, we use in each year the period between the 25th of July and the 22nd of September. Thus, we have 43,500 ($=$ 29 years $\times$ 60 calendar days $\times$ 25 counties) observations in our county-level data set. In the case of the individual-level data, the sample is restricted to mothers aged between 16 to 45. Gestation length is measured in weeks. Premature birth is a binary indicator with value 1 if gestation length is shorter than 37 weeks. Low birth weight is a binary indicator with value 1 if birth weight is below 2,500 gram. Very low birth weight is a binary indicator with value 1 if birth weight is below 1,500 gram. We exclude outliers, defined as follows: i. observations with a gestation length below 24 and above 44 weeks and ii. observations with a birth weight below 500 and above 6000 grams.

Table 4: **The Effect of the Ghost Month on the Number of Deaths**

	(1) Deaths	(2) Accidental deaths	(3) Non-accidental deaths
PERIOD BEFORE THE GM			
gm^{-5}	−0.006	−0.013	−0.007
	(0.008)	(0.023)	(0.009)
PERIOD DURING THE GM			
gm^{1-10}	−0.048***	−0.091***	−0.042***
	(0.007)	(0.019)	(0.007)
gm^{11-20}	−0.037***	−0.098***	−0.029***
	(0.007)	(0.020)	(0.007)
$gm^{21-last}$	−0.031***	−0.071***	−0.026***
	(0.006)	(0.019)	(0.007)
PERIOD AFTER THE GM			
gm^{+5}	0.007	0.014	0.006
	(0.008)	(0.022)	(0.009)
HOLIDAYS CONTROLS			
weekend	0.001	0.092***	−0.012***
	(0.004)	(0.012)	(0.004)
Moon Festival	0.022	0.199***	−0.005
	(0.021)	(0.065)	(0.023)
Qixi Festival	0.015	0.020	0.014
	(0.016)	(0.043)	(0.018)
Gregorian calendar year fixed-effects	Yes	Yes	Yes
Gregorian calendar day fixed-effects	Yes	Yes	Yes
County fixed-effects	Yes	Yes	Yes
R-squared	0.809	0.302	0.791
Number of observations	30,750	30,750	30,750
Mean of (undivided) dependent variable	10.782	1.323	9.262
S.D. of (undivided) dependent variable	8.045	1.512	7.188

Notes: This table summarizes the estimated effect of the Ghost Month on the daily number of deaths (column 1), accidental deaths (column 2), and non-accidental deaths (column 3). Dependent variables are divided by their sample mean. Thus, estimated coefficients can be interpreted as semi-elasticities. Robust standard errors are reported in parentheses, where stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Information on data sources and sample definitions are provided in the notes to Table 3.

Table 5: **The Effect of the Ghost Month on Cause-Specific Deaths**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Accidental deaths					Non-accidental deaths				
	Traffic	Drowning	Falling	Poisoning	Electric	Diabetes	Neoplasm of liver	Neoplasm of trachea	Cerebro- -vascular	Chronic liver
Period before the GM										
gm^{-5}	0.026	-0.003	-0.073	0.016	-0.005	0.022	-0.017	0.006	0.037	-0.029
	(0.032)	(0.066)	(0.070)	(0.094)	(0.144)	(0.037)	(0.037)	(0.039)	(0.042)	(0.038)
Period during the GM										
gm^{1-10}	-0.067***	-0.208***	-0.074	-0.037	-0.085	-0.081***	-0.032	-0.004	-0.132***	-0.006
	(0.026)	(0.050)	(0.056)	(0.076)	(0.118)	(0.031)	(0.030)	(0.031)	(0.033)	(0.032)
gm^{11-20}	-0.080***	-0.248***	-0.018	-0.021	-0.225**	-0.030	0.002	-0.003	-0.076**	0.024
	(0.027)	(0.054)	(0.059)	(0.077)	(0.113)	(0.032)	(0.031)	(0.032)	(0.033)	(0.033)
$gm^{21-last}$	-0.076***	-0.246***	0.030	-0.095	-0.092	-0.054*	-0.030	-0.040	-0.054*	0.008
	(0.026)	(0.047)	(0.058)	(0.075)	(0.113)	(0.030)	(0.030)	(0.031)	(0.032)	(0.032)
Period after the GM										
gm^{+5}	-0.039	0.066	-0.072	0.063	-0.099	-0.017	0.083**	0.053	-0.027	0.020
	(0.030)	(0.058)	(0.066)	(0.092)	(0.132)	(0.036)	(0.035)	(0.038)	(0.038)	(0.038)
Holidays controls										
$weekend$	0.060***	0.466***	-0.068*	0.000	-0.091	-0.039**	-0.023	0.002	0.008	-0.015
	(0.016)	(0.034)	(0.036)	(0.048)	(0.071)	(0.019)	(0.018)	(0.019)	(0.021)	(0.020)
$Moon\,Festival$	0.304***	0.102	0.114	0.184	0.056	-0.131	-0.031	-0.092	0.158	0.008
	(0.102)	(0.153)	(0.171)	(0.276)	(0.355)	(0.083)	(0.095)	(0.082)	(0.118)	(0.098)
$Qixi\,Festival$	0.032	0.190	-0.028	-0.065	0.064	-0.002	-0.008	0.033	-0.054	-0.020
	(0.058)	(0.121)	(0.139)	(0.176)	(0.305)	(0.066)	(0.074)	(0.078)	(0.073)	(0.082)
Gregorian calendar year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gregorian calendar day fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.203	0.078	0.060	0.037	0.013	0.251	0.209	0.233	0.166	0.150
Number of observations	30,750	30,750	30,750	30,750	30,750	30,750	30,750	30,750	30,750	30,750
Mean of (undivided) dependent variable	0.654	0.201	0.124	0.071	0.031	0.481	0.473	0.433	0.400	0.398
S.D. of (undivided) dependent variable	0.943	0.528	0.364	0.274	0.180	0.831	0.784	0.766	0.704	0.682

Notes: This table summarizes the estimated effect of the Ghost Month on the daily number of cause-specific deaths. Dependent variables are divided by their sample mean. Thus, estimated coefficients can be interpreted as semi-elasticities. Method of estimation is ordinary least squares. Robust standard errors are reported in parentheses, where stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Information on data sources and sample definitions are provided in the notes to Table 3. ICD-9 codes classification for cause-specific deaths are as follows. Motor vehicle traffic accidents: E810-E819 (column 1); Accidental drowning and submersion: E910 (column 2); Accidental falls: E880-E888 (column 3); Accidental poisoning: E850-E869 (column 4); Accidents caused by electric current: E925 (column 5); Diabetes mellitus: 250 (column 6); Malignant neoplasm of liver and intrahepatic bile ducts: 155 (column 7); Malignant neoplasm of trachea, bronchus, and lung: 162 (column 8); Acute but ill-defined cerebrovascular disease: 436 (column 9); Chronic liver disease and cirrhosis: 571 (column 10).

Table 6: **The Effect of the Ghost Month on the Number of Hospital Admissions**

	(1) Admissions	(2) Surgery	(3) No surgery
Period before the GM			
gm^{-5}	0.024	0.034**	0.016
	(0.016)	(0.017)	(0.017)
Period during the GM			
gm^{1-10}	−0.028**	−0.079***	0.008
	(0.013)	(0.014)	(0.014)
gm^{11-20}	−0.047***	−0.101***	−0.009
	(0.013)	(0.014)	(0.015)
$gm^{21-last}$	−0.040***	−0.102***	0.004
	(0.013)	(0.013)	(0.014)
Period after the GM			
gm^{+5}	0.060***	0.084***	0.043**
	(0.017)	(0.018)	(0.018)
Holidays controls			
weekend	−0.394***	−0.422***	−0.375***
	(0.008)	(0.009)	(0.009)
Moon Festival	−0.543***	−0.548***	−0.540***
	(0.046)	(0.051)	(0.044)
Qixi Festival	−0.062**	−0.081***	−0.048
	(0.027)	(0.030)	(0.030)
Gregorian calendar year fixed-effects	Yes	Yes	Yes
Gregorian calendar day fixed-effects	Yes	Yes	Yes
County fixed-effects	Yes	Yes	Yes
R-squared	0.847	0.854	0.814
Number of observations	17,550	17,550	17,550
Mean of (undivided) dependent variable	66.145	27.322	38.823
S.D. of (undivided) dependent variable	84.212	37.444	48.292

Notes: This table summarizes the estimated effect of the Ghost Month on the daily number of hospital admissions (column 1), hospital admissions with undergoing surgeries (column 2), and hospital admissions without undergoing surgeries (column 3). Dependent variables are divided by their sample mean. Thus, estimated coefficients can be interpreted as semi-elasticities. Method of estimation is ordinary least squares. Method of estimation is ordinary least squares. Robust standard errors are reported in parentheses, where stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Information on data sources and sample definitions are provided in the notes to Table 3.

Table 7: **The Effect of the Ghost Month on the Number Hospital Admissions by deferability**

	(1)	(2)	(3)	(4)
	Hospital admissions by deferability			
	1^{st} quartile	2^{nd} quartile	3^{rd} quartile	4^{th} quartile
	Most deferrable	...	...	Least deferrable
PERIOD BEFORE THE GM				
gm^{-5}	0.038	0.042	0.005	0.038**
	(0.032)	(0.032)	(0.023)	(0.018)
PERIOD DURING THE GM				
gm^{1-10}	−0.159***	−0.090***	−0.041**	−0.026*
	(0.026)	(0.025)	(0.018)	(0.014)
gm^{11-20}	−0.223***	−0.158***	−0.060***	−0.044***
	(0.026)	(0.025)	(0.019)	(0.014)
$gm^{21-last}$	−0.199***	−0.157***	−0.055***	−0.056***
	(0.025)	(0.024)	(0.018)	(0.013)
PERIOD AFTER THE GM				
gm^{+5}	0.089***	0.079**	0.049**	0.050***
	(0.034)	(0.031)	(0.022)	(0.018)
HOLIDAYS CONTROLS				
$weekend$	−0.705***	−0.592***	−0.417***	−0.208***
	(0.015)	(0.015)	(0.011)	(0.009)
$Moon\,Festival$	−1.003***	−0.850***	−0.550***	−0.239***
	(0.099)	(0.088)	(0.065)	(0.042)
$Qixi\,Festival$	−0.067	−0.060	−0.073**	−0.067*
	(0.063)	(0.055)	(0.036)	(0.036)
Gregorian calendar year fixed-effects	Yes	Yes	Yes	Yes
Gregorian calendar day fixed-effects	Yes	Yes	Yes	Yes
County fixed-effects	Yes	Yes	Yes	Yes
R-squared	0.716	0.721	0.805	0.859
Number of observations	14,850	14,850	14,850	14,850
Mean of (undivided) dependent variable	4.650	3.186	5.817	10.382
S.D. of (undivided) dependent variable	7.762	5.124	8.198	13.537

Notes: This table summarizes the estimated effect of the Ghost Month on the daily number of hospital admissions with undergoing surgeries by the degree of "deferability". The latter is approximated by weekend admissions rates at the diagnosis-level as suggested by (Card et al., 2009). We compute the fraction of weekend admissions (of all admissions) for all diagnosis using data in the period between 1982 and 1992. This gives us a distribution of fractions of weekend admissions rates across all diagnosis, reflecting a decreasing degree of "deferability" as one moves from the left to the right tail. We then compute quartiles for weekend admissions rates and split the diagnosis codes into four groups, where column (1) represents the most deferrable admissions and column (4) represents the least deferrable admissions. Dependent variables are divided by their sample mean. Thus, estimated coefficients can be interpreted as semi-elasticities. Method of estimation is ordinary least squares. Method of estimation is ordinary least squares. Robust standard errors are reported in parentheses, where stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Information on data sources and sample definitions are provided in the notes to Table 3.

Table 8: **The Effect of the Ghost Month on the Number of Birth, Gestational Length, and Expected Number of Births**

	(1) Births	(2) Gestation	(3) Expected births
Period before the GM			
gm^{-5}	0.0518***	−0.0007***	0.0147***
	(0.0058)	(0.0001)	(0.0054)
Period during the GM			
gm^{1-10}	−0.0459***	−0.0001	−0.0106**
	(0.0049)	(0.0001)	(0.0046)
gm^{11-20}	−0.0244***	0.0002	−0.0045
	(0.0050)	(0.0001)	(0.0047)
$gm^{21-last}$	−0.0472***	0.0001	−0.0141***
	(0.0048)	(0.0001)	(0.0046)
Period after the GM			
gm^{+5}	0.0547***	0.0008***	0.0236***
	(0.0063)	(0.0001)	(0.0058)
Holidays controls			
$weekend$	−0.0614***	0.0001	−0.0607***
	(0.0030)	(0.0001)	(0.0029)
$Moon\,Festival$	−0.0262*	−0.0003	−0.0118
	(0.0159)	(0.0004)	(0.0149)
$Qixi\,Festival$	0.0065	0.0003	−0.0051
	(0.0105)	(0.0003)	(0.0107)
Gregorian calendar year fixed-effects	Yes	Yes	Yes
Gregorian calendar day fixed-effects	Yes	Yes	Yes
County fixed-effects	Yes	Yes	Yes
R-squared	0.903	0.097	0.913
Number of observations	43,500	1,537,169	43,500
Mean of (undivided) dependent variable	36.086	39.218	35.309
S.D. of (undivided) dependent variable	32.783	1.609	31.889

Notes: This table summarizes the estimated effect of the Ghost Month on the daily number of births (column 1), on gestational length in individual-level data (column 2), and daily number of expected births (column 3). The expected number of births are calculated in individual-level by combining the date of conception and a regular gestational length of 40 weeks. This variable is used to infer on the adaption in conception behavior. Dependent variables are divided by their sample mean. Thus, estimated coefficients can be interpreted as semi-elasticities. Method of estimation is ordinary least squares. Robust standard errors are reported in parentheses, where stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Information on data sources and sample definitions are provided in the notes to Table 3.

Table 9: **The Effect of the Ghost Month on Birth Outcomes**

	(1) Preterm birth	(2) Birth weight	(3) LBW	(4) VLBW
Period before the GM				
gm^{-5}	0.0007	−0.0004	−0.0013*	−0.0003
	(0.0007)	(0.0005)	(0.0008)	(0.0002)
Period during the GM				
gm^{1-10}	0.0005	−0.0018***	0.0010	0.0002
	(0.0006)	(0.0004)	(0.0007)	(0.0002)
gm^{11-20}	−0.0004	−0.0002	−0.0006	−0.0000
	(0.0006)	(0.0004)	(0.0007)	(0.0002)
$gm^{21-last}$	0.0013**	−0.0004	0.0005	0.0005***
	(0.0006)	(0.0004)	(0.0007)	(0.0002)
Period after the GM				
gm^{+5}	−0.0033***	0.0027***	−0.0037***	−0.0006***
	(0.0007)	(0.0005)	(0.0008)	(0.0002)
Holidays controls				
weekend	0.0000	−0.0007***	−0.0003	0.0002
	(0.0004)	(0.0003)	(0.0004)	(0.0001)
Moon Festival	0.0029	−0.0029**	0.0024	0.0000
	(0.0019)	(0.0013)	(0.0020)	(0.0006)
Qixi Festival	−0.0013	−0.0001	−0.0002	0.0009*
	(0.0014)	(0.0010)	(0.0015)	(0.0005)
Gregorian calendar year fixed-effects	Yes	Yes	Yes	Yes
Gregorian calendar day fixed-effects	Yes	Yes	Yes	Yes
County fixed-effects	Yes	Yes	Yes	Yes
R-squared	0.011	0.018	0.003	0.001
Number of observations	1,537,169	1,537,169	1,537,169	1,537,169
Mean of (undivided) dependent variable	0.049	3195.432	0.054	0.004
S.D. of (undivided) dependent variable	-	470.671	-	-

Notes: This table summarizes the estimated effect of the Ghost Month on preterm births (column 1), birth weight (column 2), low birth weight (column 3), and very low birth weight (column 4). Dependent variable for birth weight is divided by its sample mean. Thus, the estimated coefficient can be interpreted as a semi-elasticity. Method of estimation is ordinary least squares. Robust standard errors are reported in parentheses, where stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Information on data sources and sample definitions are provided in the notes to Table 3.

Web Appendix

This Web Appendix (not for publication) provides additional material discussed in the unpublished manuscript 'The Effect of Superstition on Health: Evidence from the Taiwanese Ghost Month' by Martin Halla, Chia-Lun Liu, and Jin-Tan Liu.

Table A.1: Share of Population with Different Superstitious Beliefs

	Lucky charm (mascot or talisman)			**Horoscope**		
	Share of respondents who:			*Share of respondents who:*		
Country	Possess one	Think it protects or helps	Definitely think it protects	Consult it to know about future	Consult it every day	Take it into account in daily life
Austria	25.30	52.91	8.21	67.00	13.48	18.42
Belgium	13.98	31.27	4.06	.	.	.
Bulgaria	18.96	93.10	32.02	67.97	16.58	.
Belarus	16.62	64.11	4.97	61.02	0.82	.
Croatia	35.64	60.82	10.19	65.33	4.41	47.40
Czech Republic	33.84	55.57	3.75	78.13	6.05	33.63
Denmark	15.48	34.57	2.60	.	.	.
Estonia	21.13	71.16	4.93	74.54	12.27	47.76
Finland	11.67	42.28	1.60	71.21	3.29	24.98
France	16.78	34.93	2.43	58.61	11.37	41.02
Germany	24.96	51.51	2.71	62.18	7.64	53.88
Greece	36.35	71.10	6.29	41.64	3.87	32.62
Hungary	14.46	28.75	4.28	.	.	.
Iceland	13.41	52.95	3.22	61.62	11.10	14.86
Ireland	12.21	46.18	5.68	.	.	.
Italy	15.49	31.42	2.24	54.68	9.37	29.98
Latvia	19.98	70.15	9.76	.	.	.
Lithuania	16.75	61.94	6.26	72.14	10.72	51.51
Luxembourg	24.20	50.31	4.37	.	.	.
Malta	9.39	18.76	1.50	.	.	.
Netherlands	11.28	46.53	1.71	.	.	.
Poland	12.52	91.73	33.83	.	.	.
Portugal	12.03	47.44	3.37	.	.	.
Romania	18.84	86.99	45.91	.	.	.
Russia	20.15	57.83	7.50	62.50	4.02	41.47
Slovakia	23.70	56.49	5.58	.	.	.
Slovenia	18.96	46.43	4.94	.	.	.
Spain	11.00	44.35	1.91	.	.	.
Sweden	16.65	38.92	2.69	.	.	.
Turkey	20.35	40.39	5.54	.	.	.
Ukraine	18.59	52.86	6.29	68.63	2.74	47.59
Great Britain	15.20	48.78	1.38	.	.	.
Northern Ireland	10.93	41.76	2.46	.	.	.
Overall	18.93	49.18	5.70	64.16	7.71	36.81

Notes: These shares are calculated based on date from the *World Values Survey*. Do you have a lucky charm such as a mascot or a talisman? Yes, no. Do you believe that a lucky charm such as a mascot or a talisman can protect or help you? Definitely not (1) to Definitely yes (10). How often do you consult your horoscope to know about your future? (1 ‘Every day’, 2 ‘Once a week’, 3 ‘Once a month’, 4 ‘Less often’, 5 ‘Never’). How often do you take this into account in your daily life? 1 ‘Always’, 2 ‘Most of the time’, 3 ‘Sometimes’, 4 ‘Not very’.

Table A.2: Socio-economic Correlates of Superstitious Beliefs

	Lucky charm (mascot or talisman)			Horoscope		
		Respondent			*Respondent*	
	possess one	thinks it protects or helps	definitely think it protects	consults it to know about future	Consult it every day	takes it into account in daily life
Female	0.059***	0.091***	0.019***	0.154***	0.043***	0.133***
	(0.007)	(0.011)	(0.006)	(0.011)	(0.009)	(0.017)
Age	−0.003***	−0.004***	−0.000	−0.006***	−0.001*	−0.005***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Married	−0.049***	−0.037***	−0.007**	0.003	−0.008	−0.020
	(0.007)	(0.007)	(0.003)	(0.014)	(0.005)	(0.014)
Employed	0.002	0.010	−0.003	0.051***	0.006	0.029***
	(0.005)	(0.006)	(0.003)	(0.009)	(0.005)	(0.009)
Education (8 point-scale)	−0.004**	−0.010***	−0.005***	−0.001	−0.006**	−0.014**
	(0.002)	(0.002)	(0.001)	(0.006)	(0.002)	(0.005)
Household income (10 point-scale)	0.002	−0.001	−0.001	0.006*	−0.000	0.001
	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.003)
Town size (3 point-scale)	0.016***	0.008	−0.001	0.013	0.007*	−0.009
	(0.005)	(0.005)	(0.002)	(0.010)	(0.003)	(0.008)
Number of observations	32,527	29,446	29,446	17,804	17,804	14,781
R-squared	0.05	0.12	0.11	0.12	0.04	0.11
Mean of dependent var.	0.19	0.50	0.06	0.64	0.08	0.37

Notes: All estimations control for country and year fixed-effects. Standard errors are clustered at the country-level.

Table A.3: **The Effect of the Ghost Month on Hospital Readmissions**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Outcome: Readmit in 30 days						
	All	Surgery	No Surgery	Hospital admissions with surgeries by deferrability			
				1st quartile	2nd quartile	3rd quartile	4th quartile
				Most deferrable	...	...	Least deferrable
Period before the GM							
gm^{-5}	0.0024**	0.0033**	0.0017	−0.0001	0.0054	0.0075**	0.0020
	(0.0012)	(0.0016)	(0.0018)	(0.0031)	(0.0045)	(0.0037)	(0.0023)
Period during the GM							
gm^{1-10}	0.0024**	0.0009	0.0025*	0.0031	−0.0009	0.0013	0.0006
	(0.0010)	(0.0013)	(0.0015)	(0.0029)	(0.0038)	(0.0030)	(0.0019)
gm^{11-20}	0.0006	0.0007	−0.0001	0.0026	0.0023	−0.0035	0.0019
	(0.0011)	(0.0014)	(0.0015)	(0.0030)	(0.0040)	(0.0030)	(0.0020)
$gm^{21-last}$	0.0015	0.0021	0.0002	0.0031	0.0011	−0.0018	0.0041**
	(0.0010)	(0.0013)	(0.0015)	(0.0029)	(0.0039)	(0.0030)	(0.0019)
Period after the GM							
gm^{+5}	−0.0007	−0.0003	−0.0004	−0.0002	0.0008	−0.0003	−0.0008
	(0.0012)	(0.0015)	(0.0018)	(0.0032)	(0.0044)	(0.0036)	(0.0022)
Holidays controls							
$weekend$	0.0040***	0.0031***	0.0040***	0.0004	0.0088***	0.0015	0.0035***
	(0.0007)	(0.0010)	(0.0010)	(0.0023)	(0.0030)	(0.0021)	(0.0013)
$Moon\,Festival$	0.0118***	0.0073	0.0140**	−0.0122	0.0188	−0.0017	0.0132*
	(0.0042)	(0.0055)	(0.0060)	(0.0147)	(0.0235)	(0.0113)	(0.0071)
$Qixi\,Festival$	0.0051*	0.0050	0.0050	−0.0032	0.0109	0.0031	0.0081
	(0.0026)	(0.0034)	(0.0037)	(0.0069)	(0.0097)	(0.0078)	(0.0050)
Gregorian calendar year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gregorian calendar day fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age and gender controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diagnosis controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.038	0.026	0.043	0.035	0.044	0.018	0.019
Number of observations	861,591	356,774	504,817	69,029	47,275	86,323	154,099
Mean of dependent variable	0.085	0.055	0.105	0.085	0.114	0.097	0.061

Notes: This table summarizes the estimated effect of the Ghost Month on hospital readmissions in 30 days (column 1), with undergoing surgeries (column 2), without undergoing surgeries (column 3), and by deferrability (columns 4-7). We compute the fraction of weekend admissions at the diagnosis-level using data in the period between 1982 and 1992 to approximate the deferability of an admission (Card et al., 2009). This gives us a distribution of fractions of weekend admissions rates across all diagnosis, reflecting a decreasing degree of "deferability" as one moves from the left to the right tail. We then compute quartiles for fraction of weekend admissions and split the diagnosis codes into four groups, where column 4 represents the most deferrable admissions and column 7 represents less deferrable admissions. Method of estimation is ordinary least squares. Robust standard errors are reported in parentheses, where stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Information on data sources and sample definitions are provided in the notes to Table 3.

Table A.4: **The Effect of the Ghost Month on Post-discharge Mortality**

	(1)	(2)	(3)	(4)	(5)
	Hospital admissions with surgeries Outcome: Die in 30 days				
	All	by deferrability			
		1^{st} quartile	2^{nd} quartile	3^{rd} quartile	4^{th} quartile
		Most deferrable	...	...	Least deferrable
Period before the GM					
gm^{-5}	−0.0004	−0.0016***	0.0003	−0.0003	−0.0001
	(0.0003)	(0.0005)	(0.0013)	(0.0009)	(0.0004)
Period during the GM					
gm^{1-10}	−0.0000	0.0001	−0.0014	0.0005	0.0001
	(0.0003)	(0.0006)	(0.0012)	(0.0008)	(0.0003)
gm^{11-20}	0.0003	0.0007	0.0009	0.0006	−0.0001
	(0.0003)	(0.0006)	(0.0014)	(0.0008)	(0.0003)
$gm^{21-last}$	0.0002	0.0006	0.0015	0.0001	−0.0002
	(0.0003)	(0.0006)	(0.0013)	(0.0008)	(0.0003)
Period after the GM					
gm^{+5}	−0.0002	0.0000	−0.0005	−0.0007	0.0001
	(0.0004)	(0.0006)	(0.0014)	(0.0009)	(0.0004)
Holidays controls					
weekend	0.0000	0.0004	0.0002	0.0005	−0.0004*
	(0.0002)	(0.0005)	(0.0009)	(0.0006)	(0.0002)
Moon Festival	0.0006	−0.0018**	0.0051	−0.0007	0.0008
	(0.0012)	(0.0008)	(0.0080)	(0.0023)	(0.0015)
Qixi Festival	0.0000	−0.0013	0.0041	0.0004	−0.0009
	(0.0008)	(0.0012)	(0.0032)	(0.0022)	(0.0007)
Gregorian calendar year fixed-effects	Yes	Yes	Yes	Yes	Yes
Gregorian calendar day fixed-effects	Yes	Yes	Yes	Yes	Yes
County fixed-effects	Yes	Yes	Yes	Yes	Yes
Age and gender controls	Yes	Yes	Yes	Yes	Yes
Diagnosis controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.028	0.018	0.062	0.014	0.010
Number of observations	354,329	68,795	46,795	85,470	153,222
Mean of dependent variable	0.003	0.002	0.006	0.004	0.001

Notes: This table summarizes the estimated effect of the Ghost Month on mortality from shifting hospital admissions with undergoing surgeries by the degree of "deferability". We compute the fraction of weekend admissions at the diagnosis-level using data in the period between 1982 and 1992 to approximate the deferability of an admission (Card et al., 2009). This gives us a distribution of fractions of weekend admissions rates across all diagnosis, reflecting a decreasing degree of "deferability" as one moves from the left to the right tail. We then compute quartiles for fraction of weekend admissions and split the diagnosis codes into four groups, where column 2 represents the most deferrable admissions and column 5 represents less deferrable admissions. Method of estimation is ordinary least squares. Robust standard errors are reported in parentheses, where stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Information on data sources and sample definitions are provided in the notes to Table 3.