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Three Essays in Health Economics

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Doctor of Philosophy
in
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by

Han Xiao

Committee in charge:

Professor Heather Royer, Chair
Professor Kelly Bedard
Professor H.E. (Ted) Frech, III

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The Dissertation of Han Xiao is approved.

Professor Kelly Bedard

Professor H.E. (Ted) Frech, III

Professor Heather Royer, Committee Chair

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Curriculum Vitæ
Han Xiao

Education

2024	Ph.D. in Economics (Expected), University of California, Santa Barbara.
2018	M.A. in Economics, University of California, Santa Barbara.
2017	M.A. in Economics, Duke University.
2015	B.S. in Economics, University of Macau.

Fields of Interest

Health Economics, Applied Microeconomics, Labor Economics

Working Papers

How Hospitals Respond to Patient Death: Evidence from Maternal Death and C-section

Natural Disasters and Family Planning: Evidence on Birth and Migration

Publications

"Direct oral anticoagulants versus warfarin in the treatment of cerebral venous thrombosis (ACTION-CVT): a multicenter international study." *Stroke* 53.3 (2022): 728-738.

"Perioperative Acute Ischemic Stroke in Patients with Atrial Fibrillation." *Annals of Neurology* (2023).

"Antithrombotic Treatment for Stroke Prevention in Cervical Artery Dissection: The STOP-CAD Study." *Stroke* (2024).

Teaching Experience

Head Teaching Assistant	Principles of Economics: Micro
Teaching Assistant	Principles of Economics: Micro
	Principles of Economics: Macro
	Intermediate Microeconomics Theory
	Intermediate Macroeconomics
	Financial Management
	Summer Research Academies: Pain and Prejudice

Abstract

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This dissertation consists of three chapters in health economics, focusing on health and medical decision-making under risks.

The first chapter investigates the impacts of maternal death on subsequent C-section rates, contributing valuable insights into the use of medical procedures in the context of childbirth. Using the New York State Inpatient Database from Healthcare Cost and Utilization Project (HCUP SID), I examine how treatment patterns change following maternal death at the hospital level. To model the substantial differences in practice patterns across mothers of different medical risks, mothers are categorized into low-, middle-, and high-risk groups based on an aggregate measure of their age, pregnancy complications, and admission type (emergency or non-emergency). Leveraging the randomness in the timing of maternal deaths across hospitals, I estimate the aggregate effects of maternal death and effects by mothers' risk groups. I find a 1-percentage-point increase in C-section rate following maternal death at the hospital level, and such effects are driven by a 2-percentage-point increase among the middle-risk mothers. However, no significant effects are observed among low- and high-risk mothers. This finding is consistent with predictions in prior studies that the appropriate method of delivery is usually evident for mothers at the extremes of the risk spectrum, and it is the "marginal" patients that require more physician discretion. I do not find discernible changes in health outcomes including stillborn and complications during labor and delivery, suggesting that the rise in C-section rates is likely a defensive practice. Treatment effects are stronger

among physicians with more experience in performing C-sections, highlighting the role of physicians' beliefs about their comparative advantage. Small hospitals (average quarterly admission below 400) exhibit a slightly larger increase in C-section rates following maternal death, implying that shocks within smaller networks have larger impacts.

The second chapter examines the short-term impacts of various natural disasters on birth rates in the United States. The research distinguishes between different types of disasters, including hurricanes, floods, tornadoes, severe storms, fires, severe ice storms, and snowstorms. Using Federal Emergency Management Agency (FEMA) disaster declaration summaries and the Restricted-Use National Vital Statistics System Natality Data, I compare the birth rates in counties that have declared a disaster with the control counties. To ensure the comparability between the treatment and control counties, I estimate the propensity for each type of natural disaster to occur in every county using a rich set of county-level geographic and weather variables. I then employ propensity trimming to include counties with a type-specific disaster propensity between 0.1 and 0.9 in the analysis for each type of natural disaster. Findings suggest that hurricanes, floods, severe storms, and fires have a small but significant effect on birth rates. Using migration information from the American Community Survey (ACS), I show that the decline in fertility is unlikely to be driven by out-migration. Rather, it is attributed to fertility decisions. This research contributes to the literature on the fertility effects of natural disasters by contrasting the impacts across different disaster types. While individual occurrences of these incidents may have relatively smaller impacts, their frequency is significantly higher, and their scope is significantly larger across broader geographic regions.

The third chapter is joint work with physicians and bio-statisticians. Anticoagulation therapy is commonly interrupted in patients with atrial fibrillation (AF) for elective procedures. However, the risk factors of acute ischemic stroke (AIS) during the periprocedural period remain uncertain. We performed a nationwide analysis to evaluate AIS risk

factors in patients with AF undergoing elective surgical procedures. Using the Nationwide Readmission Database, we included electively admitted adult patients with AF and procedural Diagnosis-Related Group codes from 2016 to 2019. Diagnoses were identified based on International Classification of Disease, 9th revision-Clinical Modification (ICD-10 CM) codes. We constructed a logistic regression model to identify risk factors and developed a new scoring system incorporating CHA_2DS_2VASc to estimate periprocedural AIS risk. Of the 1,045,293 patients with AF admitted for an elective procedure, the mean age was 71.5 years, 39.2% were women, and 0.70% had a perioperative AIS during the index admission or within 30 days of discharge. Active cancer (adjusted OR [aOR]=1.58, 95% confidence interval [CI]=1.42–1.76), renal failure (aOR=1.14, 95% CI=1.04–1.24), neurological surgery (aOR=4.51, 95% CI=3.84–5.30), cardiovascular surgery (aOR=2.74, 95% CI=2.52–2.97), and higher CHA2DS2VASc scores (aOR 1.25 per point, 95% CI 1.22–1.29) were significant risk factors for periprocedural AIS. The new scoring system (area under the receiver operating characteristic curve [AUC]=0.68, 95% CI=0.67-0.79) incorporating surgical type and cancer outperformed CHA_2DS_2VASc (AUC=0.60, 95% CI=0.60 to 0.61). In patients with AF, periprocedural AIS risk increases with the CHA_2DS_2VASc score, active cancer, and cardiovascular or neurological surgeries. Studies are needed to devise better strategies to mitigate perioperative AIS risk in these patients.

JEL: I12, I18, J13, D91

Contents

Chapter 1

How Hospitals Respond to Patient Death: Evidence from Maternal Death and C-section

1.1 Introduction

The past three decades witnessed the dramatic increase in the rate of cesarean section (C-section) over the world (Boerma et al. 2018).[1] In the US, the national C-section rate rose from 20.7% in 1996 to the high of 32.1% in 2021.[2] Today, almost one in three babies

[1]Cesarean Section is a surgical procedure in which a baby is delivered through an incision made in the mother's abdomen and uterus, rather than through the traditional vaginal birth. It is typically done when a vaginal birth is not safe or possible for the mother or baby due to various medical reasons, such as complications during pregnancy, labor, or delivery. C-sections can also be planned in advance for various medical or personal reasons.

[2]Data source: CESAREANRATES.ORG, NTSV and Total Cesarean Rates, United States, 1994-2019 (https://www.cesareanrates.org/ntsvdashboard) and CDC Center for Health Statistics (https://www.cdc.gov/nchs/fastats/delivery.htm).

is born via a major surgery. There is ongoing debate about whether the C-section rate in the United States exceeds an optimal level. The World Health Organization stated in 1985 that: "there is no justification for any region to have a rate higher than 10-15%" (Moore 1985). A more recent study of 194 World Health Organization member states during the period from 2005 to 2014 reveals that C-section rates exceeding 19 percent do not lead to better maternal or infant outcomes (Molina et al. 2015). Moreover, the health consequences of C-sections are mixed. Correlational evidence indicates that C-section delivery is associated with higher rates of maternal and infant morbidity (Bodner et al. 2011, Xie et al. 2015). Notably, infants quasi-randomly born in high C-section hospitals have lower hospital readmission rate in the neonatal period, but higher probability of an emergency department visit one year after birth (Card, Fenizia and Silver 2023).

Maternal death draws considerable attention and concern from the medical community, public health organizations, and society at large. The incidence of maternal mortality exhibits an upward trend in recent years. According to a summary report from the National Vital Statistics System, maternal mortality rate for the year 2021 stood at 0.329 deaths per 1,000 live births, marking a significant surge when compared to the corresponding rates of 0.238 in 2020, 0.201 in 2019, and 0.174 in 2018 (Hoyert 2022). Additionally, there has been significant discussion about the increasing trend in maternal mortality since the year 2000 (Carroll 2017, MacDorman et al. 2016, Callaghan 2012). Despite the rising trend, it is essential to recognize that maternal death remains a relatively infrequent event in the hospital setting, drawing significant attention at the hospital level. From 2008-2021, in-hospital maternal mortality ranges between 0.046 and 0.106 per 1,000 discharges (Fink et al. 2023), compared to a total inpatient hospital death rate of around 20 per 1,000 hospitalizations in 2010 (Hall, Levant and DeFrances 2013).

This paper investigates the impacts of maternal death on subsequent C-section rates at the hospital level. Maternal death, being an unforeseeable event, draws significant attention within the hospital environment. Changes in delivery practices are expected following such an event because individuals tend to alter their actions after being exposed to realizations of low-probability risks (Shurtz, Goldstein and Chodick 2022, Gallagher 2014, Cameron and Shah 2015). Such response arise through several channels. First, physicians who have direct exposure to such a rare adverse event are inclined to reassess the probability of making medical errors and risk of malpractice. Since C-section is generally regarded as a defensive practice (Dranove and Watanabe 2010, Cheng et al. 2014), physicians are likely to respond to elevated perceived malpractice risk by increasing C-section rates. Second, physicians within the same hospital are also likely to perceive increased risks upon learning about such an event. Third, we anticipate organizational changes following maternal death case review and implementation of treatment protocols that influence how physicians practice.

Using the New York State Inpatient Database from Healthcare Cost and Utilization Project (HCUP NYSID), I investigate the effects of maternal death during hospitalization on subsequent treatment patterns at the hospital level. To identify these effects, I leverage the variations in the timing of maternal deaths across hospitals, comparing mothers who deliver in hospitals that have recently experienced maternal death to those in hospitals that have not yet encountered such an event. My identification strategy relies on the randomness of the exact timing of maternal deaths across hospitals.

To model the substantial differences in practice patterns across mothers of different medical risks, I construct *C-section risk*, an aggregate measure of maternal medical risks, using a rich set of pregnancy complications, mothers' age, and admission type associated with the discharge record. C-section risk is an important indicator for physician decision-making. Prior research suggest that physicians make decisions according to patients' medical risks, and follow a threshold strategy in which physicians evaluate patients' medical risks and perform C-sections based on a specific cutoff point. Furthermore, these studies suggest that the appropriate method of delivery is usually evident for mothers at the extremes of the risk spectrum. For instance, a young mother without pregnancy complications is almost always recommended to deliver vaginally, while a mother with multiple gestation, a breech presentation, and a history of C-sections is highly likely to undergo a C-section. It's among the mothers with intermediate medical risks, the "marginal" cases, physician discretion plays a more significant role (Currie and MacLeod 2008, Frakes 2012). Hence, maternal death is expected to have heterogeneous effects on mothers of different medical risks. To capture such differences, I further classify mothers into three risk categories: I define the low-risk group to consist of mothers whose C-section risk fall below the 35th percentile, and the high-risk group to include mothers with a C-section risk above the 85th percentile. The middle-risk group comprises mothers whose C-section risk between the 35th and 85th percentiles.

I then estimate the aggregate effects and effects of maternal death by risk groups using a staggered difference-in-differences framework. The findings suggest that hospital C-section rate increase by 1 percentage point following maternal death. Such increase is driven by mothers in the middle-risk group, where maternal death leads to a 2-percentage-point increase. No obvious effects are detected among low- and high-risk mothers. Notably, I do not find any evidence that the increase in procedure use is health-improving, suggesting that the increase in C-section rates is likely a defensive practice without resulting in better health outcomes. Moreover, maternal death is associated with increased use of other procedures during labor and delivery, including induction, assisted delivery, and laceration repair. These findings imply that maternal death updates physicians' beliefs about their probability of making medical errors, leading to a higher perceived malpractice risk. Such changes in beliefs result in higher C-section rate following maternal death, and a general tendency to increase procedure use during labor and delivery.

In addition, I demonstrate the role of physicians' beliefs about their comparative advantage in procedure choice: effects are larger among physicians with more experience in performing C-sections. This suggests that when facing elevated perceived malpractice risk, physicians who have performed more C-sections are more confident about performing additional C-sections. Physicians without such belief also raise their C-section rates, but by a smaller amount. The effects are slightly larger among smaller hospitals with average quarterly admission below 400. This suggests that shocks of maternal death have larger impacts within smaller networks.

This research contributes additional insights to the existing literature in several ways. First, I identify a new source of nonmedical factor: maternal death, that drives up C-section rates at hospital level by 2 percentage points among middle-risk mothers. In the same spirit of the malpractice literature, exposure to adverse events triggers re-evaluation of perceived malpractice risk, and thus prompt increase in procedure use. However, these studies find smaller effects. Grant and McInnes (2004) show that malpractice claims resulting in large awards are associated with a 1-percentage-point increase in physician risk-adjusted C-section rates. However, Gimm (2010) finds no evidence after adding physician and year fixed effects. Later works focuses on the exact timing of being contacted about a lawsuit, Dranove and Watanabe (2010) find very small and short-lived increase in C-section rates: immediate hospital-level increase by 0.06 percentage points, and delayed physician increase by 0.13 percentage points 9–12 months later.

Next, my findings show that an ex-ante adverse event, one has not yet resulted in malpractice litigation, can also prompt changes in treatment styles. Unlike the studies that focus on being contacted about the ex-post realized malpractice lawsuits, I examine the period right after maternal death. Note that Maternal death may not always result in malpractice lawsuits, but the heightened perceived malpractice risk is significant enough to trigger shifts in delivery practices. Such changes in practice patterns may precede being contacted about a potential lawsuit. Dranove and Watanabe (2010) and Durrance and Hankins (2018) find very small or insignificant effects in C-section after physicians being contacted about a lawsuit. While Shurtz (2013) discovers an increase in C-section rate by 2.2 percentage points following an adverse event. The key distinction is that Shurtz (2013) takes a slightly different approach by exploring the effects of the set of medical errors that later resulting in malpractice lawsuits. The timing of the event is defined as when the medical error occurs, rather than being contacted about the lawsuit at a later time. These findings suggest that physicians may have already modified their treatment approaches following an adverse event, but before any potential lawsuits were initiated. In essence, the changes in practice styles may precede the legal process.

Additionally, this paper examines the effects of a localized shock at the hospital level, and evaluates system-wide response. First, Maternal deaths are more localized shocks as compared to aggregate shifts in malpractice pressure, for example, state-level tort reforms (Kim 2007, Baicker, Fisher and Chandra 2007, Currie and MacLeod 2008, Frakes 2012, Esposto 2012, Cano-Urbina and Montanera 2017), state- and county-level malpractice premiums (Dubay, Kaestner and Waidmann 1999, Tussing and Wojtowycz 1997). It is important to note that state- and county-level shocks represent more aggregated influences on malpractice risk, and their impacts on perceived malpractice risk are expected to be smaller than localized shocks that involve personal exposure. Second, maternal death, a critical adverse event, is anticipated to significantly raise perceived malpractice risk at system-wide level, impacting larger groups of physicians. However, studies on physician-level malpractice litigation usually focus on a small subset of physicians who have encountered malpractice lawsuits in their careers (Grant and McInnes 2004, Gimm 2010, Dranove and Watanabe 2010, Durrance and Hankins 2018, Shurtz 2013).

Moreover, my findings represent an interaction of the malpractice literature and medical decision-making literature. On one hand, I show that maternal death, an unanticipated medical event, changes physician treatment patterns, aligning with the medical decision-making literature. This adds to the expanding body of studies that examine the impact of exposure to realizations of low- probability risks on a broader range of medical decision-makings. Choudhry et al. (2006) find that physicians are less likely to prescribe Warfarin after experiencing an adverse bleeding event during Warfarin treatment. Wang, Barnett and Cohen (2022) find empirical evidence that exposure to breast or colorectal cancer diagnoses increases cancer screening rates within one year. Shurtz, Goldstein and Chodick (2022) show that physicians increase use of colonoscopy tests three months following colon cancer diagnosis. On the other hand, I find that C-section rates increase following maternal deaths, irrespective of the method of delivery. While Singh (2021) shows that physicians are more likely to switch delivery method after experiencing labor and delivery complications in the prior patient. The key distinction is that maternal death is perceived as a more severe patient outcome, triggering a thorough re-evaluation of perceived malpractice risk. In contrast, less severe patient outcomes tend to trigger more heuristic-based responses from physicians.

Finally, I find that the increase in C-section rates is driven by middle-risk mothers. These mothers are mostly above 30 years old and have previously delivered via C-sections. This finding sheds light on recent initiatives to reduce hospital C-section rates. While many initiatives have targeted low-risk-first-born, my findings underline the importance of directing more attention to the middle-risk mothers.

The rest of the paper is organized as follows. Section 1.2 describes the background of this study, Section 1.3 demonstrates the effects of maternal death in a simple conceptual framework, Section 2.2 summarizes the data, Section 1.5 illustrates the main identification strategies, Section 1.6 presents the main results and robustness checks, and Section 1.7 discusses and concludes.

1.2 Background

1.2.1 Malpractice Pressure and C-section

The goal of malpractice law is to penalize physician negligence that causes adverse patient outcomes, and compensate the injured patients. However, the "negligence rule", a set of requirements that determines a successful claim, place a strong emphasis on showing that the provider took less care than that which is customarily practiced by the average member of profession in good standing (Waters 2005, Kessler and McClellan 1996, Danzon 1985).

Obstetrics is one of the fields that has been hit hard by medical malpractice concerns, and C-section is generally regarded as a defensive response because physicians are likely to believe that cesarean delivery reduces the risk of malpractice (Dranove and Watanabe 2010). A survey on clinicians and finds that having had lawsuits and daily worry of suits were associated with higher likelihood of recommending C-section (Cheng et al. 2014). More generally, higher resource use is associated with lower probability of malpractice claims, after adjusting for patient characteristics (Jena et al. 2015).

Moreover, prior studies suggest that malpractice pressure plays a crucial role in driving up the unnecessary use of C-sections (Cheng et al. 2014, Wagner 2000, Dranove and Watanabe 2010). Physicians are more likely to choose procedures that are of high-cost and low-benefit for patients in the fear of lawsuits, and the excess care and medical spending are not associated with better health outcomes (Baicker, Buckles and Chandra 2006, Dranove and Watanabe 2010, Shurtz 2013, Baicker, Fisher and Chandra 2007, Fisher et al. 2003, Baicker, Fisher and Chandra 2007).

1.2.2 Personal Experience and Risk Assessment

Maternal death, a critical adverse event during labor and delivery, is anticipated to raise providers' perceived malpractice risk when they directly encounter or closely learn such distressing outcomes. Moreover, this heightened risk perception is expected to be more prominent than variations induced by aggregate-level changes in malpractice pressure: for example, tort reforms or variations in regional malpractice premiums.

This phenomenon can be attributed to the cognitive biases of "optimistic bias" and "availability heuristic". Optimistic bias suggests that individuals generally perceive negative events as less likely to happen to them personally (Weinstein 1980 Weinstein 1987, Larwood 1978, Perloff and Fetzer 1986, Burger and Burns 1988, Perloff and Fetzer 1986). The availability heuristic complements this idea by proposing that personal experiences can moderate the optimistic bias, leading to changes in people's risk attitudes (Weinstein 1987, Weinstein 1989, Perloff 1983, Helweg-Larsen 1999, Jakiela and Ozier 2019). It has been documented that individuals tend to use the availability heuristic when evaluating the likelihood of events. This cognitive bias leads them to rely more on recent and memorable experiences, making negative events they have encountered recently more readily available in their memory. Consequently, exposure to recent negative events can lead to an increase in their expectations of facing similar risks in the future (Tversky and Kahneman 1973).

Hence, healthcare providers might not respond strongly to aggregate-level shocks due to optimistic bias. This partly explains the inconsistent findings on the effects of tort reforms and regional shifts in malpractice pressure on C-section rates. However, when exposed to maternal death, the availability heuristic comes into play, leading to a more significant response. Several studies demonstrate optimistic bias and availability heuristics in risk assessment. In the context of childbirth, Dranove and Watanabe

(2010) compare shocks at individual versus county level. They present empirical evidence indicating that obstetricians tend to raise their C-section rates after experiencing their first lawsuit, whereas variations in litigation rates at the county level do not have any significant influence on C-section rates.

These heuristics are also documented in more general settings. For example, empirical studies indicate that despite the rising occurrence of extreme weather and natural disasters, the public generally do not perceive climate change as a direct and personal risk. However, those who have experienced health impacts of air pollution and financial losses due to natural disasters are more inclined to view climate change as a significant and immediate threat. Consequently, these individuals are more likely to take proactive measures in response to the perceived risks (Lujala, Lein and Rød 2015, Whitehead 2014, Knuth et al. 2014).

1.2.3 Hospital Response to Malpractice

There are several reasons why maternal death triggers changes in delivery patterns at hospital level. First, hospitals are at-risk of malpractice lawsuits when adverse patient events occur. Under the joint and several liability rules, all parties that are found to be have contributed to the patient's injury or harm are held to be liable for the damages awarded to the patient.[3] If nurses or hospital staff are found to be culpable for the injury, the patient may sue the employer of the nurses or hospital staff. Thus, hospitals are motivated to implement system-wide changes in practices to reduce the chances of being deemed responsible in the future (Currie and MacLeod 2008).

Furthermore, although hospitals and physicians are largely insured against malprac-

[3]Prior to March 2011, New York state followed the traditional joint and several liability rules where each defendant found to be even partially at fault for a plaintiff's injury could be held individually liable for the full amount of the damages awarded to the plaintiff. After the 2011 modification, defendants are only liable for paying their proportionate share of the damages.

tice lawsuits, the non-financial loss is substantial and non-insurable. These cost include lost time, stress, and damage to reputation (Currie and MacLeod 2008, Kessler 2011). Healthcare providers who made a payment to settle a claim are listed in the National Practitioner's Data Bank. In addition, most of the malpractice records are searchable online. For example, Medical Board of California list providers' administrative disciplinary actions and court orders as public records associated with their license information.

Finally, hospitals are healthcare providers' daily workspace that engage collaboration and information exchange. Prior studies show that physicians acquire information through interacting with peers and from the hospitals they practice (Chung et al. 2003, Burke, Fournier and Prasad 2007). Thus, it is reasonable to assume that maternal death, a rare adverse event, strikes physicians in the same hospital. Hospitals may also implement system-wide treatment protocols that influence practice (Dranove and Watanabe 2010). Liukka et al. (2020) summaries literature on actions after adverse events. For healthcare organizations specifically, these actions include defensive and constructive changes at institutional level, and substantial learning from adverse events. There are documented evidence of obstetrical clinical guidelines implemented at hospital level to recommend certain type of practice (Chaillet et al. 2006).

1.3 Conceptual Framework

In this section, I demonstrate how maternal death leads to physicians' changes in delivery practices by a simple conceptual framework similar to Currie and MacLeod (2008) and Shurtz (2014). In summary, physicians' procedural choice is modeled as the following threshold strategy: physicians rank mothers by their medical risks, and perform vaginal delivery up to their C-section threshold. Mothers with medical risks above the threshold are delivered via C-section. Maternal death leads to an update to physicians' prior beliefs on their probability of making medical errors during delivery (or probability of malpractice). Such belief updating process results in a lower C-section threshold, leading to higher C-section rate following maternal death. This framework also illustrates that mothers in the middle-range of medical risks benefit marginally from C-section: C-section has a positive but small benefit for these mothers, but it is unclear whether the benefit outweighs the cost due to medial errors. Consequently, changes in C-section following maternal death are driven by mothers in the middle-risk group.

The setup and basic framework are borrowed from Currie and MacLeod (2008) and Shurtz (2014). Let j denote the delivery method, and $j \in \{v, c\}$, where v indicates vaginal birth, and c indicates C-section. Mothers' medical risks are represented by $s \in [o, \bar{s}]$. Larger s means that mothers are of worse medical conditions, and are more likely to deliver via C-section. $b(j, s)$ is mothers' medical benefits from delivery method j, assume the following holds for all s:

Assumption 1 $b(v, 0) >> b(c, 0)$, $b(v, \bar{s}) << b(c, \bar{s})$, and $\partial b(c, s)/\partial s > \partial b(v, s)/\partial s$ for all s.

In other words, for mothers of very low medical risks, vaginal births have much larger medical benefits. Mothers of very high medical risks benefit substantially from C-section. $\partial b(c, s)/\partial s > \partial b(v, s)/\partial$ implies that the benefits from a C-section increase faster than the benefits from vaginal birth as medical risks s increases. Hence, there is a unique s_L such that:

$$b(v, s_L) = b(c, s_L)$$

$$b(v, s) > b(c, s), \forall s < s_L$$

$$b(v, s) < b(c, s), \forall s > s_L$$

Intuitively, for small enough $s < s_L$, it is obvious that vaginal delivery is more medically appropriate than C-section.

Let $H(j,s,p)$ denote the expected costs associated with medical errors or malpractice, where p is the probability of making medical errors or risk of malpractice. These costs involves financial and non-financial costs for example, emotional burden for adverse patient outcome, damage to professional reputations, and time costs dealing with legal procedures, etc.

Assumption 2 $H(v,0,p) << H(c,0,p)$ and $H(v,\bar{s},p) >> H(c,\bar{s},p)$, $\partial H(v,s,p)/\partial s > \partial H(c,s,p)/\partial s$ for all s.

Assumption 2 implies that expected malpractice costs associated with vaginal births are significantly smaller than C-section at lower ends of medical risks, and substantially higher at higher ends of medical risks. As s increases, expected costs of malpractice increase faster with vaginal delivery than C-section. Similarly, there is a unique s_H where $s_H > s_L$ such that:

$$H(v,s_H,p) = H(c,s_H,p)$$

$$H(v,s,p) < H(c,s,p), \forall s < s_H$$

$$H(v,s,p) > H(c,s_H,p), \forall s > s_H$$

This indicates that for any large enough value of $s > s_H$, expected costs of malpractice are always smaller in C-section than vaginal delivery.

Under the current legal system, C-section is generally regarded as a defensive practice. Hence, as p increases, the expected rise in malpractice cost associated with C-section, is always lower than vaginal delivery.

Assumption 3 $\partial H(v,s,p)/\partial p > \partial H(c,s,p)/\partial p$ for all s.

Physicians maximize the following utility function by choosing delivery method, j:

$$u(j, s, p) = b(j, s) - H(j, s, p)$$

Assumption 1, 2 and utility function jointly imply that:

$$u(v, s, p) = b(v, s) - H(v, s, p) > b(c, s) - H(c, s, p) = u(c, s, p), \forall s < s_L$$

$$u(v, s, p) = b(v, s) - H(v, s, p) < b(c, s) - H(c, s, p) = u(c, s, p), \forall s > s_H$$

One can show that there exists a threshold level of medical risks, s^c, where $s_L < s^c < s_H$, such that

$$u(v, s^c) = u(c, s^c)$$

$$u(v, s, p) > u(c, s, p), \forall s < s^c$$

$$u(v, s, p) < u(c, s, p), \forall s > s^c$$

. Taken together, the following condition holds for s^c:

$$b(v, s^c) - H(v, s^c, p) = b(c, s^c) - H(c, s^c, p) \tag{1.1}$$

The intuition of the setup is that physicians choose delivery method j to maximize their utility. For mothers in the low-risk group where $s < s_L$, physicians always choose vaginal delivery because $u(v, s, p) > u(c, s, p), \forall s < s_L$; for mothers in the high-risk group where $s > s_H$, $u(v, s, p) < u(c, s, p), \forall s > s_H$. For mothers in the middle-risk group where $s_L < s < s_H$, physicians adopt a threshold strategy and deliver vaginally for mothers in the range $s \in [s_L, s^c]$, and perform C-section for mothers in the range $s \in [s^c, s_L]$.

Now consider the incident of maternal death. Suppose before exposure to maternal death, physician's prior beliefs about probability of medical errors or malpractice is denoted by p. Suppose that probability of maternal death is α if there is no mistakes, and β if there is mistake, thus:

$$P(MaternalDeath|Error) = \alpha$$

$$P(MaternalDeath|NoError) = \beta$$

By construction, $\alpha > \beta$, maternal deaths are more likely to occur conditional on medical errors. After exposure to maternal death, physicians update their beliefs following Bayesian rule:

$$\begin{aligned} & P(Error|MaternalDeath) \\ =& \frac{p \times P(MaternalDeath|Error)}{p \times P(MaternalDeath|Error) + (1-p) \times P(MaternalDeath|NoError)} \\ =& \frac{\alpha p}{\alpha p + \beta(1-p)} > p \end{aligned} \tag{1.2}$$

This shows that maternal death leads to a posterior higher than p, and this Bayesian belief updating process indicates that physicians perceive higher malpractice risk following maternal death.

For simplicity, this belief updating process can be modeled as increase in p, the probability of making medical errors (or malpractice risk). Totally differentiating Equation 1.1 helps us understand the role of p in delivery practices. Let $\Delta b(s^c) = b(c, s^c) - b(v, s^c)$, and $\Delta H(s^c, p) = H(c, s^c, p) - H(v, s^c, p)$, Equation 1.1 can be written as:

$$\Delta b(s^c) = \Delta H(s^c, p)$$

Total differentiate with respect to p:

$$\frac{\partial s^c}{\partial p} = \frac{\partial \Delta H(s^c,p)}{\partial p} / [\frac{\partial \Delta b(s^c)}{\partial s^c} - \frac{\partial \Delta H(s^c,p)}{\partial s^c}] < 0 \tag{1.3}$$

$\frac{\partial \Delta b(s^c)}{\partial s^c} > 0$ by Assumption 1, $\frac{\partial \Delta H(s^c,p)}{\partial s^c} < 0$ by Assumption 2, and $\frac{\partial \Delta H(s^c,p)}{\partial p} < 0$ by Assumption 3. Therefore, when maternal death occur, physicians perceive higher malpractice risk, p, decreasing the C-section threshold, s^c. This only impacts mothers in the middle-risk group where $s_L < s < s_H$. As the threshold s^c decreases, C-section rate within middle-risk group increases.

1.4 Data and Summary Statistics

1.4.1 Data Source

My analysis relies on the Health Care and Utilization Project (HCUP) New York State Inpatient Database (NYSID) by Agency for Healthcare and Research and Quality (AHRQ). The database consists of all inpatient hospital discharges in New York State between 2003 and 2017. The database records detailed patient-level information on admission, discharge, diagnoses and procedures.

Admission information includes types of admission (emergency, urgent, elective, etc.), admission year, month, quarter and time of the day. Discharge information includes patient disposition (routine discharge, transfer to another facility, died in hospitalization, etc.), discharge quarter, hospital length of stay and total charges. The exact date of admission and discharge is not released to ensure patient confidentiality.

Diagnosis and procedure information is coded using International Classification of Diseases, Ninth Revision and Tenth Revision, Clinical Modification (ICD-9-CM/PCS and

ICD-10-CM/PCS).[4] In my analysis, all relevant medical conditions are identified using ICD-9-CM and ICD-10-CM diagnosis classification codes, and all relevant procedures are identified using ICD-9-PCS and ICD-10-PCS codes. The database also includes a rich set of patient demographic characteristics, including age, gender, race, and county of residence.

To focus on deliveries, I restrict the sample to include all deliveries identified by Diagnosis Related Groups (DRGs) and Medicare Severity Diagnosis Related Groups (MS-DRGs).[5] I identify 3,484,322 delivery discharges in hospitals in New York State from 2003 to 2017, including 1,154,284 (33%) cesarean deliveries and 2,330,038 (67%) vaginal deliveries.[6]

1.4.2 Classification of Low, Middle, and High- Risk Mothers

Following previous studies (Smith et al. 2004, Currie and MacLeod 2017, Robinson, Royer and Silver 2022), the likelihood of mothers to deliver through C-section depend on a rich set of factors related to maternal medical risks: mothers' age, mothers' pregnancy-related complications, and admission type (whether the admission is an emergency). Table A.2 details the list of medical risks and summaries them among mothers discharged from the following categories of hospitals: all hospitals, hospitals without maternal death, and hospitals with maternal death.

Table A.2 column (1) provides the general profile of mothers in New York State. The average age at birth is 29, and around 16% of mothers have had C-section in previous

[4]ICD-9-CM/PCS and ICD-10-CM/PCS are the official systems of assigning codes to diagnoses and procedures associated with hospital utilization in the United States. More details under the following link: `https://www.cdc.gov/nchs/icd/index.htm`

[5]Diagnosis-Related Group (DRG) and Medicare Severity-Diagnosis Related Group (MS-DRG), are systems used in the United States to classify inpatient hospital cases into groups for the purpose of Medicare reimbursement and healthcare management. The MS-DRG system was introduced in 2007 as an enhanced and more refined version of the original DRG system. Details for MS-DRGs can be found via the following link: `https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/MS-DRG-Classifications-and-Software`.

delivery. Hypertension and eclampsia during pregnancy are the most common pregnancy complications, which happens in 4.4% of mothers. More than half of admissions are elective, and 20% of mothers are admitted through emergency. Comparing across groups, mothers who give birth in hospitals where maternal deaths occur are, on average, characterized by relatively older age, elevated medical risk profiles, and a reduced likelihood of being admitted electively.

To quantify mothers' medical risks, I follow the methodologies in prior works to construct an aggregate measure: C-section risk.[7] I first estimate the following equation 1.4 using data from hospitals that never report any maternal deaths in the sample period (control hospitals) with logistic regression. By excluding discharges from hospitals with maternal death, the coefficients only capture the marginal contribution of each predictor based on the "good decisions" that are made in hospitals without maternal deaths

$$Prob(CSection_{ij} = 1) = F(\phi M_{ij} + \rho_j + \epsilon_{ij}) \tag{1.4}$$

where $Csection_{ij}$ is a dummy variable equals to 1 if mother i in hospital j delivers through C-section. M_{ij} is a set of maternal medical risks as listed in table A.2. ρ_j are dummy variables indicating each hospital, or hospital fixed effects, and ϵ_{ij} represents unobserved information related to C-section decision-making. ϕ captures marginal contribution to C-section by mothers' medical conditions, and ρ_j are hospital-level C-section rate after adjusting for differences in maternal medical risks across hospitals. More specifically, a larger ρ_j means that hospital j is, on average, more likely to perform C-section. I include hospital fixed effects because prior studies show evidence on geographic variations on C-section, suggesting that practice patterns can significantly differ across hospitals (Baicker, Buckles and Chandra 2006, Robinson, Royer and Silver 2022). Then I estimate the

[7] C-section risk can also be interpreted as propensity to perform C-section. Mothers of higher medical risks are also associated with higher propensity to deliver via C-section.

predicted C-section risk using the estimated marginal contribution $\hat{\phi}$, mothers' medical conditions M_{ij}, but leaving out hospital dummies as suggested in the following Equation 1.5.

$$CSectionRisk_{ij} = F(\hat{\phi} M_{ij}) \tag{1.5}$$

After excluding hospital fixed effects, $CSectionRisk_{ij}$ represents mothers' likelihood of delivering via C-section conditional on maternal medical risks, netting out any hospital-level factors that potentially impact delivery method. In other words, $CSectionRisk_{ij}$ measures the appropriateness of delivering via C-section, and variations in $CSectionRisk_{ij}$ arise solely from differences in medical risks.

Figure 1.1 plots the estimated coefficients of equation 1.4, variables are sorted in descending order of marginal contribution to C-section risk. The major predictors for delivery method are: breech presentations, disproportion, previous C-section, and multiple gestation.[8] These medical risks all have estimated coefficients larger than 2, which translates to an odds ratio greater than 7. In simpler terms, mothers who experience any of these pregnancy complications are more than 7 times as likely to undergo a C-section delivery compared to mothers who do not encounter these issues.

Figure A.3a plots the distribution of C-section risk. Consistent with Currie and

[8] Short description for these medical conditions:
Breech presentation is a term used in obstetrics to describe a fetal position where the baby's buttocks or feet are positioned to be delivered first, rather than the head. This is not the typical and preferred head-down position for childbirth and may require special considerations or interventions during delivery.
Disproportion in the context of childbirth refers to an imbalance between the size of the baby's head and the mother's pelvis, making a vaginal delivery difficult or unsafe. It can lead to complications during labor and may necessitate a cesarean section.
A *previous C-section* indicates that a woman has undergone a C-section in a prior pregnancy, which can impact the mode of delivery in subsequent pregnancies, with options including a vaginal birth after cesarean (VBAC) or another C-section.
Multiple gestation, commonly known as a "multiple pregnancy," occurs when a woman is carrying more than one fetus in her womb, such as twins, triplets, or more. Managing a multiple gestation pregnancy requires specialized care and monitoring to ensure the health and well-being of both the mother and the multiple fetuses.

MacLeod (2017) and Robinson, Royer and Silver (2022), the distribution of C-section risk has two peaks: most of the density concentrates around the higher peak at the lower end of C-section risk, a smaller density concentrates around the second peak at the higher end of C-section risk. Though the exact values of C-section risk at the two peaks are not identical to previous works, the overall shape of the distribution is very similar to previous findings.

As a composite measure of maternal medical risks, C-section risk predicts actual C-section rate very well, even after netting out hospital fixed effects. Figure A.3b plots the actual C-section rate against average predicted C-section risk for mothers within each 5-percentile bin of C-section risk, with a red 45 degree line. Figure A.3b conveys the following information: first, mothers with higher predicted C-section risk are more likely to deliver through C-section after netting out the hospital effects. Since C-section risk is predicted using a rich set of maternal medical risks, this reflects the fact that mothers of higher medical risks are more likely to delivery through C-section. Second, all the points are around the 45 degree line, indicating that C-section risk is a good composite measure of maternal medical risks, such that it can be used to predict actual C-section rate.

Next, I categorize mothers into three groups based on their C-section risk measure. Previous studies have proposed a threshold strategy in which physicians assess patients' medical risks and perform C-sections based on a specific cutoff point (Currie and MacLeod 2008, Frakes 2012). Furthermore, these studies suggest that physicians exercise greater discretion when dealing with marginal patients, while the appropriate course of action is typically more evident for low- and high-risk patients. Hence, it is important to capture the differences in practice patterns across maternal risk groups. I define the low-risk group to consist of mothers whose C-section risk measure falls below the 35th percentile, and the high-risk group to include mothers with a C-section risk measure above the 85th percentile. The middle-risk group comprises mothers whose C-section risk falls between the 35th and 85th percentiles.

The choice of the 35th and 85th percentiles as cutoff points is based on the fact that the distribution peaks at these 2 values. Moreover, the risk profiles across groups indicate that mothers below the 35th percentile cutoff are younger with no complications, and mothers above the 85th percentile cutoff are older and with at least 1 major indicator for C-section. While middle-risk mothers are slightly older than low-risk mothers, but having fewer complications compared to high-risk mothers. I exploit variations to the cutoff points in Section 1.6.3 and show results similar to the main classification.

Figure A.3a provides a visual illustration of the distribution of risk measures and the cutoffs used to delineate the risk groups, and Figure 1.3 shows the risk profile across mothers within different risk groups. C-section rates are 12% and 90% in the low- and high-risk groups, indicating that it is usually evident that vaginal delivery is more appropriate for low-risk mothers and C-section is more appropriate for high-risk mothers. C-section rate is 31% among middle-risk mothers, which is close to the overall C-section rate. Low-risk mothers have rates of pregnancy complications close to 0. They almost have none of the following major indicators for C-section: breech presentations, disproportion, previous C-section, and multiple gestation. High-risk mothers have much higher rates of major C-section determinants as compared to low- and middle-risk mothers.

I also supply the following 3 alternative C-section risk measures by either excluding hospitals with maternal death or excluding hospital fixed effects:

- *Alternative C-section Risk 1*: I include all delivery discharges to estimate Equation 1.4, and thus the coefficients capture the marginal contribution of each predictor based on all deliveries.

- *Alternative C-section Risk 2*: I exclude hospital fixed effects by estimating the following Equation 1.6 with logistic regression, and then I predict C-section risk with Equation 1.5 using ϕ'.

$$Prob(CSection_{ij} = 1) = F(\phi' M_{ij} + \epsilon_{ij}) \tag{1.6}$$

This C-section risk measure assigns an equal likelihood of undergoing a C-section to mothers with identical medical conditions, irrespective of the hospital where they give birth. Consequently, this measure quantifies the average likelihood for C-sections across the "good hospitals", only taking into account the medical conditions of the mothers.

- *Alternative C-section Risk 3*: I include all delivery discharges and exclude hospital fixed effects in estimating Equation 1.6, and then predict using Equation 1.5. This measure represents the average likelihood for C-section across all hospitals, only taking into account the medical conditions of the mothers.

Figure A.1–A.3 display the distributions and average C-section rates in 5-percent bins for these alternative C-section risk measures. While the overall shape of these distributions is quite similar to the primary C-section risk measure, the densities are more concentrated around the two peaks if hospital intercept is excluded. Table A.3 reports the estimated marginal contribution of maternal medical risks for all C-section risk measures. All alternative methods yield very similar rankings of C-section risk for each mother. Specifically, the correlations between the rankings produced by the primary C-section risk and the alternative measures are 99.9%, 98.8%, and 98.9%, respectively.

1.4.3 Maternal Death and Dependent Variables

The main treatment variable is maternal death. I identify maternal death based on the following two variables: variables "Died during Hospitalization" and "patient disposition: died in hospital". In general, maternal death is rare, with the database recording 303 instances over a span of 15 years, the overall rate of maternal death between 2003 and 2017 is 0.1 per 1000 deliveries. Figure 1.4a plots maternal death rate per 1000 deliveries. Overtime, there is a slight downward trend in maternal death rate, though overall maternal death rate is low and fluctuates around 0.1 per 1000 deliveries. Figure 1.4b plots maternal death rate per 1000 deliveries by C-section risk groups as defined in Section 1.4.2. As can be seen, maternal death rate is lower in the low-risk group: it fluctuates around 0.05 per 1000 deliveries. For middle- and high- risk groups, the rates are similar, but we can see a slight downward trend from 0.2 to 0.1 per 1000 deliveries.

Figure A.4a plots maternal death rates by delivery method. Death rate is higher among mothers who deliver through C-section. This is mainly due to selection by medical risks: high-risk mothers are more likely to deliver through C-section. The graph shows an obvious decline of maternal death rate among cesarean delivery from 2003 to 2010. Maternal death rate among mothers deliver vaginally is comparatively stable overtime. Figure A.4b shows that Black mothers have much higher death rate relative to Hispanic and White mothers. From 2003 to 2010, maternal death rate among Black mothers decreases by approximately 50%, from 0.4 to lower than 0.2 per 1000 deliveries. For Hispanic and White, the rates are relatively stable overtime: 0.1 per 1000 deliveries for Hispanic mothers, and 0.05 per 1000 deliveries for White mothers.

Figure A.5 presents the percentage of hospitals reporting maternal death every year. Maternal deaths happen in around 10 to 15% of hospitals every year, and this percentage decreases from around 15% to a little below 10% from 2003 to 2017. In the database, half of the hospitals do not report any maternal deaths between 2003 and 2017. Figure A.6a displays the distribution number of maternal death in each hospital: 90 out of the 180 hospitals do not report any maternal death in 15 years. Among the 90 hospitals with maternal death, half report no more than 2 deaths. Figure A.6b plot the distribution by delivery method. For vaginal deliveries, very few hospitals report more than 1 death. Whereas, maternal death from C-section is less uncommon.

The main dependent variable is whether mother delivers through C-section. Delivery method is defined by MS-DRG codes associated with each discharge record.[9] Figure 1.5a plots yearly C-section rate in New York State, 2003-2017. There is a substantial increase of C-section rate from 28% in 2003, to 35% in 2008, and it flattened afterward at around 34%. This is consistent with the national trend (Osterman and Martin 2014) and displays similar patterns as prior works (Shurtz 2013, Robinson, Royer and Silver 2022). Figure 1.5b displays the yearly C-section rate by C-section risk groups as defined in Section 1.4.2. In all three groups, C-section rates exhibit a consistent pattern that mirrors the overall trend, hovering around 10% for low-risk, 30% for middle-risk, and 90% for high-risk groups. However, it's worth noting that the increase in C-section rates between 2003 and 2009 is slightly more pronounced among mothers in the middle-risk group compared to those in the other two groups.

In addition to examining C-section rates, I also investigate the impacts on the subsequent use of other obstetric procedures: induction, assisted birth, and laceration repair. These procedures are categorized based on ICD-9-CM Procedure Codes.[10] Induction encompasses both medical induction, involving the administration of medication intravenously or vaginally, and surgical induction, often referred to as 'breaking the waters.' Assisted birth is defined by whether a doctor or midwife employs forceps, vacuum extractions, or performs an episiotomy.[11] Laceration repair involves suturing or stitching tears that occur in the perineum to facilitate proper healing and prevent complications. All

[9] A.1 lists DRGs and MS-DRGs for cesarean and vaginal delivery.

[10] Because of the transition from ICD-9-PCS to ICD-10-PCS in the third quarter of 2015, the analysis of other obstetric procedures is limited to the period from the first quarter of 2003 to the third quarter of 2015. This change in the procedure coding system was substantial, so my focus remains on ICD-9-PCS coding to ensure consistency in the analysis.

[11] Episiotomy is combined with assisted birth since it is commonly performed during assisted births to minimize the risk of severe tears.

these procedures necessitate a certain degree of physician discretion and an assessment of the patient's condition during labor and delivery.

I also estimate the effects on various inpatient outcomes, focusing on several crucial metrics related to mothers' hospitalization experiences. These metrics include hospital length of stay, total charges, labor and delivery complications, and the stillborn per 1000 deliveries. The composite measure for labor and delivery complications encompasses a range of potential issues that mothers may encounter during their hospital stay, including obstructed labor, abnormalities in the forces of labor, prolonged labor, umbilical cord complications, trauma, and postpartum hemorrhage.[12] Labor and delivery complications and indicator of stillborn are identified by ICD-9-CM and ICD-10-CM Diagnosis Codes.

1.4.4 Sample Construction and Summary Statistics

My analysis focuses on 115 hospitals that consistently reported data between 2003 and 2017. I exclude hospitals that have gaps in reporting, and this drops 286,143 delivery discharges (8.21% of the full sample). This exclusion is a necessary step to address potential identification challenges. Hospitals with reporting gaps may fail to record maternal

[12]Descriptions of labor and delivery complications:
Obstructed labor, also known as dystocia, occurs when there is an obstacle preventing the baby from moving through the birth canal. This can be due to issues with the baby's position, the mother's pelvis, or other factors, and it may require medical intervention to facilitate delivery.
Abnormalities in the forces of labor refer to irregular or ineffective uterine contractions during childbirth. These irregular contractions can slow down or hinder the progress of labor, and medical interventions may be necessary to correct them.
Prolonged labor, also called "failure to progress", is when the labor process takes longer than usual, making it difficult for the baby to descend through the birth canal. It can lead to fatigue and distress for both the mother and the baby, and may require medical assistance.
Umbilical cord complications can include issues such as cord prolapse (when the cord comes out before the baby) or cord compression (when the cord is squeezed during labor). These complications can disrupt the baby's oxygen and blood supply and require immediate attention.
Trauma during childbirth can result from injuries to the mother or baby during the delivery process. This can include tears, lacerations, or other injuries to the birth canal or perineal area.
Postpartum hemorrhage is excessive bleeding that occurs after childbirth. It can be caused by the inability of the uterus to contract effectively after delivery or other factors. Immediate medical intervention is necessary to manage and control the bleeding to prevent complications.

deaths during these periods, making it uncertain whether any maternal deaths occurred in those specific quarters. Including such hospitals in the analysis could introduce significant inaccuracies in determining the precise timing of maternal deaths.

To measure the impact of maternal deaths, it's essential to find a period before such adverse events occurred where there were no previous maternal deaths. This "clean-period" allows me to attribute the effects of a single maternal death accurately, without being influenced by prior deaths. In hospitals where maternal deaths occurred, I adopt a cautious approach to define the treatment as the first maternal death with a minimum 2-year "clean-period".[13] I focus on a 2-year "clean-period" because previous research indicates that the effects of medical malpractice tend to be most significant around 2 years (8 quarters) after the adverse event (Shurtz 2013, Dranove and Watanabe 2010). To ensure the robustness of the results, I revisit the definition of "clean-period' by extending the analysis to include hospitals with 3-year, 4-year and 5-year "clean-period". The results are consistent with the main specification, and more details are discussed in Section 1.6.3. Hospitals that do not report any maternal death between 2003 and 2017 serve as the control hospitals, and hospitals ever reported maternal death in the sample period are treatment hospitals.

The final sample consists of 103 hospitals, as 12 hospitals do not meet the specified criteria. Note that the 12 hospitals excluded do not have any "clean-period" before maternal deaths, meaning that maternal deaths happen more frequently in these hospitals. The database do not report information on hospital ownership or hospital type, but it is very likely the excluded hospitals are large teaching hospitals. Thus, my analysis under-weights such hospitals.

Table 1.1 provides summary statistics for the three distinct groups: all hospitals in the

[13] If the first maternal death occurred during the first two years in the database, I consider the next maternal death within a minimum four-year "clean-period'.

sample, hospitals with maternal deaths, and hospitals without maternal deaths. Across all hospitals, the average C-section rate is approximately 33.9%, with mothers spending an average of 2.93 days in the hospital for delivery and incurring average total charges of $12,985 (adjusted in 2009 dollars).

Hospitals with maternal deaths tend to be larger in discharge volume, with an average quarterly discharge twice as large as hospitals without maternal deaths. Additionally, hospitals with maternal deaths perform more C-sections and laceration repairs on average, but fewer inductions and assisted deliveries. Notably, hospital length of stay and total charges are higher in hospitals with maternal deaths, which may be attributed to the observed higher C-section rate in these hospitals.

In terms of hospital quality, there are no systematic differences between hospitals with and without maternal deaths. Although hospitals with maternal deaths report more stillborn cases, they have a lower rate of labor and delivery complications. However, the rate of pregnancy complications is higher in hospitals with maternal deaths, and there is also a greater proportion of mothers with high C-section risk in these hospitals. This suggests that mothers with elevated medical risks are more inclined to select these hospitals. This observation aligns with the higher average length of stay and total charges observed in hospitals with maternal deaths.

Furthermore, patient compositions in hospitals with maternal deaths are more diverse, with higher proportions of Black and Hispanic, and having Medicaid coverage rather than private insurance. In summary, hospitals with maternal deaths tend to be larger and serve a more diverse patient population compared to hospitals without maternal deaths.

1.5 Identification Strategy

1.5.1 Effects of Maternal Death

To investigate the impacts of maternal death on subsequent medical decisions, I compare between mothers who deliver in hospitals where maternal deaths occurred recently, with mothers delivering in hospitals that have not yet experienced such an event. To ensure the validity of the analysis, I make a crucial assumption that the exact timing of maternal death is random across hospitals. This assumption allows me to estimate the effects of maternal death without any systematic bias. Thus, I employ the staggered difference-in-differences framework to estimate the effects of maternal death on C-section. I also control for unobserved time-invariant hospital-specific factors that could potentially confound the results, and the common time trend. This approach allows me to isolate the causal effects of maternal death on subsequent medical decisions. I start by estimating the following equation:

$$y_{ijt} = \alpha + \beta MaternalDeath_{jt} + \lambda X_{ijt} + \delta_{jc} + \gamma_t + \epsilon_{ijt} \tag{1.7}$$

where y_{ijt} represents delivery method ($y_{ijt} = 1$ for C-section, and 0 otherwise), or other procedures and inpatient outcomes of admission i in hospital j in quarter t. $MaternalDeath_{jt}$ is a dummy variable indicating post-maternal-death period, and it equals to 0 in the "clean-period" (or pre-maternal-death period) defined in Section 1.4.4. X_{ijt} consists of maternal demographic characteristics, and controls for C-section patterns across races and insurance status. δ_{jc} are set of hospital by risk-group dummies, that controls for time-invariant hospital-by-risk-group specific factors that may confound the estimates. γ_t are a set of year-by-quarter dummies that control for common time trend.

The coefficient of interest is β. It captures the aggregate effects of maternal death on future C-section decisions, consisting of the following components: first, it measures the behavioral response of the individual physician who was responsible for the specific maternal death case. Second, it accounts for potential spillover effects on other physicians within the same hospital. And third, it encompasses the broader institution-wide management changes related to C-section decisions. While these individual components contribute to the overall effect, this paper does not aim to disentangle them separately. Instead, the focus is on capturing the aggregate effects of maternal death. By considering the combined impact of these factors, the study seeks to provide valuable insights on how maternal death influences C-section rates and medical decision-making at the hospital level.

Next, I allow the treatment effect to vary across mothers within different C-section risk groups as defined in Section 1.4.2. This approach allows for a more nuanced understanding of how maternal death impacts C-section decisions based on varying levels of patient conditions. This investigation is critical for discerning differential responses among mothers with distinct risk profiles, thereby providing valuable insights into the complex dynamics of medical decision-making in the context of maternal care. Prior works suggest a threshold strategy that physicians rank patients by their medical risks and perform C-sections according to a certain cutoff point (Currie and MacLeod 2008, Frakes 2012). In addition, the model in these studies suggest physicians have more discretion over marginal patients, while the appropriate procedure is more evident in low- and high-risk patients.

I examine the effects of maternal death across risk groups by introducing the interaction terms between the treatment dummy variable, $MaternalDeath_{jt}$, and indicators of C-section risk categories. Specifically, I include three indicator variables, A_M, A_L, and A_H, representing whether a mother belongs to the middle-, low-, or high-risk group, respectively. By incorporating these interaction terms, I aim to assess how the impact of maternal death varies across different C-section risk groups.

$$y_{ijt} = \alpha + \sum_{c\in\{M,L,H\}} \beta_c MaternalDeath_{jt} \times A_c + \lambda X_{ijt} + \delta_{jc} + \gamma_t + \epsilon_{ijt} \tag{1.8}$$

The coefficients β_M, β_L, and β_H capture the effects of maternal death within the middle, low, and high C-section risk groups. These coefficients allow me to understand the specific effects of maternal death in each risk category.

In order to test for the crucial assumption of parallel trends in the period before the occurrence of maternal death, I conduct additional analyses using the event-study approach. This approach allows me to explore the dynamic effects of maternal death over time and assess whether there are any significant deviations from parallel trends in the pre-treatment period.

To implement the event-study analysis, I estimate the following equations:

$$y_{ijt} = \alpha + \sum_{k=-12,k\neq-1}^{k=12} \beta^k D^k_{jt} + \lambda X_{ijt} + \delta_{jc} + \gamma_t + \epsilon_{ijt} \tag{1.9}$$

$$y_{ijt} = \alpha + \sum_{k=-12,k\neq-1}^{k=12} \beta^k_c D^k_{jt} \times A_c + \lambda X_{ijt} + \delta_{jc} + \gamma_t + \epsilon_{ijt} \tag{1.10}$$

Equation 1.9 estimates the aggregate dynamic effects, and Equation 1.10 estimates the dynamic effects by maternal C-section risk groups. D^k_{jt} are set of dummy variables indicating number of quarters relative to maternal death in hospital j. β^k and β^k_c, with $k \geq 0$, captures the dynamic effects k quarters relative maternal death, for all mothers, and among mothers in risk category c, respectively. To test for parallel trend, β^k, β^k_c, with $k < 0$, need to be close to 0. I find no violations to parallel trend assumption (Figure 1.6).

1.5.2 Placebo Test

The identification strategy hinges on the assumption that the timing of maternal death is random. In other words, the timing of maternal death is unrelated to any hospital-specific changes in management that occur simultaneously with maternal death, and coincidentally alter the treatment patterns of obstetricians. To evaluate the validity of this assumption, I construct a placebo event: hospital adverse event. This event is defined as the total number of in-hospital deaths exceeding 2.5 standard deviations above the mean in each hospital, serving as a proxy for potential triggers for hospital-specific shifts in management.

Similar to the main identification for maternal death, I then estimate the following equations:

$$y_{ijt} = \alpha' + \sum_{c \in \{M,L,H\}} \beta'_c AdverseEvent_{jt} \times A_c + \lambda' X_{ijt} + \delta_{jc} + \gamma_t + \nu_{ijt} \tag{1.11}$$

$$y_{ijt} = \alpha' + \sum_{k=-12, k \neq -1}^{k=12} \beta_c^{k\prime} P_{jt}^k \times A_c + \lambda' X_{cjt} + \delta_{jc} + \gamma_t + \nu_{ijt} \tag{1.12}$$

where P_{jt}^k equals 1 if quarter t is k quarters from the adverse event in hospital j. If β'_c and $\beta_c^{k\prime}$, with $k \geq 0$, are not different from 0, the assumption holds that the increase in C-section rate after a maternal death is not driven by hospital-specific practices. I do not find evidence that maternal death is likely to coincide with hospital-level adverse events.

1.6 Results

1.6.1 Effects on C-section

I first explore the aggregate effects of maternal death on subsequent C-section pattern by estimating Equation 1.7. Table 1.2 column (1)-(2) presents the effects of maternal death on subsequent C-section for all mothers. Maternal death leads to a 1-percentage-point increase in C-section rate at hospital level. Figure 1.6 plots the estimates from the event study estimates where the treatment effects are not allowed to interact with maternal C-section risks. We can see an immediate jump of C-section in the quarter of maternal death, the coefficients on the quarters before maternal death are not distinguishable from 0, and the p-value for parallel trends test is 0.42.

Interacting the treatment variable with maternal C-section risk allows me to explore the effects of maternal death across groups of mothers with different C-section risks. Table 1.2 columns (3)-(4) suggest that effects of maternal death varies across risk groups. Among middle-risk mothers categorized by C-section risk, maternal death leads to a 2-percentage-point increase in Section rate, which translates to a 6% increase relative to the middle-risk mean of 32.7%. This is robust to adding a set of control variables. Figure 1.6b plots the estimated coefficients of equation 1.10 for middle-risk mothers. It shows that C-section rate increases until 8 quarters (2 years) after maternal death. It slowly goes down in later quarters. Right at the treatment quarter, C-section rate jumps up discretely by 1.5 percentage point. Parallel trend assumptions hold for the estimation for middle-risk mothers, with a p-value of 0.47 for the joint F- test for the pre-treatment quarters.

The treatment effect for low-risk mothers is -0.002 percentage points, which is small and insignificant. Figure 1.6c plots the dynamic effects for low-risk mothers, and both the pre- and post-treatment estimates are flat and insignificant from zero. Similarly, treatment effect of high-risk mothers is also small: 0.003 percentage points. Figure 1.6d plots the dynamic effects for high-risk mothers. I do not observe any obvious changes in C-section patterns for high-risk mothers around maternal death, and all the estimated coefficients are not significantly different from 0.

To test whether the effects are coincidentally driven by general hospital-level shock rather than maternal death, I estimate the dynamic effects around the quarter labeled has having "hospital adverse event". Figure 1.8 displays the estimated coefficients of the event study for hospital adverse event, as indicated in Equation 1.12. For all mothers and mothers in different C-section risk groups, I do not observe any obvious discrete jumps around the quarter with hospital adverse event, and the C-section rates around the event exhibit very different patterns to maternal death. This shows that the effects of maternal death are unlikely to be confounded by general hospital-level shocks.

For middle-risk mothers, C-section rates exhibit temporary increase both 4 quarters before and after the adverse event, though this increase is relatively small and statistically insignificant from 0. While for the other two groups, there are temporary decreases. The exact reason of this change is unclear because total number of death in the same hospital do not convey enough information on the nature of the shock nor hospital management practices. But the results provide additional evidence that hospital-level shocks have differential impacts on mothers with different C-section risk.

1.6.2 Heterogeneity

In this section, I investigate the heterogeneity of the treatment effects and examine potential underlying mechanisms. I explore this diversity along three key dimensions: first, I investigate which groups of physicians exhibit the strongest response to maternal death. Second, I explore whether treatment effects vary between small and large hospitals, defined by size of average quarterly admission. I also test whether the effects vary based on hospital proportions of Medicaid patients. Additionally, I examine whether hospitals' responses vary depending on the method of delivery associated with maternal deaths.

Physicians who have more experience with C-sections tend to respond more strongly to maternal deaths by increasing the number of additional C-sections they perform in subsequent deliveries. In Table 1.3, I present an analysis focusing on different groups of physicians, categorized based on their predicted risk-adjusted C-section rates in the periods before the treatment. This analysis is based on a subset of delivery discharges with non-missing physician identifiers, discharges with missing physician identifiers are excluded. 2756 identified physicians are categorized into low-C-section physicians (low-CS MDs), mid-C-section physicians (mid-CS MDs), and high- C-section physician (high-CS MDs) groups based on their risk-adjusted C-section rates in the pre-treatment period.[14] Physicians are then ranked in ascending order of their risk-adjusted C-section rate, low-CS Physicians are those with ranking below 500, mid-CS physicians are ranked between 500 and 2000, high-CS physicians are ranked above 2000.

Table 1.3 shows that the increase in C-section following by maternal death are driven by high-CS MDs, or those with more experience in performing C-sections: C-section rate increase by 3 percentage point among high-CS MDs, while the effects are much smaller and insignificant among low-CS MDs. This finding aligns with the concept of physicians' beliefs about their "comparative advantage" in medical procedure usage (Chandra and Staiger 2020, Robinson, Royer and Silver 2022). Physicians who specialize in performing C-sections often believe that they are better at performing this procedure, and therefore use it more frequently. This tendency in procedural choice is even more prominent when

[14]The physician identifiers in the dataset have been anonymized to ensure that they cannot be linked to external sources.

maternal deaths occur and raise their perceived malpractice risk. High-CS physicians tend to feel more confident about using the procedure they consider themselves skilled at. It's worth noting that Chandra and Staiger (2020) find evidence indicating that such treatment patterns might result in "allocative inefficiency", which means that certain treatments are overused relative to what might be medically necessary.

I also explore whether the effects differ between small and large hospitals, defined by their average quarterly admission. It is reasonable to assume that shocks led by maternal death are stronger in small hospitals due to smaller networks. Table 1.4 shows that the treatment effects are larger among smaller hospitals, where the quarterly admission volume is below 400. Another possible explanation is that larger hospitals encounter maternal deaths more frequently compared to smaller ones. In my sample, smaller hospitals, on average, experienced 1.6 maternal deaths during the sample period, whereas larger hospitals encountered 4.2 maternal deaths. Larger hospitals may have more experience in handling situations involving maternal deaths, while for smaller hospitals, such events trigger stronger responses. This finding provides further evidence that shocks at the hospital level can lead to varying degrees of institutional changes, which, in turn, contributes to the variations in C-section rates across hospitals.

Prior research link increase in C-section rates to physicians' financial incentives. To investigate whether financial incentives similarly play a role in the increase in C-section rates following maternal deaths, I categorized hospitals into two groups based on the average proportion of Medicaid mothers they serve: high-Medicaid hospitals (hospitals with proportions above the median) and low-Medicaid hospitals (hospitals with proportions below the median). If financial incentives are a contributing factor, differing effects between these two groups are anticipated, given that Medicaid reimburses at lower rates. Table 1.5 presents the estimated treatment effects within different subgroups of hospitals based on the proportion of Medicaid beneficiaries they serve. Surprisingly, the treatment effects are quite similar to the baseline results in hospitals with both a high (64.5% on average) and low (25.3% on average) proportion of Medicaid beneficiaries. This appears to contrast with the findings of a study by Shurtz (2014), which suggests that physicians' responses to malpractice laws could be influenced by their financial incentives. This finding suggests that in the context of patient deaths, responses are relatively consistent across hospitals regardless of the proportion of publicly insured patients they serve. Moreover, the effects of maternal death are unlikely to be driven by financial incentives.

Changes in delivery practices may also be driven by behavioral heuristics. A recent study finds that physicians tend to switch delivery methods when faced with labor and delivery complications, leading to increase or decrease in subsequent C-section rates (Singh 2021). To investigate whether such behavioral heuristics exist in the context of maternal death, I estimate the effects by the delivery method associated with maternal death. As shown in Table 1.6, the effects are both strong and positive in the middle-risk group, regardless of whether the maternal death is associated with C-section or vaginal delivery. This finding differs from Singh (2021), which suggests the effects by delivery method are of opposite signs. Such difference could be attributed to the fact that maternal deaths occur at a considerably lower rate than complications during labor and delivery. Consequently, the occurrence of maternal death is a significant event that prompts physicians to re-evaluate their perceived risk of malpractice. When dealing with adverse patient outcomes that are more common, physicians may rely on behavioral heuristics for decision-making.

1.6.3 Robustness Checks

In this section, I test the robustness of my results with a series of variations to the main specification. I first consider re-specifying the fixed effects in the main regression and the time window around the treatment. Then, I exclude hospitals based on the frequency of maternal death in the sample period, and I also drop potential confounding admissions. Next, I address the comparability issue between treated and control hospitals by re-weighting by control hospitals. Additionally, I consider different C-section risk cutoffs to categorize mothers into groups, and using alternative C-section risk or analysis. Finally, I test whether my results are robust to heterogeneous treatment effects by estimating the newly proposed robust estimator. In summary, the effects are robust and consistent across different specifications.

Re-specify fixed effects and time windows: I first re-specify the fixed effects in the following ways: allow both hospital and quarter fixed effects to vary with C-section risk groups; allow only quarter fixed effects to vary with C-section risk groups; not allow fixed effects to vary with C-section risk groups. Figure A.7 shows the estimated coefficients under each different model. As can be seen, the general patterns across these different models are similar: increase in C-section for middle-risk mothers, small and insignificant effects for low- and high- risk mothers. Interacting the fixed effects with risk category reduces the standard errors, suggesting time in-varying characteristics differ substantially across risk groups. Next, I vary the time window around the treatment quarter to assess the sensitivity of the results. In the baseline, I estimate the effects of maternal death around a 12 quarter window before and after the treatment quarter, and Table A.4 shows the estimated coefficients for the following time windows: -12 to 8 quarters, -8 to 12 quarters, and -8 to 8 quarters. The treatment effects are similar, indicating that my results are robust to variations in the time window.

Exclude Hospitals with Additional Maternal Deaths I re-estimate Equation 1.8 with the different restrictions on hospitals to be included in the analysis based on number of maternal deaths before and after the treatment quarter, results are reported in Table A.5. I first exclude hospitals with multiple deaths in the treatment quarter, then I exclude hospitals with any maternal deaths before the treatment quarter, finally I exclude hospitals with any maternal deaths after the treatment quarter. Results suggest that the effect on middle-risk mothers is robust: the treatment effects for middle-risk mothers are larger in magnitude compared to the baseline. One explanation is that hospitals that experience maternal deaths more frequently are less responsive to the treatment, and thus excluding these hospitals lead to an increase in the estimates. Column (4) estimate for middle-risk mothers is only statistically significant at 10% level, though the magnitude is similar to the baseline. This is mainly due to lack of power, since excluding hospitals with additional maternal deaths largely reduces the number of treated hospitals in the analysis and the sample size.

Exclude Potentially Confounding Admissions I first exclude admissions in the treatment quarter from the analysis. An important concern in my treatment assignment is at year-by-quarter level, and the exact date of maternal death is unknown.[15] This may lead to bias in the estimates. Table A.6 column (1) and (2) suggest that the effects are similar to the baseline after dropping the treatment quarter. Next, I exclude admissions that are transferred from another institution. These mothers are likely to have more severe medical conditions and higher C-section risk. Column (3) suggests that the results are similar after dropping these mothers from the analysis, indicating that the increase in C-section rate is not driven by mothers that are transferred. In addition, I also exclude mothers labeled as "against medical advice", since their medical decisions are likely not determined by physicians. Column (4) shows very similar results as the baseline, suggesting that the results are not driven by these extreme cases.

Comparability between treated and control hospitals It is natural to assume that hospitals with and without maternal deaths in the sample period may differ in various

[15] The database does not report the exact date due to data confidentiality concerns, so that I can only pin down the calendar quarter of maternal deaths. This makes it impossible to determine, within the treatment quarter, whether a mother is admitted/discharged before or after the treatment.

dimensions: hospital quality, patient composition, discharge volume, etc. Thus, the control hospitals may not be the perfect control group for my analysis. In order to tackle the non-comparability problem between the treated and control hospitals, I consider the following two tests: I first exclude the control hospitals in the analysis, the estimates are reported in Table A.7 column (2). The increase in C-section rate for middle-risk mothers is robust to excluding control hospitals, though the point estimates are smaller. Different factors may lead to smaller estimates: reducing the sample size, less-precisely estimated quarter fixed effects, negative weighting problem after excluding the never-treated group, etc. In a more proficient way, I provide the propensity weighted difference-in-differences estimates in column (3).[16] The results are very similar to the baseline after re-weighting the control hospitals. This provides additional evidence that my results are not driven by the difference between treatment and control hospitals.

Variations in C-section Risk I first vary the C-section risk cutoff to categorize mothers into different risk groups: I vary the cutoff between low- and middle-risk mothers from 35th percentile to 30th percentile, and I also vary the cutoff between middle- and high-risk mothers from 85th percentile to 90th percentile. I also allow the cutoffs to vary across years: I generate the 35th and 85th percentile C-section risk for each year, and assign mothers to risk groups according to the yearly cutoff values. Figure A.11 shows that the treatment effects are similar across variations in C-section risk cutoffs. Second, I re-estimate Equation 1.8 using alternative C-section risk measures to categorize mothers into C-section risk groups. These alternative C-section risk measures are discussed in detail in Section 1.4.2. Table A.12 shows that the estimates are similar across different C-section risk measures.

Alternative Sample Construction To address concerns related to the selection of hos-

[16]I first estimate the propensity of maternal death, $\hat{p}$, in hospitals in 2005-2017, using hospital-level characteristics in the baseline year 2003-2004. Then I re-weight never-treated hospitals by $\frac{\hat{p}}{1-\hat{p}}$.

pitals during treatment assignment, I conducted additional tests using alternative treatment assignment approaches. Specifically, I defined alternative treatment groups based on number of years before the first maternal death: the "3-year treatment" sample to includes control hospitals and hospitals where the treatment maternal deaths occur at least 12 quarters after the last maternal death. Similarly, I defined the "4-year treatment" and the "5-year treatment" sample following the same principles. Table A.8 reports the estimated effects. To supplement, I also plot event study estimates for these alternative treatment definitions are illustrated in Figure A.13, A.14 and A.15. Consistent with the main treatment definition, the results indicate no detectable effects on C-section rates for both low and high C-section risk mothers, and there is a clear and significant increase in C-section rates among middle-risk mothers. Moreover, the effects are larger in the 3-year and 4-year treatment sample, indicating stronger effects in hospitals with lower frequency of maternal death. The estimates for the 5-year treatment sample are not statistically significant, however, the point estimates are close to the baseline. These additional evidence shows that my results are not driven by sample selection.

Robustness to heterogeneous treatment effects De Chaisemartin and d'Haultfoeuille (2020) illustrates the problem of negative weights in two-way fixed effects regression when treatments are staggered. Intuitively, negative weights arise when using an earlier treated group is used as "control". In my analysis, treatments are staggered since maternal deaths happen at different points in time across hospitals. I supply the robust estimator from De Chaisemartin and D'Haultfoeuille (2022) for all mothers on aggregate and for mothers in each risk group separately, since the proposed estimator do not allow estimating the interactive treatment effects. Figure 1.7 shows that these estimates exhibit similar trend as the main event study specification. The standard errors are larger, and for the middle-risk group, fewer dynamic effects are statistically significant. This is primarily due to loss of efficiency from using the heterogeneous-robust estimator. Additionally, I estimate the sum of negative weights using the same specification for the aggregate effects (as described in Equation 1.7) and exclusively for data from the middle-risk group. This analysis reveals that only 2 out of 736 Average Treatment Effects on the Treated (ATTs) receive negative weights, with the sum of negative weights amounting to a small value of -0.00018. These findings suggest that the presence of negative weights is unlikely to introduce bias into my results. In summary, the issue of negative weights, as addressed in De Chaisemartin and d'Haultfoeuille (2020), is carefully considered in my analysis. The application of the robust estimator and the assessment of negative weights indicate that the potential bias introduced by negative weights is minimal in this context.

1.6.4 Effects on Obstetric Procedures

In this section, I explore whether maternal deaths are associated with any effects on other procedure use during labor and delivery. In the previous sections, I discuss the differential treatment effects across maternal risk groups on C-section rates, and increase in C-section rates are more prominent among middle-risk mothers because these mothers are subject to more physician discretion when making a decision on a major surgery. However, it is also interesting to explore whether such an event has any effects on the use of other procedures during labor and delivery, for the following 2 reasons. First, though I do not detect any effects on C-section among low- and high-risk mothers, they may still be influenced by such an event, but in turns of other procedures. Second, this analysis serves as an additional evidence that the same event may affect patients differently based on their medical characteristics.

In additional to C-section, I also study whether maternal death is associated with any changes in treatment patterns on the following 3 commonly used interventions during labor: induction, assisted delivery, and laceration repair. Table 1.7 suggests that the treatment effects of the above 3 procedures are also heterogeneous across maternal risk groups: use of induction exhibits increasing trend in all three groups after maternal death, with a slightly larger effect in the low-risk group. Assisted delivery increase in high-risk mothers, and physicians are more likely to perform procedures to repair lacerations during deliveries for low-risk mothers.

Induction is a procedure where physicians or midwives use medicine intravenously (medical induction) or artificially rupture the amniotic sac (surgical induction). Similar to C-section, induction of labor is also an approach to facilitate birth in complicated pregnancies or overdue mothers. Increase in induction in recent years also raises controversies since induction is not risk-free (Marchioro et al. 2019, Organization et al. 2011). Table 1.7 column (1) reports the treatment effects and mean induction rates. Overall, 30% of all mothers use labor induction. The rate of induction is around 35%, among mothers with low and middle C-section risk, and lower than 10% among mothers with high C-section risk. This is due to the fact that most of the deliveries in the high-risk group are scheduled to be C-sections, and thus the need for induction is low in this group.

The increase in induction is statistically insignificant, but the magnitudes are not negligible. The effects are larger among low-risk mothers, since C-section rate is lower in this group and thus the potential demand for induction is larger than the other two groups. This suggests that though I do not find any changes in C-section for the low- and high-risk mothers, physicians are more likely to induce labor.

I define assisted delivery as having used any of the following procedures during labor: forceps-assisted delivery, vacuum-assisted delivery, episiotomy, and other instrumental delivery. Forceps and vacuum are instruments used during delivery to apply gentle traction and help guild the fetus's head out. Use of forceps or vacuum are usually recommended under signs of fetal distress, during prolong labor. Episiotomy is a procedure that makes an incision to allow the baby to come through more easily.[17] Similar to induction, this procedure is usually recommended in the event of certain birth complications. In the traditional belief, episiotomy creates controlled incisions that heal better than natural tears. However, more recent studies do not support maternal benefits traditionally ascribed to routine episiotomy. In fact, outcomes of operative delivery may be worse due to morbidity risk, for example, increased risk of fecal incontinence (Hartmann et al. 2005, Harrison et al. 1984, Lede, Belizan and Carroli 1996, Gartland et al. 2012, Kissler et al. 2016). Utilization of operative vaginal delivery is also a defense response in certain high-risk situations when expected harm from performing the procedure outweighs the morbidity risk facing the delivery (Frakes 2012).

Table 1.7 column (2) suggests that maternal death is associated with a 2.4 percentage point increase in assisted delivery for high-risk mothers. This is likely to be explained by the fact that mothers with certain health conditions are generally advised not to try to push out the baby, for example, hypertension makes pushing more stressful and dangerous.[18] Such concerns may prompt physicians to increase the use of assisted delivery for high-risk mothers.

Obstetric laceration may lead to obstetric postpartum hemorrhage, which is the most common cause of maternal death (Evans and McSHANE 1985, Bienstock, Eke and Hueppchen 2021). Thus, repair of obstetric laceration is an important procedure to control bleeding and improve safety. While laceration repair is a common procedure in childbirth, it's worth noting that not all tears necessitate sutures, as some may heal naturally. The decision to perform laceration repair is made by the healthcare provider, considering the individual circumstances of each childbirth.

[17]Episiotomy is grouped in the assisted birth category because use of other instruments usually involves episiotomy. The National Institute for Health and Care Excellence (NICE) recommends that an episiotomy might be done if there is a need for forceps or vacuum delivery (ventouse).

[18]Reference: NHS: What happens in labor and births.

Table 1.7 column (3) shows that after maternal death, obstetric laceration repair increase by 1.8 percentage point among low-risk mothers. It is likely that before maternal death, hospitals do not tend to repair laceration as much, while maternal death prompts physicians to be more cautious by performing more laceration repair to mitigate risk of postpartum hemorrhage and mortality.

1.6.5 Effects on Inpatient Outcomes

In this section, I explore the changes in mothers' inpatient outcomes associated with a recent maternal death. I intend to answer the following 2 questions: first, do we see changes in hospital length of stay and total charges that are consistent and explainable by the changes in procedures as discussed in previous sections? Second, what are the health implications for these changes in procedure use?

Table 1.8 columns (1) and (2) presents the results for hospital length of stay and log total charges (adjusted in 2009 dollars). Though the estimated coefficients are all significant at 5% level, they are small relative to the mean, and I do not detect any substantial changes. For middle- and low- risk mothers, the evidence shows a significant increase in both hospital length of stay and log total charges. This increase is likely driven by the rise in C-section and other use of procedures, which is usually associated with longer hospital stays and higher medical costs. Interestingly, the length of stay seems to decline for high-risk mothers, though the effects are small, by only 0.054 days (1.2 hour) on average. The small decline suggests that there might be a crowding-out effect due to increased attention on middle-risk and low-risk cases.

However, the effects on stillborn or labor and delivery complications are not statistically significant at 5%, indicating that the increase in use of procedures may not be health-improving. This suggests that the increase in C-section after maternal death is likely a defensive practice that raises medical spending do not lead to better health outcomes. However, this results need to be interpreted more cautiously since a lot of related health impacts are not investigated in the scope of this paper.

1.7 Conclusion

In this paper, I investigate the effects of maternal death on medical decision-making, focusing on subsequent C-section decisions at the hospital level. I find compelling evidence that maternal death triggers increased use of C-section, and the increase is particularly pronounced among middle-risk mothers. This suggests that maternal death triggers an increase in perceived malpractice risks, which prompts physicians to practice in a way that involves performing more medical procedures. The response in C-sections is not observed for low-risk and high-risk mothers, indicating that the middle-risk mothers are more susceptible. Furthermore, I explore various dimensions of robustness to validate the main findings. The results remain consistent across different fixed effects specifications, time windows, and alternative treatment assignments. This robustness supports the reliability and validity of my conclusions. In addition, I demonstrate the notion of physicians' belief about their comparative advantage in choosing method of delivery. Physicians who specialize in C-sections respond to maternal death by performing even more C-sections, since they are more comfortable with the procedures that they have expertise when exposed to elevated perceived malpractice risk.

My findings contribute to the existing literature on defensive medicine and C-section. While previous studies have focused on Florida Hospital Inpatient Data, my research utilizes New York Hospital Inpatient Data, demonstrating that defensive practices are not unique to Florida and may be applicable to other states as well. Prior studies show evidence at individual physician level, the positive effects observed in my study indicate that the response to perceived malpractice risk can also lead to increased hospital-wide increase in C-section rates.

Comparing my research findings to 2 studies that focus on patient outcomes, I find notable similarities with the results of Han et al. (2020). Their study concludes that there is a small increase (0.2 percentage point) in C-section rates in counties following exposure to unexpected fetal death. On the other hand, the study by Singh (2021) presents a different pattern, indicating that physicians may alter their delivery methods in response to major labor and delivery complications in a prior delivery.

This finding suggests that the impact of adverse patient outcome on C-section rates may be positive or negative, depending on the relative severity and probability of the event. More severe patient outcome occurring at lower probability triggers larger changes in perceived malpractice risk, and lead to stronger impacts on C-section. Maternal death and unexpected fetal death are relatively rare occurrences, triggering a generalized response to increase procedure use among healthcare providers. In contrast, labor and delivery complications may be severe enough to prompt behavioral changes but may not significantly impact perceived malpractice risks. On the other hand, Han et al. (2020) finds smaller effects on C-section following unexpected fetal death. This may be due to the fact that their main analysis is at county level, and shocks at aggregate level are not as salient as localized shocks. Also, fetal deaths occur more often than maternal death.

Despite these interesting findings, there are certain limitations that need to be acknowledged. First, the use of hospital inpatient data from a single state restricts my ability to examine the persistence of these effects across diverse legal and healthcare settings in different geographic regions. Expanding the scope of the analysis to include data from multiple states or countries could provide a more comprehensive understanding of how defensive practices vary across different jurisdictions. However, New York State is large, and is one of the most ethnically and culturally diverse regions in the United

States. This diversity can have significant implications for childbirth practices, including potential variations in medical risks, cultural preferences, and healthcare access.

Second, while I observe an increase in C-section rates at the hospital level following maternal deaths, the exact mechanisms driving this phenomenon remain unclear. The dataset does not allow me to directly observe hospital-level management changes or personnel shifts. This opens up an intriguing avenue for potential extensions of this research. A more comprehensive understanding of the post-maternal death dynamics within hospitals can be achieved by delving deeper into the internal workings of these healthcare institutions. This could involve investigating hospital practices and policies, analyzing how medical staff respond to and adapt after the occurrence of maternal deaths, and identifying any structural or organizational changes that may influence their approach to maternal care. By shedding light on these factors, future research could offer a more comprehensive explanation of the observed increase in C-section rates, adding valuable insights to the field of maternal healthcare and medical decision-making.

Key Terms

Breech presentation occurs when the baby's buttocks or feet are positioned to come out first during delivery, instead of the head.

Disproportion in the context of childbirth refers to a situation where the size of the baby's head is larger than the mother's pelvic opening, making a vaginal delivery difficult.

Placenta previa is a condition where the placenta partially or completely covers the cervix, potentially leading to bleeding during pregnancy.

Multiple gestation refers to a pregnancy where a woman is carrying more than one fetus, such as twins or triplets.

Abruptio placentae is a serious condition where the placenta separates from the uterine wall before delivery, causing bleeding and potentially endangering the baby.

Chorioamnionitis is an infection of the membranes surrounding the fetus (chorion and amnion), often caused by bacteria ascending from the vagina.

Eclampsia is a severe complication of pregnancy characterized by high blood pressure and seizures.

Polyhydramnios is a condition where there is an excess of amniotic fluid around the fetus during pregnancy.

Oligohydramnios is a condition where there is too little amniotic fluid around the fetus during pregnancy. **Edema** refers to swelling caused by an accumulation of fluid. Edema in pregnancy often involves swelling in the feet and ankles.

Antepartum hemorrhage is bleeding from the vagina during pregnancy, occurring after the 24th week.

Renal diseases in pregnancy refer to disorders of the kidneys that may affect pregnant women, potentially impacting both maternal and fetal health.

Prolonged pregnancy, also known as post-term pregnancy, occurs when a pregnancy lasts beyond 42 weeks.

Early onset delivery refers to the birth of a baby before 37 weeks of pregnancy, indicating preterm birth.

A **papyraceous fetus** is a term used to describe a fetus that becomes flattened and parchment-like due to compression in the uterus, often in cases of multiple gestation.

Hemorrhage in early pregnancy involves bleeding during the first trimester, which can be due to various reasons, such as implantation bleeding or complications.

Induction of labor is a medical intervention used to artificially start or speed up the labor process when it hasn't started on its own or is progressing slowly. This can involve the use of medications, such as oxytocin, or other methods to stimulate contractions.

Assisted delivery refers to the use of medical techniques or instruments to aid in the delivery of a baby. This can include vacuum extraction or forceps delivery when there are concerns about the progress of labor.

Episiotomy is a surgical cut made in the perineum, the area between the vaginal opening and the anus, during childbirth. This incision is sometimes made to enlarge the vaginal opening and facilitate a smoother delivery. Episiotomies are sometimes performed during assisted deliveries to facilitate the birthing process and reduce the risk of severe tears in the perineum. However, its use has become less common in recent years, and it is usually performed under specific circumstances.

Laceration repair involves the stitching or suturing of a tear or cut in the skin or other tissues. In the context of childbirth, laceration repair commonly refers to the repair of tears that may occur in the perineum during delivery. The severity of tears can vary, and healthcare providers assess and repair them accordingly.

Figures and Tables

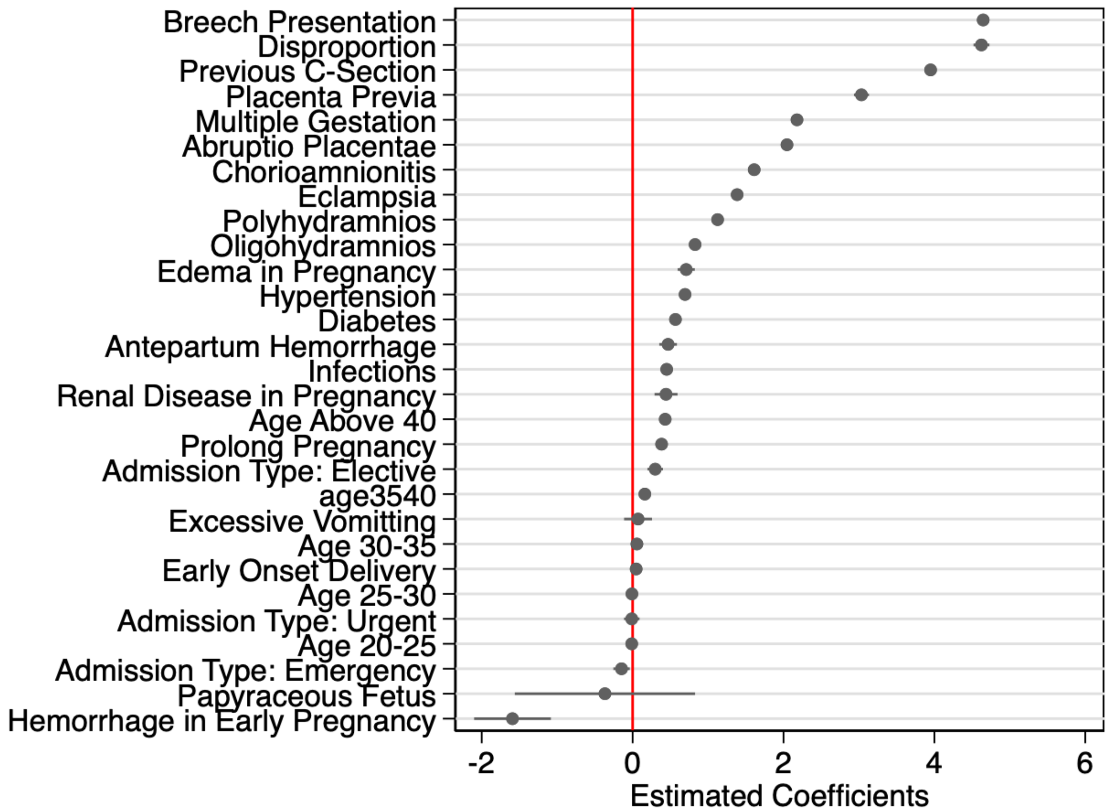
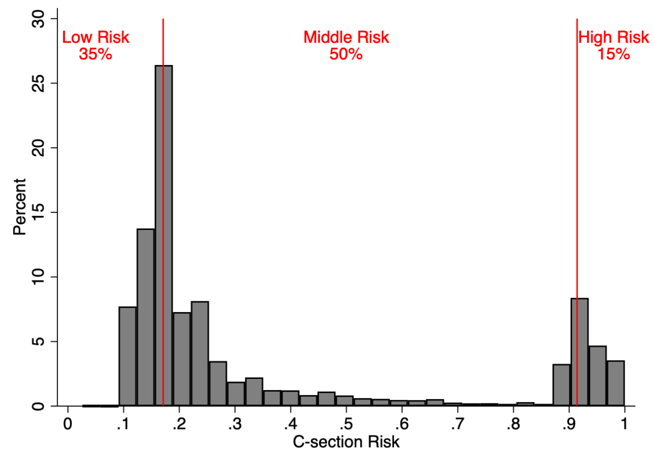
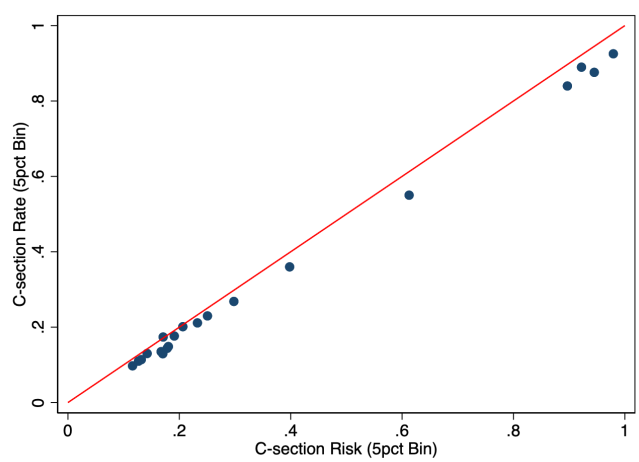


Figure 1.1 Marginal Contribution to C-section Risk
Note: Estimated by equation 1.4. Each point represents the estimated coefficient of the associated indicator for pregnancy complications, maternal age group, and admission type. Each whisker depicts the estimated 95% confidence interval. Indicators are sorted in descending order by the estimated coefficient (marginal contribution to C-section risk). Mothers' ages are in years, indicators for pregnancy complications are dummy variables equal to 1 if the discharge record includes such diagnosis identified by ICD-9-CM/ICD-10-CM diagnosis codes. Delivery discharges are identified by deliveries MS-DRGs. Refer to Key Terms Section for meanings of pregnancy complications.



(a) Distribution of C-section Risk



(b) Distribution and C-section Rate by C-section Risk

Figure 1.2 Distribution and C-section Rate by C-section Risk
Note: C-section risk is estimated by equation 1.4 with discharges from control hospitals, and then predicted by Equation 1.5 using all delivery discharges. Variables included in the estimation are pregnancy complications, maternal age group, and admission type. Mothers' ages are in years, indicators for pregnancy complications are dummy variables equal to 1 if discharge record includes such diagnosis identified by ICD-9-CM/ICD-10-CM diagnosis codes. Delivery discharges are identified by deliveries MS-DRGs. Panel (a) depicts the histogram of C-section Risk. Red vertical lines represent the cutoffs between maternal risk groups: mothers with C-section risk below 35th percentile are categorized as low-risk mothers, mothers with C-section risk above 85th percentile are categorized as high-risk mothers, and mothers with C-section risk between 35th and 85th percentile are middle-risk mothers. Panel (b) plots C-section rate of mothers within each 5-percentile bin of predicted C-section risk. For each point, the x-value represents the average predicted C-section risk within each 5-percentile bin. The y-value represents C-section rate of mothers within each 5-percentile bin of predicted C-section risk. The red line represents the 45 degree line, indicating that points along this line have equal x and y values.

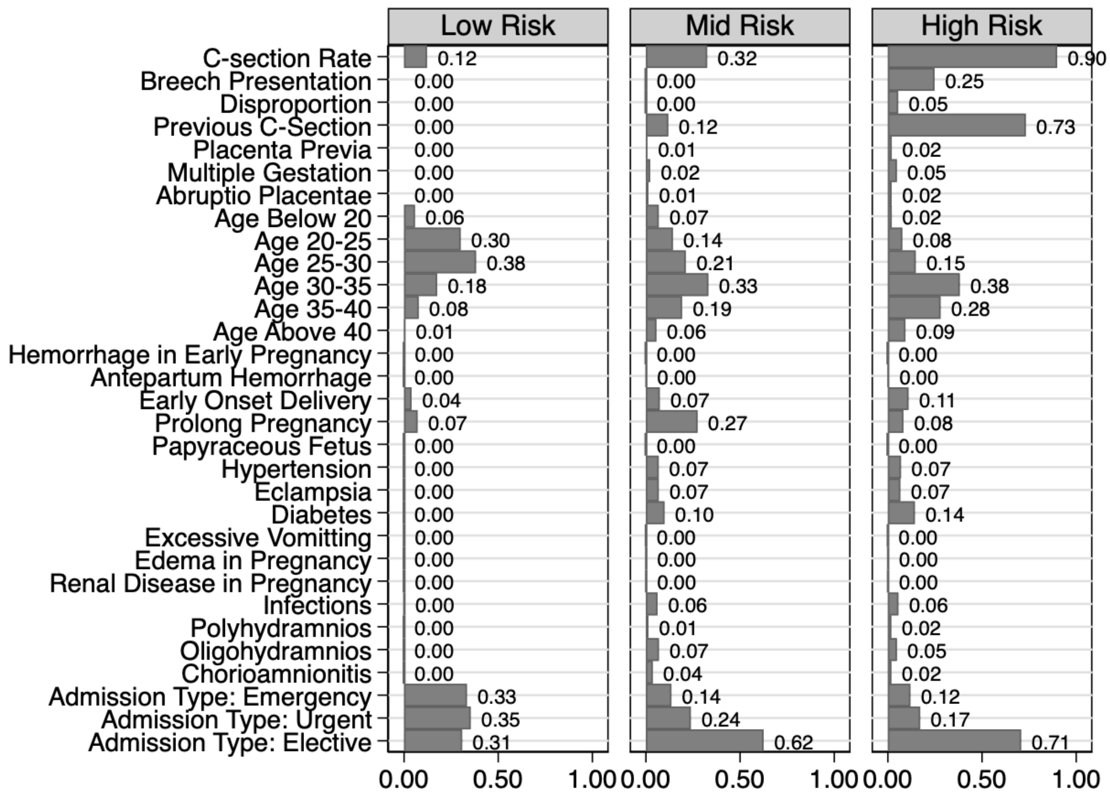
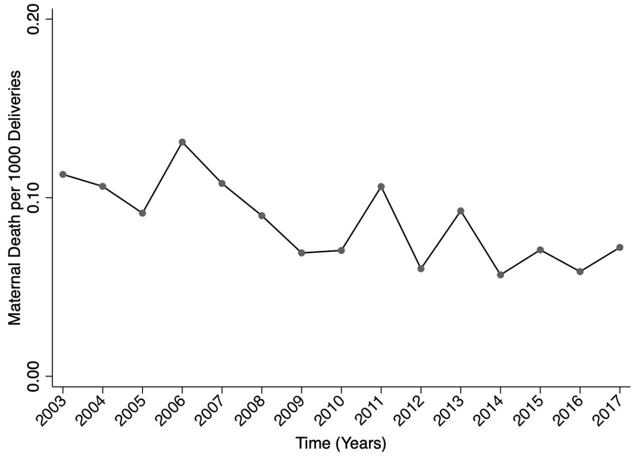
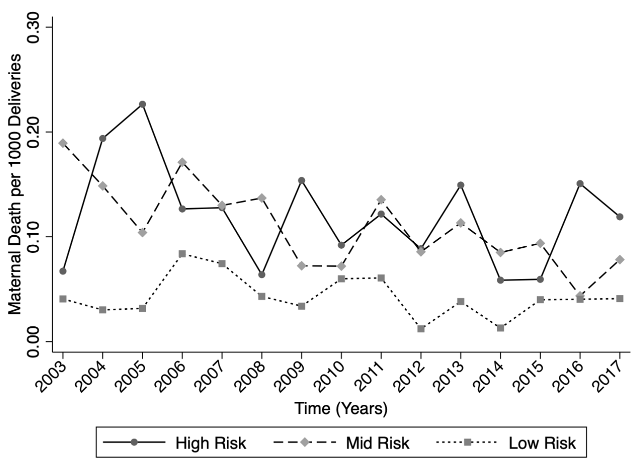


Figure 1.3 Risk Profile by C-section Risk Group
Note: Each bar represents the average value of the associated indicator for mothers in relevant C-section risk groups. Mothers' ages are in years, indicators for pregnancy complications are dummy variables equal to 1 if discharge record includes such diagnosis identified by ICD-9-CM/ICD-10-CM diagnosis codes. Delivery discharges are identified by deliveries MS-DRGs. Risk cutoffs are 35th and 85th percentile of the predicted C-section risk: mothers with C-section risk below 35th percentile are categorized as low-risk mothers, mothers with C-section risk above 85th percentile are categorized as high-risk mothers, and mothers with C-section risk between 35th and 85th percentile are middle-risk mothers. Refer to Key Terms Section for meanings of pregnancy complications.



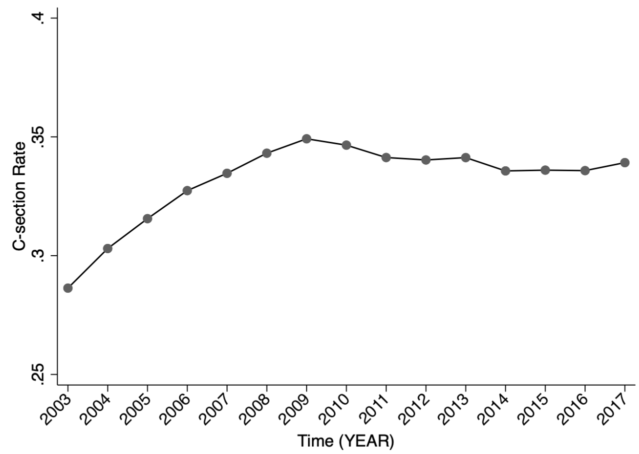
(a) Maternal Death Rate (Per Thousand Deliveries)



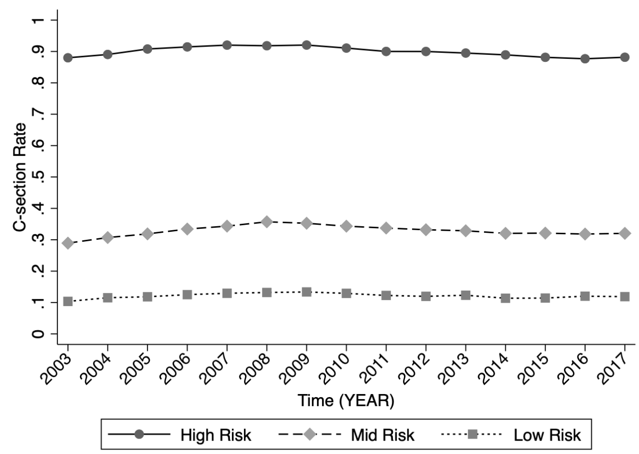
(b) Maternal Death Rate by C-section Risk Groups (Per Thousand Deliveries)

Figure 1.4 Maternal Death Rate Overtime

Note: The y-label scales in panel (a) and panel (b) are different. Panel (a) depicts maternal death rate for all delivery discharges in New York State Inpatient Database 2003 to 2017. Panel (b) depicts maternal death rate by C-section risk groups. Delivery discharges are identified by MS-DRGs, excluding deliveries with missing information in hospital identifier, admission year and quarter. Data is collapsed at yearly level. Mothers with C-section risk below 35th percentile are categorized as low-risk mothers, mothers with C-section risk above 85th percentile are categorized as high-risk mothers, and mothers with C-section risk between 35th and 85th percentile are middle-risk mothers.



(a) Overall C-section Rate



(b) C-section Rate by C-section Risk

Figure 1.5 C-section Rate Overtime
Note: The y-label scales in panel (a) and panel (b) are different. Panel (a) depicts C-section rate for all delivery discharges in New York State Inpatient Database from 2003 to 2017. Panel (b) plots C-section rate across maternal C-section risk groups. Delivery discharges are identified by MS-DRGs, excluding deliveries with missing information in hospital identifier, admission year and quarter. Data is collapsed at yearly level. Mothers with C-section risk below 35th percentile are categorized as low-risk mothers, mothers with C-section risk above 85th percentile are categorized as high-risk mothers, and mothers with C-section risk between 35th and 85th percentile are middle-risk mothers.

Table 1.1 Summary Statistics for the Constructed Sample

	(1) All Hospitals	(2) Hospitals with Maternal Death	(3) Hospitals without Maternal Death	(4) Difference
Procedure Use				
C-Section	0.339	0.342	0.327	-0.016***
	(0.473)	(0.474)	(0.469)	(0.001)
Induction	0.296	0.288	0.327	0.039***
	(0.456)	(0.453)	(0.469)	(0.001)
Assisted Delivery	0.145	0.143	0.151	0.008***
	(0.352)	(0.351)	(0.358)	(0.001)
Laceration Repair	0.340	0.344	0.327	-0.016***
	(0.474)	(0.475)	(0.469)	(0.001)
Inpatient Outcome				
Hospital Length of Stay (Days)	2.929	2.996	2.666	-0.330***
	(2.250)	(2.417)	(1.387)	(0.002)
Total Charges in 2009 Dollars	12985.074	13663.313	10323.930	-3339.382***
	(12948.433)	(13690.755)	(9010.370)	(15.193)
Number of Admissions (Quarter)	763.048	857.377	392.918	-464.459***
	(475.152)	(469.201)	(275.518)	(0.486)
Stillborn ($\times$ 1000)	5.676	5.981	4.482	-1.499***
	(75.127)	(77.103)	(66.797)	(0.103)
Maternal Medical and C-section Risk				
Any Labor and Delivery Complication	0.338	0.329	0.376	0.048***
	(0.473)	(0.470)	(0.484)	(0.001)
Any Pregnancy Complication	0.553	0.561	0.521	-0.040***
	(0.497)	(0.496)	(0.500)	(0.001)
Low C-section Risk	0.341	0.343	0.331	-0.012***
	(0.474)	(0.475)	(0.471)	(0.001)
Mid C-section Risk	0.520	0.517	0.535	0.018***
	(0.500)	(0.500)	(0.499)	(0.001)
High C-section Risk	0.139	0.140	0.134	-0.006***
	(0.346)	(0.347)	(0.341)	(0.001)
Maternal Demographics				
Age	29.304	29.428	28.817	-0.611***
	(6.102)	(6.100)	(6.087)	(0.009)
Black	0.144	0.164	0.069	-0.095***
	(0.351)	(0.370)	(0.253)	(0.000)
Hispanic	0.172	0.191	0.097	-0.095***
	(0.377)	(0.393)	(0.296)	(0.000)
Within county	0.728	0.728	0.729	0.001
	(0.445)	(0.445)	(0.445)	(0.001)
Primary Payer				
Medicare	0.006	0.004	0.010	0.006***
	(0.074)	(0.066)	(0.100)	(0.000)
Medicaid	0.422	0.440	0.349	-0.091***
	(0.494)	(0.496)	(0.477)	(0.001)
Private Insurance	0.525	0.513	0.571	0.058***
	(0.499)	(0.500)	(0.495)	(0.001)
N	2750912	2192215	558697	2750912
Num Hospitals	103	61	42	103

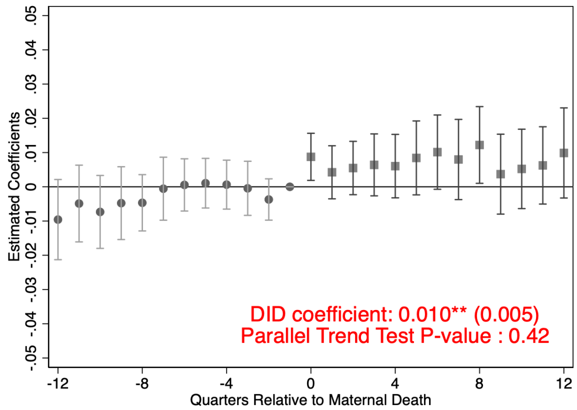
Note: Table provides summary statistics of the constructed sample. Induction, Assisted Delivery and Laceration Repair are summarized for 2003-2014 based on ICD-9-CM procedure codes, other variables are summarized over the full sample period, 2003-2017. Mothers' ages are in years, indicators for pregnancy complications and labor and delivery complications are dummy variables equal to 1 if discharge record includes such diagnosis identified by ICD-9-CM/ICD-10-CM diagnosis codes. Delivery discharges are identified by deliveries MS-DRGs. Within county means patient state county code is the same as hospital state county code. Standard errors are in parenthesis. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 1.2 Main Results:

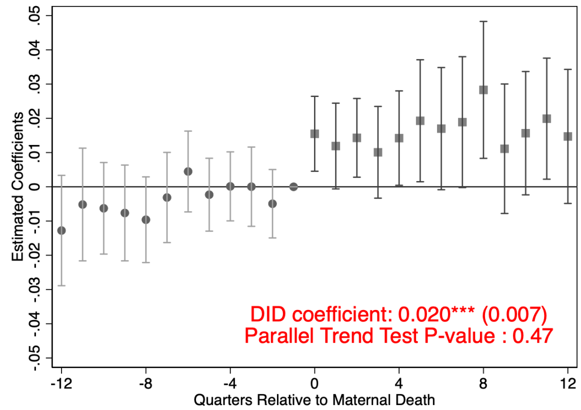
Effects of Maternal Death on C-section

	Aggregate Effect		By Risk Group	
	(1)	(2)	(3)	(4)
MaternalDeath	0.010**	0.010**		
	(0.005)	(0.005)		
MidRisk*MaternalDeath			0.020***	0.020***
			(0.007)	(0.007)
LowRisk*MaternalDeath			-0.001	-0.002
			(0.003)	(0.003)
HighRisk*MaternalDeath			0.003	0.003
			(0.003)	(0.003)
Quarter FE	Yes	Yes	Yes	Yes
Hospital by Risk FE	Yes	Yes	Yes	Yes
Control	No	Yes	No	Yes
N	1412902	1412902	1412902	1412902
Mean	0.337	0.337	0.337	0.337
Mean (Mid-risk)			0.327	0.327
Mean (Low-Risk)			0.126	0.126
Mean (High-Risk)			0.913	0.913

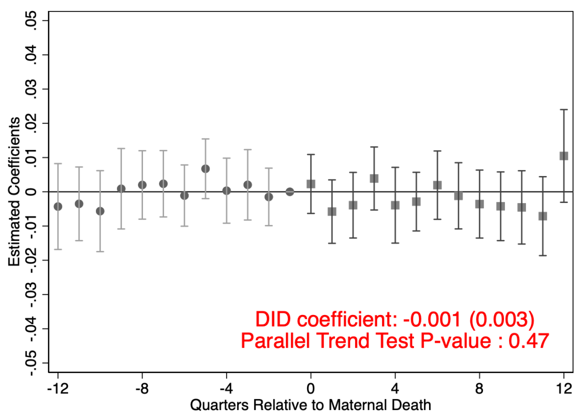
Note: Each column is a separate regression, the outcome variable is whether mother delivers via C-section. Column (1)-(2) are the OLS estimates of Equation 1.7, and the coefficient measures the aggregate effects of maternal death. Column (3)-(4) are the OLS estimates of Equation 1.8, and coefficients measure the effects of maternal death for each C-section risk group. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Column (1) and (3) exclude control variables. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.



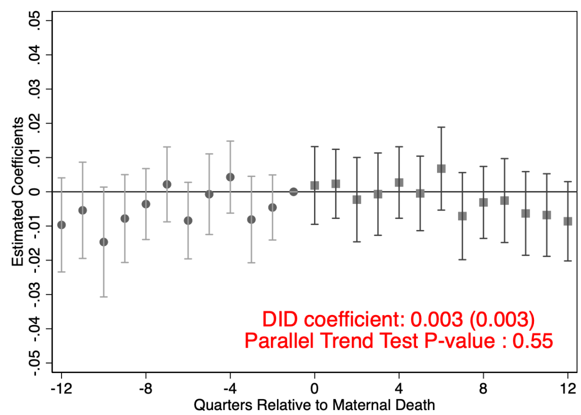
(a) All Mothers



(b) Middle-Risk Mothers

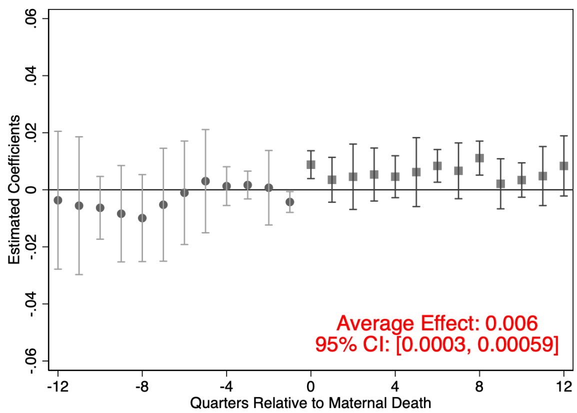


(c) Low-Risk Mothers

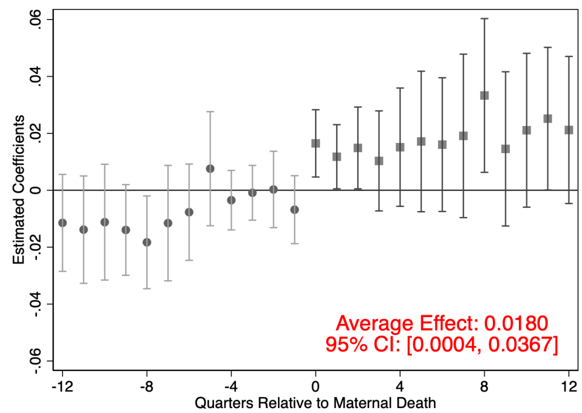


(d) High-Risk Mothers

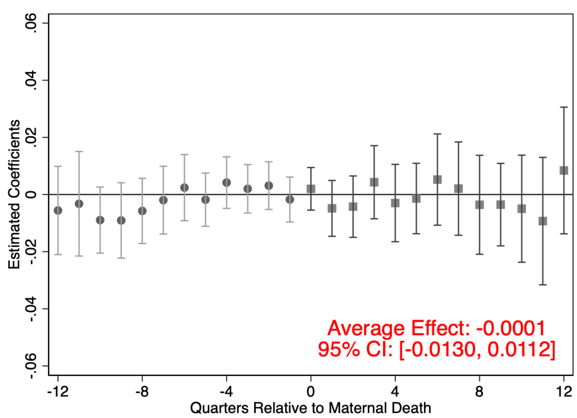
Figure 1.6 Event Study: Dynamic Effects of Maternal Death on C-section
Note: Each point represents a coefficient corresponding to the number of quarters since maternal death, and each whisker depicts the estimated 95% confidence interval. Panel (a) plots aggregate effects for all mothers, panel (b)-(d) plot effects by risk groups. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.



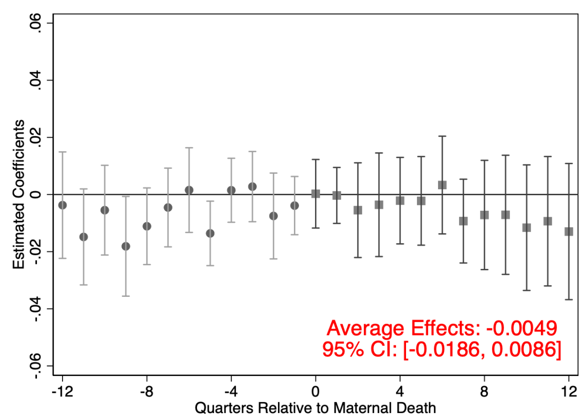
(a) All Mothers



(b) Middle-Risk Mothers

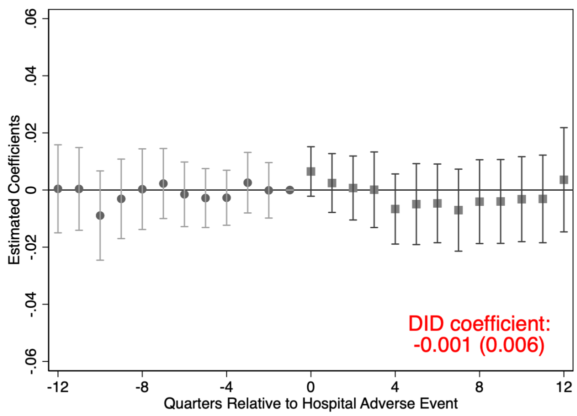


(c) Low-Risk Mothers

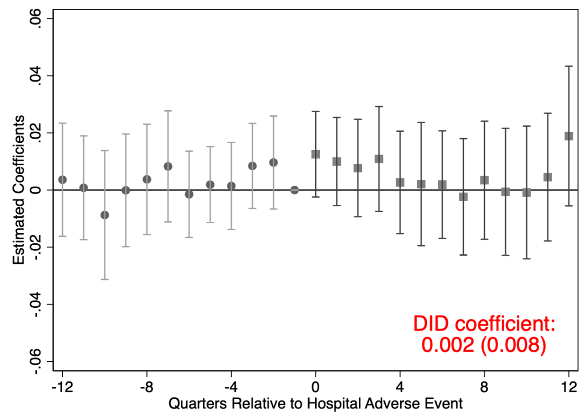


(d) High-Risk Mothers

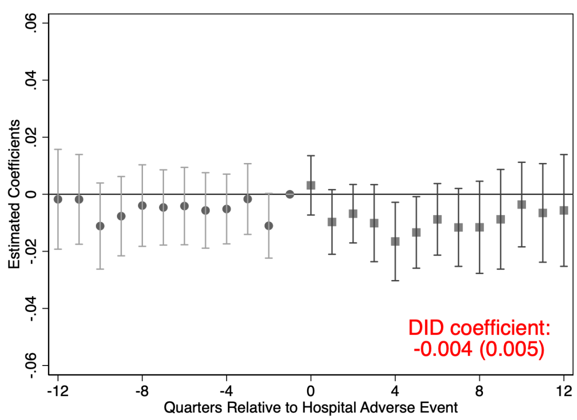
Figure 1.7 Robust DID Estimators: Dynamic Effects of Maternal Death on C-section
Note: These estimates are computed using the robust estimators proposed by De Chaisemartin and d'Haultfoeuille (2020). Each point represents a coefficient corresponding to the number of quarters since maternal death, and each whisker depicts the estimated 95% confidence interval. Panel (a) plots aggregate effects for all mothers, panel (b)-(d) plot effects by risk groups. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are clustered at hospital level using 30 boostrap replications.



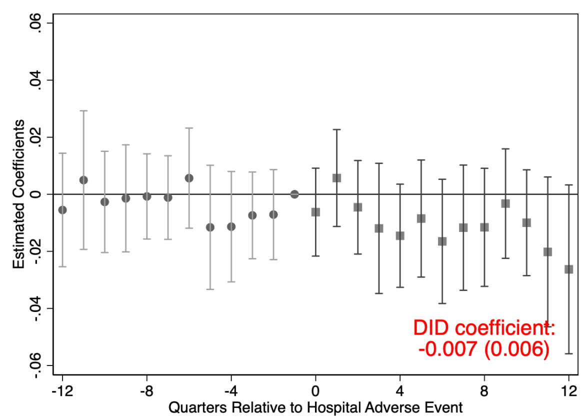
(a) All Mothers



(b) Middle-Risk Mothers



(c) Low-Risk Mothers



(d) High-Risk Mothers

Figure 1.8 Placebo Test Event Study: Dynamic Effects of Hospital Adverse Event on C-section

Note: Hospital adverse event is defined as the number of total patient deaths in the quarter exceeding 2 standard deviations over the mean. Each point represents a coefficient corresponding to the number of quarters since maternal death, and each whisker depicts the estimated 95% confidence interval. Panel (a) plots aggregate effects for all mothers, panel (b)-(d) plot effects by risk groups. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parenthesis, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 1.3 Effects of Maternal Death on C-section:

by Physician C-section Experience in Pre-treatment Period

	(1)	(2)	(3)	(4)
	Baseline	Low CS MDs	Mid CS MDs	High CS MDs
MidRisk*MaternalDeath	0.018**	0.009	0.012	0.030**
	(0.008)	(0.012)	(0.009)	(0.012)
LowRisk*MaternalDeath	-0.002	-0.008	-0.002	-0.006
	(0.004)	(0.007)	(0.005)	(0.008)
HighRisk*MaternalDeath	0.003	-0.011	0.004	-0.002
	(0.004)	(0.014)	(0.005)	(0.007)
Quarter FE	Yes	Yes	Yes	Yes
Hospital by Risk FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
N	1067551	125470	699232	242849
Mean	0.350	0.237	0.355	0.396
Mean (Mid-risk)	0.335	0.232	0.328	0.410
Mean (Low-Risk)	0.131	0.082	0.130	0.159
Mean (High-Risk)	0.919	0.839	0.922	0.937

Note: Each column represents a separate regression, and the outcome variable is whether mother delivers via C-section. This analysis is based on a subset of delivery discharges with non-missing physician identifiers, discharges with missing physician identifiers are excluded. 2756 physicians with identifiers are categorized into low-, middle, and high- C-section groups based on their risk-adjusted C-section rates in the pre-treatment period. Physicians are ranked in ascending order of their risk-adjusted C-section rate, low-CS Physicians are those with ranking below 500, mid-CS physicians are ranked between 500 and 2000, high-CS physicians are ranked above 2000. Each column is a separate regression. Column (1) presents the effects of maternal death for all delivery discharges with non-missing physician identifiers. Column (2)-(4) list the effects by low-, mid-, and high-CS physicians. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 1.4 Effects of Maternal Death on C-section:

by Hospital Average Quarterly Admission

	Baseline	Average Quarterly Admission	
	(1)	(2)	(3)
		Below 400	Above 400
MidRisk*MaternalDeath	0.020***	0.031**	0.019**
	(0.007)	(0.012)	(0.008)
LowRisk*MaternalDeath	-0.002	0.005	-0.002
	(0.003)	(0.006)	(0.004)
HighRisk*MaternalDeath	0.003	0.004	0.003
	(0.003)	(0.007)	(0.003)
Quarter FE	Yes	Yes	Yes
Hospital by Risk FE	Yes	Yes	Yes
Control	Yes	Yes	Yes
N	1412902	440839	972063
Mean	0.337	0.323	0.343
Mean (Mid-risk)	0.327	0.335	0.324
Mean (Low-Risk)	0.126	0.118	0.129
Mean (High-Risk)	0.913	0.925	0.909

Note: Each column represents a separate regression, and the outcome variable is whether mother delivers via C-section. Column (1) presents the effects of maternal death for all hospitals in the constructed sample. Column (2) reports the effects of maternal death within smaller hospitals, with average quarterly admission below 400. Column (3) reports the effects of maternal death within larger hospitals, with average quarterly admission above 400. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 1.5 Effects of Maternal Death on C-section:
Heterogeneity by Hospital Medicaid Proportions

	Baseline	Hospital Medicaid Proportion	
	(1)	(2)	(3)
		Above Median	Below Median
MidRisk*MaternalDeath	0.020***	0.020*	0.020**
	(0.007)	(0.011)	(0.009)
LowRisk*MaternalDeath	-0.002	-0.001	-0.003
	(0.003)	(0.006)	(0.004)
HighRisk*MaternalDeath	0.003	0.007	-0.000
	(0.003)	(0.006)	(0.004)
Quarter FE	Yes	Yes	Yes
Hospital by Risk FE	Yes	Yes	Yes
Control	Yes	Yes	Yes
N	1412902	588060	824842
Mean	0.337	0.324	0.346
Mean (Mid-risk)	0.327	0.365	0.305
Mean (Low-Risk)	0.126	0.123	0.128
Mean (High-Risk)	0.913	0.912	0.914

Note: Each column represents a separate regression, and the outcome variable is whether mother delivers via C-section. Column (1) presents the effects of maternal death for all hospitals in the constructed sample. Column (2) reports the effects of maternal death within hospitals with average proportion of mothers enrolled in Medicaid above the median proportion across all hospitals (around 40%). Column (3) reports the effects of maternal death within hospitals with average proportion of mothers enrolled in Medicaid below the median. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 1.6 Effects of Maternal Death on C-Section: by Delivery Method Associated with Maternal Death

	(1)	(2)	(3)
	Baseline	Vaginal	Cesarean
MidRisk*MaternalDeath	0.020***	0.025**	0.021**
	(0.007)	(0.012)	(0.009)
LowRisk*MaternalDeath	-0.002	-0.005	-0.001
	(0.003)	(0.006)	(0.004)
HighRisk*MaternalDeath	0.003	-0.001	0.005
	(0.003)	(0.006)	(0.004)
Quarter FE	Yes	Yes	Yes
Hospital by Risk FE	Yes	Yes	Yes
Control	Yes	Yes	Yes
N	1412902	759854	1157981
Mean (Middle-risk)	0.327	0.307	0.332
Mean (Low-Risk)	0.126	0.117	0.128
Mean (High-Risk)	0.913	0.909	0.921
Mean	0.337	0.320	0.342

Note: Each column represents a separate regression, and the outcome variable is whether mother delivers via C-section. Column (1) presents the effects of maternal death for all delivery discharges in the constructed sample. Column (2) presents the effects of maternal death if the delivery method associated with such event is vaginal delivery. Column (3) reports the effects of maternal death if the delivery method associated with such event is cesarean delivery. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 1.7 Effects of Maternal Death on Other Procedure Use

	(1) Induction	(2) Assisted Delivery	(3) Laceration Repair
MidRisk*MaternalDeath	0.018	0.001	0.001
	(0.011)	(0.004)	(0.005)
LowRisk*MaternalDeath	0.024	0.000	0.018***
	(0.018)	(0.005)	(0.005)
HighRisk*MaternalDeath	0.007	0.024***	-0.004
	(0.007)	(0.004)	(0.003)
Hospital by Risk FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Control	Yes	Yes	Yes
N	946037	946037	946037
Mean (Middle_risk)	0.354	0.159	0.346
Mean (Low-Risk)	0.310	0.179	0.414
Mean (High-Risk)	0.0838	0.0405	0.0428
Mean	0.302	0.150	0.329

Note: Each column represents a separate regression with different outcome variables: induction, assisted delivery, and laceration repair. This analysis is based on the period 2003- 2014 to avoid inconsistency from substantial procedure coding changes during the transitioning from ICD-9-PCS to ICD-10-PCS in 2015. Indicators for procedure use are dummy variables equal to 1 if discharge record includes such procedure identified by ICD-9-PCS procedure codes. Column (1) reports the effects of maternal death on induction, including medical induction and surgical induction. Column (2) estimates the effects of maternal death on assisted delivery, including use of forceps, vacuum, other instruments, and episiotomy. Column (3) estimates the effects of maternal death on repair of obstetric laceration. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Refer to Key Terms Section for meanings of procedures.

Table 1.8 Effects of Maternal Death on Inpatient Outcomes

	(1)	(2)	(3)	(4)
	Length of Stay	Log Total Charges	Stillborn ($\times$1000)	L&D Complications
MidRisk*MaternalDeath	0.038**	0.077***	-0.437	0.000
	(0.018)	(0.029)	(0.362)	(0.007)
LowRisk*MaternalDeath	0.025**	0.068**	0.277	-0.012
	(0.011)	(0.033)	(0.354)	(0.010)
HighRisk*MaternalDeath	-0.054**	0.062**	-1.135	-0.017*
	(0.024)	(0.026)	(0.770)	(0.009)
Hospital by Risk FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
N	1412901	1412816	1412902	1412902
Mean (Middle_risk)	2.943	9.183	4.920	0.366
Mean (Low-Risk)	2.442	8.962	4.744	0.361
Mean (High-Risk)	3.580	9.437	8.360	0.246
Mean	2.855	9.140	5.329	0.348

Note: Each column represents a separate regression with different outcome variables: hospital length of stay (number of days), log total charges adjusted in 2009 dollars, stillborn ($\times$1000), labor and delivery complications. Indicators for labor and delivery compilations are dummy variables equal to 1 if discharge record includes any diagnosis of labor and delivery complication identified by ICD-9-CM/ ICD-10-CM diagnosis codes. Column (1) reports the effects of maternal death on hospital length of stay. Column (2) reports the effects of maternal death log total charges. Column (3) reports the effects of maternal death on stillborn. Column (4) reports the effects of maternal death on having any labor and delivery complications. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Chapter 2

Natural Disasters and Family Planning: Evidence on Birth and Migration

2.1 Introduction

In the United States, hundreds of natural disasters strike every year: in 2021, 1,162 natural disasters are declared by counties, including 528 severe ice storms, 228 hurricanes, 213 severe storms, and 113 floods (Federal Emergency Management Agency (FEMA) disaster declaration summaries). These natural disaster incidents result in enormous damages, including fatalities, financial loss, and mental distress. Furthermore, climate science suggests that the number and severity of natural disasters are expected to increase as a result of increase in greenhouse gas emissions (Boustan et al. 2020, IPCC 2012).

This paper investigates the short-term effects of climate-related and higher-frequency natural disasters on birth rates. Prior studies focus on the longer-term fertility effects of a one-time natural disaster of high severity: Hurricane Katrina (Seltzer and Nobles 2017), Red River Flood (Tong, Zotti and Hsia 2011), Hurricane Hugo (Cohan and Cole 2002). However, the effects of higher-frequency and medium-severity natural disasters are understudied. While individual occurrence of these incidents may have relatively smaller impacts, their frequencies are significantly higher, and their scope are larger across broader geographic regions. As a result, their collective impacts are non-negligible. In addition, it is an important task to contrast across the effects of different types of natural disasters, to provide a more comprehensive understanding of how natural disasters and family planning decisions are inter-related.

Natural disasters may impact birth rates through multiple channels. On the one hand, natural disasters might lead to an increase birth rates. During such events, women often have limited access to contraceptives (Ellington et al. 2013, Leyser-Whalen, Rahman and Berenson 2011). Additionally, people are expected to spend more time at home, raising the likelihood of pregnancy (Evans, Hu and Zhao 2010). On the other hand, birth rates might decrease due to the higher opportunity cost of time after disasters. People often perceive their time as more valuable when devoted to rebuilding and renovating, or they may face financial losses and prefer to work more to save for childbearing in the future. Another factor that could lead to a decrease in birth rates is stress exposure. Experiencing extreme weather events during pregnancy can subject mothers to high levels of stress, resulting in worse birth outcomes and even lost pregnancies (Liu, Liu and Tseng 2015,Currie and Rossin-Slater 2013,Dunkel Schetter 2011).

I examine the impacts of the following types of natural disasters on birth rates: hurricanes, floods, tornadoes, severe storms, fires, severe ice storms, and snowstorms, for the period of 1989-2019. Given that the likelihood of various types of disasters differ among geographic regions, my initial step involves quantifying the propensity for each type of natural disaster to occur in every county. Subsequently, I trim the sample based on this propensity to ensure comparability. I leverage the exact timing of natural disaster start date as declared in FEMA, and compare counties recently experienced an incident with those have not yet experienced such an event. The timing and type of natural disasters are obtained from FEMA disaster declaration summaries. County-by-year-by-month level birth rates are computed using the restricted use Natality Files from the National Center for Health Statistics (NCHS), and county population data from county-level population estimates from National Cancer Institute Surveillance, Epidemiology, and End Results Program (SEER).

My findings suggest that hurricanes, floods, and fires lead to a small decline in birth rates within the 12-month period after the incident start date. Specifically, hurricanes lead to a 8.5-percentage-point decrease in birth rates, floods lead to a 8.6-percentage-point decline, and severe storms lead to 7.8-percentage-point decrease. Fires have slightly larger impacts on birth rate: they lead to a 9.3-percentage-point decline. While hurricanes and floods trigger an immediate and temporary fertility response, effects of fires seem to be gradual and cumulative. Such effects are unlikely to be driven by out-migration after disasters, suggesting the decline in birth rate is attributed to individuals' family planning decisions. On the contrary, severe ice storms and snowstorms tend to increase birth rates by approximately 6 percentage points.

This paper contributes to the literature on the fertility effects of natural disasters. Instead of focusing on the effects of a one-time event of high severity and focusing on a localized area, I show that large-scale climate events of extensive geographic scope also lead to changes in fertility. Seltzer and Nobles (2017) show that after Hurricane Katrina, Black fertility fell and remained 4% below the expected values, while White fertility increased by 5% in New Orleans. Cohan and Cole (2002) find that following Hurricane Hugo, marriage, birth and divorce rates increase in counties declared disaster. In addition, there is a net increase of 41 births per 100,000 population in in South Carolina. Tong, Zotti and Hsia (2011) conclude that the crude birth rates decline from 13.1 per 1000 in the 3 years pre-disaster, to 12.2 following the flood in North Dakota.

This paper also relates to an expanding set of literature on the effects of natural disasters in general. Previous studies explore the effects of natural disasters on economic growth (Berlemann and Wenzel 2018, Tran, Wilson et al. 2020), mortgage market (Sastry 2022, Issler et al. 2020, Kousky, Palim and Pan 2020), and migration (Boustan et al. 2020, Sheldon and Zhan 2022).

The rest of the paper proceeds as follows: Section 2.2 summarizes multiple datasets used in the analysis, Section 2.3 describes the methodology, Section 2.4 discusses the results, and Section 2.5 concludes.

2.2 Data

In this paper, I use data from multiple sources, and link them by county FIPS codes because FEMA reports disaster declarations at the county level. These datasets include: natural disaster declaration data, county-level birth and population estimates, county local economic indicators, county geographic characteristics, and migration data from American Community Survey (ACS).

2.2.1 Natural Disaster Declaration Data

The Federal Emergency Management Agency (FEMA) started reporting the information of federally declared natural disasters since 1950s. These declarations are made by the President of the United States in response to requests from state governors when a natural or man-made disaster overwhelms the ability of the state and local governments to respond effectively. FEMA data provides information on the declaration date of a disaster, incident type of the disasters (hurricane, storm, etc), county or counties impacted by the disaster. When one incident impacts multiple counties, it will be recorded multiple times in the FEMA declaration summaries data.

I restrict the set of incidents to include only natural disasters, excluding incidents of the following categories: human cause, terrorist, biological, toxic substances, chemical, dam/levee break. Figure 2.1 plots the raw counts of reported natural disaster incidents (counties) between 1990 and 2019. There are a total of 36,295 federally declared natural disasters in the period, and the most common disasters are: severe storm, which has a raw count of 15,977 that represents 44.02% of all declarations, hurricane, with a raw count of 7,064, representing 19.46% of all disasters, and flood, with a raw count of 5,107, representing 14.07% of all disasters. Figure 2.2 shows the number of counties affected overtime. There are substantial variations in the number of declarations across years, and most of the variations are driven by the number of wildfires, storms, hurricanes, and floods reported in each year.

2.2.2 Birth Data and Population Estimates

I use birth data from National Vital Statistics System of National Center for Health Statistics (NCHS). I use the restricted Natality Files 1989-2019 to compute county-level birth rates.

The NCHS Natality Files report birth certificate information on date of birth, mother's county of residence, mother's demographic characteristics including age, marital status, and education. I first estimate the conception year and birth using the actual birth year and month, netting out the gestational length.[1] I then aggregate births by mother's county of residence and estimated conception year and month to compute county-by-month level number of total births. Counties in Virginia, Alaska and Hawaii are excluded from the analysis due to substantial county boundary changes.

I use county-level population estimates from National Cancer Institute Surveillance, Epidemiology, and End Results Program (SEER). These estimates are generated through a cooperative effort involving the U.S. Census Bureau, and the NCHS. This data is specifically designed for use in cancer surveillance and epidemiological research and is maintained by the National Cancer Institute (NCI).

SEER data provides county-level population estimates by gender, age and race since 1969. The primary purpose of this data is to provide accurate and up-to-date population estimates for the counties covered by the SEER program. These estimates are essential for calculating cancer incidence rates,

[1] Since the exact date of birth is not available in the dataset, I assume that all the birth occurs on the 15th of the month of birth.

conducting cancer research, and understanding the impact of cancer on specific geographic areas. For the period of 1990-2019, single-year-of-age county population estimates were produced by obtaining data from sources such as Woods & Poole and the Census Bureau, adjusting for specific states. [2] This data includes population figures for individuals aged one to eighty-four and is broken down by year (1990-2019), state and county, race (White, Black, Other), and sex (male, female). Proportions are calculated for each single year of age to the total population within specified age groups (e.g., 1-4, 5-9, etc.) by year, county, race and sex. The proportions are then applied to each age group by year, county, race, and sex, using the Woods & Poole and the Census Bureau population estimates.

I merge the aggregated county-by-month Vital Statistics data with the SEER county-level population estimates to compute county-level birth rates by conception month as follows:[3]

$$\text{Birth Rate}_{cmy} = \frac{\text{Total Birth}_{cmy} \times 1000 \times 12}{\text{Population}_{cmy}} \tag{2.1}$$

Birth Rate$_{cmy}$ is the birth rate in county c, conception month m, and year y, and is computed by the ratio of total births conceived in county c year y month m to county-level population in year y, and annualized by multiplying 12. In the heterogeneous analysis, birth rates are computed using county total birth and population by specific age and race categories.

Figure 2.3 plots the average birth rate for all counties, hurricane-prone, flood-prone, and fire-prone counties. The overall average birth rate is 12.95 per 1000 population per year. This graph suggests a similar downward-trend in birth rate in all four groups of counties. In addition, the birth rate gap between flood-prone counties and all counties widens from 1990-2000. Hurricane- and flood-prone counties seem to have a larger decline in birth rate after 2005.

2.2.3 County Characteristics Data

County geographic characteristics data is pooled from multiple sources. I define shoreline and watershed counties based on Decadal Demographic Trends (Coastal) by National Oceanic and Atmospheric Administration's (NOAA) Office of Coastal Management. Climate zone information is from the Inter-

[2] Adjustments include data in Hawaii and new counties in Alaska and Colorado, and then structure the data into consistent records. Adjustments were made to account for changes in geographic and demographic classifications, and final estimates were aggregated into broad race categories.

[3] By World Health Organization Indicator Metadata Registry, crude birth rate is defined as "The ratio between the number of live births in a population during a given year and the total mid-year population for the same year, usually multiplied by 1,000.".

national Energy Conservation Code (IECC) categorization: counties are classified into 8 climate zones based on average temperature and humidity. Natural amenity data is reported by US Department of Agriculture, the main variable, natural amenity scale, quantifies the physical attributes of a county area that make it an attractive place to live. It is determined based on several factors, including mild winter conditions, abundant winter sunshine, pleasant summer temperatures, low summer humidity, varied topography, and the presence of water bodies. These factors collectively represent the environmental qualities that are generally preferred by most people. I also obtain monthly weather data from County Mapping provided by National Centers for Environmental Information. The information includes average temperature, minimum temperature, maximum temperature, heating degree days, cooling degree days, precipitation, and humidity (Palmer Z Index) information. County coordinates information, county latitude and longitude, is from Simplemaps Interactive Maps and Data.

I use county economic information from Regional Economic Information System (REIS) local area economic measures 1989-2019, prepared by the Regional Economic Measurement division of the Bureau of Economic Analysis (BEA). I extract annual county-level data on population, per-capita income, employment and average wage. I also include poverty measure from the 1990 Census: Population by Poverty Status in 1989 provided by the US Census Bureau.

2.2.4 Migration Data

I obtain migration information from American Community Survey (ACS) 1-year estimates 2006-2019. ACS is an ongoing survey conducted by the U.S. Census Bureau, and it is also one of the largest surveys. It collects detailed demographic, social, economic, and housing information from a representative sample of households across the United States. Migration information is determined by survey respondents' current residence and residence one year ago.

2.3 Identification

2.3.1 Propensity Score Trimming

Directly comparing counties recently experienced natural disasters with counties without or not yet experienced such event may introduce bias in the estimates for the following reasons. First, specific regions may have a higher likelihood of encountering particular disasters (for instance, coastal areas are more prone to flooding and hurricanes), and thus the advent of specific type of disasters is not random across all counties. Second, individuals self-sort to different geographic locations, for example, risk-averse individual are more likely to sort into counties with lower probability of natural disasters. While this type of risk preference may in turn correlates with their family planning decisions.

Hence, I employ propensity score trimming to improve the comparability across counties. While specific regions may have a higher likelihood of encountering particular disasters, the occurrence of a disaster is somewhat unpredictable: the exact location and timing of the occurrence is plausibly random across counties within the trimmed sample. Individuals dwelling in these counties are also more likely to have similar risk preferences, and experienced comparable climate conditions that indirectly contributes to their migration and fertility decisions.

I estimate the following equation using logistic regression and then predict the propensity for each county to experience type j natural disaster:

$$Prob(Disaster_{cj} = 1) = F(\alpha_0 + \alpha_1 Location_c + \alpha_2 Climate_c + \alpha_3 Geographic_c) \tag{2.2}$$

where $j \in$ {Hurricane, Flood, Severe Storm, Fire, Severe Ice Storm, Snowstorm}. $Disaster_{ij}$ is a dummy indicator for whether county c experienced any natural disasters in category j during 1989-2019. $Location_c$ are set of location indicators including whether county c is a shoreline or watershed county, county longitudes and latitudes. $Climate_c$ are set of climate characteristics including average temperature, minimum and maximum temperature, cooling and heating degree days, average precipitation and humidity. $Geographic_c$ include land surface form topography code and percent of water area in county c.[4]

Figure 2.4 - 2.8 illustrate the propensity score and counts of incidents by incident type. As we can see, hurricane occurrences concentrate in the southeast coastal areas. Storms and floods are wide-spread and occurs more frequently than other types of disasters. Tornadoes happen more frequently in central US and around the area known as "Tornado Alley". More cold weather incidents happen in Northeast and the Upper Midwest, however, Southern states also declared these events when uncommon weather patterns lead to large economic impacts. Using the estimated propensity scores, I trim the data to

[4]Topography code is a categorical variable. However, the magnitude of the code increases with elevation, and thus I include it as a continuous variable.

include only a sample of counties with propensity scores between 0.1 and 0.9 for the analysis of each type of natural disasters.

2.3.2 Effects on Birth Rate

Using the trimmed sample, I explore the effects of different categories of natural disasters on birth rate by estimating the following difference-in-differences regression:

$$\text{Birth Rate}_{cmy} = \beta_0 + \beta_j DisasterDeclare_{jcmy} + X^C_{cmy} + X^E_{cy} + \delta_c + \lambda_{my} + \gamma_{cz,m} + \epsilon_{cmy} \tag{2.3}$$

where y_{cmy} is the birth rate in county c month m year y, β_0 is the intercept term, $DisasterDeclare_{jcmy}$ equals to 1 if county c declared type j disaster in year y month m. X^W_{cmy} controls for monthly county-level weather, and X^E_{cy} are economic and demographic characteristics including per-capita income, employment-to-population ratio, percent of female, percent of working-age population, percent of Black, and county natural amenity scale. δ_c are dummy variables indicating each county, which controls for county time-invariant characteristics. λ_{my} are year-by-month fixed effects which controls for the common time trend. $\gamma_{cz,m}$ are month-by-climate zone fixed effects to control for seasonality in births. This regression is weighted by county population.

The coefficients of interests is β_j, which measures the short-run effects of category j natural disaster on birth rate within 12 months after the incident start date. By comparing counties recently experienced a natural disaster with similar counties that have not yet experienced such an event, these coefficients capture the causal effects of natural disasters on fertility decisions aggregated at county level.

To test for the parallel trends on birth rate before natural disasters, I estimate the following event study regression around a 12-month window before and after each disaster declaration. In my event study analysis, I only consider natural disaster incidents with event windows that do not overlap with any other event windows of the same type of disasters occurring in the same county. Natural disasters with overlapping event windows are excluded from this analysis. This approach allows me to establish "disaster-free" control periods, ensuring that they are not influenced by any prior disasters.

$$\text{Birth Rate}_{cmy} = \beta_0 + \sum_{k=-12}^{k=12} \beta^k_j D^k_{jcmy} + X^W_{cmy} + X^E_{cy} + \delta_c + \lambda_{my} + \gamma_{cz,m} + \epsilon_{cmy} \tag{2.4}$$

where D^k_{jcmy} equals to 1 if month m year y is k months relative to disaster j declaration month. If parallel trends assumption hold, and the pre-treatment trends are parallel between the treatment and control group, the coefficients β_j^k are insignificant from zero for $k < 0$.

2.3.3 Effects on Migration

I use ACS 2006-2019 to estimate the effects of natural disasters on migration. Treatment is assigned based on the reported residence one year ago, and out-migration equals to 1 if current residence is in a different county or Public Use Microdata Area (PUMA) from residence one year ago. The treatment group is the respondents who reside in a county or PUMA, that had a disaster declaration in the previous year. The control group is the respondents residing in counties or PUMAs that have not had disaster declarations in the previous year.

$$\text{Migrate}_{icy} = \alpha_0 + \alpha_{1j} DisasterDeclare_{jc,y-1} + X_{icy} + \delta_c + \lambda_y + \epsilon_{icmy} \tag{2.5}$$

Migrate_{icy} equals to 1 if respondent i residing in county or PUMA c in the previous year, indicate to currently reside in another county or PUMA in the survey year. α_0 is the intercept term, $DisasterDeclare_{jc,y-1}$ equals to 1 if county or PUMA c declared type j disaster in the previous year. X_{icy} is a set of individual controls including age, race education, and household income, δ_c and λ_y are county or PUMA and year fixed effects. This regression is weighted by ACS person weight. α_{1j} is the coefficient of interest, which captures the causal effect of type j natural disaster on individuals' decision to migrate out of their county or PUMA of residence.

Alternatively, I also explore the dynamic effects of natural disasters on migration by estimating the following event-study regression:

$$\text{Migrate}_{icy} = \alpha_0 + \sum_{k=-2}^{k=2} \alpha_{1j}^k D_{jc,y-1}^k + X_{icy} + \delta_c + \lambda_y + \epsilon_{icmy} \tag{2.6}$$

The event-study specification includes similar terms as in Equation 2.5, except that $D_{jc,y-1}^k$ equals to 1 if year $y-1$ (year prior to every ACS survey year) is k years relative to disaster j declaration in county or PUMA c. Note that ACS do not intend to follow the same respondents across years, and the pooled sample is not a panel dataset at individual level, but a repeated cross-sectional dataset at county or PUMA level. Thus, respondents residing in county or PUMA c in year $y-3$, $y-2$, y and $y+1$ might not have experienced the disaster that happen in year $y-1$. Hence, α_{1j}^k captures the dynamic effects of disaster type j on migration conditional on residing in county or PUMA c, k years relative to disaster declaration. Figure B.1-B.2 plot the dynamic effects of natural disasters on out-migration, the results are consistent with the estimated coefficients from Equation 2.5.

2.4 Results

2.4.1 Effects on Birth Rate

Figure 2.11 and 2.12 plot the dynamic effects from Equation 2.4, and the difference-in-differences coefficients from Equation 2.3, of natural disasters on birth rates by type. Most of the natural disasters: hurricanes, floods, fires, tornadoes, and severe storms have negative effects on birth rate. While severe ice storms and snowstorms have positive impacts.

Figure 2.11a and 2.11b show that the effects of hurricane and flood are negative and are of similar magnitudes: hurricane leads to a 8.5-percentage-point decrease in birth rate, and flood leads to a 0.086-percentage-point decrease, within the 12-month period post incident start date. We can see that birth rates respond immediate to hurricane and flood, with a discontinuous drop right after disaster declaration. However, birth rates bounce back relatively quickly in 8 to 10 months after declaration. Figure 2.11c plots the dynamic effects of fire on birth rate. The overall effect of fire is slightly larger: a 9.3-percentage-point decrease in birth rate within the 12-month period post incident start date. In addition, as compared to hurricane and flood, the effects of fire seem to be gradual.

Tornado has a negative effect on birth rate: a 7.5-percentage-point decrease. The estimate is imprecise, but we can see a clear trend that birth rates have leveled-down in the post-tornado periods. Severe storm leads to a 7.8-percentage-point decline in birth rate. The pre-treatment coefficients suggest that counties that have declared severe storm tend to have relatively lower birth rates as compared to the control counties. However, I do not find any evidence that the decline in birth rates after severe storm declaration is driven by the pre-treatment difference in levels. Instead, the reduction in birth rates is immediate and twice as large as the pre-treatment difference.

Figure 2.12c and 2.12d plots the event-study estimates of severe ice storm and snowstorm on birth rate. Unlike the aforementioned natural disasters, severe ice storm and snowstorm seem to trigger a slight increase in births in the 12-month period after incident start date. A severe ice storm leads to a gradual increase in birth rates, peaking at 3% in the fifth month after the declaration month. However, the overall birth rate trend resembles the pre-treatment periods, with a slight increase for each month. Overall, a severe storm leads to a 5.8-percentage-point increase in birth rate. A snowstorm leads to a jump in birth rate right after the month of declaration, the overall impact within the 12-month period post-declaration is 6.2 percentage point. However, the coefficient is only significant at 10% level.

The effects of hurricane, flood and severe storm seem to be immediate but temporary, phasing out around 8 to 10 months after the incident start date, while the effects of fire seem to be gradual. This is reasonable since fire tend to last longer: as reported in FEMA, the average duration of a fire is 118 days (4 months), while the average durations for hurricane, flood and severe storm, are 20, 43, and 25 days, respectively. In addition, fire tend to have cumulative effects. Studies suggest that exposure to wildfires and poor air quality is associated with total motile sperm count, and lower blastocyst yield (Kornfield et al. 2024, Rubin et al. 2021).

2.4.2 Effects on Migration

Table 2.3 shows the regression results for Equation 2.5. According to Panel A, where all counties and PUMAs are included, individuals are slightly more likely to migrate after being exposed to tornadoes and severe ice storms. For all other disaster types, the estimates are imprecise, suggesting small or even negative effects on migration within one year. Panel B shows similar results for hurricane, flood, fire, and severe ice storm. Compared to Panel A, tornado and severe storm lead to larger increase in out-migration in counties that can be matched one-to-one to PUMAs. However, due to data limitation, it is unclear whether this result applies to counties that are not included in the analysis.[5] This is particularly questionable for severe storm, since in the county-level analysis, only 59 counties are included. Alternatively, Figure B.1-B.2 show consistent results: I do not find that individuals are more likely to migrate out of their county or PUMA of residence within one year after exposure to a natural disaster.

The small short-run effects of hurricane, flood, and fire on migration provide supporting evidence that their effects on birth rate are unlikely to be driven by migration. Although results suggest that a severe storm might lead to an increase in out-migration at the county level, it cannot fully explain the post-declaration changes in birth rates as presented in Figure 2.12b. If individuals migrate out

[5]The counties that can be matched to PUMAs one-to-one are those with population close to 100,000, since "PUMAs are non-overlapping, statistical geographic areas that partition each state or equivalent entity into geographic areas containing no fewer than 100,000 people each" (U.S. Census Bureau, Public Use Microdata Areas).

permanently, it is unlikely for us to see a bounce-back of birth rates in month 8 to 12 after severe storm declaration. On the contrary, it is possible that the decline in birth rates after a tornado is driven by out-migration, since the tornado have large impacts on out-migration, and birth rates decrease gradually without a fast recovery. For severe ice storm and snowstorm, since the effects are positive, out-migration is unlikely to be a concern.

This migration pattern is reasonable since relocation is costly, especially after hurricane, flood, and severe storm. Individuals and families are likely to have encountered financial losses, and studies suggest that property prices decline after hurricanes and floods (Morgan 2007, Ortega and Taşpınar 2018). In addition, households who apply to the FEMA buyout program often wait up to five years for approval (Sheldon and Zhan 2022).

2.4.3 Heterogeneity

To further understand the mechanism of the effects of disasters on birth rate, I first explore whether natural disasters have different effects across counties differ by disaster propensity and poverty level. Columns (2)-(3) of Table 2.4-2.5 report the difference-in-differences coefficients by disaster type, split by counties with high- and low-propensity of type-specific disaster exposure. Reduction in birth rates after hurricane, flood, and severe ice storm are driven by high-propensity counties. For other types of disasters, effects do not differ significantly between high- and low-propensity counties. A possible explanation is that the decline in property value following each hurricane and flood, is larger in hurricane- and flood-prone counties, and thus leading to more severe financial losses in these counties. Previous studies suggest that hurricanes and floods lead to significantly lower property value, and due to changes in the perceived risk of flooding, houses that are not directly damaged in the disaster also experienced similar decline in value. This suggests that people update their risk perception once they receive new disaster information (Ortega and Taşpınar 2018, Morgan 2007, Bin and Polasky 2004, Bin and Landry 2013).

Table 2.4-2.5 columns (4)-(5) report the difference-in-differences coefficients by counties of high- and low-poverty rate. We may notice that hurricanes, floods, and severe storms tend to reduce birth rates by a larger amount in relatively richer counties. This is surprising since, in theory, poorer counties are more vulnerable to financial losses due to natural disasters (Cutter, Boruff and Shirley 2012, Van Zandt et al. 2012). This finding suggests that the opportunity cost channel dominates, especially in the case of hurricanes, floods, and severe storms, richer households find that their time is more valuable spent on rebuilding and renovating (Evans, Hu and Zhao 2010). In addition, richer neighborhoods tend to renovate their properties more quickly, while poorer neighborhoods generally do not start renovation until 4 to 5 years later, when the recovery funds were distributed (Harwood 2023).

Next, I explore the heterogeneity across age and race. Table 2.6 and 2.7 report the difference-in-differences coefficients from Equation 2.3 by mothers' age and race, and across different disaster types. Columns (2)-(4) show that for all types of disasters, the effects are driven by age group 15-34. This is not surprising since this subpopulation is more active in fertility. In addition, it is likely that the younger age cohort tend to delay births after the exposure to a natural disaster.

Columns (4)-(5) report the coefficients by race. For most natural disasters that lead to decline in birth rates (including floods, fires, tornadoes), the effects are driven by White mothers; for those that lead to increase in birth rates, i.e., severe ice storms and snowstorms, we can see that the effects of Black mothers are slightly larger, however, the coefficients are not statistically significant. This is consistent with the opportunity cost channel, since on average, the black-white family income gap persists (MacDorman et al. 2016). It is interesting to notice that Black mothers are more vulnerable to hurricanes, and the decline in birth rates after exposure to hurricanes is much larger for Black mothers than White mothers. This pattern can be explained by the race composition in hurricane-prone locations, Table B.2 shows that percentage of Black population is significantly larger in hurricane exposure counties, and Black population is also hit the hardest by Hurricane Katrina (Seltzer and Nobles 2017).

2.5 Conclusion

In summary, this paper investigates the impact of natural disasters on birth rate, shedding light on contrasting the effects across different types of disasters. The findings stand out by exploring the short-term changes in birth rates after disasters. Despite the individually smaller impacts of each county-level disaster incident, collectively natural disasters leave a significant influence due to their higher occurrences across various geographic regions.

I explore the effects of high-frequency natural disasters: hurricane, flood, tornado, severe storm, fire, severe ice storm, and snowstorm, on birth rates from 1989-2019. To ensure the accuracy of my findings, I employ propensity trimming to include counties with a type-specific disaster propensity between 0.1 and 0.9, so that the treatment and control counties are more comparable. I then leverage the random timing of the occurrence of each natural disaster, to estimate the impacts on county-by-month birth rates. Most natural disasters, hurricanes, floods, fires, severe storms, lead to decrease in birth rates, though the magnitude of the decrease is small: below 0.1% relative to the mean. On the contrary, severe ice storms and snowstorms lead to small increase in birth rates.

However, due to data limitation, I am not able to identify the potential interactions between migration and fertility. It is unclear whether families, those have decided to give birth, move after exposure to disasters, and then give birth in another county; or exposure to disasters have changed their risk perceptions such that they decide not to give birth at all. It is interesting to study the overall impacts.

My findings reveal the complexity of the relationship between fertility and natural disasters. Multiple channels are in effect, with the opportunity cost channel dominating for hurricanes, floods, and severe storms. I find that richer counties seem to have experienced a larger decline in birth rate after these disasters, however, birth rates rebounded relatively quickly. People's risk perception of natural disasters might also influence their fertility decisions, through the channel of property value and financial losses.

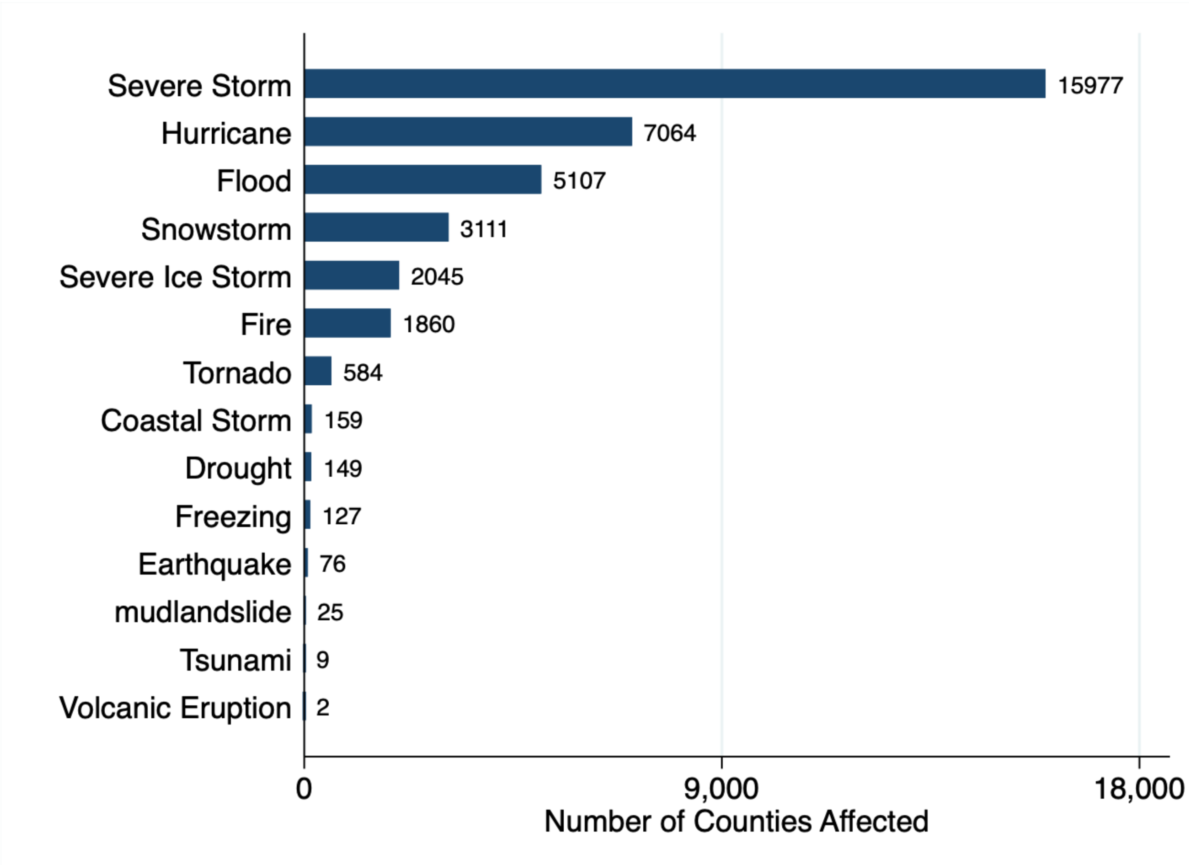


Figure 2.1 Number of Counties Affected by Incident Type, FEMA 1990-2019
Note: Raw counts of county declarations after excluding human-cause disasters: terrorist, biological, toxic substances. Type of incident defined by FEMA declaration summaries, variable: incidenttype.

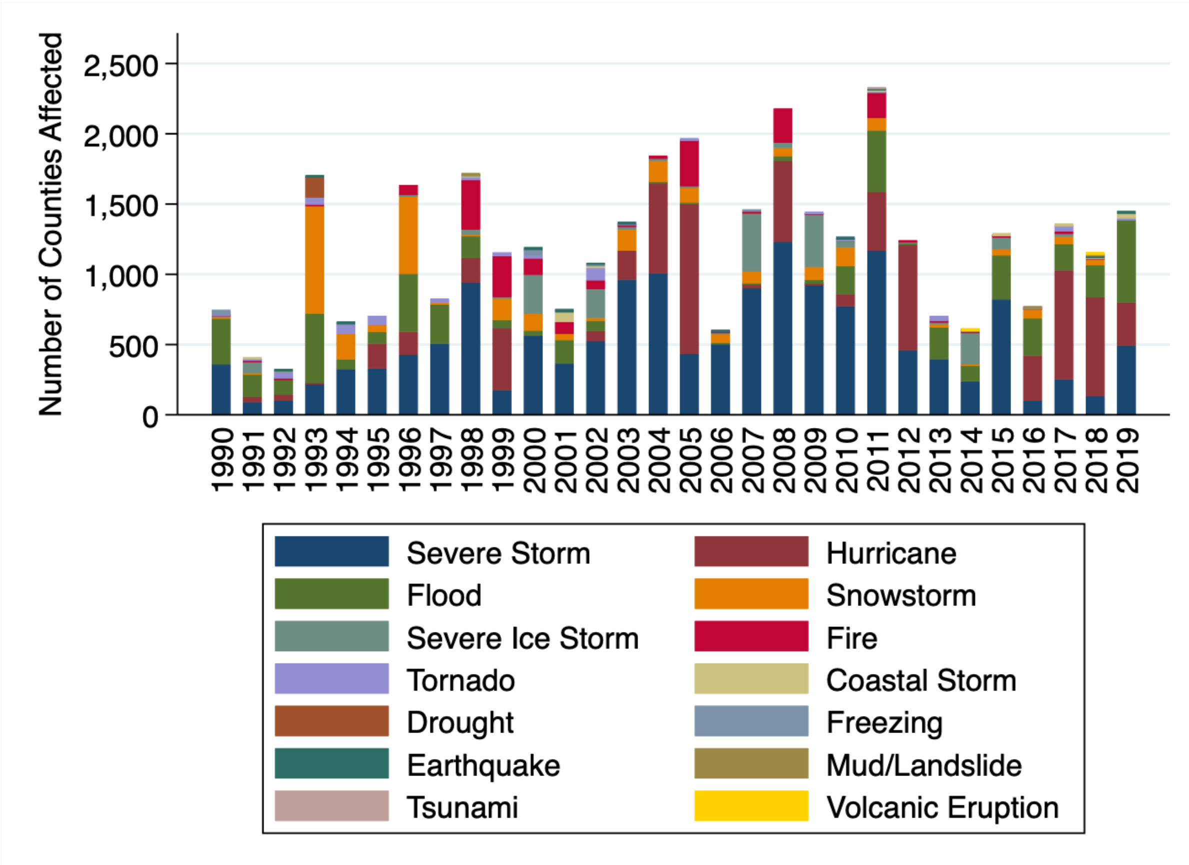


Figure 2.2 Number of Counties Affected by Incident Type Overtime, FEMA 1990-2019
Note: Raw counts of county declarations after excluding human-cause disasters: terrorist, biological, toxic substances. Type of incident defined by FEMA declaration summaries, variable: incidenttype. Year of incident is defined as the year when the incident is declared, variable: begindate.

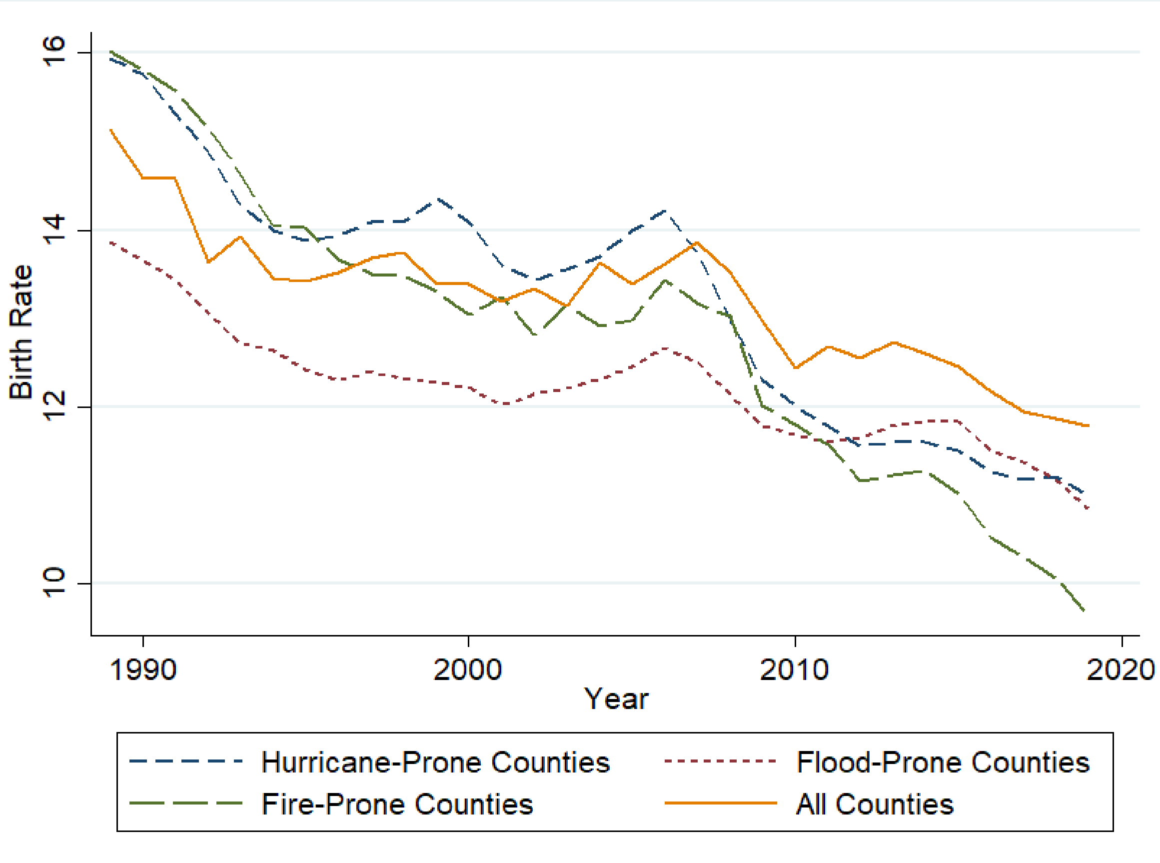
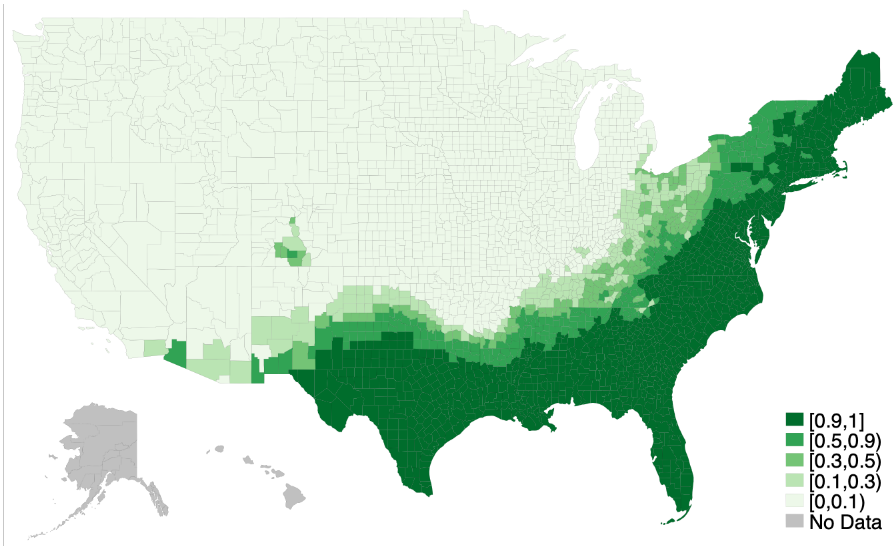
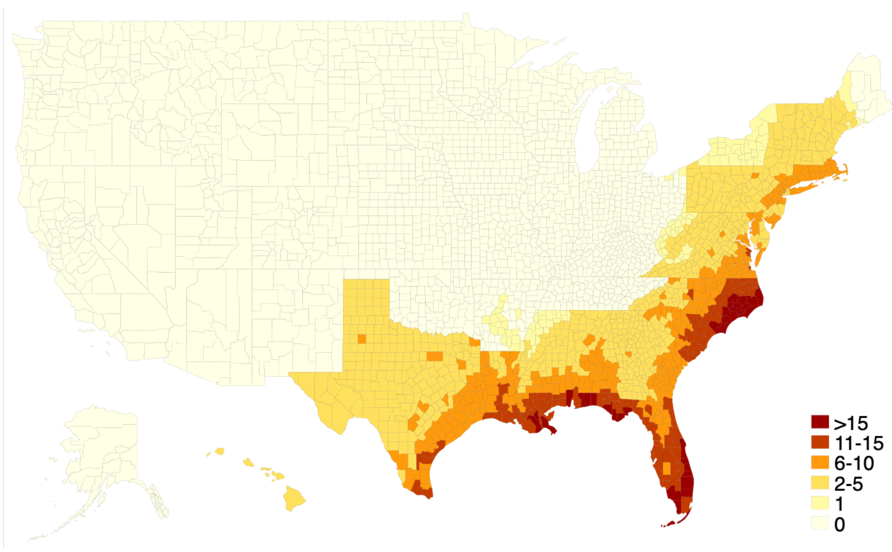


Figure 2.3 Birth Rates, 1990-2019
Note: Birth rate is computed by total births per 1000 population each year. Hurricane-prone, flood-prone, and fire-prone counties are counties with a propensity> 0.5 to have declared hurricane, flood, and fire in 1989-2020, respectively.

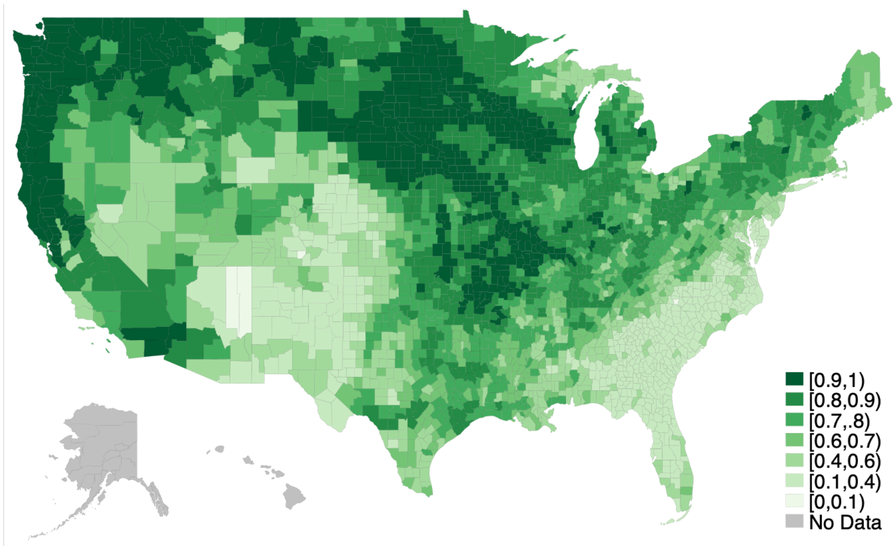


(a) Hurricane Propensity

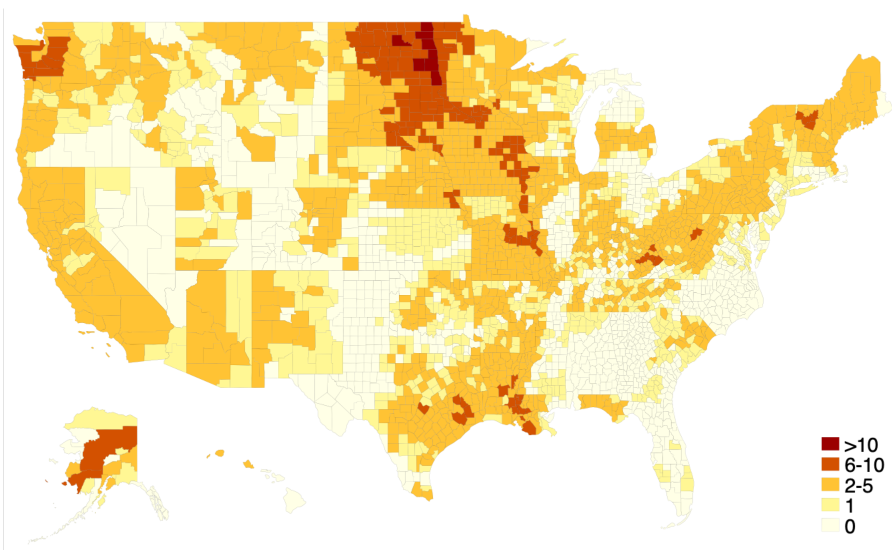


(b) Hurricane Counts of Incidents

Figure 2.4 Propensity Scores and Counts of Hurricane
Note: (a) plots county-level estimated propensity score for hurricanes. Propensity score estimated by Equation 2.2. Outcome variable is whether a county has experienced any hurricanes in the sample period, variables to estimate propensity scores include: county locations: whether counties are coastal (shoreline or watershed), county longitude and latitude, county climate information: average, minimum and maximum temperature, average precipitation, humidity score, geographic information: percent of water area, land surface form topography code. (b) plots the raw counts of hurricanes in each county in the sample period.

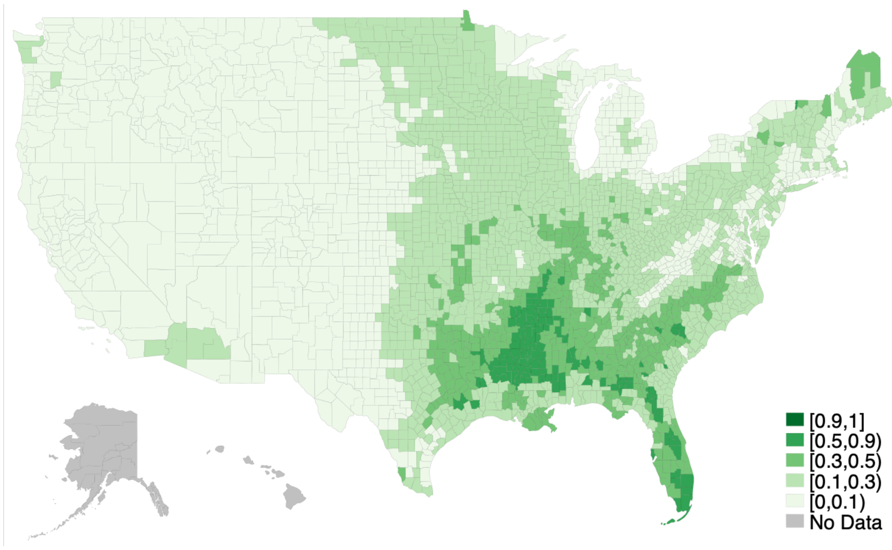


(a) Flood Propensity

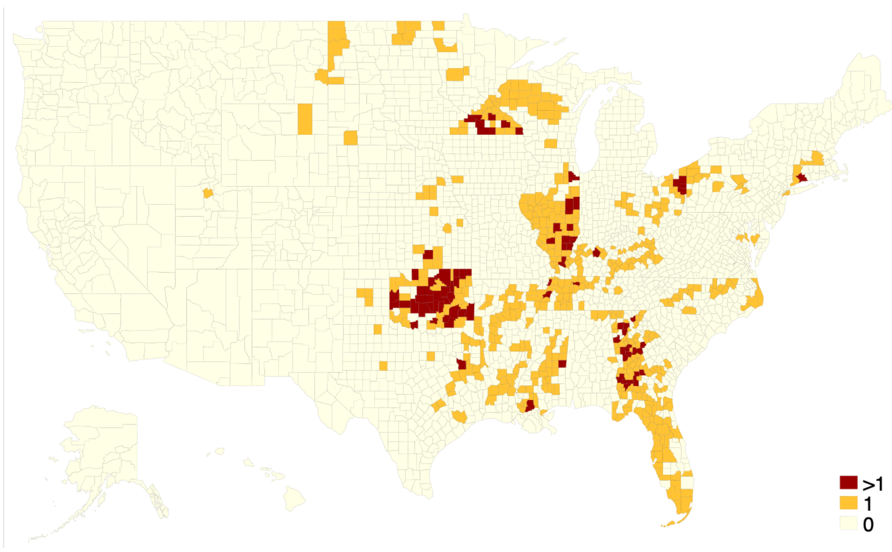


(b) Flood Counts of Incidents

Figure 2.5 Propensity Scores and Counts of Flood
Note: (a) plots county-level estimated propensity score for floods. Propensity score estimated by Equation 2.2. Outcome variable is whether a county has experienced any floods in the sample period, variables to estimate propensity scores include: county locations: whether counties are coastal (shoreline or watershed), county longitude and latitude, county climate information: average, minimum and maximum temperature, average precipitation, humidity score, geographic information: percent of water area, land surface form topography code. (b) plots the raw counts of storms & floods in each county in the sample period.

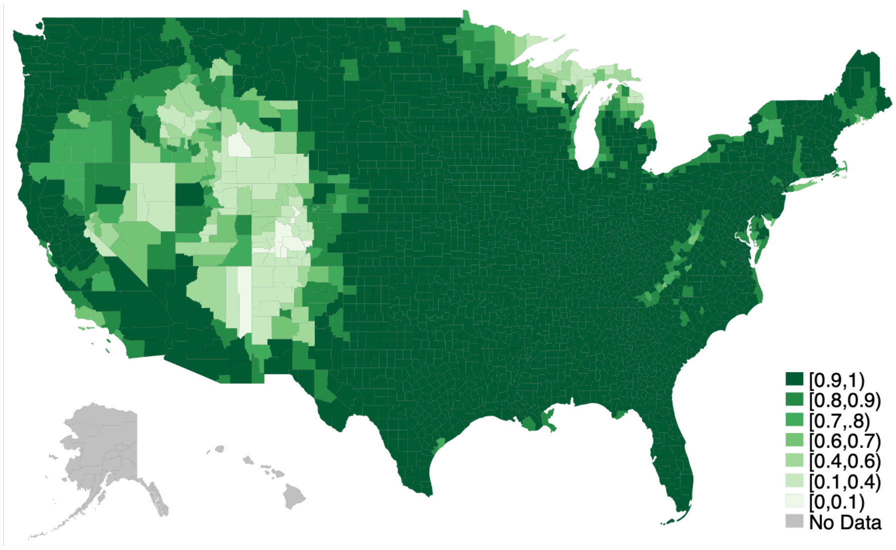


(a) Tornado Propensity

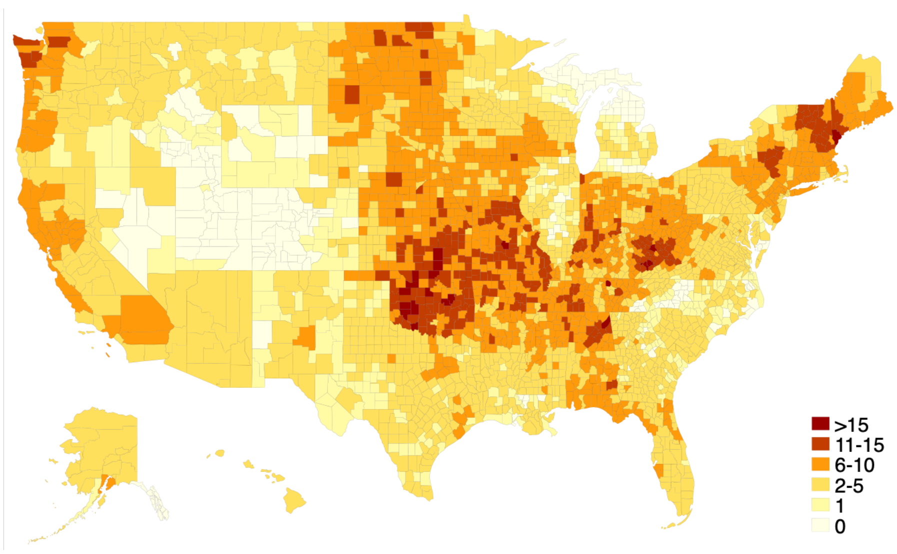


(b) Tornado Counts of Incidents

Figure 2.6 Propensity Scores and Counts of Tornado
Note: (a) plots county-level estimated propensity score for tornadoes. Propensity score estimated by Equation 2.2. Outcome variable is whether a county has experienced any tornadoes in the sample period, variables to estimate propensity scores include: county locations: whether counties are coastal (shoreline or watershed), county longitude and latitude, county climate information: average, minimum and maximum temperature, average precipitation, humidity score, geographic information: percent of water area, land surface form topography code. (b) plots the raw counts of tornadoes in each county in the sample period.

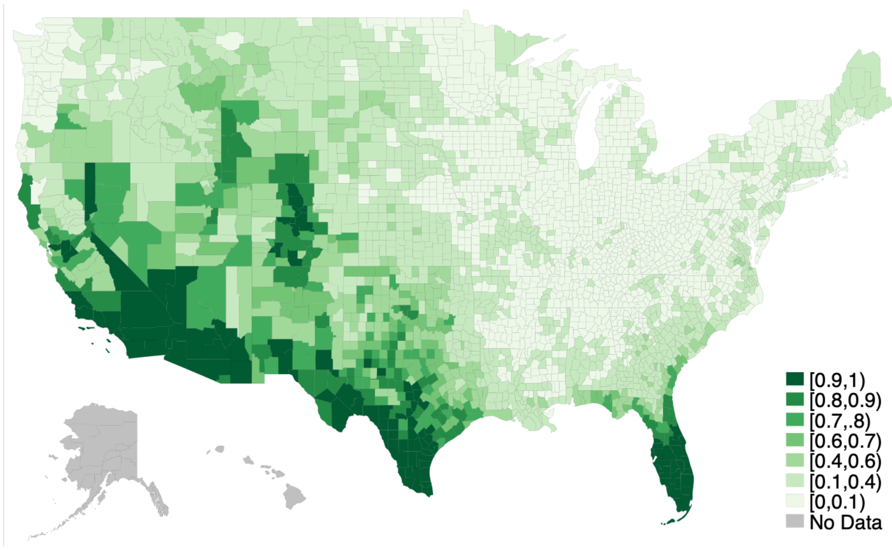


(a) Severe Storm Propensity

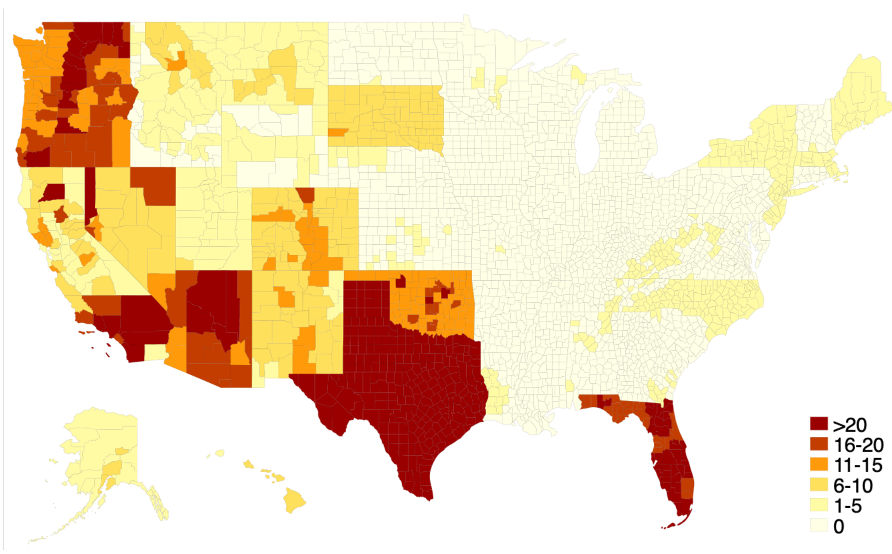


(b) Severe Storm Counts of Incidents

Figure 2.7 Propensity Scores and Counts of Severe Storm
Note: (a) plots county-level estimated propensity score for severe storms. Propensity score estimated by Equation 2.2. Outcome variable is whether a county has experienced any severe storm incidents in the sample period, variables to estimate propensity scores include: county locations: whether counties are coastal (shoreline or watershed), county longitude and latitude, county climate information: average, minimum and maximum temperature, average precipitation, humidity score, geographic information: percent of water area, land surface form topography code. (b) plots the raw counts of cold weather incidents in each county in the sample period.

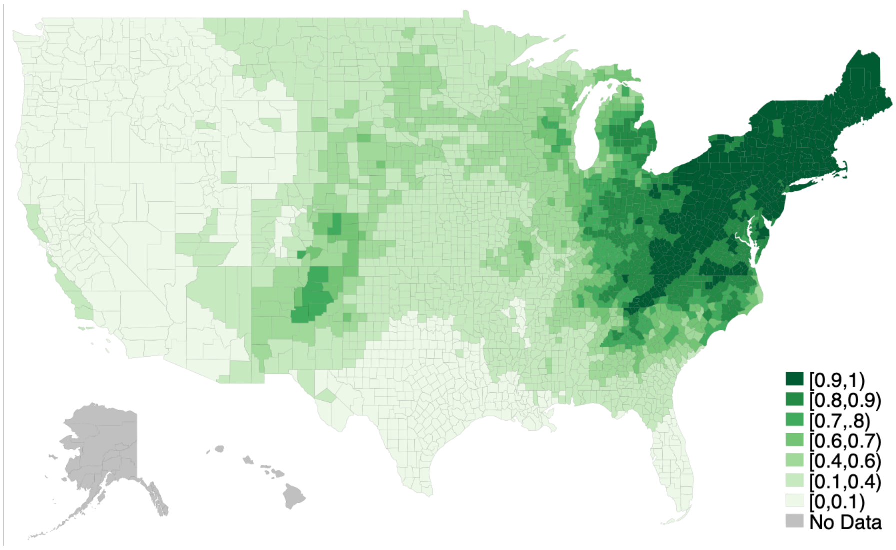


(a) Fire Propensity

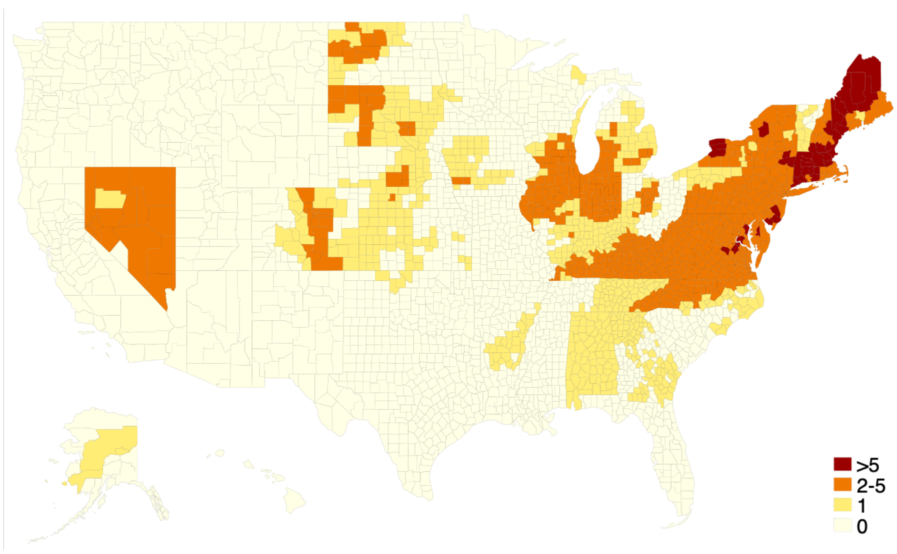


(b) Fire Counts of Incidents

Figure 2.8 Propensity Scores and Counts of Fire
Note: (a) plots county-level estimated propensity score for wildfires. Propensity score estimated by Equation 2.2. Outcome variable is whether a county has experienced any severe storm incidents in the sample period, variables to estimate propensity scores include: county locations: whether counties are coastal (shoreline or watershed), county longitude and latitude, county climate information: average, minimum and maximum temperature, average precipitation, humidity score, geographic information: percent of water area, land surface form topography code. (b) plots the raw counts of cold weather incidents in each county in the sample period.

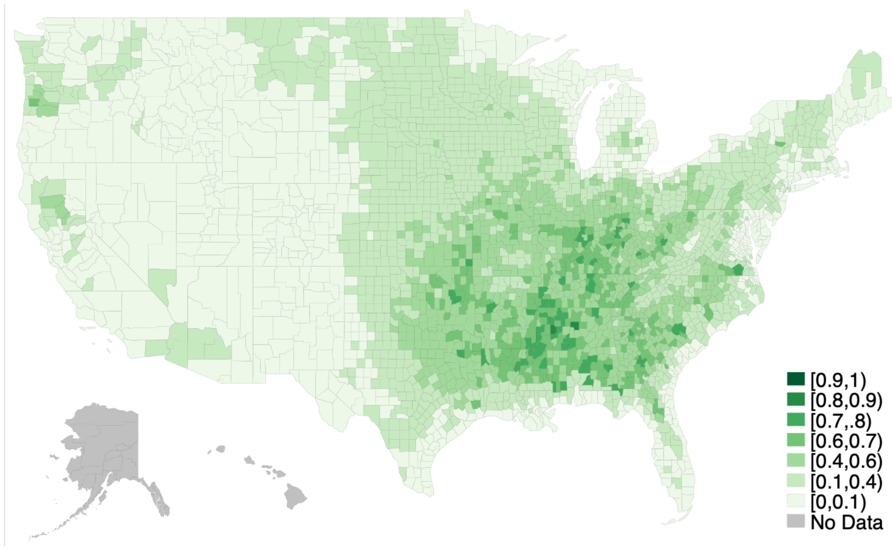


(a) Snowstorm Propensity

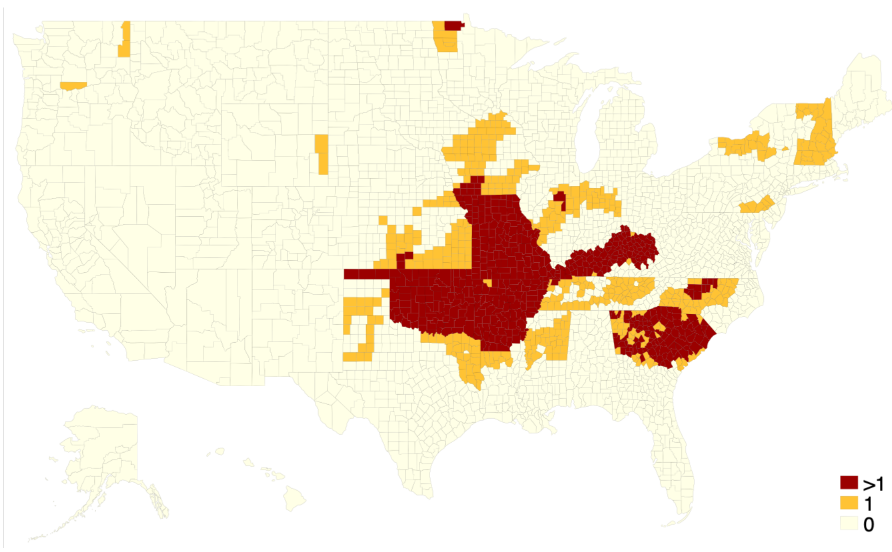


(b) Snowstorm Counts of Incidents

Figure 2.9 Propensity Scores and Counts of Snowstorm
Note: (a) plots county-level estimated propensity score for snowstorms. Propensity score estimated by Equation 2.2. Outcome variable is whether a county has experienced any severe storm incidents in the sample period, variables to estimate propensity scores include: county locations: whether counties are coastal (shoreline or watershed), county longitude and latitude, county climate information: average, minimum and maximum temperature, average precipitation, humidity score, geographic information: percent of water area, land surface form topography code. (b) plots the raw counts of cold weather incidents in each county in the sample period.



(a) Severe Icestorm Propensity



(b) Severe Icestorm Counts of Incidents

Figure 2.10 Propensity Scores and Counts of Severe Icestorm
Note: (a) plots county-level estimated propensity score for severe ice storms. Propensity score estimated by Equation 2.2. Outcome variable is whether a county has experienced any severe storm incidents in the sample period, variables to estimate propensity scores include: county locations: whether counties are coastal (shoreline or watershed), county longitude and latitude, county climate information: average, minimum and maximum temperature, average precipitation, humidity score, geographic information: percent of water area, land surface form topography code. (b) plots the raw counts of cold weather incidents in each county in the sample period.

Table 2.1 Summary Statistics for All Counties and Propensity Trimmed Samples for Hurricane, Flood, Fire Analysis

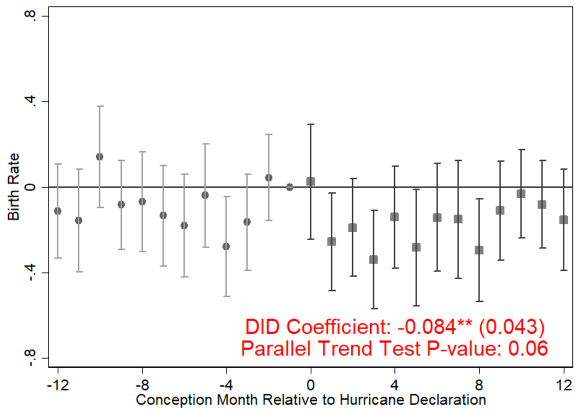
	(1) All Counties	(2) Hurricane	(3) Flood	(4) Fire
Outcome Variables				
Birth Rate	12.549	12.417	12.607	12.843
	(4.716)	(4.018)	(4.648)	(5.283)
Birth Rate, Black	13.383	12.640	13.216	13.333
	(124.958)	(102.519)	(111.610)	(125.842)
Birth Rate White	11.850	11.843	11.907	12.016
	(5.072)	(4.397)	(5.030)	(5.636)
Birth Rate, Age 15-34	44.300	43.678	44.118	45.289
	(17.964)	(15.008)	(17.386)	(20.153)
Birth Rate, Age 35-49	6.054	5.075	5.921	6.231
	(6.631)	(4.806)	(6.354)	(7.588)
Demographic Controls				
Pct Black Population	0.088	0.084	0.104	0.105
	(0.144)	(0.130)	(0.153)	(0.157)
Pct White Population	0.882	0.900	0.871	0.855
	(0.155)	(0.131)	(0.159)	(0.169)
Pct Female	0.503	0.506	0.504	0.501
	(0.020)	(0.018)	(0.021)	(0.023)
Pct Age 15-49	0.460	0.466	0.463	0.458
	(0.055)	(0.047)	(0.054)	(0.059)
Per-capita Income	28647.326	26353.686	28454.480	28848.916
	(12303.349)	(9844.974)	(12285.119)	(13120.417)
Employment/Population	0.510	0.467	0.504	0.525
	(0.157)	(0.125)	(0.162)	(0.174)
Weather Controls				
Cooling Degree Days	105.317	104.290	113.329	117.288
	(157.152)	(153.500)	(163.423)	(169.458)
Heating Degree Days	413.266	377.054	387.538	388.787
	(425.900)	(377.389)	(409.601)	(412.128)
Precipitation	3.286	3.812	3.346	2.945
	(2.474)	(2.277)	(2.397)	(2.479)
Max Temperature	65.903	66.986	67.093	67.684
	(18.507)	(16.986)	(18.061)	(18.194)
Min Temperature	43.640	44.875	44.675	44.265
	(17.160)	(15.573)	(16.932)	(17.266)
Average Temperature	54.775	55.934	55.887	55.978
	(17.716)	(16.167)	(17.376)	(17.592)
N	1106700	228780	913260	534936

Note: This table summarizes outcome and control variables included in Equation 2.3 and 2.4. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. Column (2)-(4) summarize the propensity trimmed sample for the following 4 types of disasters: hurricanes, floods, and fires. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. All statistics are reported for the period 1989-2019.

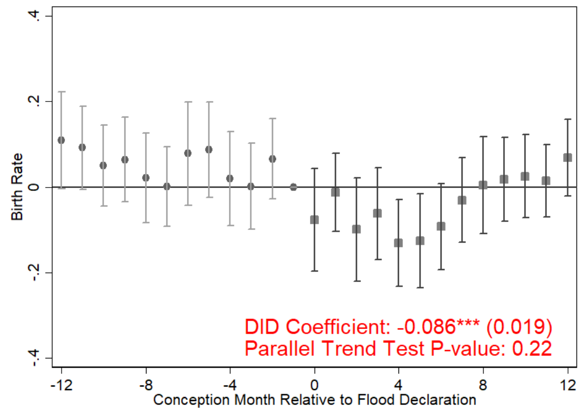
Table 2.2 Summary Statistics for Propensity Trimmed Sample for Tornado, Severe Storm, Severe Ice Storm and Snowstorm Analysis

	(1) Tornado	(2) Severe Storm	(3) Severe Ice Storm	(4) Snowstorm
Outcome Variables				
Birth Rate	12.530	12.241	12.508	12.587
	(4.053)	(5.066)	(4.489)	(4.649)
Birth Rate, Black	13.938	12.612	13.544	13.710
	(116.778)	(163.986)	(123.814)	(131.707)
Birth Rate White	11.761	11.752	11.765	11.801
	(4.486)	(5.390)	(4.866)	(5.027)
Birth Rate, Age 15-34	44.172	43.164	44.452	44.831
	(15.032)	(18.015)	(17.298)	(17.832)
Birth Rate, Age 35-49	5.643	6.962	5.676	5.785
	(5.194)	(6.880)	(6.251)	(6.597)
Demographic Controls				
Pct Black Population	0.115	0.030	0.100	0.099
	(0.161)	(0.058)	(0.155)	(0.158)
Pct White Population	0.863	0.923	0.876	0.873
	(0.165)	(0.108)	(0.163)	(0.170)
Pct Female	0.506	0.497	0.505	0.504
	(0.020)	(0.021)	(0.020)	(0.019)
Pct Age 15-49	0.462	0.455	0.460	0.458
	(0.053)	(0.062)	(0.054)	(0.054)
Per-capita Income	27800.867	30209.744	27889.795	28082.191
	(11179.126)	(14605.379)	(11343.433)	(11442.121)
Employment/Population	0.491	0.553	0.500	0.507
	(0.138)	(0.226)	(0.138)	(0.142)
Weather Controls				
Cooling Degree Days	123.757	41.931	113.640	102.736
	(167.472)	(87.978)	(160.480)	(149.037)
Heating Degree Days	370.304	574.552	390.537	423.583
	(412.146)	(465.520)	(414.710)	(435.547)
Precipitation	3.711	2.325	3.526	3.292
	(2.445)	(1.927)	(2.460)	(2.358)
Max Temperature	67.610	58.942	66.835	65.532
	(18.214)	(18.513)	(18.238)	(18.626)
Min Temperature	45.970	35.825	44.747	43.154
	(17.105)	(16.200)	(16.933)	(17.366)
Average Temperature	56.794	47.386	55.795	54.346
	(17.585)	(17.172)	(17.496)	(17.890)
N	762600	153636	822120	777480

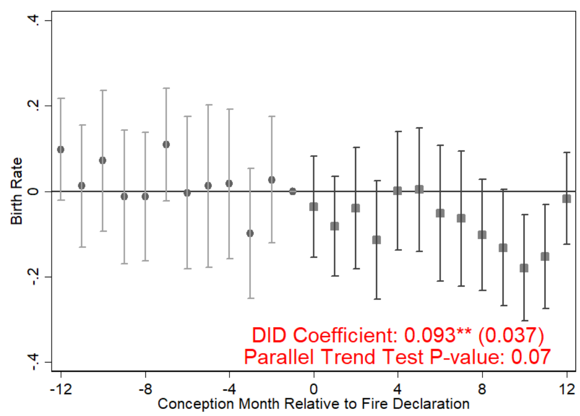
Note: This table summarizes outcome and control variables included in Equation 2.3 and 2.4. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. Column (2)-(4) summarize the propensity trimmed sample for the following 4 types of disasters: tornadoes, severe storms, ice storms, and snowstorms. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. All statistics are reported for the period 1989-2019.



(a) Hurricane

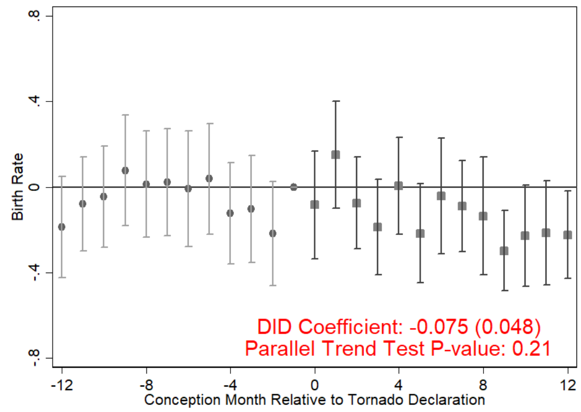


(b) Flood

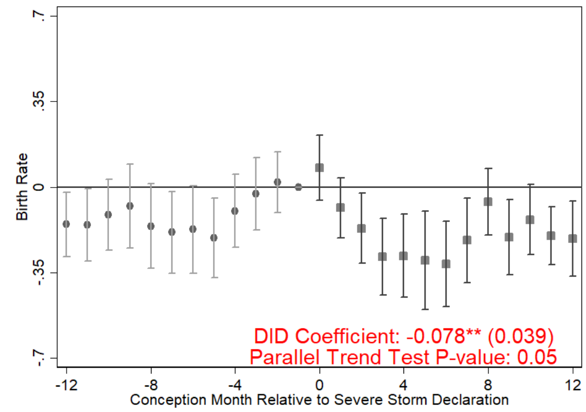


(c) Fire

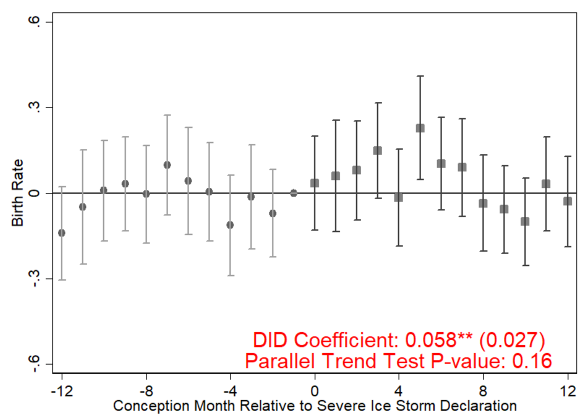
Figure 2.11 Effects of Hurricanes, Floods, and Fires on Birth Rate
Note: Figure plots the estimated coefficients from Equation 2.3 for $j = \{\text{Hurricane, Flood, Fire}\}$, on the propensity trimmed sample with type-specific disaster propensity between 0.1 and 0.9. Outcome variable is birth rate. Each subfigure represents the estimates from a separate regression for each disaster type. Control variables are: county monthly average, minimum and maximum temperature, cooling and heating degree days, precipitation, humidity (Palmer Z Index), county percent of female, employment-to-population ratio, per-capita income and average wages. County, year-by-month, and month-by-climate zone fixed effects are included. Standard errors are clustered at county level.



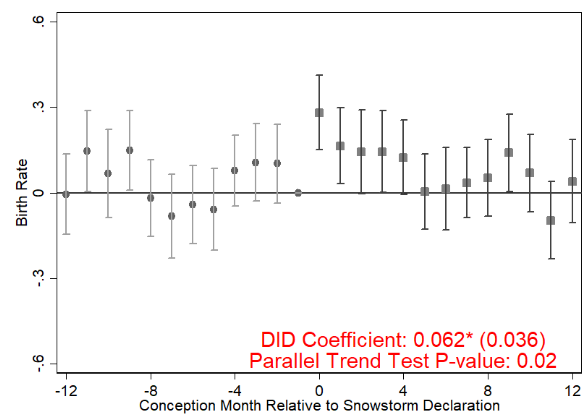
(a) Tornado



(b) Severe Storm



(c) Severe Icestorm



(d) Snowstorm

Figure 2.12 Effects of Tornadoes, Severe Storms, Severe Ice Storms, and Snowstorms on Birth Rate

Note: Figure plots the estimated coefficients from Equation 2.3 for j = {Tornado, Severe Storm, Severe Ice Storm, Snowstorm}, on the propensity trimmed sample with type-specific disaster propensity between 0.1 and 0.9. Outcome variable is birth rate. Each subfigure represents the estimates from a separate regression for each disaster type. Control variables are: county monthly average, minimum and maximum temperature, cooling and heating degree days, precipitation, humidity (Palmer Z Index), county percent of female, employment-to-population ratio, per-capita income and average wages. County, year-by-month, and month-by-climate zone fixed effects are included. Standard errors are clustered at county level.

Table 2.3 Effects Natural Disasters on Out-Migration

	(1) Hurricane	(2) Flood	(3) Fire	(4) Tornado	(5) Severe Storm	(6) Severe Ice Storm	(7) Snowstorm
Panel A: All Counties or PUMAs							
Declaration Previous Year	-0.0044*	-0.0028	-0.0069*	0.0071*	0.0036	0.0041**	-0.0007
	(0.0024)	(0.0017)	(0.0038)	(0.0040)	(0.0046)	(0.0016)	(0.0046)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County or PUMA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num Counties or PUMAs	199	903	338	766	93	695	660
N	3465551	20440302	7936331	18665406	1964822	14237636	12893636
Mean	0.0623	0.0650	0.0680	0.0661	0.0637	0.0659	0.0680
Panel B: Only Counties							
Declaration Previous Year	-0.0050**	-0.0004	-0.0080*	0.0307***	0.0093**	0.0042**	(na)
	(0.0021)	(0.0015)	(0.0044)	(0.0067)	(0.0042)	(0.0019)	(na)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num Counties	68	378	181	287	59	245	238
N	1871318	12875800	6098023	10546579	1513066	7717403	6163993
Mean	0.0642	0.0658	0.0678	0.0672	0.0622	0.0678	0.0695

Note: Each column within each panel represents a separate regression of 2.5 for a specific type of natural disasters. For each regression, counties or PUMAs included in the analysis are those with a propensity of specific type of disasters between 0.1 and 0.9 (or with the minimum and maximum propensity between 0.1 and 0.9 for PUMAs that consist of multiple counties). The outcome variable is whether respondent migrate out from his/her county/PUMA residence in the previous year. Control variables are: age, race, education, and household income. Panel A include all counties or PUMAs in the analysis, Panel B only include counties that can be matched to PUMAs one-to-one. County and year fixed effects are included. The regressions are weighted by ACS person weights. Standard errors are clustered at county level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 2.4 Heterogeneity by County Disaster Propensity and Poverty: Effects of Hurricanes, Floods, and Fires

	Baseline	By Propensity		By Poverty	
	(1)	(2) High	(3) Low	(4) High	(5) Low
Hurricane					
Declaration	-0.085**	-0.179**	0.013	-0.043	-0.161
	(0.043)	(0.072)	(0.048)	(0.062)	(0.098)
N	133667	24350	109317	91588	41399
Mean	13.29	12.81	13.37	13.75	12.92
Flood					
Declaration	-0.086***	-0.092***	0.002	-0.076**	-0.107***
	(0.019)	(0.023)	(0.062)	(0.037)	(0.026)
N	385353	235586	149767	201073	184280
Mean	13.70	13.78	13.54	14.61	13.25
Fire					
Declaration	-0.093**	-0.107*	-0.072*	-0.150**	-0.056**
	(0.037)	(0.057)	(0.039)	(0.070)	(0.027)
N	491376	80564	410812	261466	229910
Mean	13.40	14.13	13.28	14.08	13.08
Control	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Year-by-Month FE	Yes	Yes	Yes	Yes	Yes
Month-by-Climate-Zone FE	Yes	Yes	Yes	Yes	Yes

Note: Each column within each panel represents a separate regression of 2.3 for a specific type of natural disasters, by county disaster propensity and poverty level. Samples are split by type-specific disaster propensity: high-propensity counties consist of counties with disaster propensity>0.5, and low-propensity counties consist of counties with disaster propensity≤ 0.5. Counties are also ranked by poverty rate reported in the 1990 Census (Population by Poverty Status in 1989), high-poverty counties consist of counties with poverty rate above medium, and low-poverty counties consist of counties with poverty rate below medium. For each regression, counties included in the analysis are those with a propensity of specific type of disasters between 0.1 and 0.9. The outcome variable is birth rate. Control variables are: county monthly average, minimum and maximum temperature, cooling and heating degree days, precipitation, humidity (Palmer Z Index), county percent of female, employment-to-population ratio, per-capita income and average wages. County, year-by-month, and month-by-climate zone fixed effects are included. Standard errors are clustered at county level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 2.5 Heterogeneity by County Disaster Propensity and Poverty:

Effects of Tornadoes, Severe Storms, Severe Ice Storms, and Snowstorms

	Baseline	By Propensity		By Poverty	
	(1)	(2) High	(3) Low	(4) High	(5) Low
Tornado					
Declaration	-0.075	0.078	-0.085*	-0.076	-0.061
	(0.048)	(0.206)	(0.047)	(0.073)	(0.063)
N	564235	32370	531865	299809	264426
Mean	13.42	13.62	13.41	13.95	13.16
Severe Storm					
Declaration	-0.078**	-0.072*	-0.063	0.118	-0.095**
	(0.039)	(0.042)	(0.119)	(0.073)	(0.043)
N	65376	45154	20222	21924	43452
Mean	14.56	14.71	12.17	16.27	14.24
Severe Ice Storm					
Declaration	0.058**	0.113**	0.012	0.080*	0.048
	(0.027)	(0.045)	(0.031)	(0.048)	(0.034)
N	514300	127882	386046	270169	244131
Mean	13.47	14.11	13.26	13.61	13.40
Snowstorm					
Declaration	0.062*	0.048	0.071	0.082	0.075*
	(0.036)	(0.050)	(0.076)	(0.071)	(0.043)
N	446749	128702	318047	252297	194449
Mean	13.74	13.62	13.81	13.95	13.62
Control	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Year-by-Month FE	Yes	Yes	Yes	Yes	Yes
Month-by-Climate-Zone FE	Yes	Yes	Yes	Yes	Yes

Note: Each column within each panel represents a separate regression of 2.3 for a specific type of natural disasters, by county disaster propensity and poverty level. Samples are split by type-specific disaster propensity: high-propensity counties consist of counties with disaster propensity$>$ 0.5, and low-propensity counties consist of counties with disaster propensity$\leq$ 0.5. Counties are also ranked by poverty rate reported in the 1990 Census (Population by Poverty Status in 1989), high-poverty counties consist of counties with poverty rate above medium, and low-poverty counties consist of counties with poverty rate below medium. For each regression, counties included in the analysis are those with a propensity of specific type of disasters between 0.1 and 0.9. The outcome variable is birth rate. Control variables are: county monthly average, minimum and maximum temperature, cooling and heating degree days, precipitation, humidity (Palmer Z Index), county percent of female, employment-to-population ratio, per-capita income and average wages. County, year-by-month, and month-by-climate zone fixed effects are included. Standard errors are clustered at county level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 2.6 Heterogeneity by Mothers' Age and Race:

Effects of Hurricanes, Floods, and Fires

	Baseline	By Age			By Race	
	(1)	(2) Age 15-49	(3) Age 15-34	(4) Age 35-49	(5) Black	(6) White
Hurricane						
Declaration	-0.085**	-0.177**	-0.253*	-0.064	-0.312**	-0.045
	(0.043)	(0.088)	(0.141)	(0.051)	(0.138)	(0.045)
N	133667	133607	133607	133607	132598	133607
Mean	13.29	27.31	42.78	6.767	16.56	12.38
Flood						
Declaration	-0.086***	-0.167***	-0.237***	-0.045*	-0.031	-0.104***
	(0.019)	(0.037)	(0.056)	(0.024)	(0.050)	(0.022)
N	385353	385328	385328	385328	375898	385328
Mean	13.70	27.62	41.64	8.769	16.16	12.80
Fire						
Declaration	-0.093**	-0.182***	-0.270**	-0.025	-0.037	-0.111***
	(0.037)	(0.069)	(0.107)	(0.027)	(0.099)	(0.033)
N	491376	491376	491376	491376	475781	491376
Mean	13.40	27.19	41.71	8.039	16.49	12.33
Control	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-by-Climate-Zone FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column within each panel represents a separate regression of 2.3 for a specific type of natural disasters, by mothers' age and race. For each regression, counties included in the analysis are those with a propensity of specific type of disasters between 0.1 and 0.9. The outcome variable is birth rate. Control variables are: county monthly average, minimum and maximum temperature, cooling and heating degree days, precipitation, humidity (Palmer Z Index), county percent of female, employment-to-population ratio, per-capita income and average wages. County, year-by-month, and month-by-climate zone fixed effects are included. Standard errors are clustered at county level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 2.7 Heterogeneity by Mothers' Age and Race:

Effects of Tornadoes, Severe Storms, Severe Ice Storms, and Snowstorms

	Baseline	By Age			By Race	
	(1)	(2) Age 15-49	(3) Age 15-34	(4) Age 35-49	(5) Black	(6) White
Tornado						
Declaration	-0.075	-0.128	-0.228	0.056	-0.008	-0.088
	(0.048)	(0.090)	(0.150)	(0.057)	(0.105)	(0.065)
N	564235	564115	564115	564115	553240	564115
Mean	13.42	27.24	41.55	8.147	16.13	12.53
Severe Storm						
Declaration	-0.078**	-0.157*	-0.222*	-0.024	-0.087	-0.078**
	(0.039)	(0.086)	(0.114)	(0.039)	(0.089)	(0.036)
N	65376	65376	65376	65376	63055	65376
Mean	14.56	28.76	42.79	10.00	15.13	14.36
Severe Ice Storm						
Declaration	0.058**	0.113**	0.179**	-0.013	0.105	0.045
	(0.027)	(0.056)	(0.090)	(0.038)	(0.085)	(0.031)
N	514300	514180	514180	514180	495921	514180
Mean	13.47	27.20	41.44	8.124	16.04	12.66
Snowstorm						
Declaration	0.062*	0.115	0.117	0.091*	0.075	0.030
	(0.036)	(0.070)	(0.115)	(0.048)	(0.130)	(0.039)
N	446749	446749	446749	446749	431996	446749
Mean	13.74	27.84	42.72	7.545	16.77	12.72
Control	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-by-Climate-Zone FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column within each panel represents a separate regression of 2.3 for a specific type of natural disasters, by mothers' age and race. For each regression, counties included in the analysis are those with a propensity of specific type of disasters between 0.1 and 0.9. The outcome variable is birth rate. Control variables are: county monthly average, minimum and maximum temperature, cooling and heating degree days, precipitation, humidity (Palmer Z Index), county percent of female, employment-to-population ratio, per-capita income and average wages. County, year-by-month, and month-by-climate zone fixed effects are included. Standard errors are clustered at county level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Chapter 3

Perioperative Acute Ischemic Stroke in Patients with Atrial Fibrillation

with Liqi Shu, Wei Jiang, Nils Henninger, Thanh N Nguyen, James E Siegler, Adam de Havenon, Eric D Goldstein, Daniel Mandel, Maheen Rana, Fawaz Al-Mufti, Jennifer Frontera, Karen Furie, Shadi Yaghi[1]

3.1 Introduction

Atrial fibrillation (AF) is the most common pathological cardiac arrhythmia and is associated with thromboembolic complications, such as acute ischemic stroke (AIS) (Li et al. 2022). The peri-operative management of patients with AF undergoing elective surgical procedures is challenging as it typically requires interruption of oral anticoagulation (OAC) to mitigate procedural bleeding risk. However, holding anticoagulation increases the risk of thromboembolic complications, such as AIS (Lin et al. 2019). Although peri-operative AIS rarely occurs during elective surgical procedures, it has been linked to increased morbidity and mortality, with AF identified as the most common contributing factor (Ng et al. 2011; Parikh and Cohen 1993).

[1]The content of Chapter 3 C was the accepted manuscript of an article published in Annals of Neurology, Vol 94, Issue 2, Page 321-329, Copyright John Wiley & Sons, Inc. (2023). The article is available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/ana.26678. The reuse of the content in this dissertation is permitted by the publisher with License Number 5765420208007.

A randomized controlled trial found that peri-operative discontinuation of OAC without heparin bridging was noninferior to heparin bridging for the prevention of arterial thromboembolism (Douketis et al. 2015). However, this study mainly focused on non-cardiovascular and non-neurological surgery, in which bleeding complications are detrimental (Rajagopalan et al. 2019; Robba et al. 2017; Whitlock, Crowther and Ng 2005; Al-Attar et al. 2019). Reinert and colleagues found that AF, diabetes, and in-hospital stroke are independent risk factors for peri-operative stroke-related mortality in the non-cardiovascular, non-neurological surgery population (Reinert et al. 2021). These studies demonstrated several risk factors for AIS after elective procedures in patients with AF, such as interruption of anticoagulation therapy, surgical type, age, sex, and medical comorbidities.

Several risk factor algorithms and scores, including the CHA2DS2VASc score, the Hypertension, Abnormal renal/liver function, Stroke, Bleeding, Labile, Elderly, and Drugs (HAS-BLED) score, the ATRIA score, and the GARFIELD-AF risk model have been developed to guide in stroke prevention management in patients with AF (Fox et al. 2017; Fang et al. 2011; Pisters et al. 2010; Lip et al. 2010). However, a comprehensive analysis that assessed risk factors in a larger surgical population, including cardiovascular and neurological surgery, was not available. Considering the substantial clinical burden of peri-operative strokes in patients with AF, our study aimed to determine the risk factors for peri-operative AIS (within 30 days) in patients with AF and compare risks of different types of surgery using a large contemporary nationwide cohort in the United States. By identifying these factors, we hope to improve risk stratification, and ultimately reduce the burden of peri-operative strokes in this high-risk population.

3.2 Methods

3.2.1 Institutional Review Board Approval

The study was conducted using the Nationwide Readmissions Database (NRD), which is a publicly available, de-identified database provided by the Healthcare Cost and Utilization Project (HCUP) at https://www.hcup-us.ahrq.gov/. As the data utilized in our study are entirely de-identified and publicly available, the need for institutional review board (IRB) approval was waived by the Lifespan IRB, in accordance with the ethical standards of the responsible committee on human experimentation.

3.2.2 Patient Population

We included all adult patients who were electively hospitalized with principal or non-principal AF codes and a procedural Diagnoses Related Group (DRG) code from 2016 to 2019. Due to the possibility of centers using AIS codes in patients with prior but not new stroke, patients who had history of stroke (Z86.73) during the index admission were excluded. AF and AIS were identified based on standard and validated International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10 CM) codes, which is available since October 2015 (Alhajji, Kawsara and Alkhouli 2020; Yang et al. 2018; Chamberlain et al. 2022; Jensen et al. 2012). Patients who died during the index admission or had a length of stay >30 days during the index admission were excluded. Patients who were admitted in December were excluded because the NRD is unable to track patients over years. Patients who had an endovascular procedural DRG or had an index admission stroke with carotid endarterectomy procedural ICD codes were excluded.

3.2.3 Patient Characteristics

Demographic information included age, sex, insurance status (Medicaid, Medicare, private insurance, and self-pay), and median income by zip code (divided into quartiles based on HCUP thresholds; quartile 1 has the lowest income and quartile 4 has the highest income). Medicare insurance is a national insurance for persons age >65 years, and some people under 65 years with certain disabilities or conditions. Medicaid insurance is a combined federal and state program that provides health insurance coverage to some people with limited income and resources. Clinical information included active cancer, congestive heart failure, diabetes mellitus, recreational drug abuse, hypertension, peripheral vascular disease, and renal failure generated with the Elixhauser Comorbidity Software (version 3.7), provided by HCUP. History of coronary artery disease and hyperlipidemia were identified by ICD codes (Supplementary Table S1). The CHA2DS2VASc score was calculated for each patient based on the aforementioned information without a history of stroke category (score range=0–7). Procedures were grouped into neurosurgical, cardiovascular, and other procedures based on their DRG codes (see Supplementary Table S1).

3.2.4 Outcome

The primary outcome was peri-operative stroke. The Society for Neuroscience in Anesthesiology and Critical Care and American Heart Association/American Stroke Association Consensus Statement defined a peri-operative stroke as a brain infarction of ischemic or hemorrhagic etiology that occurs during surgery or within 30 days after surgery (Mashour et al. 2014; Benesch et al. 2021). Therefore, we defined peri-operative AIS as a principal and non-principal diagnosis of AIS during the index hospitalization or within 30 days after the index hospitalization.

3.2.5 Statistical Analysis

We compared baseline characteristics between patients with versus without peri-operative AIS using weighted groups and univariable logistic regression. Backward stepwise logistic regression was performed to optimize model performance with independent predictor variables. Three different logistic regression models were constructed to determine odds ratios (ORs) of demographic, clinical factors, and procedural types associated with peri-operative AIS. Model 1 used variables identified with backward stepwise regression. Model 2 included the CHA2DS2VASc score while excluding variables that were components of the CHA2DS2VASc score. Model 3 used variables included in model 2 except that the CHA2DS2VASc score was included as a categorical variable (trichotomized to 0–1 vs 2–4 vs 5–7). A scoring system, including procedure type and cancer add-on to the CHA2DS2VASc score, was developed using a nomogram. The periprocedural AIS predictive value with the new scoring system was tested using receiver operating characteristic curve (ROC) under nonparametric assumptions and accuracy was determined using area under the curve (AUC). This model was compared to CHA2DS2VASc score and number of risk factors using the χ^2 test (DeLong test) (DeLong, DeLong and Clarke-Pearson 1988), and was internally validated with a 100-iteration bootstrap method.

To verify the robustness of our analysis, a sensitivity analysis excluding patients with index admission AIS was performed. Further sensitivity analysis using weighted propensity score matching with caliper 0.05 without replacement was performed to evaluate the OR of neurosurgical and cardiovascular surgeries as compared to other surgical procedures. Variables used for matching were those significantly different between cardiovascular surgery versus other surgery as well as between neurological surgery versus other surgery using backward stepwise logistic regressions with a threshold of $p < 0.05$. All analyses were performed using STATA (version 15, StataCorp) and $p < 0.05$ was considered for statistical significance. Patients with missing data were dropped if the analysis involved the missing data. Data visualizations were performed using package forest plot in R (version 4.1.1).

3.3 Results

3.3.1 Baseline Characteristics of the Patients

A total of 1,557,331 patients were identified with AF diagnosis undergoing elective procedures. Of these, 512,038 patients were subsequently excluded as shown in the flowchart, leaving 1,045,293 patients for analysis (Figure 3.1). Of these, 7272 (0.7%) were diagnosed with peri-operative AIS, of which 66.8% occurred during the index hospitalization and 33.2% occurred during 30-day follow-up.

3.3.2 Univariate Analyses of Factors Associated with Peri-Operative Acute Ischemic Stroke

Demographic and clinical characteristics of included patients are shown in Figure 3.2. In univariable logistic regression, factors associated with perioperative stroke were: age (OR per year increase 1.03, 95% confidence interval [CI]=1.02–1.03, $p<0.001$), female sex (OR=1.15, 95% CI=1.07–1.24, $p<0.001$), Medicare insurance (OR=1.19, 95% CI=1.13–1.24, $p<0.001$), coronary artery disease (OR=1.41, 95% CI=1.31–1.51, $p<0.001$), congestive heart failure (OR=1.69, 95% CI=1.57–1.82, $p<0.001$), diabetes mellitus (OR= 1.34, 95% CI=1.24–1.44, p¡0.001), hyperlipidemia (OR=1.11, 95% CI=1.03–1.20, $p=0.006$), arterial hypertension (OR=1.33, 95% CI=1.21–1.46, $p<0.001$), peripheral vascular disease (OR=1.67, 95% CI=1.54–1.81, $p<0.001$), and renal failure (OR=1.44, 95% CI=1.31– 1.55, $p<0.001$). The CHA2DS-2VASc score (OR=1.31, 95% CI=1.28–1.35, $p<0.001$) was also associated with peri-operative stroke, particularly with a CHA2DS2VASc score ≥ 2 (OR=2.60, 95% CI=2.18–3.11, $p<0.001$). Additionally, we found that neurological surgery (OR=2.57, 95% CI=2.19–3.01, $p<0.001$) and cardiovascular surgery (OR=2.04, 95% CI=1.87–2.22, $p<0.001$) were associated with a higher risk of perioperative AIS in patients with AF. Private insurance (OR=0.70, 95% CI=0.63–0.77, $p<0.001$) and small hospital bed size (OR=0.62, 95% CI=0.55–0.71, $p<0.001$) were associated with a lower peri-operative AIS risk.

3.3.3 Multivariable Analysis of Predictors of Peri-Operative Stroke

After stepwise logistic regression analysis (model 1), demographic, clinical factors, and procedural types significantly associated with peri-operative AIS were age (adjusted OR [aOR]=1.03 per year, 95% CI=1.02–1.03, p<0.001), female sex (aOR=1.29, 95% CI=1.20–1.39, p<0.001), cancer (aOR=1.55, 95% CI=1.40–1.73, p<0.001), congestive heart failure (aOR=1.35, 95% CI=1.24–1.46, p<0.001), diabetes mellites (aOR=1.25, 95% CI=1.16–1.35, p<0.001), peripheral vascular disease (aOR=1.20, 95% CI=1.10–1.31, p<0.001), renal failure (aOR=1.14, 95% CI=1.04–1.24, p=0.005), neurosurgical procedure (aOR=4.66, 95% CI=3.96–5.49, p<0.001), and cardiovascular procedure (aOR=2.89, 95% CI=2.64–3.16, p<0.001; Table 3.1).

In model 2 including CHA2DS2VASc score (aOR=1.25 per point, 95% CI=1.22–1.29, p<0.001), cancer (aOR=1.58, 95% CI=1.42–1.76, p<0.001), and renal failure (aOR=1.14, 95% CI=1.04–1.24, p=0.005), as well as neurosurgical (aOR=4.51, 95% CI=3.84–5.30, p<0.001) and cardiovascular (aOR= 2.74, 95% CI=2.52–2.97, p<0.001) type procedures were independently associated with peri-operative AIS. Results did not meaningfully change when the CHA2DS2VASc score was included as categorical variables: using 0 to 1 as reference, score 2 to 4 (aOR=2.03, 95% CI=1.70–2.42, p¡0.001) and score ≥ 5 (aOR=3.05, 95% CI=2.53–3.68, p<0.001) were associated with increased peri-operative AIS risk (see Table 3.1).

3.3.4 Scoring System and Risks of Peri-Operative AIS

Based on the above findings, a scoring system was developed and compared with CHA2DS2VASc score for peri-operative AIS risk stratification in patients with AF undergoing elective procedures. The CHA2DS2VASc score was still used with its original 0 to 9 score (ie, the periprocedural stroke was not counted). The new scoring system utilized nomogram regression with the CHA2DS2VASc score, cancer, and surgical type. Based on the cancer and surgical type score in relation to the CHA2DS2VASc score on the nomogram, cancer was assigned a score of 2, cardiovascular surgery was assigned a score of 4, and neurosurgical surgery was assigned a score of 6 (Table 3.2). The new score (AUC=0.68, 95% CI=0.67-0.69) outperformed CHA2DS2VASc (AUC=0.60, 95% CI=0.60-0.61; χ^2 p<0.001) for periprocedural AIS (Fig 3). For low-risk patients with a score $\leq$4, the rate of periprocedural AIS was 0.21%. For moderate risk patients with scores from 5 to 8, the rate of periprocedural AIS was 0.70%. For high-risk patients with a score $\geq$8, the rate of periprocedural AIS was 1.48% (see Table 3.2).

3.3.5 Sensitivity Analyses of Types of Procedure and Risks of Peri-Operative AIS

When we repeated the analyses by excluding index admission AIS, renal failure (aOR=1.12, 95% CI =0.97–1.28, p=0.124) was no longer associated with 30-day AIS, whereas cancer (aOR=1.55, 95% CI=1.32–1.82, p<0.001), CHA2DS2VASc score (aOR= 1.32, 95% CI=1.27–1.38, p¡0.001), neurological surgery (aOR=1.76, 95% CI=1.45–2.15, p<0.001), and cardiovascular surgery (aOR=1.54, 95% CI=.35–1.75, p<0.001) kept the positive association.

In the propensity score matching sensitivity analysis, results were unchanged for neurological surgery (aOR=8.02, 95% CI=6.12–10.52, p<0.001) and cardiovascular surgery (aOR=3.12, 95% CI=2.80–3.47, p<0.001).

3.4 Discussion

3.4.1 Main Findings

Previous studies indicated that AF is independently associated with postoperative AIS (Prasada et al. 2022), however, contributing risk factors remain poorly understood. In our study, we found that the components of the CHA2DS2VASc score as well as the type of surgery (neurological or cardiovascular) were predictors of peri-operative AIS in patients with AF. This is in line with studies of patients with AF showing that advanced age (Gialdini et al. 2014), female sex (Wagstaff et al. 2014), congestive heart failure (Iguchi et al. 2021), diabetes mellitus (Gage et al. 2001), and peripheral vascular disease (Bjerring Olesen et al. 2012), played an important role in stroke risk. Additionally, in this study, we found cancer to be associated with peri-operative stroke. Malignancy is known to cause a hypercoagulable state, which in turn increases the risk of thrombosis. On the other hand, malignancy can increase the risk of bleeding, thus making peri-operative management challenging (Zamorano 2016). Furthermore, renal failure (Eikelboom et al. 2021) can increase the propensity to thrombosis and thus increase the risk of AIS (Navi et al. 2021). Last, both cardiovascular surgery and neurological surgeries are significantly associated with peri-operative AIS (Spence et al. 2019; Gaudino et al. 2019*b*). In patients undergoing cardiovascular surgery, thromboembolism due to surgical manipulation or AF or cerebral hypoperfusion, can lead to peri-operative AIS (Gaudino et al. 2019*b*; Gaudino et al. 2019*a*). In patients undergoing neurological surgery, in addition to AF, direct vascular injury or arterial compression from retraction can also lead to peri-operative AIS (Berger et al. 2019).

The CHA2DS2VASc score consists of many aspects, including congestive heart failure, hypertension, age, diabetes mellitus, prior stroke or transient ischemic attack or thromboembolism, vascular disease, and sex. It is recommended in patients with AF, for AIS risk stratification being that it was an independent predictor of thromboembolic events (January et al. 2019). Not surprisingly, our results showed a significant association between the CHA2DS2VASc score and peri-operative AIS, which correspond to the recommendation of the guideline (January et al. 2019). Furthermore, the risk score system we developed performed better than the CHA2DS2VASc score, which implied that it can risk stratify peri-operative AIS for patients with AF more accurately.

3.4.2 Mechanisms of Associations

Patients with AF are at increased risk of postoperative atrial fibrillation-related complications because of the need to interrupt anticoagulation at the time of surgery, and this risk is particularly high in types of surgery that require longer interruption of anticoagulation, such as cardiac surgery and neurosurgery. It has been shown that AF occurring in the peri-operative period is more strongly associated with stroke in patients undergoing non-cardiac surgery (Lin et al. 2019). However, most current studies focus on peri-operative-onset AF rather than chronic AF, Lin et al. (2019), Douketis et al. (2015), Gialdini et al. (2014), Di Biase et al. (2014) and studies on patients with AF undergoing neurosurgery or cardiac surgery are lacking. The present study found a strong correlation between these 2 high-risk types of surgery for AIS in patients with AF, where the duration of surgery is relatively long, the risk of bleeding is relatively high, and the anticoagulation resumption is often delayed.

3.4.3 Clinical Implications

This study has several clinical implications. First, it provides elements for risk stratification in patients with known AF undergoing elective surgery. The peri-operative stroke risk is dependent on the patient's characteristics (CHA2DS2VASc score) and the type of surgery (cardiac surgery, neurological surgery, vs other). For instance, patients with CHA2DS2VASc <2 undergoing "other" types of surgery have a risk of 0.06%, whereas patients with CHA2DS2VASc ≥ 5 undergoing neurological surgery have >8-fold increased risk of 0.52%. Therefore, in high-risk patients, careful weighing of bleeding and thromboembolic risk is crucial to determine when anticoagulation can be safely resumed (Raval et al. 2017). This information is particularly useful as 12.5% of patients with AF undergo elective surgeries per annum (Douketis et al. 2015), and this puts 10s of 1,000s of US patients at risk of stroke every year. Future clinical trials may be warranted to test early resumption of anticoagulation in high-risk patients or evaluate whether left atrial appendage (LAA) occlusion is protective against peri-operative ischemic stroke.

3.4.4 Strengths and Limitations

Our study has several limitations, first, it is a retrospective study with limited patient-level data and we do not have information regarding the precise timing of stroke events during elective surgical admissions. As a result, there is a possibility that some strokes occurred before the elective surgery, which would be distinct from post-procedure strokes defined as peri-operative strokes. Nevertheless, within the context of elective surgical admissions, surgeries would likely be postponed or canceled if a patient experienced a stroke prior to the procedure. Moreover, the stroke might still be related to the cessation of anticoagulation in anticipation of surgery. Because of this limitation, we were only able to include any stroke that occurred during the index admission instead of post-procedure stroke. However, in a sensitivity analysis that excluded patients who had a stroke during the index admission, the findings of our study did not meaningfully change. Second, we lack data on the type of AF (valvular vs non-valvular AF) and pattern of AF (paroxysmal vs persistent vs permanent). Some of the AFs may have developed post-procedurally, but postoperative AF is also associated with significant thromboembolic risk and is recommended to administer antithrombotic medication (IIa level evidence B) by the American College of Cardiology, American Heart Association, and Heart Rhythm Society, as advised for patients with non-peri-operative AF (Bessissow et al. 2015; January et al. 2014). Third, we lack data on the treatments used, such as whether they were on anticoagulation or not, and when anticoagulation was held and resumed, which is important for further analysis of the timing of resumption of anticoagulation to reduce postoperative strokes due to AF. We also do not know the stroke severity or outcomes of patients with peri-operative AIS, which may be important for patient education. Last, potential administrative coding error may occur, and our analysis is dependent on the accuracy of the data coding. Because the data were obtained from the nationwide re-admissions database, which is not a clinical research database, there might be potential limitations in terms of quality control and accuracy compared to a prospective clinical research database.

On the other hand, our study has several strengths. The use of validated diagnostic codes as well as the large-scale study provides statistical power and makes our findings generalizable. Our data also provide preliminary data to inform sample size and refining selection of variables for a potential randomized control trial.

3.5 Conclusions

In this study, we show that the CHA2DS2VASc score, cancer, and surgery types (neurological or cardiovascular) are valuable for peri-operative stroke risk stratification in patients with AF. Prospective studies are needed to validate our findings and test whether early resumption of anticoagulation, bridging therapy, or LAA occlusion may be protective in reducing the risk of peri-operative stroke in high-risk patients.

3.6 Acknowledgments

The authors greatly appreciate Zhaowei Jiang for her valuable assistance in creating the graphical abstract using BioRender.com.

3.7 Author Contributions

L.S. and S.Y. contributed to the conception and design of the study. L.S., W.J., and H.X. contributed to the acquisition and analysis of data. L.S., W.J., N.H., T.N.N., J.E.S., A.D.H., E.D.G., D.M., M.R., F.A.M., J.F., K.F., and S.Y. contributed to the drafting a significant portion of the manuscript for important intellectual content.

3.8 Potential Conflicts of Interest

All authors have completed and submitted the appropriate disclosure forms. A.D.H. holds royalties or licenses from UpToDate and receives consulting fees from NovoNordisk and Integra. S.Y. holds royalties or licenses from UpToDate. T.N.N. participates on data safety monitoring boards of various trials, serves on the advisory board of Idorsia, and participates as the president-elect of SVIN society. N.H. holds grants to his institution and participates on the research committee of the World Stroke Organization. F.A.M. receives consulting fees from Stryker, Imperative Care, Cerenovus, AstraZeneca, and Rapid Medical and serves on the board of directors of SVIN. Further details regarding potential conflicts of interest can be found in the submitted forms.

Figures and Tables

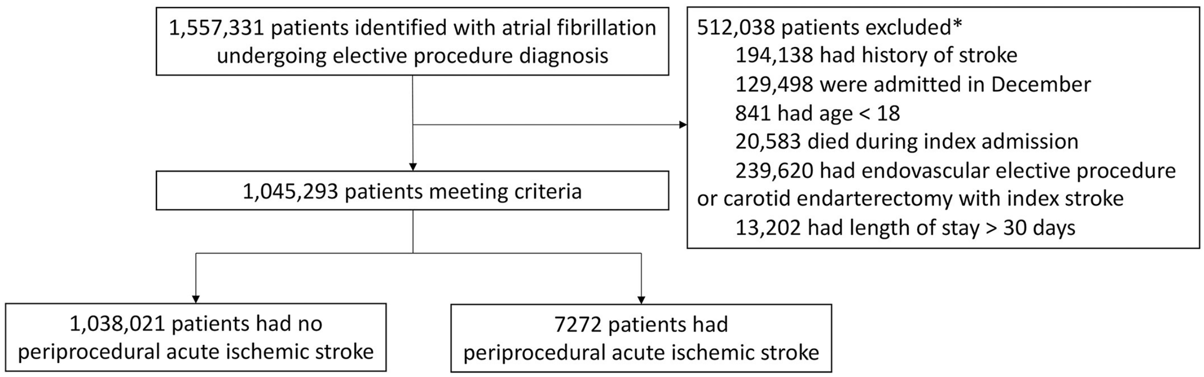


Figure 3.1 Flowchart of patient inclusion and exclusion.
Notes: Patients are counted for multiple exclusion criteria.

Odds Ratio Plot

	Missing	Primary outcome (n = 7,272)	No primary outcome (n = 1,038,021)	Odds ratio	p–value
Age	0	73.74±0.18	71.43±0.04	1.026	<0.001
Sex (female)	0	3098/7272(42.6%)	406367/1038021(39.1%)	1.154	<0.001
Insurance					
Private insurance	876	1025/7263(14.1%)	197341/1037154(19.0%)	0.7	<0.001
Medicare	876	5913/7263(81.4%)	785331/1037154(75.7%)	1.185	<0.001
Medicaid	876	167/7263(2.3%)	27830/1037154(2.7%)	0.948	0.144
Self–pay	876	158/7263(2.2%)	26652/1037154(2.6%)	0.958	0.176
Medical history	**0**				
Coronary artery disease	0	3711/7272(51.0%)	440976/1038021(42.5%)	1.411	<0.001
Active cancer	0	962/7272(13.2%)	143264/1038021(13.8%)	0.953	0.368
Congestive heart failure	0	2628/7272(36.1%)	260458/1038021(25.1%)	1.69	<0.001
Diabetes mellitus	0	2698/7272(37.1%)	317664/1038021(30.6%)	1.338	<0.001
Drug abuse	0	53/7272(0.7%)	7541/1038021(0.7%)	1.002	0.99
Hyperlipidemia	0	4457/7272(61.3%)	609504/1038021(58.7%)	1.113	0.006
Hypertension	0	6204/7272(85.3%)	844531/1038021(81.4%)	1.331	<0.001
Peripheral vascular disease	0	1683/7272(23.1%)	158727/1038021(15.3%)	1.668	<0.001
Renal failure	0	1761/7272(24.2%)	190478/1038021(18.4%)	1.422	<0.001
Procedure	**0**				
Other	0	2408/7272(33.1%)	624386/1038021(60.2%)	0.328	<0.001
Neurological procedure	0	1300/7272(17.9%)	81170/1038021(7.8%)	2.567	<0.001
Cardiovascular procedure	0	3564/7272(49.0%)	332465/1038021(32.0%)	2.039	<0.001
CHA2DS2VASc	0	4 (3–5)	3 (2–4)	1.312	<0.001
CHA2DS2VASc >=2	0	7000/7272(96.2%)	942552/1038021(90.8%)	2.604	<0.001

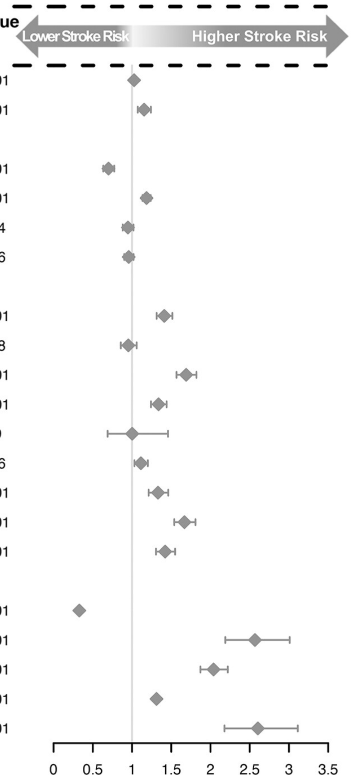


Figure 3.2 Baseline characteristics with unadjusted effect estimates of patients undergoing procedures, stratified by the occurrence of acute ischemic stroke.

Table 3.1 OR with 95% CI for association of demographic, clinical factors, and procedural types with the risk of peri-operative acute ischemic stroke

Acute ischemic stroke, N=1045293	OR	95% CI	p > |t|
Model 1			
Age	1.026	1.022–1.031	0.000
Sex (F)	1.292	1.201–1.389	0.000
Active cancer	1.552	1.395–1.727	0.000
Congestive heart failure	1.346	1.242–1.458	0.000
Diabetes mellitus	1.252	1.158–1.352	0.000
Peripheral vascular disease	1.196	1.096–1.305	0.000
Renal failure	1.137	1.039–1.243	0.005
Procedure: Other	reference		
Neurological procedure	4.658	3.956–5.485	0.000
Cardiovascular procedure	2.885	2.635–3.158	0.000
Model 2			
Active cancer	1.578	1.419–1.756	0.000
Renal failure	1.135	1.039–1.24	0.005
Procedure: Other	reference		
Neurological procedure	4.511	3.838–5.303	0.000
Cardiovascular procedure	2.735	2.515–2.974	0.000
CHA2DS2VASc (per point)	1.254	1.219–1.291	0.000
Model 3			
Active cancer	1.577	1.417–1.754	0.000
Renal failure	1.197	1.098–1.306	0.000
Procedure: Other	reference		
Neurological procedure	4.525	3.849–5.319	0.000
Cardiovascular procedure	2.803	2.58–3.046	0.000
CHA2DS2VASc 0–1	reference		
CHA2DS2VASc 2–4	2.027	1.695–2.424	0.000
CHA2DS2VASc >4	3.052	2.531–3.679	0.000

Table 3.2 Risk score components derived based on nomogram and rate of peri-operative acute ischemic stroke in patients with AF in low, moderate, and high risk categories

Components	**Score**
CHA2DS2VASc	0–7
Cancer	2
Surgical type	
Other	0
Cardiovascular	4
Neurosurgery	6
Total	17

Risk category	**Score**	**Peri-operative stroke rate**
Low risk	0–4	0.21%
Moderate risk	5–8	0.70%
High risk	8–17	1.48%

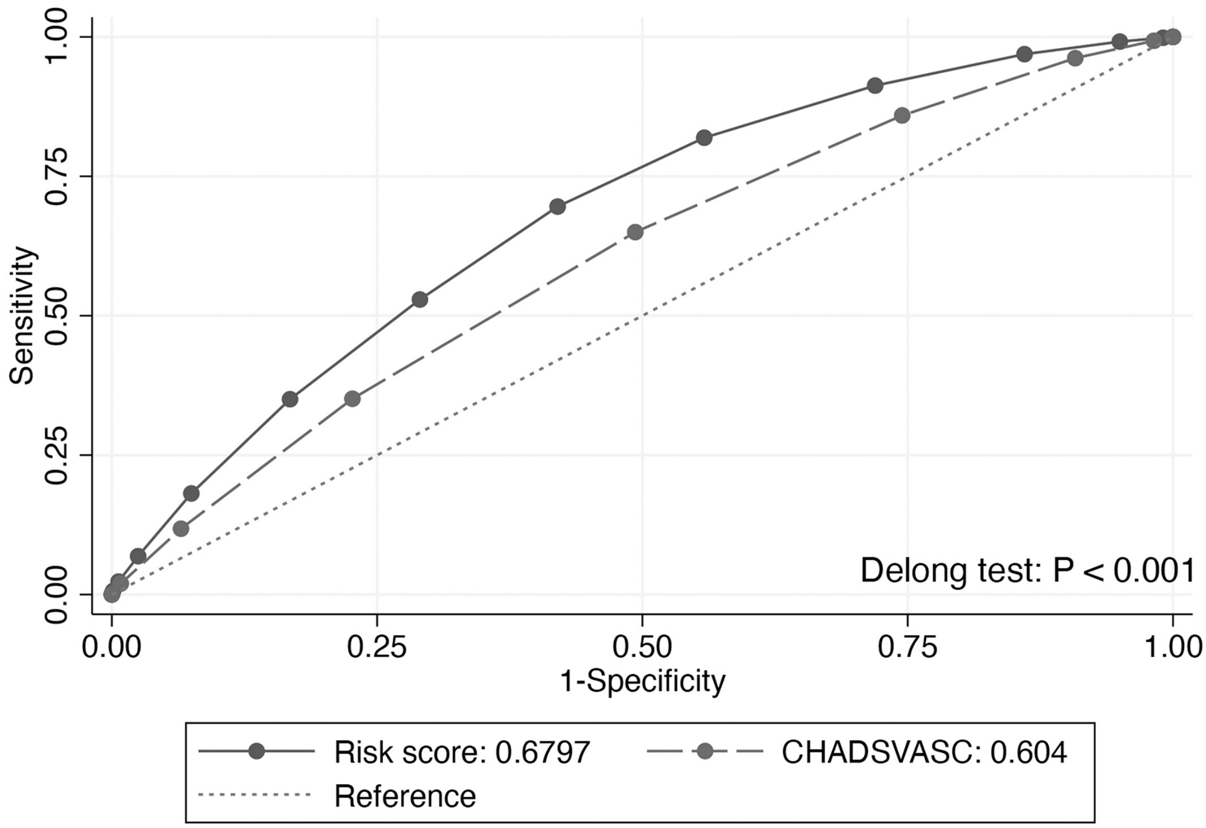


Figure 3.3 Receiver operating characteristic curve of peri-operative stroke prediction using CHA2DS2VASc score, and the risk score developed.

Appendix A

Appendix for "How Hospitals Respond to Patient Death: Evidence from Maternal Death and C-section

Table A.1 All Deliveries DRGs and MS-DRGs

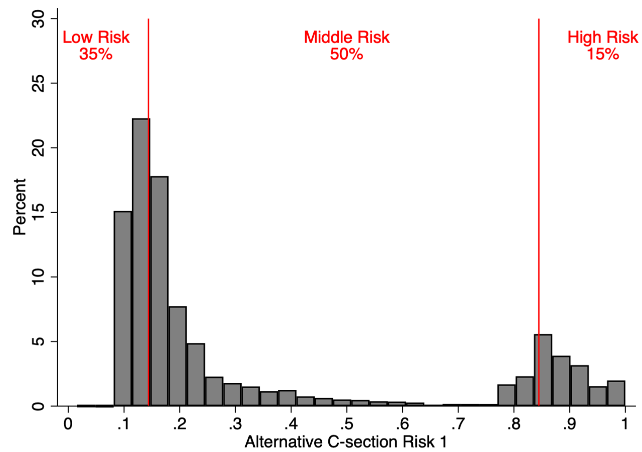
2003- 2006 (DRG)	**2007- 2014** (MS-DRG)
Cesarean Deliveries	
370 CESAREAN SECTION W CC	765 CESAREAN SECTION WITH CC/MCC
371 CESAREAN SECTION W/O CC	766 CESAREAN SECTION WITHOUT CC/MCC
Vaginal Deliveries	
372 VAGINAL DELIVERY W COMPL	767 VAGINAL DELIVERY WITH STERILIZATION
373 VAG DELIVERY W/O COMPL	768 VAGINAL DELIVERY WITH O.R. PROCEDURE
374 VAG DELIV W STERIL OR DC	774 VAGINAL DELIVERY WITH COMPLICATING DIAGNOSES
375 VAG DELIV W OTH OR PROC	775 VAGINAL DELIVERY WITHOUT COMPLICATING DIAGNOSES

Note: Diagnosis-Related Group (DRG) and Medicare Severity-Diagnosis Related Group (MS-DRG), are systems used in the United States to classify inpatient hospital cases into groups for the purpose of Medicare reimbursement and health-care management. The MS-DRG system was introduced in 2007 as an enhanced and more refined version of the original DRG system, and thus the two versions of the codes are listed separately. In the context of labor and deliveries, the transition from DRG to MS-DRGs aimed to capture additional information related to severity of illness (SOI) and risk of mortality (ROM). However, the fundamental structure of the DRG system, which includes codes specific to obstetric cases and method of delivery, remained in place. I refer to the definition provided in the AHRQ Inpatient Quality Indicators 33, Primary Cesarean Delivery Rate, technical specifications, to identify delivery discharges under different versions, details under this link: `https://qualityindicators.ahrq.gov/measures/all_measures`.

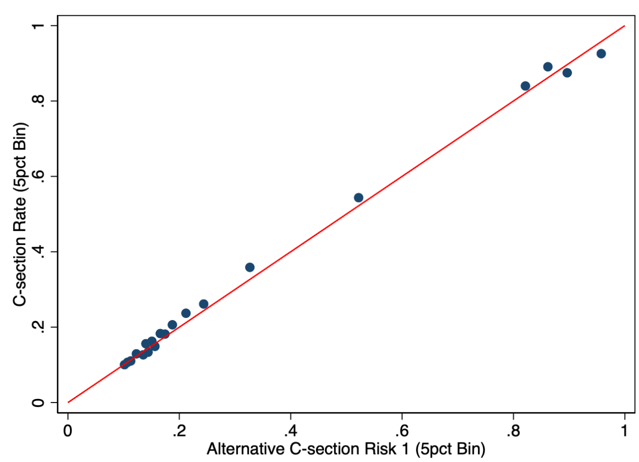
Table A.2 Summary Statistics: Maternal Medical Risks

	(1) All Hospitals	(2) Hospitals without Maternal Death	(3) Hospitals with Maternal Death	(4) Difference
Age	29.183	28.680	29.309	-0.629***
	(6.127)	(6.077)	(6.133)	(0.008)
Hemorrhage in Early Pregnancy	0.000	0.000	0.000	0.000***
	(0.015)	(0.016)	(0.014)	(0.000)
Placenta Previa	0.007	0.005	0.007	-0.002***
	(0.082)	(0.072)	(0.084)	(0.000)
Abruptio Placentae	0.009	0.008	0.010	-0.002***
	(0.096)	(0.088)	(0.098)	(0.000)
Antepartum Hemorrhage	0.003	0.003	0.003	-0.000
	(0.053)	(0.052)	(0.053)	(0.000)
Hypertension	0.044	0.046	0.044	0.002***
	(0.205)	(0.209)	(0.204)	(0.000)
Eclampsia	0.044	0.029	0.047	-0.018***
	(0.204)	(0.167)	(0.212)	(0.000)
Excessive Vomitting	0.001	0.001	0.001	0.000***
	(0.033)	(0.035)	(0.033)	(0.000)
Prolong Pregnancy	0.176	0.167	0.179	-0.012***
	(0.381)	(0.373)	(0.383)	(0.001)
Edema in Pregnancy	0.002	0.003	0.002	0.001***
	(0.044)	(0.053)	(0.042)	(0.000)
Renal Disease in Pregnancy	0.002	0.002	0.002	-0.000***
	(0.042)	(0.040)	(0.043)	(0.000)
Infections	0.040	0.031	0.042	-0.012***
	(0.196)	(0.172)	(0.201)	(0.000)
Multiple Gestation	0.018	0.013	0.019	-0.007***
	(0.132)	(0.111)	(0.137)	(0.000)
Breech Presentation	0.034	0.031	0.035	-0.004***
	(0.181)	(0.173)	(0.183)	(0.000)
Disproportion	0.007	0.011	0.007	0.004***
	(0.086)	(0.105)	(0.081)	(0.000)
Previous C-Section	0.160	0.156	0.161	-0.005***
	(0.367)	(0.363)	(0.368)	(0.000)
Diabetes	0.070	0.056	0.073	-0.017***
	(0.255)	(0.230)	(0.260)	(0.000)
Polyhydramnios	0.009	0.009	0.009	-0.000
	(0.096)	(0.095)	(0.096)	(0.000)
Oligohydramnios	0.042	0.028	0.045	-0.017***
	(0.199)	(0.164)	(0.207)	(0.000)
Chorioamnionitis	0.021	0.009	0.024	-0.014***
	(0.143)	(0.097)	(0.152)	(0.000)
Admission Type: Emergency	0.203	0.039	0.244	-0.206***
	(0.402)	(0.193)	(0.430)	(0.000)
Admission Type: Urgent	0.270	0.267	0.270	-0.004***
	(0.444)	(0.442)	(0.444)	(0.001)
Admission Type: Elective	0.524	0.690	0.482	0.207***
	(0.499)	(0.463)	(0.500)	(0.001)
N	3484322	698721	2785601	3484322
Num Hospitals	103	61	42	103

Note: Table shows averages of delivery admission records across groups of hospitals: all hospitals, hospitals without maternal death, hospitals with maternal death. Column (4) reports the difference between hospital with and without maternal deaths. Mothers' ages are in years, indicators for pregnancy complications are dummy variables equal to 1 if discharge record includes such diagnosis identified by ICD-9-CM/ICD-10-CM diagnosis codes. Delivery discharges are identified by deliveries DRGs/MS-DRGs. Standard errors are in parentheses. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Refer to Key Terms Section for meanings of pregnancy complications.

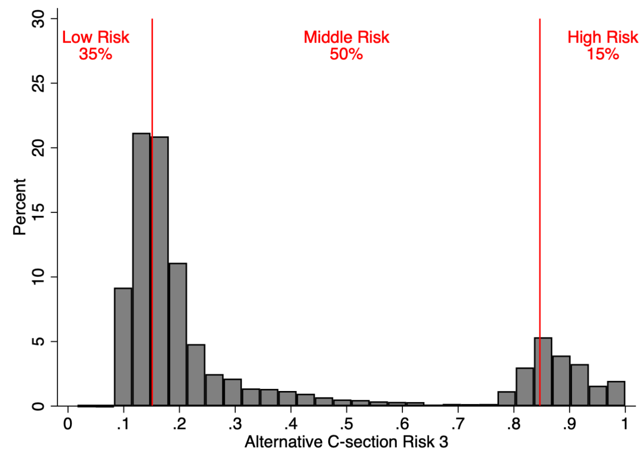


(a) Distribution of *Alternative C-section Risk 1*

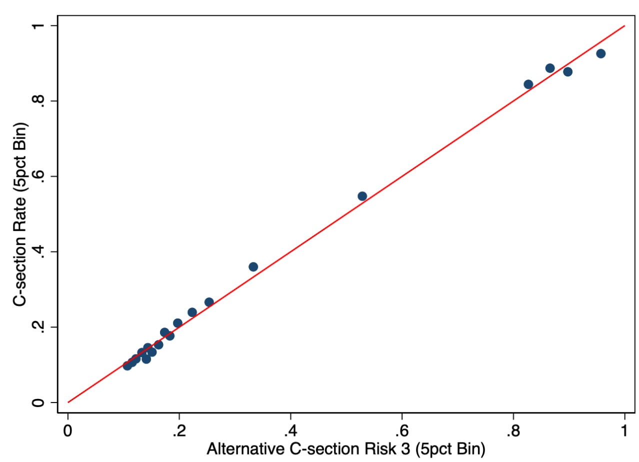


(b) C-section Rate by *Alternative C-section Risk 1*

Figure A.1 Distribution and C-section Rate by *Alternative C-section Risk 1*
Note: *Alternative C-section risk 1* is estimated by Equation 1.4 and then predicted by Equation 1.5 using all delivery discharges. Variables included in the estimation are pregnancy complications, maternal age group, and admission type. Mothers' ages are in years, indicators for pregnancy complications are dummy variables equal to 1 if discharge record includes such diagnosis identified by ICD-9-CM/ICD-10-CM diagnosis codes. Delivery discharges are identified by deliveries DRGs/MS-DRGs. Panel (a) depicts the histogram of *Alternative C-section risk 1*. Red vertical lines represent the cutoffs between maternal risk groups: mothers with C-section risk below 35th percentile are categorized as low-risk mothers, mothers with C-section risk above 85th percentile are categorized as high-risk mothers, and mothers with C-section risk between 35th and 85th percentile are middle-risk mothers. Panel (b) plots C-section rate of mothers within each 5-percentile bin of predicted C-section risk. For each point, the x-value represents the average predicted C-section risk within each 5-percentile bin. The y-value represents the C-section rate of mothers within each a 5-percentile bin of predicted C-section risk. The red line represents the 45 degree line, indicating that points along this line have equal x and y values.

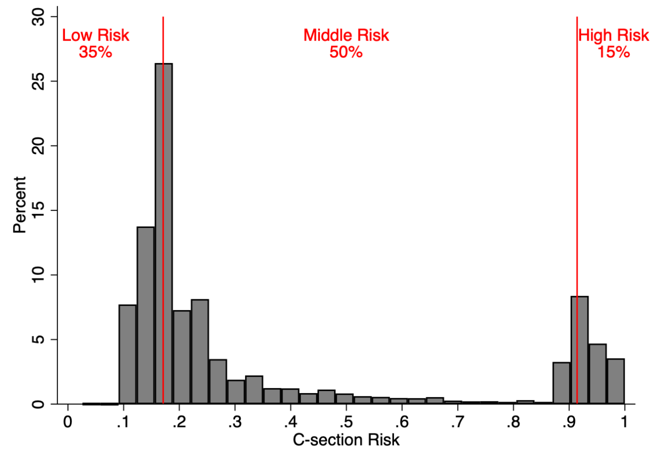


(a) Distribution of *Alternative C-section Risk 2*

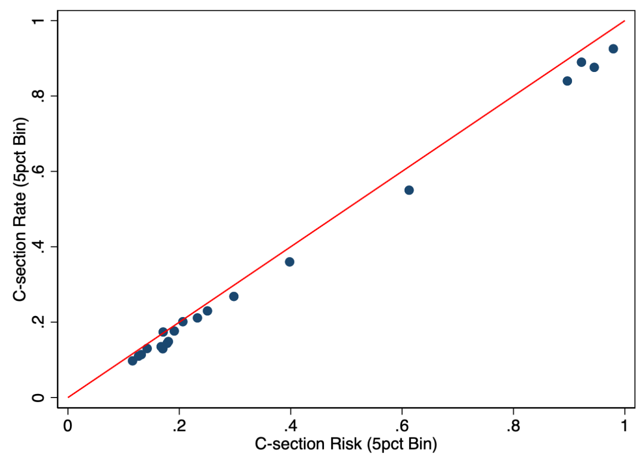


(b) C-section Rate by *Alternative C-section Risk 2*

Figure A.2 Distribution and C-section Rate by *Alternative C-section Risk 2*
Note: *Alternative C-section risk 2* is estimated by Equation 1.6 (no hospital fixed effects) with discharges from control hospitals, and then predicted by Equation 1.5 using all delivery discharges. Variables included in the estimation are pregnancy complications, maternal age group, and admission type. Mothers' ages are in years, indicators for pregnancy complications are dummy variables equal to 1 if discharge record includes such diagnosis identified by ICD-9-CM/ICD-10-CM diagnosis codes. Delivery discharges are identified by deliveries DRGs/MS-DRGs. Panel (a) depicts the histogram of *Alternative C-section risk 2*. Red vertical lines represent the cutoffs between maternal risk groups: mothers with C-section risk below 35th percentile are categorized as low-risk mothers, mothers with C-section risk above 85th percentile are categorized as high-risk mothers, and mothers with C-section risk between 35th and 85th percentile are middle-risk mothers. Panel (b) plots C-section rate of mothers within each 5-percentile bin of predicted C-section risk. For each point, the x-value represents the average predicted C-section risk within each 5-percentile bin. The y-value represents the C-section rate of mothers within each a 5-percentile bin of predicted C-section risk. The red line represents the 45 degree line, indicating that points along this line have equal x and y values.



(a) Distribution of *Alternative C-section Risk 3*



(b) C-section Rate by *Alternative C-section Risk 3*

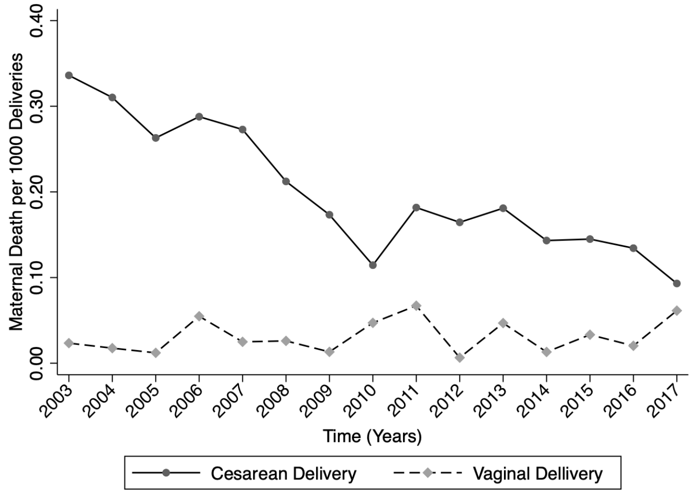
Figure A.3 Distribution and C-section Rate by *Alternative C-section Risk 3*

Note: *Alternative C-section risk 3* is estimated by Equation 1.6 (no hospital fixed effects) and then predicted by Equation 1.5 using all delivery discharges. Variables included in the estimation are pregnancy complications, maternal age group, and admission type. Mothers' ages are in years, indicators for pregnancy complications are dummy variables equal to 1 if discharge record includes such diagnosis identified by ICD-9-CM/ICD-10-CM diagnosis codes. Delivery discharges are identified by deliveries DRGs/MS-DRGs. Panel (a) depicts the histogram of *Alternative C-section risk 3*. Red vertical lines represent the cutoffs between maternal risk groups: mothers with C-section risk below 35th percentile are categorized as low-risk mothers, mothers with C-section risk above 85th percentile are categorized as high-risk mothers, and mothers with C-section risk between 35th and 85th percentile are middle-risk mothers. Panel (b) plots C-section rate of mothers within each 5-percentile bin of predicted C-section risk. For each point, the x-value represents the average predicted C-section risk within each 5-percentile bin. The y-value represents the C-section rate of mothers within each a 5-percentile bin of predicted C-section risk. The red line represents the 45 degree line, indicating that points along this line have equal x and y values.

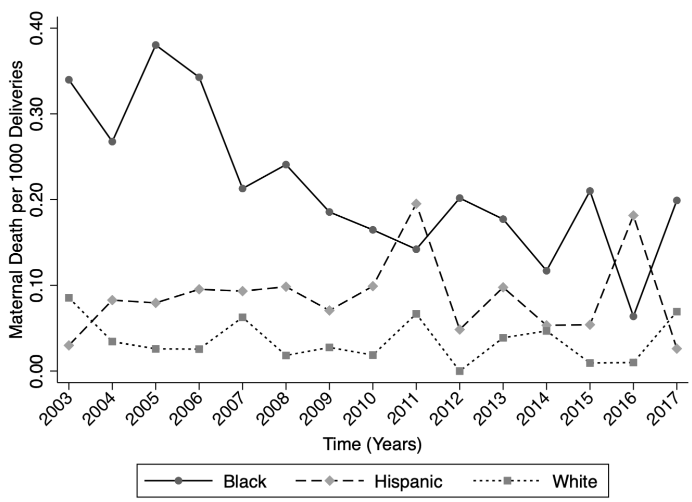
Table A.3 Logistic Regression Model of C-section Risk and Alternative C-section Risks

	(1) C-section Risk	(2) Alternative C-section Risk 1	(3) Alternative C-section Risk 2	(4) Alternative C-section Risk 3
Age 20-25	-0.0116	0.0149**	-0.0440***	-0.00563
	(0.0156)	(0.00714)	(0.0154)	(0.00707)
Age 25-30	-0.00902	0.0788***	0.00326	0.0770***
	(0.0153)	(0.00693)	(0.0150)	(0.00684)
Age 30-35	0.0571***	0.176***	0.130***	0.188***
	(0.0155)	(0.00696)	(0.0150)	(0.00680)
Age 35-40	0.162***	0.296***	0.270***	0.311***
	(0.0167)	(0.00737)	(0.0161)	(0.00718)
Age Above 40	0.432***	0.613***	0.551***	0.619***
	(0.0221)	(0.00930)	(0.0215)	(0.00910)
Hemorrhage in Early Pregnancy	-1.592***	-1.907***	-1.526***	-1.896***
	(0.259)	(0.133)	(0.259)	(0.132)
Placenta Previa	3.033***	3.031***	2.997***	2.971***
	(0.0507)	(0.0207)	(0.0500)	(0.0205)
Abruptio Placentae	2.046***	1.602***	1.967***	1.558***
	(0.0328)	(0.0135)	(0.0322)	(0.0134)
Antepartum Hemorrhage	0.470***	0.400***	0.511***	0.384***
	(0.0594)	(0.0261)	(0.0588)	(0.0259)
Hypertension	0.695***	0.590***	0.668***	0.555***
	(0.0145)	(0.00659)	(0.0143)	(0.00649)
Eclampsia	1.386***	1.298***	1.364***	1.261***
	(0.0169)	(0.00629)	(0.0166)	(0.00621)
Excessive Vomitting	0.0723	0.114***	0.127	0.0940**
	(0.0946)	(0.0430)	(0.0934)	(0.0427)
Early Onset Delivery	0.0469***	0.0832***	0.0767***	0.0868***
	(0.0162)	(0.00611)	(0.0160)	(0.00604)
Prolong Pregnancy	0.384***	0.337***	0.325***	0.282***
	(0.00890)	(0.00383)	(0.00870)	(0.00376)
Papyraceous Fetus	-0.367	-0.531**	-0.382	-0.572**
	(0.610)	(0.261)	(0.610)	(0.259)
Edema in Pregnancy	0.711***	0.844***	0.525***	0.777***
	(0.0579)	(0.0297)	(0.0567)	(0.0292)
Renal Disease in Pregnancy	0.443***	0.496***	0.413***	0.454***
	(0.0777)	(0.0316)	(0.0764)	(0.0313)
Infections	0.452***	0.417***	0.479***	0.415***
	(0.0179)	(0.00698)	(0.0176)	(0.00690)
Multiple Gestation	2.179***	2.020***	2.121***	1.965***
	(0.0291)	(0.0109)	(0.0286)	(0.0107)
Breech Presentation	4.647***	4.129***	4.553***	4.047***
	(0.0352)	(0.0130)	(0.0349)	(0.0129)
Disproportion	4.624***	3.990***	4.560***	3.932***
	(0.0539)	(0.0237)	(0.0536)	(0.0235)
Previous C-Section	3.950***	3.477***	3.875***	3.435***
	(0.0115)	(0.00456)	(0.0113)	(0.00448)
Diabetes	0.568***	0.509***	0.528***	0.490***
	(0.0138)	(0.00552)	(0.0136)	(0.00545)
Polyhydramnios	1.127***	1.050***	1.097***	1.015***
	(0.0306)	(0.0135)	(0.0301)	(0.0134)
Oligohydramnios	0.828***	0.672***	0.860***	0.695***
	(0.0176)	(0.00655)	(0.0173)	(0.00647)
Chorioamnionitis	1.612***	1.409***	1.567***	1.328***
	(0.0274)	(0.00845)	(0.0268)	(0.00830)
Admission Type: Emergency	-0.146***	-0.0715**	-0.278***	-0.297***
	(0.0556)	(0.0291)	(0.0546)	(0.0267)
Admission Type: Urgent	-0.0111	-0.00765	0.0591	-0.212***
	(0.0523)	(0.0289)	(0.0516)	(0.0266)
Admission Type: Elective	0.300***	0.290***	0.208***	0.0568**
	(0.0522)	(0.0287)	(0.0514)	(0.0266)
Observations	698695	3484295	698721	3484322
Pseudo R^2	0.36	0.32	0.34	0.31
Corr with C-section Risk	1	0.990	0.988	0.989

Note: Each column shows the coefficients from estimating Equation 1.4 or Equation 1.6 using logistic regression under different specifications. Refer to Key Terms Section for meanings of pregnancy complications.



(a) Maternal Death Rate by Delivery Method (Per Thousand Deliveries)



(b) Maternal Death Rate by Race (Per Thousand Deliveries)

Figure A.4 Maternal Death Rate by Delivery Method and Race
Note: Panel (a) depicts maternal death rate in New York State Inpatient Database from 2003 to 2017 by delivery method: cesarean or vaginal delivery. Panel (b) depicts maternal death rate in New York State Inpatient Database from 2003 to 2017 by race: Black, Hispanic or white. Sample consists of all delivery discharges identified by DDRG/MS-DRGs, excluding deliveries with missing information in hospital identifier, admission year and quarter. Data is collapsed at yearly level. Maternal death is defined by the variable: Died During Hospitalization.

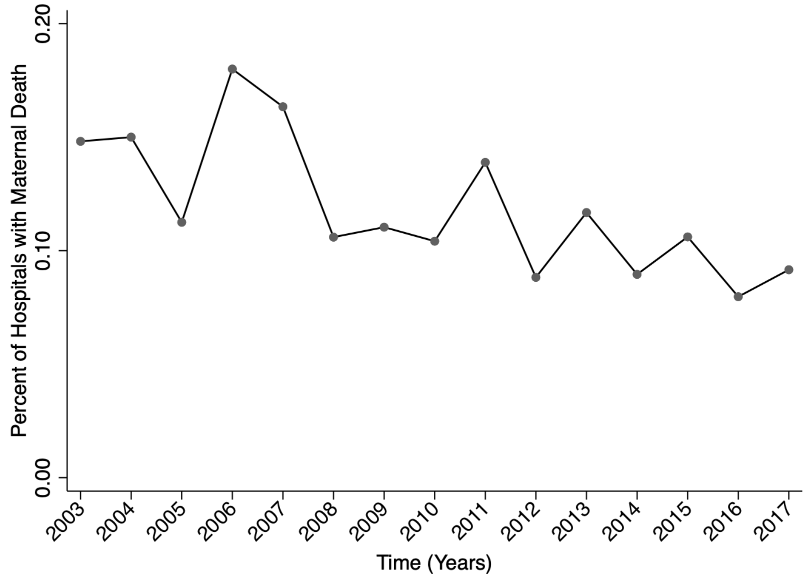
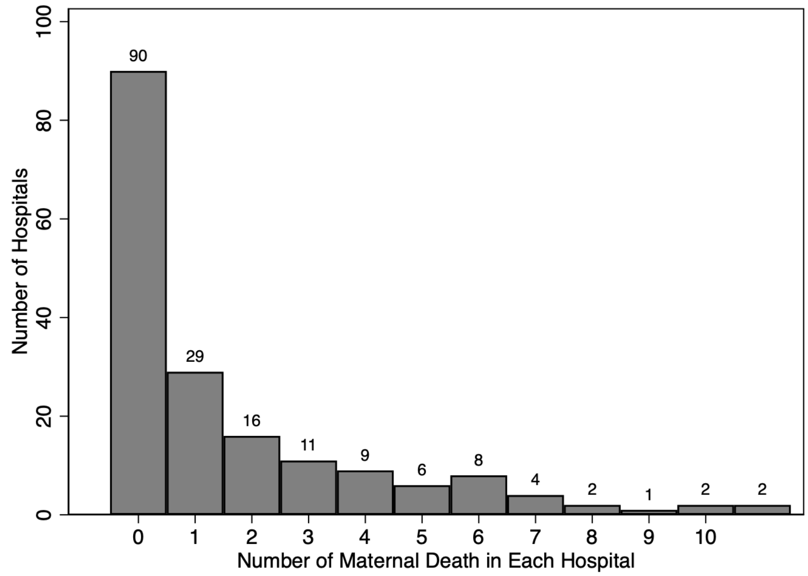
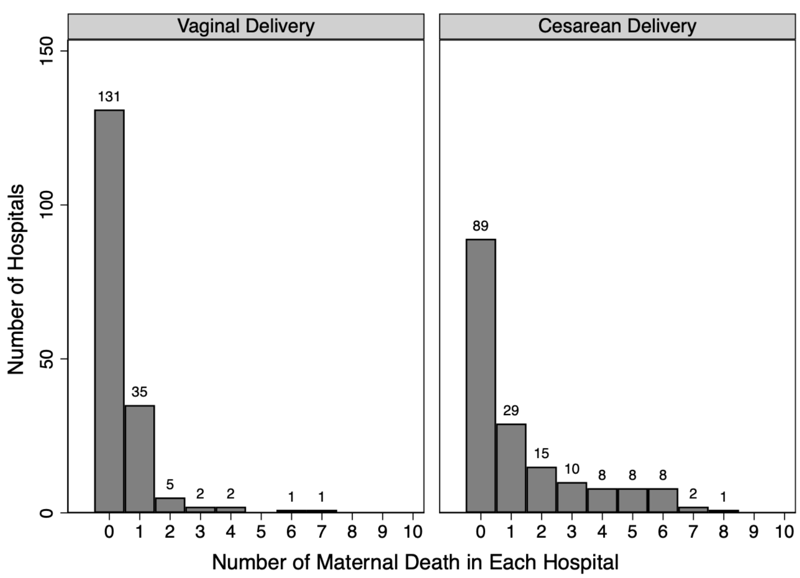


Figure A.5 Percent of Hospitals with Maternal Death
Note: Figure depicts the percentage of hospitals reporting maternal death. Sample consists of all delivery discharges identified by DRG/MS-DRG, excluding deliveries with missing information in hospital identifier, admission and year. Hospital is identified by HCUP hospital identifier. Maternal death is defined by the variable: Died during hospitalization.



(a) Overall



(b) By Delivery Method

Figure A.6 Histogram of Number of Maternal Death in Each Hospital
Note: Panel (a) depicts the histogram of number of maternal death in each hospital in New York State Inpatient Database from 2003-2017. Panel (b) plots the histogram of number of maternal death in each hospital in New York State Inpatient Database from 2003-2017 by delivery method: cesarean delivery and vaginal delivery. Sample consists of all deliveries identified by MS-DRG, excluding deliveries with missing information in hospital identifier, admission year, quarter and month. Data is collapsed at hospital level. Maternal death is defined by the variable: Died during hospitalization.

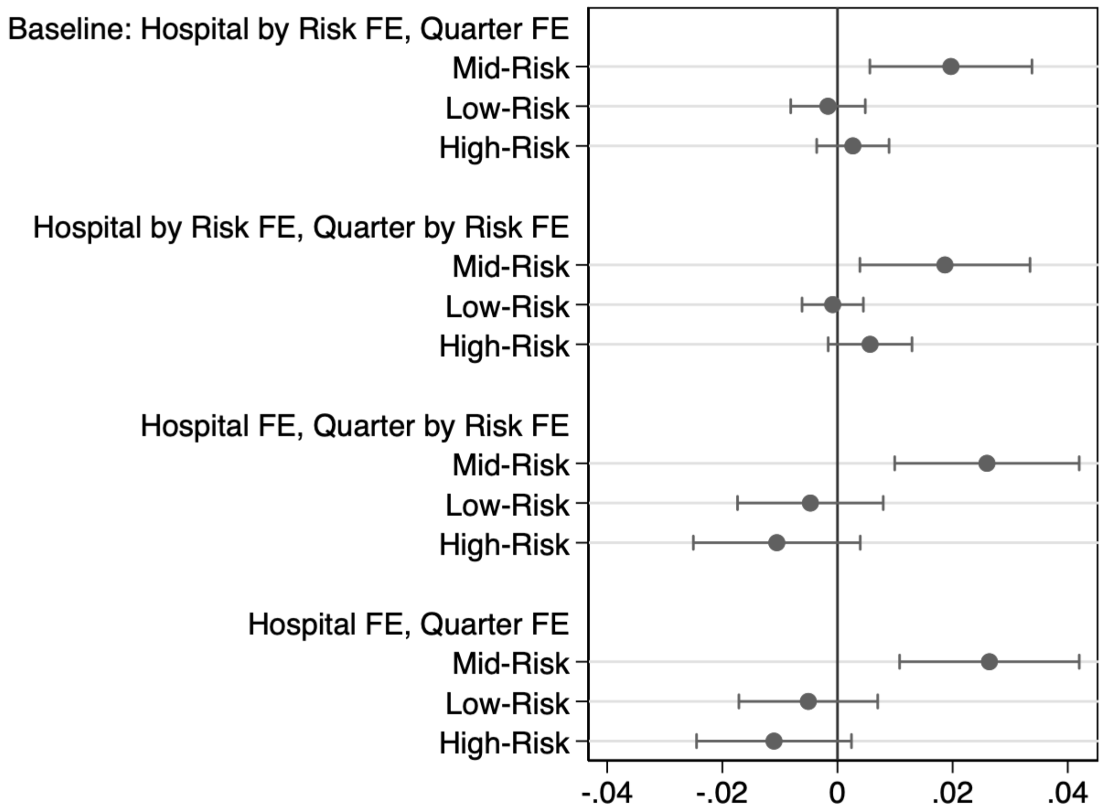


Figure A.7 Effects of Maternal Death on C-section: Variations in Fixed Effects Specifications

Note: This figure shows the estimated effects of maternal deaths on subsequent C-section under different fixed effects specifications. Each model presents the estimated coefficients of equation 1.8 using a different fixed effects specification. Each point represents a coefficient, and each whisker depicts the estimated 95% confidence interval. For each specification, the estimated coefficients and the 95% confidence intervals are plotted separately for mid-risk, low-risk and high-risk mothers. The outcome variable is whether mother i delivers via C-section. Control variables include maternal demographic characteristics and insurance status. Standard errors are clustered at hospital level.

Table A.4 Effects of Maternal Death on C-section:
Varying Time Window around Maternal Death

	(1)	(2)	(3)	(4)
	Baseline	-12 to 8	-8 to 12	-8 to 8
MidRisk*MaternalDeath	0.020***	0.020***	0.018***	0.017***
	(0.007)	(0.007)	(0.007)	(0.006)
LowRisk*MaternalDeath	-0.002	-0.001	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
HighRisk*MaternalDeath	0.003	0.004	-0.000	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Hospital by Risk FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
N	1412902	1290941	1275989	1154028
Mean	0.337	0.336	0.338	0.336
Mean (Mid-risk)	0.327	0.325	0.328	0.325
Mean (Low-Risk)	0.126	0.125	0.126	0.126
Mean (High-Risk)	0.913	0.914	0.915	0.916

Note: Each column presents the estimated coefficients for equation 1.8 with different time window around maternal death. The outcome variable is whether mother delivers via C-section. Column (1) shows the estimates coefficients from the baseline time window around maternal death: 12 quarters before and 12 quarters after maternal death. Column (2)-(4) shows the estimated coefficients using a time window of: 8 quarters before and 12 quarters after, 12 quarters before and 8 quarters after, 8 quarters before and 8 quarters after, respectively. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parenthesis, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table A.5 Effects of Maternal Death on C-section:

Restrictions on Additional Maternal Deaths

	(1) Baseline	(2) Exclude Multiple Deaths	(3) Exclude Pre Deaths	(4) Exclude Post Deaths
MidRisk*MaternalDeath	0.020***	0.022***	0.022**	0.021*
	(0.007)	(0.007)	(0.010)	(0.011)
LowRisk*MaternalDeath	-0.002	-0.002	-0.006	-0.001
	(0.003)	(0.003)	(0.004)	(0.005)
HighRisk*MaternalDeath	0.003	0.004	0.006	0.004
	(0.003)	(0.003)	(0.004)	(0.005)
Hospital by Risk FE	Yes	Yes	Yes	Yes
Quarter by Risk FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
N	1412902	1359138	969702	821073
Mean (Mid-risk)	0.327	0.329	0.321	0.314
Mean (Low-Risk)	0.126	0.126	0.124	0.123
Mean (High-Risk)	0.913	0.914	0.918	0.921
Mean	0.337	0.336	0.329	0.338

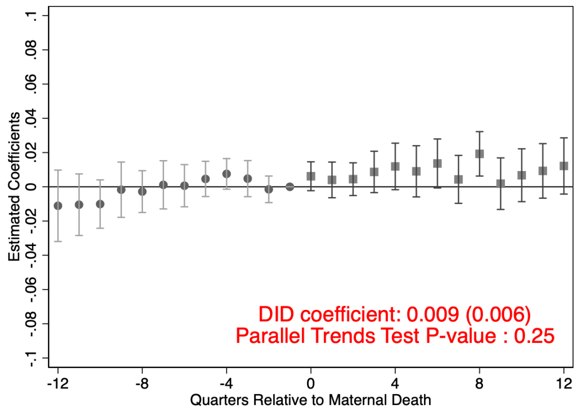
Note: Each column presents the estimated coefficients for equation 1.8 with different restrictions on hospitals with additional maternal deaths. Outcome variable is whether mother delivers via C-section. Column (1) is the baseline: no restrictions, all hospitals in the constructed sample are included. Column (2) shows the estimated coefficients after excluding hospitals with multiple deaths in the same quarter. Column (3) shows the estimated coefficients hospitals with additional maternal deaths before. Column (4) shows the estimated coefficients excluding hospitals with additional maternal deaths after. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table A.6 Effects of Maternal Death on C-section:

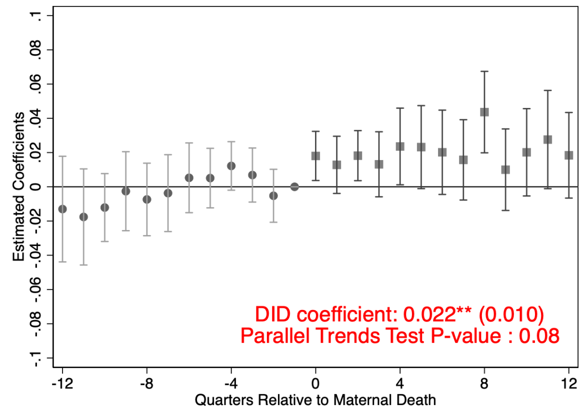
Exclude Selective Admissions

	(1) Baseline	(2) Exclude Treatment Quarter	(3) Exclude Trasnfer-in	(4) Exclude Against Advice
MidRisk*MaternalDeath	0.020***	0.020***	0.019***	0.020***
	(0.007)	(0.007)	(0.007)	(0.007)
LowRisk*MaternalDeath	-0.002	-0.002	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)
HighRisk*MaternalDeath	0.003	0.002	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Hospital by Risk FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
N	1412902	1376091	1403341	1410926
Mean (Mid-risk)	0.327	0.327	0.327	0.327
Mean (Low-Risk)	0.126	0.125	0.126	0.126
Mean (High-Risk)	0.913	0.913	0.913	0.913
Mean	0.337	0.337	0.337	0.337

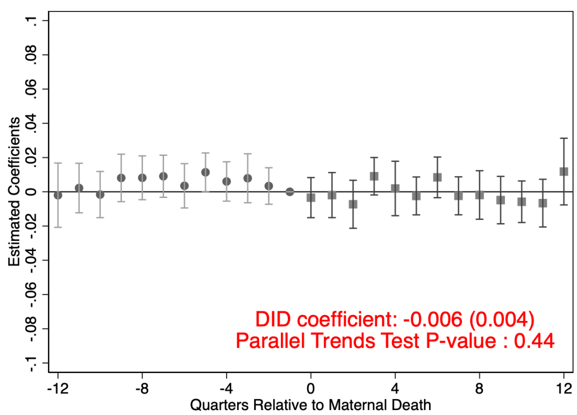
Note: Each column presents the estimated coefficients for equation 1.8 with different restrictions on delivery discharges to be included in the analysis. Outcome variable is whether mother delivers via C-section. Column (1) is the baseline: include all delivery discharges in the constructed sample. Column (2) excludes discharges in the the same quarter of maternal death. Column (3) excludes discharges that are labeled as "transferred-in" from another institution. Column (4) excludes discharges that are labeled as "discharged against medical advice". Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.



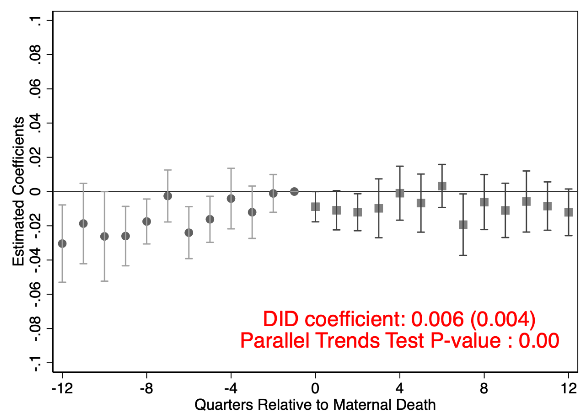
(a) All Mothers



(b) Middle-Risk Mothers



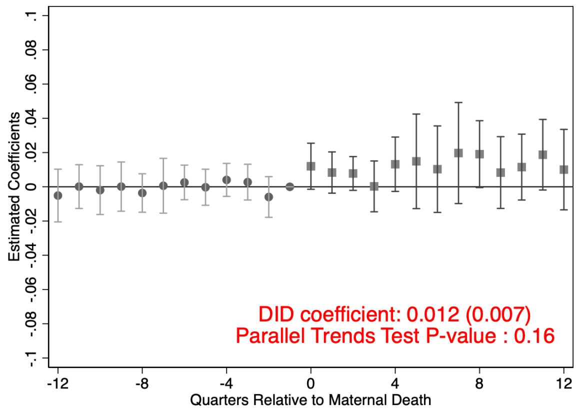
(c) Low-Risk Mothers



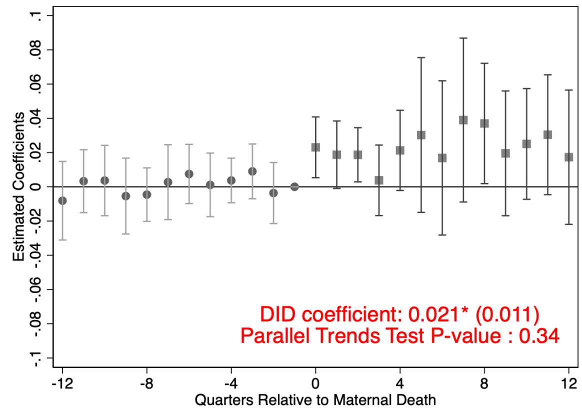
(d) High-Risk Mothers

Figure A.8 Dynamic Effects of Maternal Death on C-section: Exclude Hospitals with Additional Maternal Deaths Before

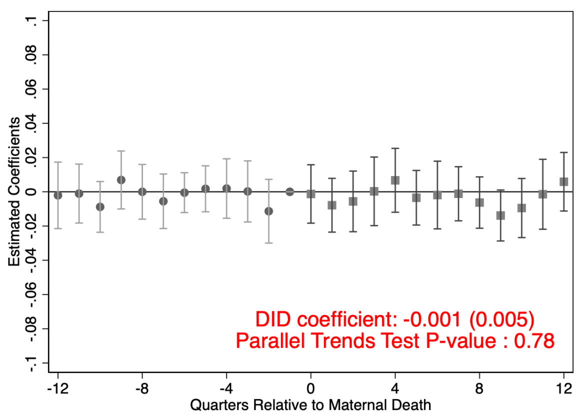
Note: This figure plots the dynamic effects of maternal death on C-section, excluding hospitals with additional maternal deaths before. Panel (a) plots the estimated coefficients of Equation 1.9, panel (b)-(d) plots the estimated coefficients of Equation 1.10 for Middle-, Low-, High-risk mothers, respectively. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.



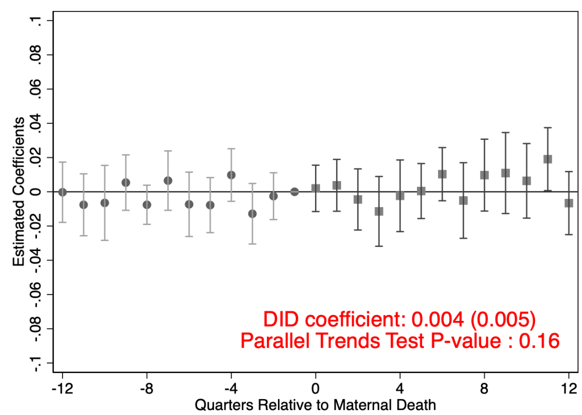
(a) All Mothers



(b) Middle-Risk Mothers



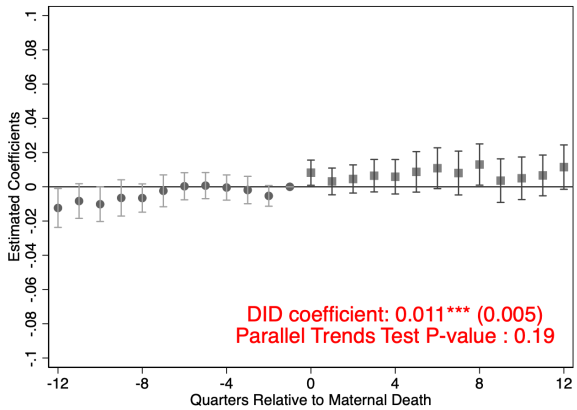
(c) Low-Risk Mothers



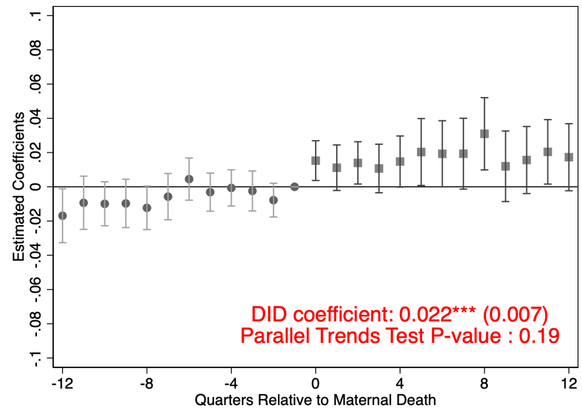
(d) High-Risk Mothers

Figure A.9 Dynamic Effects of Maternal Death on C-section: Exclude Hospitals with Additional Maternal Deaths After

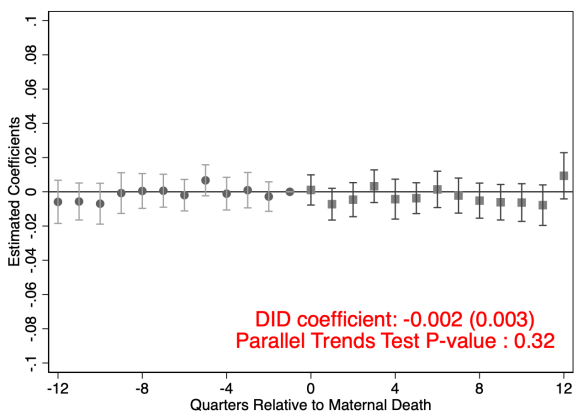
Note: This figure plots the dynamic effects of maternal death on C-section, excluding hospitals with additional maternal deaths after. Panel (a) plots the estimated coefficients of Equation 1.9, panel (b)-(d) plots the estimated coefficients of Equation 1.10 for Middle-, Low-, High-risk mothers, respectively. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.



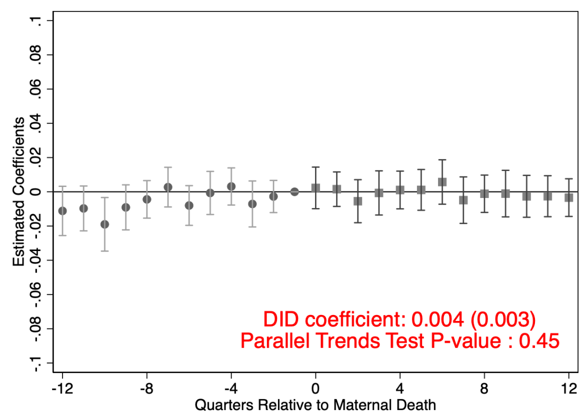
(a) All Mothers



(b) Middle-Risk Mothers



(c) Low-Risk Mothers



(d) High-Risk Mothers

Figure A.10 Dynamic Effects of Maternal Death on C-section: Exclude Hospitals with Multiple Deaths in the Same Quarter
Note: This figure plots the dynamic effects of maternal death on C-section, excluding hospitals with multiple maternal deaths in the same quarter. Panel (a) plots the estimated coefficients of Equation 1.9, panel (b)-(d) plots the estimated coefficients of Equation 1.10 for Middle-, Low-, High-risk mothers, respectively. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table A.7 Hospital Comparability

	Baseline	Exclude Control Hospitals	P-Weighted
MidRisk*MaternalDeath	0.020***	0.016***	0.019***
	(0.007)	(0.005)	(0.007)
LowRisk*MaternalDeath	-0.002	-0.005	-0.002
	(0.003)	(0.004)	(0.003)
HighRisk*MaternalDeath	0.003	-0.001	0.002
	(0.003)	(0.004)	(0.003)
Quarter FE	Yes	Yes	Yes
Hospital by Risk FE	Yes	Yes	Yes
Control	Yes	Yes	Yes
N	1412902	854205	1375719
Mean (Middle_risk)	0.327	0.342	0.339
Mean (Low-Risk)	0.126	0.130	0.130
Mean (High-Risk)	0.913	0.908	0.914
Mean	0.337	0.344	0.343

Note: Each column is a separate regression, outcome variable is whether mother delivers via C-section. Column (1) is the baseline that includes all hospitals in the constructed sample. Column (2) excludes the control hospitals, i.e., hospitals without maternal deaths in the sample period. Column (3) presents the propensity-weighted difference-in-differences estimates: I first estimates the hospitals' predicted probability of having maternal death in 2005-2017, $\hat{p}$, using data in 2003-2004, then I weight the control hospitals by $\frac{\hat{p}}{1-\hat{p}}$. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

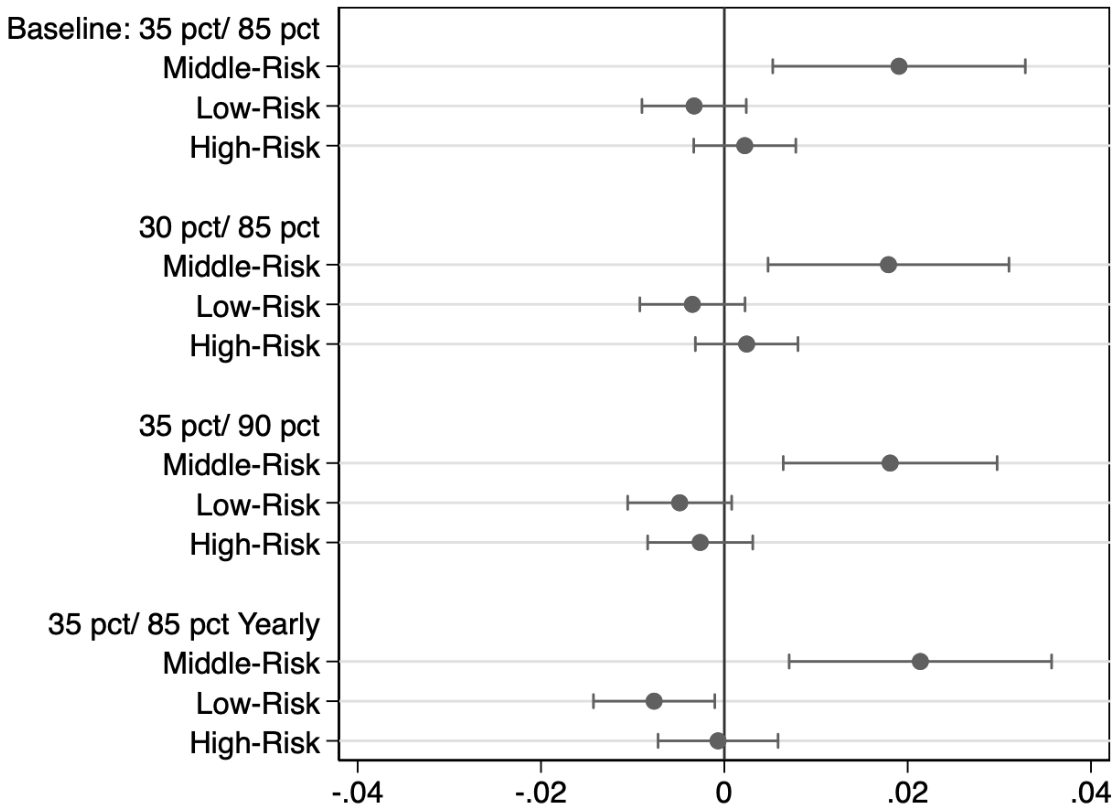


Figure A.11 Effects of Maternal Death on C-section: Varying C-section Risk Cutoff
Note: Each model presents the estimated coefficients of equation 1.8 using different cutoff of C-section risk to categorize low-risk, mid-risk, and high-risk mothers. Outcome variable is whether mother delivers via C-section. Each point represents a coefficient, and each whisker depicts the estimated 95% confidence interval. The baseline model picks the 35th percentile of C-section risk as the cutoff between low- and middle-risk mothers, and 85th percentile of C-section risk as the cutoffs between middle- and high-risk mothers. The two models following pick the 35th and 90th, 30th and 85th as the cutoffs. The last model picks the 35th and 85th percentile of mothers in the same year as the cutoffs. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are clustered at hospital level.

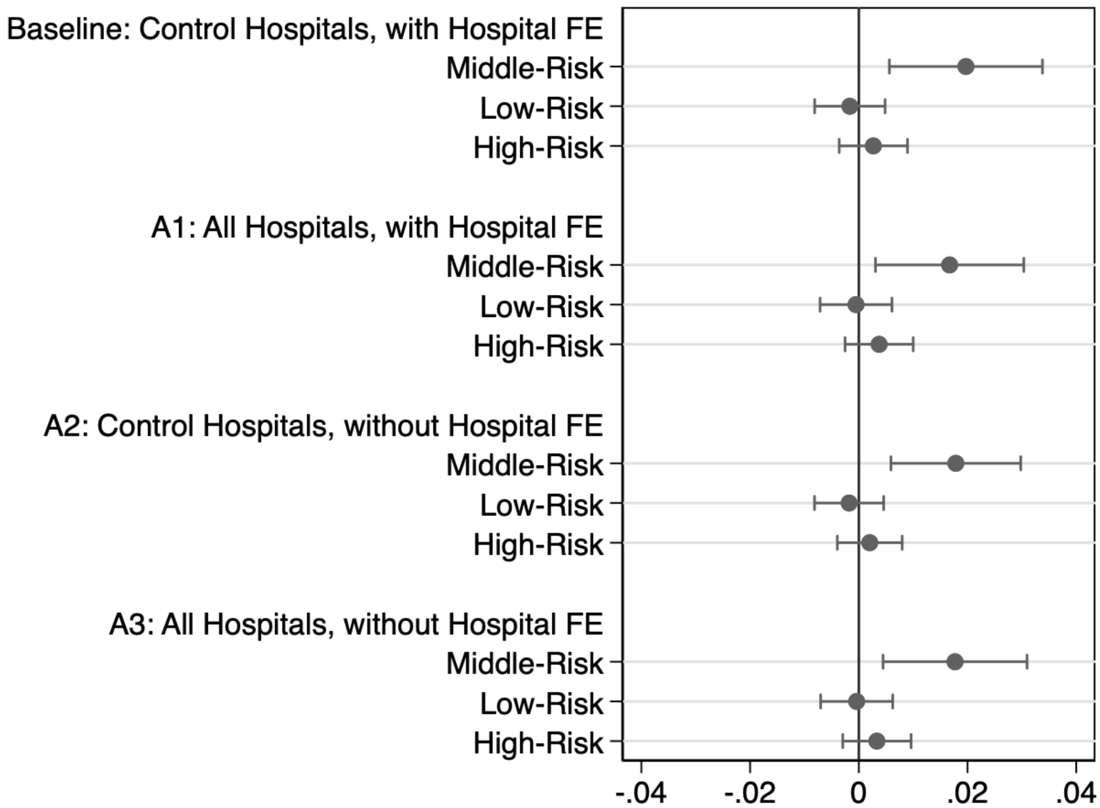
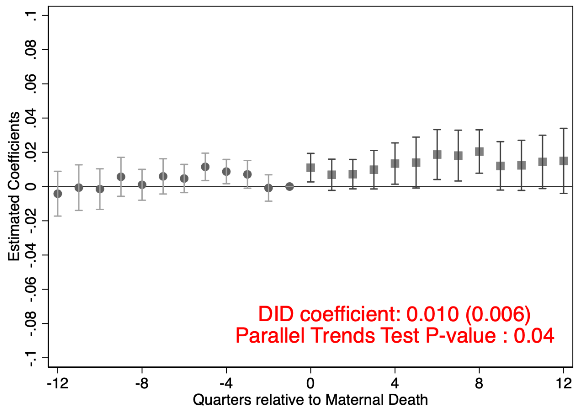


Figure A.12 Effects of Maternal Death on C-section: Alternative C-section Risk
Note: This figure shows the estimated coefficients for equation 1.8 with alternative C-section risks measures. Outcome variable is whether mother delivers via C-section. Each point represents a coefficient, and each whisker depicts the estimated 95% confidence interval. The baseline model uses the main C-section risk to categorize mothers into risk groups. The three models following use *Alternative C-section Risk 1*, *Alternative C-section Risk 2*, and *Alternative C-section Risk 3*, to categorize mothers into risk groups. Refer to Section 1.4.2 for how these measures are constructed. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are clustered at hospital level.

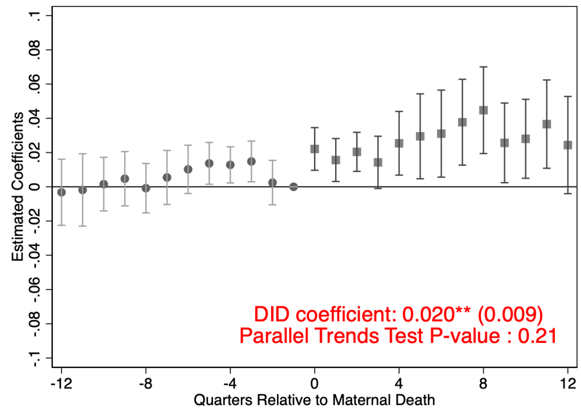
Table A.8 Effects of Maternal Death on C-section:
Alternative Sample Construction

	(1) Baseline: 2-year	(2) 3-year	(3) 4-year	(4) 5-year
MidRisk*MaternalDeath	0.020***	0.022**	0.024**	0.017
	(0.007)	(0.009)	(0.011)	(0.014)
LowRisk*MaternalDeath	-0.002	-0.004	0.000	-0.002
	(0.003)	(0.004)	(0.004)	(0.006)
HighRisk*MaternalDeath	0.003	0.003	0.005	0.003
	(0.003)	(0.004)	(0.005)	(0.007)
Hospital by Risk FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
N	1412902	1124872	899101	757955
Mean (Middle_risk)	0.327	0.328	0.319	0.309
Mean (Low-Risk)	0.126	0.127	0.125	0.120
Mean(High-Risk)	0.913	0.919	0.919	0.918
Mean	0.337	0.339	0.335	0.331

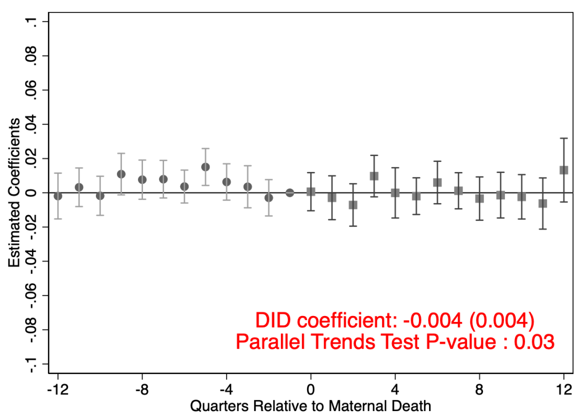
Note: Each column is a separate regression, and outcome variable is whether mother delivers via C-section. Column (1) is the baseline that include hospitals with a 2-year "clean-period" before maternal death. Column (2)-(4) increase the length of the "clean-period" to be 3-5 years. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.



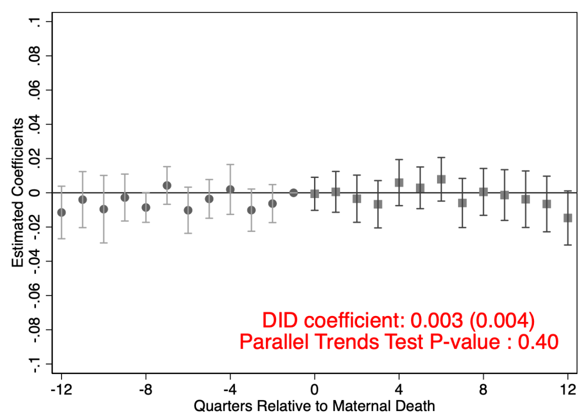
(a) All Mothers



(b) Middle-Risk Mothers

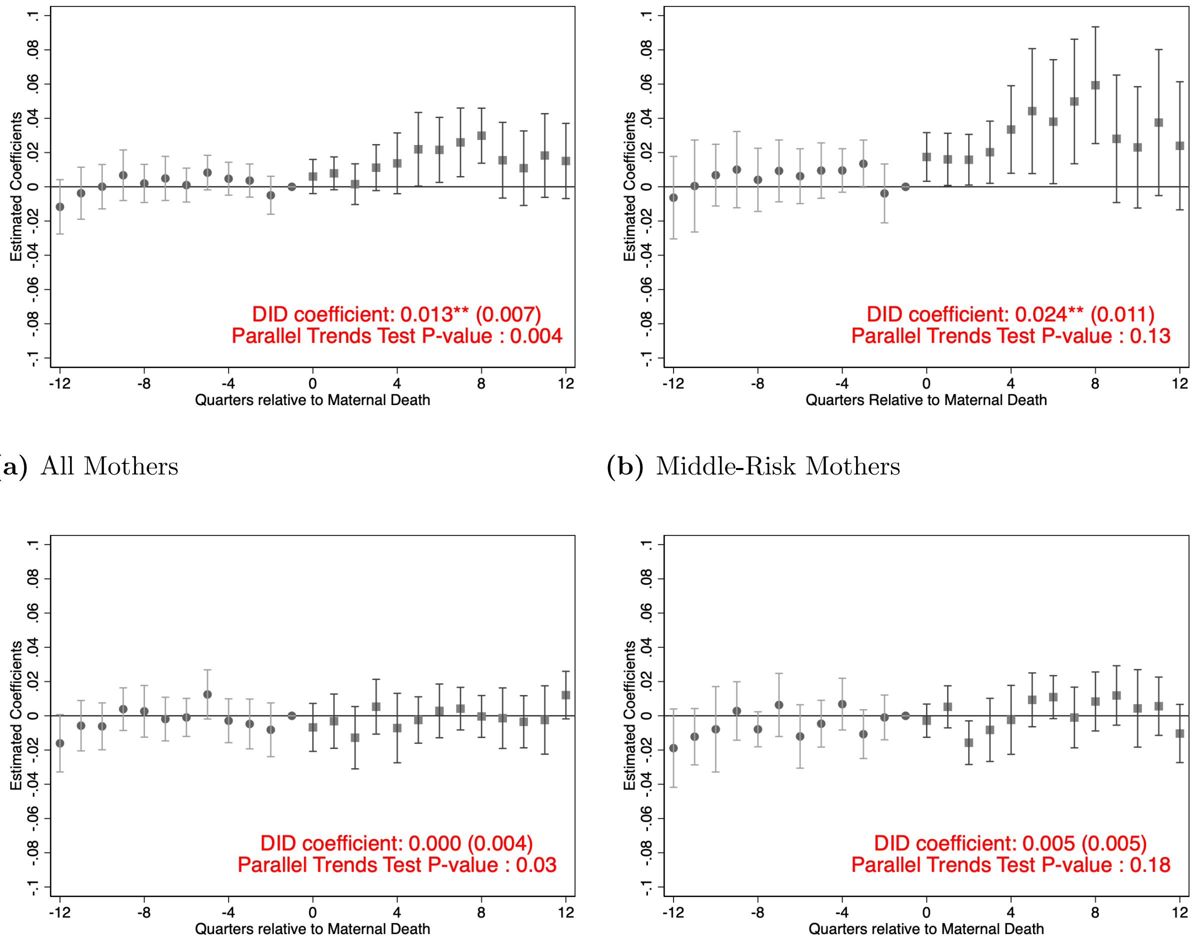


(c) Low-Risk Mothers



(d) High-Risk Mothers

Figure A.13 Dynamic Effects on C-section: Sample of 3-year “Clean-Period”
Note: Analysis is based on sample of hospitals with 3-year “clean-period” before maternal death. Each point represents a coefficient corresponding to the number of quarters since maternal death, and each whisker depicts the estimated 95% confidence interval. Panel (a) plots aggregate effects for all mothers, panel (b)-(d) plot effects by risk groups. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.



(a) All Mothers

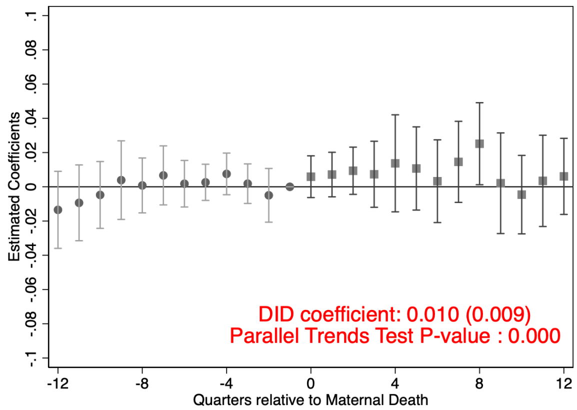
(b) Middle-Risk Mothers

(c) Low-Risk Mothers

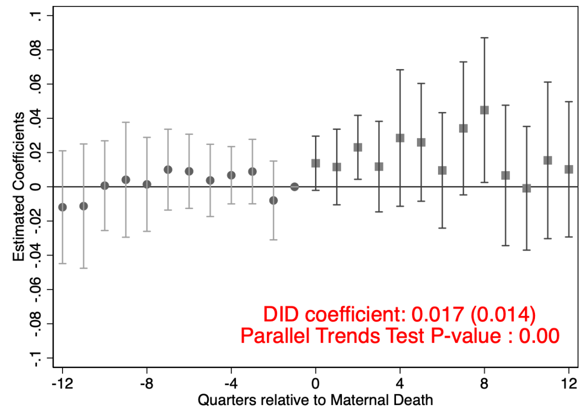
(d) High-Risk Mothers

Figure A.14 Dynamic Effects on C-section: Sample of 4-year "Clean-Period"

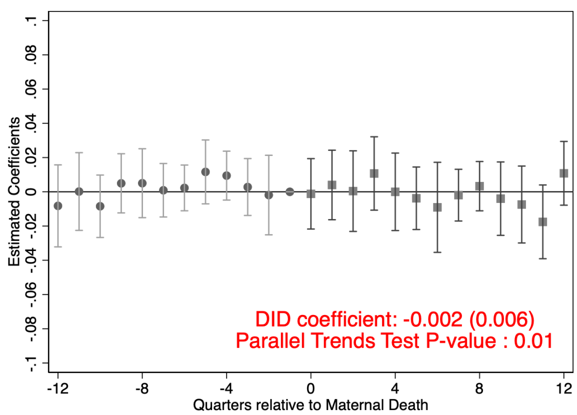
Note: Analysis is based on sample of hospitals with 4-year "clean-period" before maternal death. Each point represents a coefficient corresponding to the number of quarters since maternal death, and each whisker depicts the estimated 95% confidence interval. Panel (a) plots aggregate effects for all mothers, panel (b)-(d) plot effects by risk groups. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.



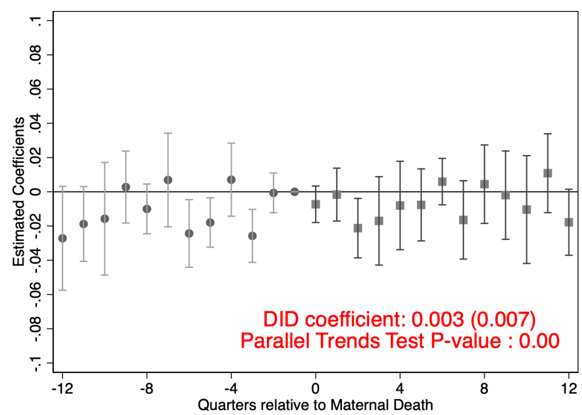
(a) All Mothers



(b) Middle-Risk Mothers



(c) Low-Risk Mothers



(d) High-Risk Mothers

Figure A.15 Dynamic Effects on C-section: Sample of 5-year "Clean-Period"
Note: Analysis is based on sample of hospitals with 5-year "clean-period" before maternal death. Each point represents a coefficient corresponding to number of quarters since maternal death, and each whisker depicts the estimated 95% confidence interval. Panel (a) plots aggregate effects for all mothers, panel (b)-(d) plot effects by risk groups. Control variables include maternal demographic characteristics and insurance status. Quarter fixed effects and hospital-by-risk-group fixed effects are included in the regression. Standard errors are in parentheses, and are clustered at hospital level. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Appendix B

Appendix for "Natural Disasters and Family Planning: Evidence on Birth and Migration"

Table B.1 Trimmed and Untrimmed Sample for Hurricane Analysis:

Variables to Estimate Propensity Score

		Untrimmed			Trimmed		
	All Counties	Treat	Control	Diff	Treat	Control	Diff
Weather Variables							
Cooling Degree Days	91.257	133.662	64.421	-69.241***	84.370	87.526	3.156
	(138.863)	(167.208)	(109.250)	(1.602)	(128.098)	(128.292)	(2.992)
Heating Degree Days	448.357	304.365	539.478	235.112***	421.048	408.273	-12.774
	(463.970)	(367.007)	(494.814)	(4.575)	(427.429)	(399.814)	(9.684)
Precipitation	3.199	4.134	2.607	-1.527***	4.182	4.216	0.033
	(2.532)	(2.672)	(2.246)	(0.027)	(2.732)	(2.470)	(0.061)
Max Temperature	64.471	70.283	60.793	-9.490***	64.714	65.329	0.615
	(19.009)	(16.274)	(19.685)	(0.192)	(17.510)	(16.778)	(0.401)
Min Temperature	41.784	48.304	37.659	-10.645***	42.918	43.349	0.431
	(18.197)	(16.108)	(18.237)	(0.184)	(16.756)	(16.039)	(0.383)
Average Temperature	53.130	59.297	49.228	-10.069***	53.820	54.341	0.522
	(18.488)	(16.087)	(18.842)	(0.187)	(17.020)	(16.284)	(0.389)
Location Variables							
Shoreline Counties	0.110	0.183	0.063	-0.120***	0.042	0.027	-0.015***
	(0.312)	(0.387)	(0.243)	(0.004)	(0.201)	(0.163)	(0.004)
Watershed Counties	0.197	0.337	0.109	-0.229***	0.084	0.070	-0.015**
	(0.398)	(0.473)	(0.311)	(0.005)	(0.278)	(0.255)	(0.006)
Geographic Variables							
Pct Water Area	4.497	5.860	3.634	-2.226***	3.575	2.424	-1.151***
	(11.052)	(12.043)	(10.283)	(0.124)	(9.370)	(7.252)	(0.197)
Amenity Scale	0.064	0.466	-0.191	-0.657***	-0.020	-0.239	-0.219***
	(2.321)	(1.384)	(2.724)	(0.022)	(1.210)	(1.985)	(0.038)
Plains	0.486	0.559	0.441	-0.118***	0.305	0.361	0.055***
	(0.500)	(0.497)	(0.496)	(0.005)	(0.461)	(0.480)	(0.011)
Tablelands	0.065	0.082	0.055	-0.027***	0.130	0.073	-0.057***
	(0.247)	(0.274)	(0.228)	(0.003)	(0.336)	(0.260)	(0.007)
Plains with Hills	0.071	0.067	0.074	0.007***	0.028	0.048	0.020***
	(0.257)	(0.250)	(0.262)	(0.003)	(0.165)	(0.215)	(0.004)
Open Hills/Mountains	0.236	0.186	0.267	0.082***	0.263	0.270	0.007
	(0.424)	(0.389)	(0.443)	(0.004)	(0.440)	(0.444)	(0.010)
Hills/Mountains	0.142	0.108	0.163	0.055***	0.274	0.248	-0.025**
	(0.349)	(0.310)	(0.369)	(0.004)	(0.446)	(0.432)	(0.010)
N	35700	13836	21864	35700	3420	3960	7380

Note: This table compares the trimmed and untrimmed sample for hurricane analysis. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. In the untrimmed sample, all counties are included. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Both samples are split into the treated counties: the counties that have ever declared hurricane, and control counties: the counties that have never declared hurricane in the sample period. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. Statistics are reported for the period 1989-2019.

Table B.2 Trimmed and Untrimmed Sample for Hurricane Analysis:

Birth Rates and Control Variables

		Untrimmed			Trimmed		
	All Counties	Treat	Control	Diff	Treat	Control	Diff
Birth Rates							
Birth Rate	14.600	15.207	14.216	-0.990***	14.087	14.418	0.331***
	(5.008)	(4.679)	(5.169)	(0.053)	(4.182)	(4.241)	(0.098)
Birth Rate, Black	15.193	18.771	12.828	-5.943***	16.192	14.087	-2.105
	(112.306)	(69.008)	(133.375)	(1.098)	(85.767)	(34.144)	(1.569)
Birth Rate White	13.868	13.898	13.850	-0.049	13.380	13.959	0.579***
	(4.947)	(4.813)	(5.030)	(0.053)	(4.082)	(4.170)	(0.096)
Birth Rate, Age 15-34	46.634	46.708	46.587	-0.121	44.464	44.946	0.481
	(16.632)	(14.969)	(17.605)	(0.174)	(14.020)	(13.046)	(0.317)
Birth Rate, Age 35-49	5.170	5.060	5.240	0.181***	4.426	4.172	-0.254**
	(6.225)	(4.948)	(6.912)	(0.063)	(4.220)	(5.325)	(0.111)
Demographic Controls							
Pct Black Population	0.082	0.172	0.025	-0.147***	0.093	0.065	-0.028***
	(0.141)	(0.180)	(0.058)	(0.002)	(0.144)	(0.103)	(0.003)
Pct White Population	0.897	0.818	0.947	0.129***	0.898	0.923	0.025***
	(0.148)	(0.180)	(0.095)	(0.002)	(0.144)	(0.105)	(0.003)
Pct Female Population	0.510	0.513	0.507	-0.006***	0.514	0.513	-0.001***
	(0.016)	(0.018)	(0.014)	(0.000)	(0.013)	(0.012)	(0.000)
Pct Age 15-49	0.485	0.497	0.477	-0.020***	0.489	0.498	0.008***
	(0.052)	(0.048)	(0.053)	(0.001)	(0.044)	(0.036)	(0.001)
Local Economic Controls							
Per-capita Income	14683.521	14578.925	14749.747	170.821***	14051.018	13296.418	-754.599***
	(3286.568)	(3827.515)	(2890.350)	(37.962)	(2657.203)	(2676.296)	(62.236)
Employment/Population	0.474	0.453	0.487	0.034***	0.442	0.436	-0.005**
	(0.136)	(0.137)	(0.134)	(0.001)	(0.106)	(0.104)	(0.002)
N	35688	13836	21852	35688	3420	3960	7380

Note: This table compares the trimmed and untrimmed sample for hurricane analysis. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. In the untrimmed sample, all counties are included. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Both samples are split into the treated counties: the counties that have ever declared hurricane, and control counties: the counties that have never declared hurricane in the sample period. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. Statistics are reported for the period 1989-2019.

Table B.3 Trimmed and Untrimmed Sample for Flood Analysis:

Variables to Estimate Propensity Score

		Untrimmed			Trimmed		
	All Counties	Treat	Control	Diff	Treat	Control	Diff
Weather Variables							
Cooling Degree Days	91.257	83.432	109.442	26.010***	90.856	111.258	20.401***
	(138.863)	(132.352)	(151.380)	(1.684)	(138.877)	(152.461)	(1.803)
Heating Degree Days	448.357	479.692	375.534	-104.157***	449.707	368.906	-80.801***
	(463.970)	(481.633)	(410.958)	(5.002)	(464.433)	(406.627)	(5.220)
Precipitation	3.199	3.070	3.498	0.428***	3.281	3.529	0.247***
	(2.532)	(2.509)	(2.559)	(0.029)	(2.549)	(2.570)	(0.031)
Max Temperature	64.471	63.097	67.664	4.567***	64.298	67.946	3.648***
	(19.009)	(19.483)	(17.447)	(0.209)	(18.958)	(17.307)	(0.218)
Min Temperature	41.784	40.566	44.617	4.051***	41.843	44.893	3.050***
	(18.197)	(18.508)	(17.122)	(0.203)	(18.231)	(17.038)	(0.213)
Average Temperature	53.130	51.834	56.144	4.310***	53.073	56.423	3.350***
	(18.488)	(18.891)	(17.140)	(0.204)	(18.489)	(17.028)	(0.214)
Location Variables							
Shoreline Counties	0.110	0.097	0.140	0.043***	0.106	0.144	0.037***
	(0.312)	(0.295)	(0.347)	(0.004)	(0.308)	(0.351)	(0.004)
Watershed Counties	0.197	0.174	0.253	0.079***	0.195	0.260	0.065***
	(0.398)	(0.379)	(0.434)	(0.005)	(0.397)	(0.439)	(0.005)
Geographic Variables							
Pct Water Area	4.497	4.066	5.497	1.430***	4.523	5.635	1.111***
	(11.052)	(9.824)	(13.428)	(0.144)	(10.768)	(13.638)	(0.155)
Amenity Scale	0.064	-0.094	0.429	0.523***	-0.099	0.429	0.527***
	(2.321)	(2.400)	(2.082)	(0.025)	(2.262)	(2.094)	(0.026)
Plains	0.486	0.452	0.565	0.113***	0.507	0.579	0.072***
	(0.500)	(0.498)	(0.496)	(0.006)	(0.500)	(0.494)	(0.006)
Tablelands	0.065	0.056	0.086	0.030***	0.063	0.089	0.026***
	(0.247)	(0.230)	(0.280)	(0.003)	(0.244)	(0.285)	(0.003)
Plains with Hills	0.071	0.064	0.088	0.024***	0.080	0.090	0.010***
	(0.257)	(0.245)	(0.284)	(0.003)	(0.272)	(0.287)	(0.003)
Open Hills/Mountains	0.236	0.256	0.188	-0.069***	0.204	0.176	-0.028***
	(0.424)	(0.437)	(0.390)	(0.005)	(0.403)	(0.381)	(0.005)
Hills/Mountains	0.142	0.171	0.073	-0.099***	0.145	0.066	-0.079***
	(0.349)	(0.377)	(0.260)	(0.003)	(0.352)	(0.248)	(0.004)
N	35700	24960	10740	35700	19092	10368	29460

Note: This table compares the trimmed and untrimmed sample for flood analysis. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. In the untrimmed sample, all counties are included. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Both samples are split into the treated counties: the counties that have ever declared flood, and control counties: the counties that have never declared flood in the sample period. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. Statistics are reported for the period 1989-2019.

Table B.4 Trimmed and Untrimmed Sample for Flood Analysis:

Birth Rates and Control Variables

		Untrimmed			Trimmed		
	All Counties	Treat	Control	Diff	Treat	Control	Diff
Birth Rates							
Birth Rate	14.600	14.387	15.096	0.709***	14.498	15.171	0.673***
	(5.008)	(4.798)	(5.434)	(0.061)	(4.650)	(5.416)	(0.063)
Birth Rate, Black	15.193	14.882	15.911	1.029	15.645	16.306	0.661
	(112.306)	(126.848)	(67.653)	(1.054)	(128.394)	(68.741)	(1.165)
Birth Rate White	13.868	13.783	14.066	0.283***	13.852	14.107	0.254***
	(4.947)	(4.644)	(5.583)	(0.061)	(4.540)	(5.584)	(0.064)
Birth Rate, Age 15-34	46.634	46.365	47.258	0.893***	46.087	47.377	1.289***
	(16.632)	(16.093)	(17.806)	(0.200)	(15.279)	(17.680)	(0.206)
Birth Rate, Age 35-49	5.170	5.212	5.074	-0.138*	5.075	5.101	0.026
	(6.225)	(6.061)	(6.589)	(0.074)	(5.840)	(6.634)	(0.078)
Demographic Controls							
Pct Black Population	0.082	0.061	0.131	0.071***	0.076	0.136	0.059***
	(0.141)	(0.120)	(0.169)	(0.002)	(0.133)	(0.171)	(0.002)
Pct White Population	0.897	0.916	0.854	-0.062***	0.905	0.849	-0.056***
	(0.148)	(0.134)	(0.170)	(0.002)	(0.138)	(0.172)	(0.002)
Pct Female Population	0.510	0.510	0.510	0.001***	0.510	0.510	0.000
	(0.016)	(0.015)	(0.018)	(0.000)	(0.015)	(0.018)	(0.000)
Pct Age 15-49	0.485	0.481	0.493	0.011***	0.486	0.493	0.007***
	(0.052)	(0.052)	(0.051)	(0.001)	(0.049)	(0.052)	(0.001)
Local Economic Controls							
Per-capita Income	14683.521	14619.022	14833.344	214.322***	14567.492	14848.762	281.270***
	(3286.568)	(3247.963)	(3369.931)	(38.474)	(3398.883)	(3407.442)	(41.537)
Employment/Population	0.474	0.471	0.481	0.010***	0.465	0.481	0.016***
	(0.136)	(0.118)	(0.171)	(0.002)	(0.123)	(0.173)	(0.002)
N	35688	24948	10740	35688	19080	10368	29448

Note: This table compares the trimmed and untrimmed sample for flood analysis. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. In the untrimmed sample, all counties are included. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Both samples are split into the treated counties: the counties that have ever declared flood, and control counties: the counties that have never declared flood in the sample period. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. Statistics are reported for the period 1989-2019.

Table B.5 Trimmed and Untrimmed Sample for Fire Analysis:

Variables to Estimate Propensity Score

		Untrimmed			Trimmed		
	All Counties	Treat	Control	Diff	Treat	Control	Diff
Weather Variables							
Cooling Degree Days	91.257	123.218	81.477	-41.740***	116.508	92.958	-23.550***
	(138.863)	(169.660)	(126.366)	(2.006)	(160.413)	(138.050)	(2.419)
Heating Degree Days	448.357	367.957	472.957	105.000***	367.134	445.107	77.973***
	(463.970)	(414.582)	(475.361)	(5.368)	(404.122)	(467.270)	(6.782)
Precipitation	3.199	2.572	3.391	0.818***	2.502	3.007	0.505***
	(2.532)	(2.421)	(2.534)	(0.031)	(2.467)	(2.557)	(0.040)
Max Temperature	64.471	68.868	63.125	-5.743***	68.964	64.999	-3.966***
	(19.009)	(18.083)	(19.082)	(0.229)	(17.507)	(18.945)	(0.286)
Min Temperature	41.784	44.799	40.862	-3.937***	44.300	41.579	-2.720***
	(18.197)	(17.655)	(18.261)	(0.222)	(17.232)	(18.485)	(0.280)
Average Temperature	53.130	56.837	51.996	-4.841***	56.636	53.292	-3.344***
	(18.488)	(17.697)	(18.576)	(0.224)	(17.186)	(18.597)	(0.281)
Location Variables							
Shoreline Counties	0.110	0.156	0.095	-0.061***	0.112	0.121	0.009*
	(0.312)	(0.363)	(0.294)	(0.004)	(0.315)	(0.326)	(0.005)
Watershed Counties	0.197	0.263	0.177	-0.085***	0.179	0.225	0.047***
	(0.398)	(0.440)	(0.382)	(0.005)	(0.383)	(0.418)	(0.006)
Geographic Variables							
Pct Water Area	4.497	4.497	4.497	-0.000	2.927	4.101	1.174***
	(11.052)	(9.573)	(11.466)	(0.126)	(6.274)	(8.368)	(0.113)
Amenity Scale	0.064	1.832	-0.477	-2.309***	1.656	0.413	-1.243***
	(2.321)	(2.262)	(2.055)	(0.028)	(1.889)	(1.937)	(0.030)
Plains	0.486	0.429	0.504	0.075***	0.440	0.450	0.010
	(0.500)	(0.495)	(0.500)	(0.006)	(0.496)	(0.498)	(0.008)
Tablelands	0.065	0.143	0.041	-0.102***	0.167	0.046	-0.122***
	(0.247)	(0.351)	(0.199)	(0.004)	(0.373)	(0.209)	(0.005)
Plains with Hills	0.071	0.099	0.063	-0.036***	0.104	0.090	-0.013***
	(0.257)	(0.299)	(0.243)	(0.004)	(0.305)	(0.287)	(0.005)
Open Hills/Mountains	0.236	0.148	0.263	0.115***	0.135	0.312	0.177***
	(0.424)	(0.355)	(0.440)	(0.005)	(0.341)	(0.463)	(0.006)
Hills/Mountains	0.142	0.181	0.129	-0.051***	0.154	0.102	-0.051***
	(0.349)	(0.385)	(0.336)	(0.005)	(0.361)	(0.303)	(0.005)
N	35700	8364	27336	35700	6240	11016	17256

Note: This table compares the trimmed and untrimmed sample for hurricane analysis. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. In the untrimmed sample, all counties are included. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Both samples are split into the treated counties: the counties that have ever declared hurricane, and control counties: the counties that have never declared hurricane in the sample period. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. Statistics are reported for the period 1989-2019.

Table B.6 Trimmed and Untrimmed Sample for Fire Analysis:

Birth Rates and Control Variables

		Untrimmed			Trimmed		
	All Counties	Treat	Control	Diff	Treat	Control	Diff
Birth Rates							
Birth Rate	14.600	14.877	14.516	-0.362***	14.572	15.044	0.472***
	(5.008)	(5.761)	(4.751)	(0.069)	(5.398)	(5.643)	(0.087)
Birth Rate, Black	15.193	16.759	14.718	-2.041	16.942	16.254	-0.688
	(112.306)	(126.860)	(107.504)	(1.565)	(142.866)	(151.560)	(2.378)
Birth Rate White	13.868	14.404	13.704	-0.700***	14.043	13.863	-0.180**
	(4.947)	(5.734)	(4.668)	(0.069)	(5.313)	(5.592)	(0.086)
Birth Rate, Age 15-34	46.634	47.416	46.394	-1.022***	47.128	48.205	1.077***
	(16.632)	(18.787)	(15.906)	(0.227)	(17.921)	(18.896)	(0.290)
Birth Rate, Age 35-49	5.170	5.770	4.986	-0.784***	5.351	5.439	0.088
	(6.225)	(7.868)	(5.613)	(0.092)	(7.669)	(6.909)	(0.117)
Demographic Controls							
Pct Black Population	0.082	0.055	0.090	0.035***	0.060	0.123	0.064***
	(0.141)	(0.077)	(0.154)	(0.001)	(0.082)	(0.179)	(0.002)
Pct White Population	0.897	0.910	0.893	-0.017***	0.900	0.853	-0.048***
	(0.148)	(0.100)	(0.160)	(0.001)	(0.108)	(0.185)	(0.002)
Pct Female Population	0.510	0.505	0.511	0.006***	0.505	0.509	0.004***
	(0.016)	(0.018)	(0.015)	(0.000)	(0.018)	(0.018)	(0.000)
Population Age 15-49	0.485	0.484	0.485	0.001	0.481	0.480	-0.000
	(0.052)	(0.058)	(0.050)	(0.001)	(0.056)	(0.055)	(0.001)
Local Economic Controls							
Per-capita Income	14683.521	15033.948	14576.253	-457.695***	14649.550	14495.467	-154.083***
	(3286.568)	(3904.297)	(3064.836)	(46.543)	(3430.376)	(3149.622)	(52.795)
Employment/Population	0.474	0.473	0.474	0.002	0.472	0.490	0.018***
	(0.136)	(0.142)	(0.134)	(0.002)	(0.140)	(0.159)	(0.002)
N	35688	8364	27324	35688	6240	11004	17244

Note: This table compares the trimmed and untrimmed sample for fire analysis. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. In the untrimmed sample, all counties are included. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Both samples are split into the treated counties: the counties that have ever declared fire, and control counties: the counties that have never declared fire in the sample period. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. Statistics are reported for the period 1989-2019.

Table B.7 Trimmed and Untrimmed Sample for Tornado Analysis:

Variables to Estimate Propensity Score

		Untrimmed			Trimmed		
	All Counties	Treat	Control	Diff	Treat	Control	Diff
Weather Variables							
Cooling Degree Days	91.257	116.066	85.093	-30.972***	118.995	102.535	-16.459***
	(138.863)	(150.594)	(135.090)	(1.957)	(152.128)	(145.422)	(2.147)
Heating Degree Days	448.357	370.308	467.746	97.439***	361.060	423.198	62.138***
	(463.970)	(428.740)	(470.318)	(5.797)	(423.065)	(463.154)	(6.206)
Precipitation	3.199	3.869	3.033	-0.836***	3.927	3.628	-0.299***
	(2.532)	(2.587)	(2.490)	(0.034)	(2.593)	(2.559)	(0.037)
Max Temperature	64.471	67.508	63.716	-3.792***	67.893	65.316	-2.577***
	(19.009)	(17.976)	(19.183)	(0.242)	(17.795)	(18.962)	(0.259)
Min Temperature	41.784	45.527	40.855	-4.673***	45.947	43.334	-2.613***
	(18.197)	(17.602)	(18.223)	(0.235)	(17.493)	(18.466)	(0.254)
Average Temperature	53.130	56.521	52.288	-4.233***	56.923	54.328	-2.595***
	(18.488)	(17.718)	(18.579)	(0.237)	(17.576)	(18.643)	(0.255)
Location Variables							
Shoreline Counties	0.110	0.074	0.118	0.044***	0.069	0.075	0.006*
	(0.312)	(0.262)	(0.323)	(0.004)	(0.254)	(0.264)	(0.004)
Watershed Counties	0.197	0.147	0.210	0.063***	0.131	0.145	0.014***
	(0.398)	(0.354)	(0.407)	(0.005)	(0.338)	(0.352)	(0.005)
Geographic Variables							
Pct Water Area	4.497	3.951	4.632	0.681***	3.707	3.531	-0.176
	(11.052)	(8.976)	(11.506)	(0.126)	(8.302)	(8.214)	(0.118)
Amenity Scale	0.064	-0.384	0.175	0.559***	-0.403	-0.627	-0.224***
	(2.321)	(1.767)	(2.427)	(0.025)	(1.765)	(1.730)	(0.025)
Plains	0.486	0.650	0.446	-0.205***	0.675	0.557	-0.117***
	(0.500)	(0.477)	(0.497)	(0.006)	(0.468)	(0.497)	(0.007)
Tablelands	0.065	0.046	0.070	0.024***	0.034	0.054	0.020***
	(0.247)	(0.209)	(0.255)	(0.003)	(0.181)	(0.226)	(0.003)
Plains with Hills	0.071	0.029	0.082	0.053***	0.025	0.036	0.011***
	(0.257)	(0.167)	(0.274)	(0.003)	(0.156)	(0.185)	(0.002)
Open Hills/Mountains	0.236	0.209	0.242	0.033***	0.204	0.249	0.045***
	(0.424)	(0.407)	(0.428)	(0.005)	(0.403)	(0.432)	(0.006)
Hills/Mountains	0.142	0.066	0.160	0.094***	0.062	0.104	0.042***
	(0.349)	(0.248)	(0.367)	(0.004)	(0.241)	(0.306)	(0.004)
N	35700	7104	28596	35700	6756	17844	24600

Note: This table compares the trimmed and untrimmed sample for tornado analysis. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. In the untrimmed sample, all counties are included. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Both samples are split into the treated counties: the counties that have ever declared tornado, and control counties: the counties that have never declared tornado in the sample period. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. Statistics are reported for the period 1989-2019.

Table B.8 Trimmed and Untrimmed Sample for Tornado Analysis:

Birth Rates and Control Variables

		Untrimmed			Trimmed		
	All Counties	Treat	Control	Diff	Treat	Control	Diff
Birth Rates							
Birth Rate	14.600	14.499	14.626	0.127**	14.468	14.373	-0.094
	(5.008)	(4.107)	(5.208)	(0.058)	(4.018)	(4.365)	(0.059)
Birth Rate, Black	15.193	16.413	14.880	-1.533*	16.236	15.271	-0.965
	(112.306)	(37.335)	(124.477)	(0.874)	(29.309)	(82.172)	(0.718)
Birth Rate White	13.868	13.388	13.988	0.600***	13.356	13.593	0.237***
	(4.947)	(4.105)	(5.128)	(0.057)	(4.021)	(4.269)	(0.058)
Birth Rate, Age 15-34	46.634	45.695	46.867	1.172***	45.604	45.903	0.300
	(16.632)	(12.948)	(17.420)	(0.185)	(12.703)	(14.300)	(0.188)
Birth Rate, Age 35-49	5.170	4.554	5.324	0.770***	4.506	4.778	0.273***
	(6.225)	(4.217)	(6.622)	(0.064)	(4.165)	(4.824)	(0.062)
Demographic Controls							
Pct Black Population	0.082	0.130	0.070	-0.060***	0.135	0.099	-0.035***
	(0.141)	(0.160)	(0.133)	(0.002)	(0.162)	(0.155)	(0.002)
Pct White Population	0.897	0.850	0.909	0.059***	0.846	0.888	0.042***
	(0.148)	(0.161)	(0.143)	(0.002)	(0.160)	(0.158)	(0.002)
Pct Female Population	0.510	0.513	0.509	-0.004***	0.513	0.512	-0.001***
	(0.016)	(0.015)	(0.016)	(0.000)	(0.015)	(0.016)	(0.000)
Pct Age 15-49	0.485	0.490	0.484	-0.006***	0.490	0.485	-0.005***
	(0.052)	(0.047)	(0.053)	(0.001)	(0.047)	(0.052)	(0.001)
Local Economic Controls							
Per-capita Income	14683.521	14318.431	14774.257	455.826***	14208.137	14310.391	102.255**
	(3286.568)	(3048.161)	(3337.041)	(41.200)	(2900.177)	(2967.456)	(41.695)
Employment/Population	0.474	0.447	0.480	0.033***	0.444	0.465	0.021***
	(0.136)	(0.119)	(0.139)	(0.002)	(0.118)	(0.123)	(0.002)
N	35688	7104	28584	35688	6756	17844	24600

Note: This table compares the trimmed and untrimmed sample for tornado analysis. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. In the untrimmed sample, all counties are included. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Both samples are split into the treated counties: the counties that have ever declared tornado, and control counties: the counties that have never declared tornado in the sample period. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. Statistics are reported for the period 1989-2019.

Table B.9 Trimmed and Untrimmed Sample for Severe Storm Analysis:

Variables to Estimate Propensity Score

		Untrimmed			Trimmed		
	All Counties	Treat	Control	Diff	Treat	Control	Diff
Weather Variables							
Cooling Degree Days	91.257	94.693	44.576	-50.117***	41.223	25.400	-15.823***
	(138.863)	(140.958)	(94.785)	(2.066)	(85.127)	(61.659)	(2.130)
Heating Degree Days	448.357	437.628	594.087	156.459***	587.507	667.259	79.752***
	(463.970)	(460.349)	(487.881)	(10.179)	(504.388)	(496.161)	(15.165)
Precipitation	3.199	3.264	2.315	-0.949***	2.349	1.622	-0.726***
	(2.532)	(2.548)	(2.104)	(0.045)	(2.081)	(1.353)	(0.049)
Max Temperature	64.471	64.894	58.721	-6.173***	58.615	56.044	-2.570***
	(19.009)	(18.943)	(18.973)	(0.397)	(19.415)	(19.105)	(0.584)
Min Temperature	41.784	42.292	34.894	-7.397***	35.201	31.482	-3.719***
	(18.197)	(18.147)	(17.463)	(0.367)	(17.771)	(16.392)	(0.512)
Average Temperature	53.130	53.596	46.810	-6.786***	46.910	43.765	-3.145***
	(18.488)	(18.432)	(18.081)	(0.379)	(18.403)	(17.632)	(0.544)
Location Variables							
Shoreline Counties	0.110	0.104	0.191	0.088***	0.275	0.211	-0.064***
	(0.312)	(0.305)	(0.393)	(0.008)	(0.447)	(0.408)	(0.013)
Watershed Counties	0.197	0.191	0.289	0.099***	0.389	0.293	-0.096***
	(0.398)	(0.393)	(0.453)	(0.009)	(0.488)	(0.455)	(0.014)
Geographic Variables							
Pct Water Area	4.497	4.128	9.505	5.377***	14.236	11.590	-2.646***
	(11.052)	(10.096)	(19.232)	(0.393)	(22.661)	(21.744)	(0.670)
Amenity Scale	0.064	-0.052	1.633	1.685***	1.462	2.082	0.620***
	(2.321)	(2.240)	(2.796)	(0.058)	(3.100)	(2.626)	(0.085)
Plains	0.486	0.498	0.324	-0.175***	0.368	0.218	-0.150***
	(0.500)	(0.500)	(0.468)	(0.010)	(0.482)	(0.413)	(0.013)
Tablelands	0.065	0.070	0.005	-0.065***	0.075	0.008	-0.067***
	(0.247)	(0.255)	(0.070)	(0.002)	(0.263)	(0.086)	(0.005)
Plains with Hills	0.071	0.058	0.255	0.197***	0.168	0.308	0.140***
	(0.257)	(0.233)	(0.436)	(0.009)	(0.374)	(0.462)	(0.013)
Open Hills/Mountains	0.236	0.243	0.137	-0.106***	0.175	0.173	-0.002
	(0.424)	(0.429)	(0.344)	(0.007)	(0.380)	(0.378)	(0.012)
Hills/Mountains	0.142	0.131	0.279	0.148***	0.214	0.293	0.079***
	(0.349)	(0.338)	(0.449)	(0.009)	(0.410)	(0.455)	(0.013)
N	35700	33252	2448	35700	3360	1596	4956

Note: This table compares the trimmed and untrimmed sample for severe storm analysis. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. In the untrimmed sample, all counties are included. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Both samples are split into the treated counties: the counties that have ever declared severe storm, and control counties: the counties that have never declared severe storm in the sample period. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. Statistics are reported for the period 1989-2019.

Table B.10 Trimmed and Untrimmed Sample for Severe Storm Analysis:

Birth Rates and Control Variables

		Untrimmed			Trimmed		
	All Counties	Treat	Control	Diff	Treat	Control	Diff
Birth Rates							
Birth Rate	14.600	14.578	14.904	0.326**	14.964	15.209	0.244
	(5.008)	(4.915)	(6.134)	(0.127)	(5.206)	(5.987)	(0.175)
Birth Rate, Black	15.193	15.629	9.190	-6.439***	17.075	6.944	-10.131***
	(112.306)	(115.707)	(43.487)	(1.109)	(185.722)	(49.225)	(3.487)
Birth Rate White	13.868	13.824	14.478	0.654***	14.440	14.969	0.529***
	(4.947)	(4.839)	(6.204)	(0.128)	(5.028)	(5.952)	(0.172)
Birth Rate, Age 15-34	46.634	46.571	47.487	0.916**	47.297	49.259	1.962***
	(16.632)	(16.371)	(19.844)	(0.412)	(16.900)	(19.851)	(0.576)
Birth Rate, Age 35-49	5.170	5.095	6.193	1.098***	6.134	6.721	0.587**
	(6.225)	(5.957)	(9.068)	(0.187)	(6.037)	(8.162)	(0.229)
Demographic Controls							
Pct Black Population	0.082	0.084	0.049	-0.035***	0.029	0.014	-0.016***
	(0.141)	(0.142)	(0.108)	(0.002)	(0.056)	(0.044)	(0.001)
Pct White Population	0.897	0.895	0.928	0.033***	0.930	0.958	0.028***
	(0.148)	(0.150)	(0.113)	(0.002)	(0.109)	(0.069)	(0.003)
Pct Female Population	0.510	0.510	0.501	-0.010***	0.504	0.498	-0.005***
	(0.016)	(0.015)	(0.022)	(0.000)	(0.016)	(0.016)	(0.000)
Pct Age 15-49	0.485	0.484	0.490	0.006***	0.491	0.483	-0.008***
	(0.052)	(0.051)	(0.061)	(0.001)	(0.046)	(0.064)	(0.002)
Local Economic Controls							
Per-capita Income	14683.521	14657.507	15038.616	381.109***	15610.393	14995.872	-614.521***
	(3286.568)	(3273.439)	(3441.899)	(72.010)	(3919.602)	(3825.749)	(117.231)
Employment/Population	0.474	0.471	0.511	0.040***	0.499	0.520	0.021***
	(0.136)	(0.127)	(0.218)	(0.004)	(0.176)	(0.247)	(0.007)
N	35688	33252	2436	35688	3360	1596	4956

Note: This table compares the trimmed and untrimmed sample for severe storm analysis. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. In the untrimmed sample, all counties are included. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Both samples are split into the treated counties: the counties that have ever declared severe storm, and control counties: the counties that have never declared severe storm in the sample period. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. Statistics are reported for the period 1989-2019.

Table B.11 Trimmed and Untrimmed Sample for Severe Ice Storm Analysis:

Variables to Estimate Propensity Score

		Untrimmed			Trimmed		
	All Counties	Treat	Control	Diff	Treat	Control	Diff
Weather Variables							
Cooling Degree Days	91.257	98.999	87.630	-11.369***	99.880	95.616	-4.264**
	(138.863)	(136.254)	(139.924)	(1.561)	(136.528)	(142.076)	(1.732)
Heating Degree Days	448.357	394.060	473.790	79.730***	390.947	451.168	60.221***
	(463.970)	(419.048)	(481.486)	(4.996)	(416.269)	(477.637)	(5.522)
Precipitation	3.199	3.789	2.923	-0.867***	3.823	3.269	-0.554***
	(2.532)	(2.513)	(2.493)	(0.028)	(2.522)	(2.576)	(0.032)
Max Temperature	64.471	66.323	63.603	-2.720***	66.441	64.458	-1.983***
	(19.009)	(17.277)	(19.708)	(0.205)	(17.178)	(19.596)	(0.227)
Min Temperature	41.784	44.010	40.742	-3.268***	44.153	41.890	-2.263***
	(18.197)	(17.092)	(18.601)	(0.200)	(17.042)	(18.625)	(0.221)
Average Temperature	53.130	55.170	52.175	-2.995***	55.300	53.177	-2.124***
	(18.488)	(17.105)	(19.026)	(0.201)	(17.035)	(19.014)	(0.223)
Location Variables							
Shoreline Counties	0.110	0.021	0.151	0.130***	0.002	0.029	0.027***
	(0.312)	(0.144)	(0.358)	(0.003)	(0.047)	(0.168)	(0.001)
Watershed Counties	0.197	0.063	0.260	0.197***	0.037	0.126	0.089***
	(0.398)	(0.243)	(0.439)	(0.004)	(0.190)	(0.332)	(0.003)
Geographic Variables							
Pct Water Area	4.497	2.104	5.618	3.514***	1.753	2.133	0.379***
	(11.052)	(4.717)	(12.845)	(0.093)	(3.033)	(4.737)	(0.048)
Amenity Scale	0.064	-0.440	0.300	0.740***	-0.474	-0.580	-0.106***
	(2.321)	(1.538)	(2.575)	(0.022)	(1.538)	(1.929)	(0.021)
Plains	0.486	0.486	0.487	0.001	0.486	0.535	0.050***
	(0.500)	(0.500)	(0.500)	(0.006)	(0.500)	(0.499)	(0.006)
Tablelands	0.065	0.063	0.066	0.003	0.062	0.068	0.006**
	(0.247)	(0.243)	(0.249)	(0.003)	(0.240)	(0.251)	(0.003)
Plains with Hills	0.071	0.041	0.085	0.044***	0.035	0.036	0.001
	(0.257)	(0.199)	(0.279)	(0.003)	(0.184)	(0.187)	(0.002)
Open Hills/Mountains	0.236	0.306	0.203	-0.103***	0.311	0.229	-0.082***
	(0.424)	(0.461)	(0.402)	(0.005)	(0.463)	(0.420)	(0.006)
Hills/Mountains	0.142	0.104	0.159	0.055***	0.107	0.132	0.025***
	(0.349)	(0.306)	(0.366)	(0.004)	(0.309)	(0.338)	(0.004)
N	35700	11388	24312	35700	10920	15600	26520

Note: This table compares the trimmed and untrimmed sample for severe ice storm analysis. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. In the untrimmed sample, all counties are included. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Both samples are split into the treated counties: the counties that have ever declared severe ice storm, and control counties: the counties that have never declared severe ice storm in the sample period. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. Statistics are reported for the period 1989-2019.

Table B.12 Trimmed and Untrimmed Sample for Snowstorm Analysis:

Birth Rates and Control Variables

		Untrimmed			Trimmed		
	All Counties	Treat	Control	Diff	Treat	Control	Diff
Birth Rates							
Birth Rate	14.600	14.303	14.739	0.436***	14.216	14.320	0.104*
	(5.008)	(4.148)	(5.359)	(0.052)	(4.119)	(5.040)	(0.056)
Birth Rate, Black	15.193	16.225	14.691	-1.534	16.184	14.523	-1.662
	(112.306)	(86.847)	(122.792)	(1.150)	(88.464)	(124.424)	(1.330)
Birth Rate White	13.868	13.496	14.043	0.547***	13.399	13.548	0.149***
	(4.947)	(4.091)	(5.293)	(0.051)	(4.055)	(4.943)	(0.055)
Birth Rate, Age 15-34	46.634	45.900	46.978	1.077***	45.784	46.002	0.218
	(16.632)	(13.802)	(17.795)	(0.173)	(13.758)	(17.136)	(0.190)
Birth Rate, Age 35-49	5.170	4.344	5.558	1.213***	4.260	5.065	0.805***
	(6.225)	(4.525)	(6.845)	(0.061)	(4.463)	(6.650)	(0.068)
Demographic Controls							
Pct Black Population	0.082	0.105	0.071	-0.034***	0.105	0.085	-0.021***
	(0.141)	(0.155)	(0.132)	(0.002)	(0.155)	(0.148)	(0.002)
Pct White Population	0.897	0.880	0.905	0.025***	0.879	0.897	0.018***
	(0.148)	(0.155)	(0.144)	(0.002)	(0.156)	(0.157)	(0.002)
Pct Female Population	0.510	0.515	0.508	-0.007***	0.515	0.510	-0.005***
	(0.016)	(0.013)	(0.017)	(0.000)	(0.012)	(0.017)	(0.000)
Pct Age 15-49	0.485	0.486	0.484	-0.001**	0.485	0.481	-0.004***
	(0.052)	(0.049)	(0.053)	(0.001)	(0.050)	(0.052)	(0.001)
Local Economic Controls							
Per-capita Income	14683.521	14197.764	14911.166	713.402***	14087.612	14441.409	353.797***
	(3286.568)	(2771.251)	(3478.858)	(34.241)	(2681.306)	(3006.477)	(35.182)
Employment/Population	0.474	0.467	0.477	0.010***	0.466	0.466	0.000
	(0.136)	(0.114)	(0.145)	(0.001)	(0.114)	(0.124)	(0.001)
N	35688	11388	24300	35688	10920	15600	26520

Note: This table compares the trimmed and untrimmed sample for severe ices torm analysis. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. In the untrimmed sample, all counties are included. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Both samples are split into the treated counties: the counties that have ever declared severe ice storm, and control counties: the counties that have never declared severe ice storm in the sample period. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. Statistics are reported for the period 1989-2019.

Table B.13 Trimmed and Untrimmed Sample for Snowstorm Analysis:
Variables to Estimate Propensity Score

		Untrimmed			Trimmed		
	All Counties	Treat	Control	Diff	Treat	Control	Diff
Weather Variables							
Cooling Degree Days	91.257	73.581	104.881	31.300***	83.700	91.772	8.072***
	(138.863)	(115.988)	(152.810)	(1.423)	(124.340)	(134.740)	(1.636)
Heating Degree Days	448.357	481.274	422.983	-58.290***	459.281	460.759	1.478
	(463.970)	(464.967)	(461.613)	(4.948)	(459.718)	(489.418)	(5.996)
Precipitation	3.199	3.645	2.856	-0.789***	3.541	2.933	-0.609***
	(2.532)	(2.414)	(2.567)	(0.026)	(2.464)	(2.453)	(0.031)
Max Temperature	64.471	62.429	66.045	3.616***	63.650	64.464	0.814***
	(19.009)	(18.494)	(19.249)	(0.201)	(18.558)	(19.646)	(0.241)
Min Temperature	41.784	40.507	42.769	2.261***	41.385	40.979	-0.407*
	(18.197)	(17.730)	(18.489)	(0.193)	(17.877)	(19.064)	(0.233)
Average Temperature	53.130	51.471	54.409	2.938***	52.521	52.724	0.204
	(18.488)	(18.014)	(18.745)	(0.196)	(18.112)	(19.252)	(0.236)
Location Variables							
Shoreline Counties	0.110	0.117	0.104	-0.014***	0.089	0.069	-0.020***
	(0.312)	(0.322)	(0.305)	(0.003)	(0.284)	(0.253)	(0.003)
Watershed Counties	0.197	0.208	0.189	-0.018***	0.166	0.129	-0.037***
	(0.398)	(0.406)	(0.392)	(0.004)	(0.372)	(0.335)	(0.004)
Geographic Variables							
Pct Water Area	4.497	4.857	4.219	-0.638***	4.334	3.543	-0.792***
	(11.052)	(12.184)	(10.084)	(0.121)	(11.681)	(9.280)	(0.134)
Amenity Scale	0.064	-0.539	0.528	1.067***	-0.816	-0.415	0.401***
	(2.321)	(1.811)	(2.553)	(0.023)	(1.736)	(2.107)	(0.024)
Plains	0.486	0.452	0.513	0.061***	0.556	0.569	0.013**
	(0.500)	(0.498)	(0.500)	(0.005)	(0.497)	(0.495)	(0.006)
Tablelands	0.065	0.064	0.066	0.002	0.061	0.060	-0.001
	(0.247)	(0.245)	(0.248)	(0.003)	(0.240)	(0.238)	(0.003)
Plains with Hills	0.071	0.059	0.081	0.022***	0.036	0.061	0.026***
	(0.257)	(0.235)	(0.273)	(0.003)	(0.185)	(0.240)	(0.003)
Open Hills/Mountains	0.236	0.288	0.195	-0.093***	0.271	0.224	-0.047***
	(0.424)	(0.453)	(0.396)	(0.005)	(0.444)	(0.417)	(0.005)
Hills/Mountains	0.142	0.137	0.145	0.007*	0.076	0.086	0.009***
	(0.349)	(0.344)	(0.352)	(0.004)	(0.266)	(0.280)	(0.003)
N	35700	15540	20160	35700	11784	13296	25080

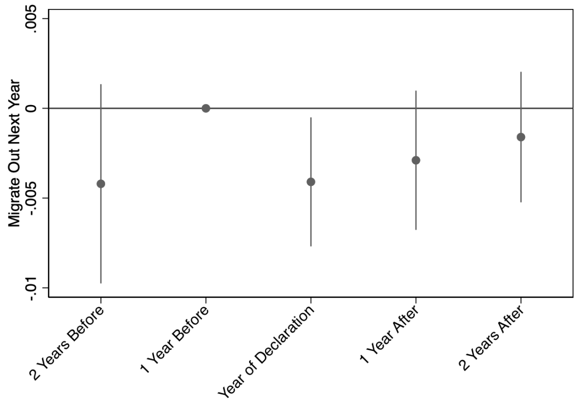
Note: This table compares the trimmed and untrimmed sample for snowstorm analysis. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. In the untrimmed sample, all counties are included. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Both samples are split into the treated counties: the counties that have ever declared snowstorm, and control counties: the counties that have never declared snowstorm in the sample period. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. Statistics are reported for the period 1989-2019.

Table B.14 Trimmed and Untrimmed Sample for Snowstorm Analysis:

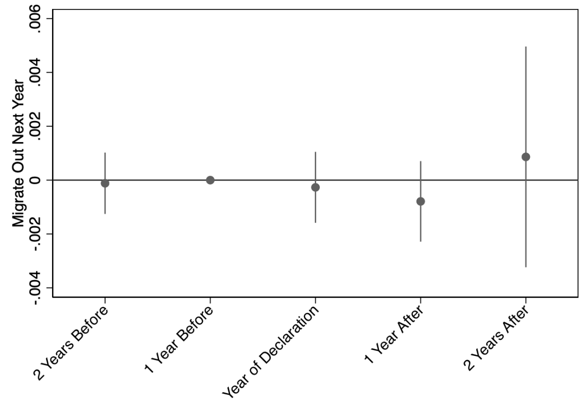
Birth Rates and Control Variables

		Untrimmed			Trimmed		
	All Counties	Treat	Control	Diff	Treat	Control	Diff
Birth Rates							
Birth Rate	14.600	14.344	14.797	0.453***	14.429	14.446	0.017
	(5.008)	(4.395)	(5.426)	(0.052)	(4.640)	(5.102)	(0.062)
Birth Rate, Black	15.193	15.467	14.981	-0.487	15.288	14.564	-0.724
	(112.306)	(123.752)	(102.576)	(1.250)	(134.539)	(98.675)	(1.538)
Birth Rate White	13.868	13.737	13.970	0.232***	13.719	13.469	-0.250***
	(4.947)	(4.311)	(5.385)	(0.051)	(4.551)	(4.993)	(0.060)
Birth Rate, Age 15-34	46.634	44.888	47.980	3.091***	45.778	47.069	1.291***
	(16.632)	(14.822)	(17.788)	(0.173)	(15.744)	(17.015)	(0.207)
Birth Rate, Age 35-49	5.170	4.888	5.388	0.500***	4.616	5.060	0.444***
	(6.225)	(5.147)	(6.935)	(0.064)	(5.417)	(6.751)	(0.077)
Demographic Controls							
Pct Black Population	0.082	0.072	0.090	0.018***	0.081	0.102	0.020***
	(0.141)	(0.125)	(0.151)	(0.001)	(0.135)	(0.169)	(0.002)
Pct White Population	0.897	0.913	0.885	-0.028***	0.902	0.874	-0.028***
	(0.148)	(0.136)	(0.156)	(0.002)	(0.148)	(0.174)	(0.002)
Pct Female Population	0.510	0.511	0.509	-0.003***	0.511	0.511	-0.000**
	(0.016)	(0.014)	(0.017)	(0.000)	(0.014)	(0.016)	(0.000)
Pct Age 15-49	0.485	0.496	0.476	-0.020***	0.491	0.474	-0.017***
	(0.052)	(0.048)	(0.053)	(0.001)	(0.050)	(0.052)	(0.001)
Local Economic Controls							
Per-capita Income	14683.521	15297.510	14210.602	-1086.908***	14870.862	13986.330	-884.532***
	(3286.568)	(3628.013)	(2910.250)	(35.606)	(3154.218)	(2581.813)	(36.694)
Employment/Population	0.474	0.479	0.470	-0.009***	0.474	0.467	-0.008***
	(0.136)	(0.143)	(0.130)	(0.001)	(0.129)	(0.109)	(0.002)
N	35688	15528	20160	35688	11772	13296	25068

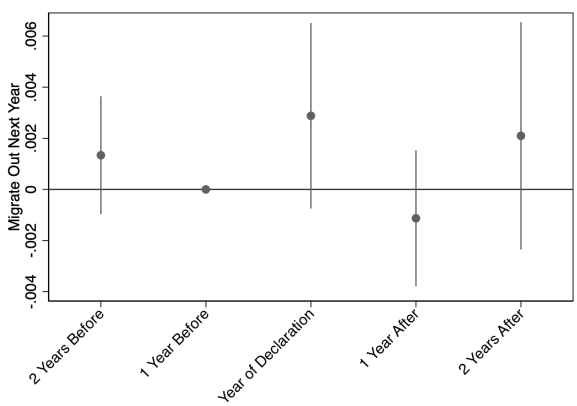
Note: This table compares the trimmed and untrimmed sample for snowstorm analysis. Column (1) summarize over all counties, excluding Hawaii, Alaska, and Virginia due to data limitation. In the untrimmed sample, all counties are included. Counties with a propensity score between 0.1 and 0.9 are included in the trimmed sample. Both samples are split into the treated counties: the counties that have ever declared snowstorm, and control counties: the counties that have never declared snowstorm in the sample period. Birth data is from NCHS natality files, population data is from SEER county population estimates, county economic indicators are from REIS database, weather data is from NCAA. Statistics are reported for the period 1989-2019.



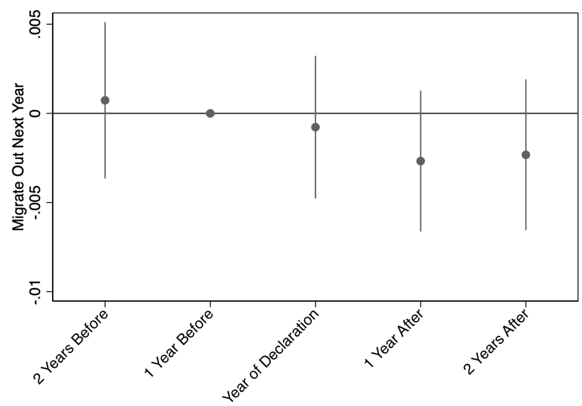
(a) Hurricane



(b) Flood



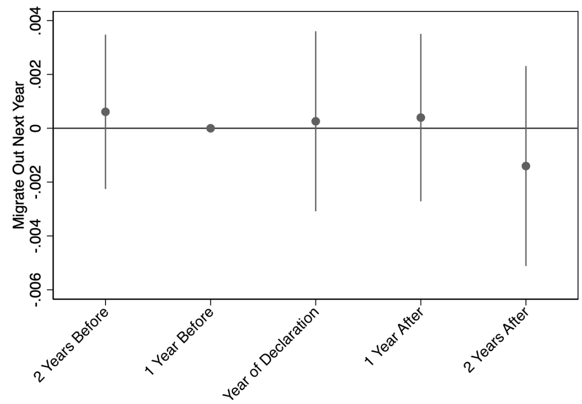
(c) Tornado



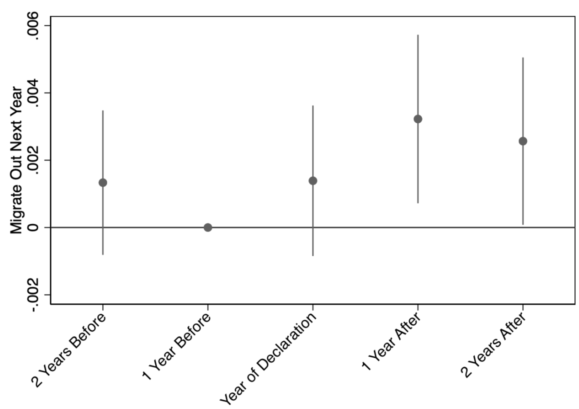
(d) Severe Storm

Figure B.1 Dynamic Effects of Hurricane, Flood, Tornado, and Severe Storm on Migration

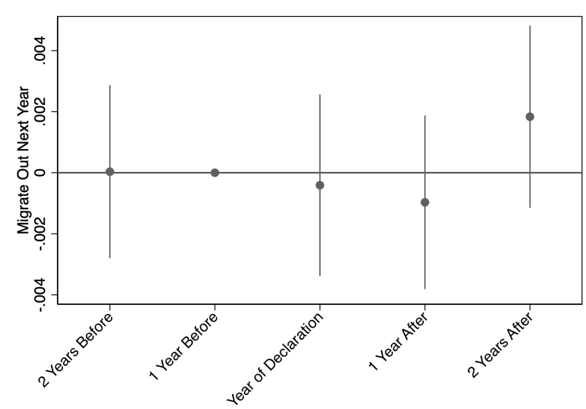
Note: Figure plots the estimated coefficients from Equation 2.6 for $j = \{\text{Hurricane, Flood, Tornado, Severe Storm}\}$, on the propensity trimmed sample with type-specific disaster propensity between 0.1 and 0.9. The outcome variable is whether respondent migrate out from his/her county/PUMA residence in the previous year. Control variables are: age, race, education, and household income. County and year fixed effects are included. The regressions are weighted by ACS person weights. Standard errors are clustered at county level.



(a) Fire



(b) Severe Ice Storm



(c) Snowstorm

Figure B.2 Dynamic Effects of Fire, Severe Ice Storm and Snowstorm on Migration
Note: Figure plots the estimated coefficients from Equation 2.6 for j = {Fire, Severe Ice Storm, Snowstorm}, on the propensity trimmed sample with type-specific disaster propensity between 0.1 and 0.9. The outcome variable is whether respondent migrate out from his/her county/PUMA residence in the previous year. Control variables are: age, race, education, and household income. County and year fixed effects are included. The regressions are weighted by ACS person weights. Standard errors are clustered at county level.

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