That Smarts!: Smartphones and Child Injuries

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Abstract

From 2005 to 2012, injuries to children under five increased by 10%. Using the expansion of ATT's 3G network, I find that smartphone adoption has a causal impact on child injuries. This effect is strongest amongst children ages 0-5, but not children ages 6-10, and in activities where parental supervision matters. I put this forward as indirect evidence that this increase is due to parents being distracted while supervising children, and not due to increased participation in accident-prone activities.

Keywords: Children, smartphones, unintentional injuries

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Nonfatal, unintentional injuries to children under five increased by 10% from 2006-07 to 2011-12 (CDC, 2012). Could the rapid adoption of smartphones explain this increase? In a Wall Street Journal article, Worthen (2012) advances the hypothesis supported by many specialists, but he notes that no study has provided causal evidence linking smartphone use to child injuries. In this paper, I fill this gap.

Specifically, I am interested in how smartphones—i.e. cell phones with the ability to browse the internet, stream videos, send and receive emails, and run various software applications—lead parents[1] to make decisions that increase the risk of child injury. Smartphones may increase injuries through two mechansims. First, they increase the opportunity cost of supervising children, and the decrease in supervision leads to more injuries. Second, they may decrease the opportunity cost of participating in risky activities, such as playing at the park or pool, and the increased participation leads to more injuries. I investigate both mechanisms and find strong evidence that smartphone adoption has caused child injuries to increase. I also find support that the increase comes from smartphones distracting parents.

Smartphones are an interesting technology to investigate for several reasons. First, in contrast to television and computers, smartphones are portable, allowing parents to use them at any time in almost any activity. Second, while cell phones also provide this mobility, they provided limited functionality compared to the diversity that smartphones provide. Finally, smartphones are a new technology that has quickly penetrated the market—Apple released the first iPhone in 2007, and as of January 2014, 58% of Americans own a smartphone (Pew Research Internet Project, 2014)—making them a prevalent and understudied device.

As I discuss below, identifying the causal effect of smartphone use on child injuries is difficult because of data and selection issues. To circumvent these problems, I use the advent of Apple's iPhone 3G combined with the rollout of AT&T's 3G network to provide exogenous variation in the ownership and use of smartphones. At the iPhone 3G's release in 2008, consumers could only use it on AT&T, and not all cities had access to its 3G network,

[1]Throughout the article I use the term parents, but the concept includes any caregiver responsible for supervising children, such as older siblings, nannies, etc.

but many gained it over time. As long as the factors contributing to AT&T's decision to enter a market are orthogonal to the factors that contribute to child injuries, then the rollout provides an identification of the effect of increasing access to smartphones on the incidence of child injuries.

I match the rollout data to hospitals tracked by the National Electronic Injury Surveillance System (NEISS), created by the Consumer Product Safety Commission (CPSC). The CPSC's main responsibility is to protect the public from the risk of injury or death from consumer products (CPSC, 2014). The organization tracks all consumer product related injuries in emergency departments at a nationally representative sample of hospitals. I am able to determine for all cases in the data from 2003 to 2012 whether the hospital was located in an area with access to 3G at the time of the injury.

Using the hospital-level variation in 3G access, I find that smartphones increase injuries to children, particularly those younger than five, a group more at risk of injury in the absence of parental supervision. My findings suggest that the expansion of smartphones can explain almost the entire increase in child injuries. Furthermore, I find that injuries increase in riskier activities, when parental supervision can make a decisive role in preventing accidents. These effects are absent in activities where the parents are not the primary supervisors and in activities where supervision makes no difference on outcomes. The evidence from these results strongly supports a scenario where parents are distracted by their smartphones and decrease supervising their children.

This paper adds to research on the external effects of mobile phone use. So far, most of the literature has focused on how phone use affects car accidents. McCartt, Hellings, and Bratiman (2006) survey 125 studies looking into the safety concerns of drivers using cell phones and find that while we have little understanding of the causal effect, most studies provide suggestive evidence. The most study reviewed in their paper comes from Redelmeier and Tibshirani (1997), who used cell phone bills to match phone use while driving and find that the risk of collision was four times higher while using a phone. After both of these studies, Bhargava and Pathania (2013) use a regression discontinuity design to examine the effects of cell phone use on car accidents and find small effects. This paper differs by looking at the advent of smartphones and the subsequent change in child injuries instead of at a technology that had existed for many years. If consumers are unaware or underestimate the effects of cell phones on accidents then we expect the short-run and long-run effects to differ as consumers learn, which might explain the discrepancies in results from data separated by 10 years.

Some research has started looking at how smartphones affect the risk of personal injury. Byington and Schwebel (2013) show that young adults who were randomly asked to use smartphones in a virtual simulation of crossing the street experienced decreased attention to traffic and greater incidence of being hit by a (virtual) car. This paper adds to Byington and Schwebel's work, going beyond the laboratory and examining how these devices are affecting real-world situations. Moreover, this paper examines how smartphone users may affect the injury risk of others.

Several other studies also provide evidence about how new media affects family interactions. La Ferrara, Chong, and Duryea (2012), using a similar empirical strategy, show that the spread of soap operas in Brazil led to a decrease in fertility. Cable television also caused decreases in fertility in India, as found by Jensen and Oster (2009), and it affected many other outcomes related to women's status, such as son preference, attitudes towards beating, female autonomy. Both of these papers posit that the mechanism behind the effects was that the technology transferred to the users new cultural values that placed greater status on women or the ideal family size. In this paper, on the other hand, I give evidence for media that changes the opportunity cost of interacting with the family. To see the difference, this mechanism says that in the case of Brazil and India, families derived more utility on the margin from watching television than from sex or domestic violence[2].

[2]Although not directly related to this literature, Olken (2009) finds that a village's exogenous availability of television and radio signals decreases the village's social capital. For other studies on the effects of media on the family, see Dahl and Price (2012)

1 Identifying the Effects of Smartphones

Fastidious observers have noted both the correlation between smartphone adoption and an increase in child injuries and the difficulty of attributing causality. In a Wall Street Journal article, Worthen (2012) reported on the connection using data similar to what I plot in Figure 1. From 2007 to 2010, injuries to children under 5 suddenly increased despite decades of decline due to improved safety equipment. As shown in Table 1, this increase happened almost exclusively to children under 5. Worthen points out that Apple released the iPhone in 2007 and smartphone adoption has rapidly increased since. But as Dr. Gary Smith, founder and director of the Center for Injury Research and Policy of the Research Institute at Nationwide Children's Hospital, says in the article, "What you have is an association. Being able to prove causality is the issue....It certainly is a question that begs to be asked."

Proving causality is not a trivial issue. First, non-experimental data can create problems to answering the question. Parents self-select into cell phone use, and this selection issue may cause estimation problems. For example, Radesky et. al (2014) observed caregiver-child interactions in a fast food restaurant and found that many of the caregivers spent significant time on their phones, and that many children made bids for attention in response. However, because of the observational nature of the study, the researchers cannot attribute any causal effects to the phone since it may be that parents who spend time on their phones when in public with their kids would find other distractions, such as a book or adult conversation, if the phone was not available.

Another issue for identification is that the researcher cannot typically observe what the parent was doing when the injury occurred. If the data record anything about the circumstances surrounding the injury, it focuses on the patient and not how others may have prevented it. Nevertheless, even if data recorded what parents were doing when their children were injured, parents would likely deny their culpability. Moreover, even if parents truthfully reported their activities, they might not know that the injury could have been prevented if they had been paying attention, so the data would misrepresent the events.

In an ideal experiment, the researcher could create two groups of parents and randomly assign one to have mobile devices and the other to abstain from using them. Over the course of the study, researchers would record how many times the children in each group were hurt and provide an estimate of the size of the causal effect. Indeed, Byington and Schwebel (2013) perform such a study by randomly assigning participants to use a smartphone when crossing the street in a virtual simulation. Although the random assignment allows them to conclude that smartphone use caused participants to decrease their attention and engage in riskier behavior, one might question how results from a virtual simulation extrapolate to the real-world where the risks have graver consequences. Yet, the experiment does suggest that smartphones can distract users and illustrates that there are conditions under which the effect on children could be identified.

I use the advent of Apple's iPhone 3G and the roll-out of AT&T's 3G network to overcome the identification issues and approximate the ideal experiment. Apple released the first iPhone in 2007 and the iPhone 3G in July 2008. The iPhone 3G contained several improvements over the original iPhone: the 3G network is twice as fast as the previous network; the App Store launched simultaneously with the iPhone 3G, providing a seamless environment for users to download games, social networking software, and other applications; the phone could use GPS technology; and the 8GB version sold at $199, a third of the price of the original iPhone (Apple, 2008)[3]. The combination of the features and the price fueled adoption: in the first three months Apple sold 6.9 million units of the iPhone 3G, easily surpassing the 6.1 million units of the original iPhone it sold in 15 months, and in the first year users downloaded over 1.5 billion applications from the App Store (Apple, 2009).

This popularity existed in spite of its limited availabilty. Not only were users required to purchase their phones through AT&T, but also not all cities had 3G at the time of the iPhone's release. The availability of 3G alters the value of having and using an iPhone and therefore the intensity of smartphone use will vary with the network's availability. Therefore,

[3]AT&T also subsidized the purchase of the phone through a contract lock-in.

the availability of 3G can act as a natural experiment, creating variation in the use of smartphones across cities, that I can use to estimate causal effects of smartphone use on child injuries.

For the roll-out to be a valid identification strategy, there needs to actually be some variation in exposure to 3G and that variation cannot be caused by other factors that would change injuries. In Figure 2 I plot both the geographic distribution of NEISS hospitals and the hospitals that had 3G in June 2008. Only about half of the hospitals had coverage when the iPhone was released, and 20% do not receive it during my sample period. Hence, the roll-out certainly creates variation, but for identification we must also understand what drives the variation in market entry. If the driving factor behind the variation is also causing injuries to increase, then I cannot attribute any causality to the roll-out. However, a hazard model, shown in Table A1, reveals that population variables drive the variation. Because population is stable over this short period, I can control for these with hospital fixed effects.

2 How Smartphones Could Cause Child Injuries

In relation to child injuries, the key feature of a smartphone is that it lowers the cost of entertainment and work. It decreases the cost of entertainment by providing easy access to games, videos, music, and websites through a mobile phone. It decreases the cost of work by providing access to email and documents. Users could access all of these things before through a computer or television, but these devices were stationary and difficult to move. With a smartphone, users could now do these things from nearly anywhere.

By lowering these costs, smartphones may increase child injuries through two mechanisms. First, smartphones could distract parents while they are supervising their children. Parents prevent injuries by supervising and warning children in risky situations. However, supervision is costly since it takes away time from other activities, such as entertainment or work. Hence, when smartphones decrease these costs, they increase the opportunity cost of watching children, and parents will decrease supervision and substitute towards smartphone use.

The second meachanism is equivalent to an income effect. With cheaper access to entertainment and work, parents might spend more time with their kids. For example, a mother might not need to be in the office because she can email from the zoo, or a father might be more willing to go to the playground because he has a new ebook. If parents and children participate more in activities that are risky, then mechanically the number of injuries will increase, even though the rate within the activity is the same.

Distinguishing between these two mechanisms helps us judge the consequences of an increase in injuries. If parents are distracted, then we might say that parents are making themselves better-off at the expense of their children. On the other hand, if parents are spending more time with their children in activities they both enjoy, then everyone might be better-off. Although I cannot say anything about the within-household bargaining problem nor make strong statements on welfare, I can at least explore the two mechanisms and leave the welfare implications to future work.

Having established how smartphones can increase injuries, I now outline the hypotheses that will guide my empirical work and help me discern between the mechanisms.

Hypothesis 1: *If smartphones increase child injuries, then areas that receive 3G will have a greater increase than those without.*

This hypothesis received detailed attention in the previous section. To summarize, the availability of 3G affects the value of a smartphone because without it owners cannot fully exploit the phone's features. Some consumers will purchase a smartphone before 3G in anticipation of the network's availability, but even then the consumer cannot use it as much as others who have the network already. Hence, injuries will increase faster in 3G areas. This hypothesis holds for both of the mechanisms.

Hypothesis 2: *Smartphones will increase injuries more for younger kids than for older kids.*

In reducing unintentional injuries, supervision has a differential impact by the child's age for two reasons. First, younger children are less able to identify risk and do so slower than older children (Hillier and Morrongiello, 1998). Parents have a strong effect on preventing unintentional injuries (Morrongiello and Dawber, 2000; Power, Olvera, and Hays, 2002; Schwebel and Brezausek, 2004), and being distracted will weaken this effect. The policies of childcare services recognize that younger children are at a greater risk of injury without proper supervision. For example, to be accredited by the National Association for the Education of Young Children (NAEYC), a daycare must observe the following staff-to-child ratios: one adult for every three children under the age of 15 months, one for every four between one and two years, one for every six children two-and-a-half to four years, and one for every eight above four years old (NAEYC, 2013). Clearly the literature and practice agree that younger children need more supervision but that need decreases as they age.

The second reason why distractions will have a smaller effect on older children is that older children participate in fewer supervised activities. Because children gain more awareness as they age, parents give them more freedom. Furthermore, older kids spend most of the day in school, where smartphones will have little to no effect on the teacher's behavior because of external enforcement. This means that even if parents adjust their supervision based on the child's age, the effect is still larger for younger kids.

Hence, the introduction of smartphones will increase injuries more for younger children because they are most at risk when distractions increase. This does not mean that older children are at no risk if their parents are distracted by smartphones, but just that the effects on younger children will be larger than on the older ones.

Hypothesis 3: *Holding participation rates constant, smartphones will increase injuries in risky activities but not in low-risk activities.*

Decreases in supervision have a differential impact based on the activity's risk-level. For instance, taking time away from watching your daughter color probably will not lead to her getting injured, while not watching her on the playground might. Therefore, we should observe an increase in injuries associated with high-risk activities but not with low-risk activities.

High-risk activities alone, however, will not inform us why injuries are increasing. While the distraction mechanism unambiuously implies that injuries will increase in high-risk activities, the participation mechanism could go either way. If smartphones decrease the opportunity cost of low-risk activities relative to high-risk activities—e.g. children play games on smartphones instead of at the park—then injuries in high-risk activities might decrease. On the other hand, if it decreases the opportunity cost of high-risk activities relative to low-risk—e.g. parents take their kids to the playground more because they can still do work there—then injuries in high-risk activities will increase. To distinguish between the participation and attention mechanisms, we need to find a high-risk activity whose participation rates do not change once parents have smartphones.

Hypothesis 4: *Placebo: If smartphones distract parents, then 3G expansion will not reduce accidents outside the purview of parents.*

If smartphones are decreasing supervision, then there should be no increase in injuries in activities where the child is supervised by someone without or unable to use a smartphone or in activities where adult supervision has a negligible impact on injuries. For example, at school, teachers face external consequences for using cell phones when they have charge over students. Because their cell phone use is restricted, we should not observe increases in injuries at schools. Similarly, in sport-related activities, injuries occur regardless of adult inputs because supervisors cannot directly intervene and verbal inputs can be drowned out by the environment. This implication provides a falsification test of the attention hypothesis.

3 Empirical Strategy

To look at the impact of smartphones on injuries, I use a difference-in-differences strategy with the staggered rollout of AT&T's 3G network. I estimate the following equation

$$\sinh^{-1}(y_{ht}) = \delta_h + \delta_t + \beta 3G_{ht} + u_{ht}$$

where y_{ht} is the number of injuries for children 10 and under at hospital h in period t, and $3G_{ht}$ indicates whether hospital h had 3G coverage at time t. I use the inverse hyperbolic sine (IHS) to resolve concerns with months where a hospital records zero injuries. In a regression framework, the IHS behaves like the log transformation (Burbidge et al. 1988), but the IHS is defined at zero. The coefficient can be interpreted as a percentage change. The results are robust to other specifications, which I include in the appendix.

Note then that the coefficient β should be interpreted as an intent-to-treat (ITT) parameter: the effect of expanding access to smartphones in an area on injuries in that area. This coefficient is not the effect of a parent owning a smartphone on his child's chance of injury. Indeed, because only a proportion of the population owns smartphones—in May 2011 about 35% of Americans owned a smartphone (Pew Research Internet Project, 2014)—for my regressions to detect an effect the injury rates for smartphone owners must be significantly higher than the ITT estimate.

For my regression to properly identify β, it must be that the presence of 3G is uncorrelated with age- and city-specific injury shocks. AT&T will enter a market based on expected profitability, which is a function of population density and income. I assume that these variables are stable over time within a city and control for them using city fixed-effects. This assumption is not unreasonable, since, as shown in Table A1, the income and population variables for a city in 2010 predict whether the city received 3G in 2008, indicating that there is some stability. Hence, I identify β using within-city variation. For city-level shocks to cause problems, the cities must experience changes that also affect child injuries at the same time 3G enters, and the changes must be permanent.

One age-specific change that could confound my analysis is patterns in age-specific cell phone adoption. My analysis focuses on injuries to children 10 and under. This group provides a good mix of children dependent on parental supervision (those under 5) and children who have less of a need. Although it seems like including kids older than 11 would be good for an additional placebo group, including these children complicates the analysis because this age group uses cell phones themselves. Indeed, according to the PewResearch Internet Project, children 12-15 are rapidly adopting cell phones during the study period. In 2004, only 18% of 12 year-olds had a cell phone (Lenhart, 2009), but by 2010 that number had jumped to almost 70% (Madden et al, 2013). Few of these kids received a cell phone before they turned 10. Hence, limiting the analysis to children 10 and under focuses on a group where the effects of cell phones should only come from the usage patterns of others.

Beyond the city-level shocks, 3G availability must also be uncorrelated to changes in age-specific shocks. Although I contend that this is a reasonable assumption as well, I relax this assumption by estimating the regression for each age group separately, generating results for every age from zero to ten.

One problem for estimation is if consumers purchase an iPhone in anticipation of 3G coming to their area, but there are two reasons why this problem is not a big concern. First, the anticipatory behavior will attenuate my results and therefore work against my hypothesis. Hence, the effect may actually be larger than I estimate. Second, even if everyone buys the iPhone on the first day, so that the entrance of 3G into a market does nothing to change who has one, the presence of 3G changes how the consumers can use the phone. Without 3G, the phones are far less effective away from a WiFi hotspot, so the 3G network still creates variation in use regardless of consumer behavior.

Some might still object that users without 3G can still use the wireless at home and apps when on-the-go. Indeed, using apps while away from wireless internet and without 3G would provide the distraction I describe, but again the presence of this effect will attenuate my measured effect, working against my hypothesis of finding an effect.

One behavioral change I have not incorporated that could confound my result is if parents change their propensity to visit the emergency room once they have access to 3G. However, the direction of the effect is ambiguous since, on the one hand, they have clearer directions to get to an emergency room but, on the other hand, also can search for whether they need to attend an emergency room. While these effects may occur, they should occur independent of age. That is, given that a smartphone makes you more likely to visit the hospital after an injury, parents should exhibit the same behavior for a two-year old as with an eight-year old. But my model contains age-specific predictions that this alternative hypothesis cannot explain.

4 Data

Data for nonfatal child injuries come from the National Electronic Injury Surveillance System (NEISS) run by the Consumer Product Safety Commission (CPSC). Using a nationally representative set of 100 hospitals, the CPSC records all ER visits in which a consumer product was associated with the injury. NEISS records the age of the patient, the location where the injury occurred, the product involved, and the hospital where the patient was treated. I use a sample of the data spanning January 2003 to December 2012.

While requiring the injury to involve a consumer product may seem restrictive, but it turns out that the CPSC broadly defines consumer product as "any article produced or distributed for use by a consumer in or around a home, school or recreational area" (CPSC, 2014). Indeed, about the only sources of injury that the data do not include are other people, nature, and motor vehicle accidents. In 2012, the CDC estimated 4,653,490 injuries to children 0-10 (CDC, 2012), and in the same year the NEISS estimated 3,120,172 injuries for that age group were associated with consumer products. Because the CPSC collects both datasets (but only allows the public to use the NEISS) the numbers are directly comparable, hence we can say that the data used in this analysis cover 67% of all unintentional injuries to children in this age group. In Table A2 I list a random sample of 20 injuries recorded in the data. Many of the injuries in the sample include falling, and the consumer product is either what the patient fell off of or onto. The table confirms that the data cover a relevant range of accidental injuries.

The data on the product involved and where the injury occurred provide leverage in analyzing the mechanism. By classifying products as high/low-risk or heavy/light-parental supervision, I can test the implications that make predictions about how injury rates should change if distraction is the mechanism. While the product data is rich in detail, the location data (i.e. whether the injury occurred at home, in a public space, etc.) is not as complete, with 25% of the injuries listing "unknown" for the location. I assume the unknown locations are random and that omitting them from the location-specific subsets does not bias the results.

I aggregate injuries at the hospital-month level. Although the data have sampling weights, I do not use them for two reasons. First, the sampling weights were made to allow the hospital's reports to represent a section of the population, but it is not clear if these weights are useful in understanding how the hospital represents the other hospitals in treatment or control status. Second, because my dependent variable is equivalent to the natural logarithm of the total injuries and because I use hospital fixed effects, the sample weights are absorbed by the fixed effects.

Another objection to using NEISS is that I only observe data on injuries that are severe enough to result in a hospital visit. Smartphones may have a much wider effect on parental negligence than I am measuring. This objection is similar to the concern about injuries involving consumer products in that they both highlight that I am observing only a subset of all injuries. Hence, my estimates can be interpreted as underestimating the total effect.

One clear limitation of using the NEISS is the privacy protections that prevent creating richer analyses. Because the NEISS contains sensitive patient information, the CPSC cannot release the hospital or city where the patient was treated. For the current analysis, the 3G roll-out data was coded separately and sent to the CPSC, who then merged the coverage data onto the NEISS and stripped away any identifiers. The CPSC agreed to provide the data because my treatment variable is binary and 3G expands in waves, creating limited opportunity to identify hospitals. Continuous variables, on the other hand, can very easily be used to map observations to locales. Thus, I cannot add variables such as population or smartphone use rates.

Data for the AT&T 3G coverage comes from AT&T press releases available on its website. With the completion of almost every 3G installation, AT&T issued a press release announcing the cities where it had extended coverage. Using the date of the press release and the cities named, I can reconstruct the rollout of coverage. To validate the press releases and fill gaps, I also grabbed historical data for the AT&T Coverage Viewer[4] from the Internet Archive Way Back Machine[5]. To construct my treatment variable, I found when each hospital received 3G coverage from AT&T. Coverage is a binary variable, and because hospitals treat many patients from the surrounding areas and that many patients in the immediate vicinity may work in the surrounding areas, my treatment variable equals one as soon as a city within 30 miles of the hospital receives 3G.

5 Results

5.1 Child Injuries after 3G

The dicussion above provides testable implications of the distraction hypothesis. If smartphones distract parents from supervising their children, then child injuries should increase after 3G enters the market. Additionally, because supervision is more important for younger children, the effect should be decreasing in age. Hence, I run regressions for each age group.

[4] http://www.wireless.att.com/coverageviewer/popUp_3g.jsp
[5] http://www.archive.org/web

Beyond allowing me to see the gradient of effects, separating the regressions allows me to make fewer restrictions on other age-specific shocks, since pooling requires me to assume children of all age groups in a city experience the same trends.

In Figure 3, I plot the difference-in-differences coefficients from my age-specific regressions, which I also report in Table A3. All of the point estimates, except for the age 10 group, are greater than zero, and the coefficients are decreasing in age. The point estimates for children one and under is about a 10% increase after 3G enters the market, while for 9 and 10 year-old children it's less than 1.5%. Furthermore, no estimate for age groups older than five is statistically significant at even the 10% level, with standard errors clustered at the hospital level. These results are robust to other specifications of the dependent variable, as shown in Figure A1.

One concern might be that these estimated effects reflect a pre-existing trend that coincides with the advent of smartphones. To address this concern, I group observations into six-month bins relative to when 3G came to the area. I restrict the coefficient on the six month period ending in the month when the area got 3G to zero to provide a baseline, thus the coefficients can be interpreted as the difference in injuries for the given bin relative to the period just before the area received 3G. I also restrict all observations that occurred more than two years before or after 3G entry to be equal to limit the number of coefficients to estimate. Based on the above regressions, we know that the post months will be positive, but if pre-existing trends explain the difference, then the coefficients for the months prior should be negative. For the regression, I pool all injuries at a hospital to kids five and younger since those age groups had the most powerful effects. In Figure 4, the plotted coefficients show that the prior months show no pattern and are all indistinguishable from zero. Hence, the measured effect cannot be explained by pre-existing trends.

The results thus far strongly indicate that hospitals experienced an increase in child injuries after AT&T expanded its 3G network into the area. The estimated effects are much larger and stronger for younger kids, and coincident trends cannot explain the large effects.

In the next section, I try to understand why injuries are increasing.

5.2 Mechanism: Attention and Participation

The model created four testable implications. The initial results from Figure 3 support the first two: injuries increased after the hospital got 3G and the change was larger for younger kids. The age gradient is the first piece of evidence in favor of the distraction effect. However, we can get a better handle on the distraction and participation effects by using the injury-level data.

To explore the mechanism, I look at specific activities from the product data. If decreased parental supervision is causing the increase in injuries, then we should see increases in injuries involved with risky activities. Using the location data, I select non-school playgrounds and pools as examples of risky activities, since parental supervision can make a large difference in injury rates. Using only this data, I run the same regressions as above and plot the coefficients in Figure 5.

The results show that playground and pool injuries increased for almost all kids under 10 after 3G entered the area. Unfortunately, these results alone cannot tell us whether the increase in injuries comes from the distraction effect or the participation effect, since either could cause this increase. Indeed, the equal effect across all ages could be because the participation mechanism is in play since the distraction effect implies a larger impact for younger kids.

To distinguish between the particpation and distraction effects, I need to identify activities whose participation rates will be unaffected by the introduction of smartphones. Because children should not be bathing, sleeping, or using stairs more if their parents have smartphones, I use injuries related to baths, beds, and stairs as examples of injuries where the participation effect is nonexistent. Figure 6 plots the coefficients from these three regressions. The patterns are striking: only the youngest children, who need the most supervision in these activities, experience an increase after 3G enters. These results match the parental supervision mechanism—parents are distracted by phones and therefore the youngest children fall in the bat, off the bed, or down the stairs.

Another test for the distraction mechanism is to look at activities where parental supervision should have no effect. A good comparison activity to the results already found is accidents at schools. Teachers face external consequences if they use a cell phone in class or on the playground, particularly if something happens when the teacher is distracted. Restricting the sample to only injuries that occur at school or daycare, I find in Figure 7(a) no change in injuries. Furthermore, looking at injuries involving school playgrounds in Figure 7(b) also yields no change. This second result is particularly interesting when compared to the large increases found on non-school playgrounds in Figure 5(a).

Finally, I look at an activity where parental supervision makes little difference but participation might increase: sports-related injuries. Spectator input has little effect on the moment-to-moment outcomes in sports, even in the small audiences that view children's sports. Thus, parental supervision has no effect on injuries. However, children might play sports more if their parents are more willing to take them to play, which would increase injuries. In the sports-only sample[6], in Figure 7(c), 3G has no effect on injuries. Because sports are one of the areas where the participation effect would be most evident, this suggests that participation is not driving the injuries.

6 Discussion and Conclusion

I argue that smartphones have caused an increase in child injuries, and that at least part of this reason is that smartphones distract parents while they are supervising their children. By using AT&T's rollout of the 3G network, I circumvent difficulties in attributing

[6]The sports included in the NEISS data are: bowling, boxing, croquet, football, golf, lacrosse, archery, horseback riding, horseshoes, mountain climbing, billiards, surfing, water skiing, volleyball, soccer, table tennis, wrestling, scuba diving, tetherball, ice hockey, handball, snowmobiles, field hockey, snow tubing, water tubing, skeet shooting, roller skating, skating, badminton, fishing, rugby, ball sports, street hockey, ice boating, cheerleading, ice skating, martial arts, fencing, shuffleboard, weight lifting, hockey, swimming, water polo, dancing, curling, snow skiing, tennis, snowboarding, softball, and baseball. Results are robust if restricted only to the five most popular American sports: football, baseball, basketball, soccer, and hockey.

the effect to smartphones. Furthermore, I find that the effect is larger for younger children and in activities where parents are primarily responsible for the children, which confirms that the mechanism behind the increase is a change in parental supervision.

Using a back of the envelope calculation, taking the 2005-06 averages in Table 1 and multiplying them by the coefficients in Figure 3, I find that 3G expansion to all hospitals would create 137,900 extra injuries to children under 5, just about equal to the 139,00 actual increase (the standard errors are large, but that is not important for this discussion). The increase is significant and should not be taken lightly, but readers also should not interpret the results to mean that smartphones are inherently dangerous. Indeed, only 6.4 out of every 1,000 parents of children 5 and under who use a smartphone experience an injury[7]. To put this number in perspective, the injury rate for cars is about 10.6 per 1,000 drivers (NHTSA, 2010). The conclusion of this paper is not that we should implement drastic measures or legislation to reduce injuries. Nevertheless, future research may entail comparing the long-run effects to the short-run effects found here, or possibly looking at how public awareness campaigns reduce the chance of injury.

The welfare implications of these results are ambiguous and depend heavily on the assumptions made. If one assumes a unitary household model, then the increase in injuries is optimal. An intrahousehold bargaining model can be used to make a case either way: parents may compensate children for the increased risk, making them no worse-off; or parents and children might contract on how much supervision parents will provide, but time-inconsistent preferences lead the parents to renege on the contract at the expense of the child. Even though child injuries should not be taken lightly, some might argue that parents were over-supplying supervision or that injuries help build character, and therefore the smartphone-induced injuries are welfare enhancing. Therefore, I do not take a stance on the welfare effects these results imply but instead conclude that the increased risk of injury should be

[7]I calculate this by taking the number of smartphone-induced injuries—137,900—and dividing it by the number of parents of children 5 and under who own a smartphone (7% of Americans, according to PewResearch Internet Project (Pew Research Center, 2011).

taken into consideration when applying a cost-benefit analysis.

The results certainly raise questions as to other domains where smartphones have an effect. Future research may include looking at how smartphones affect parental investment in children, student learning in classrooms, and employee productivity. Also, this paper looked exclusively at the effects of smartphones on those who do not use them, but more work is definitely needed on the effects of smartphones on the people who actually use them.

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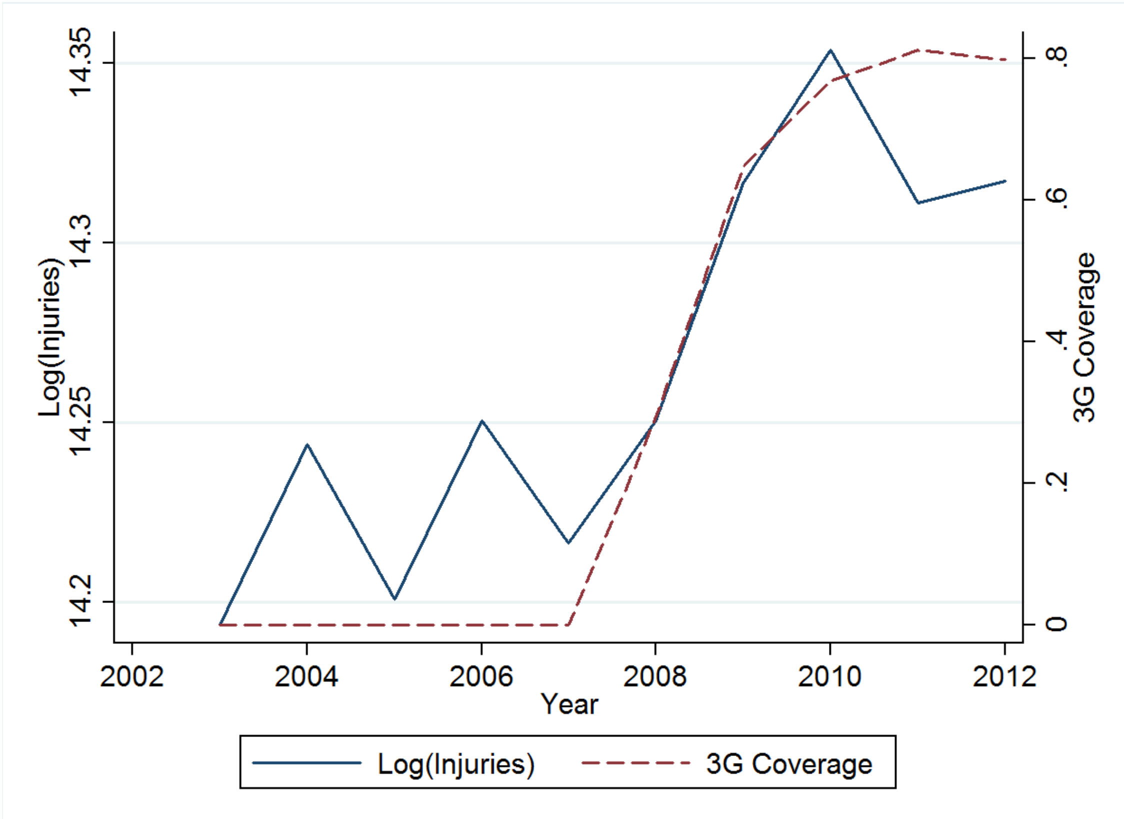

Figure 1: Nonfatal injuries involving consumer products for children under 5 in the US and Hospital 3G coverage

Notes: Injury data comes from weighted counts in the NEISS data. The 3G trend is the share of hospitals in the NEISS data that had 3G in a given year.

Table 1: Change in Annual Emergency Department Visits in NEISS Data by Age Group from 2005 to 2012

Age	2005-06 Average	2011-12 Average	Pct. Increase
0	224,443	239,015	6%
1	352,350	386,498	10%
2	370,600	400,494	8%
3	299,590	332,668	11%
4	260,815	288,085	10%
5	243,403	251,342	3%
6	218,943	222,375	2%
7	212,250	217,986	3%
8	218,486	223,527	2%
9	228,344	245,280	7%
10	256,700	266,439	4%

Notes: Data use weighted totals from the National Electronic Injury Surveillance System.

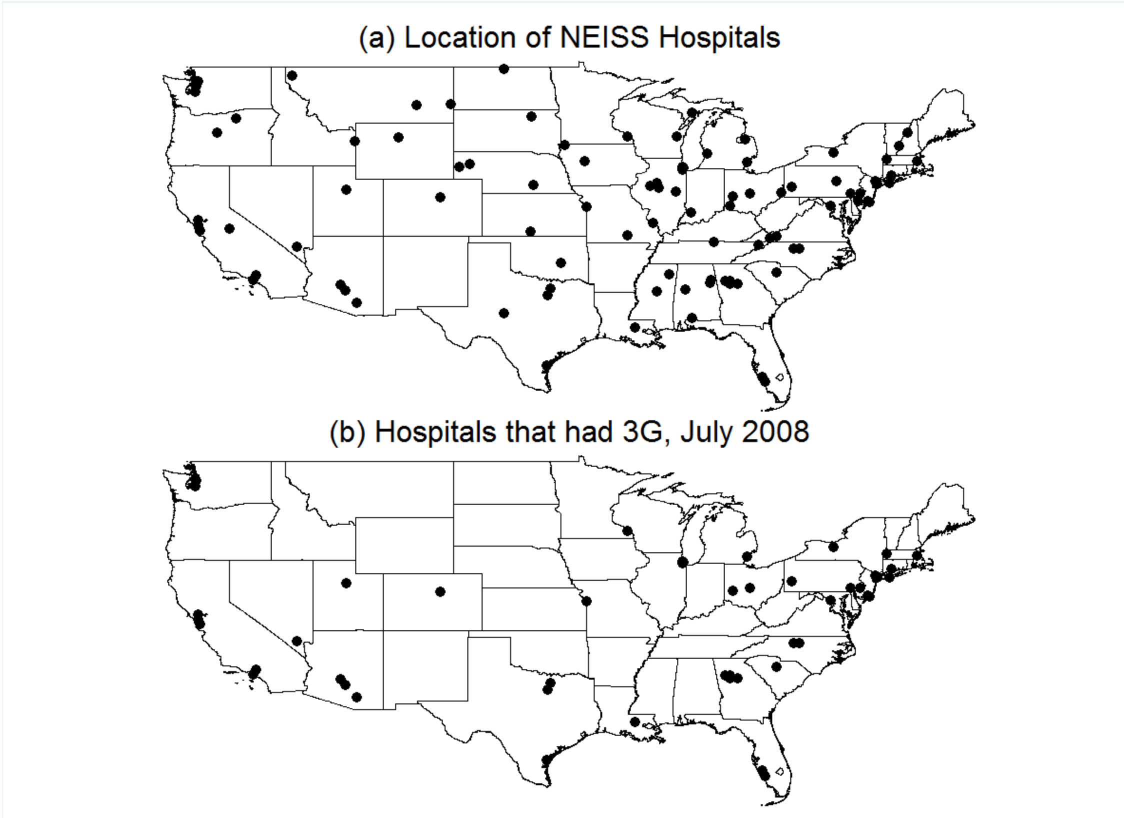

Figure 2: Geographic distribution of NEISS Hospitals and Initial 3G Coverage

Notes: Panel (a) includes the location of all hospitals in the NEISS data. Panel (b) uses the subset of hospitals that had 3G at the time of the iPhone 3G's release.

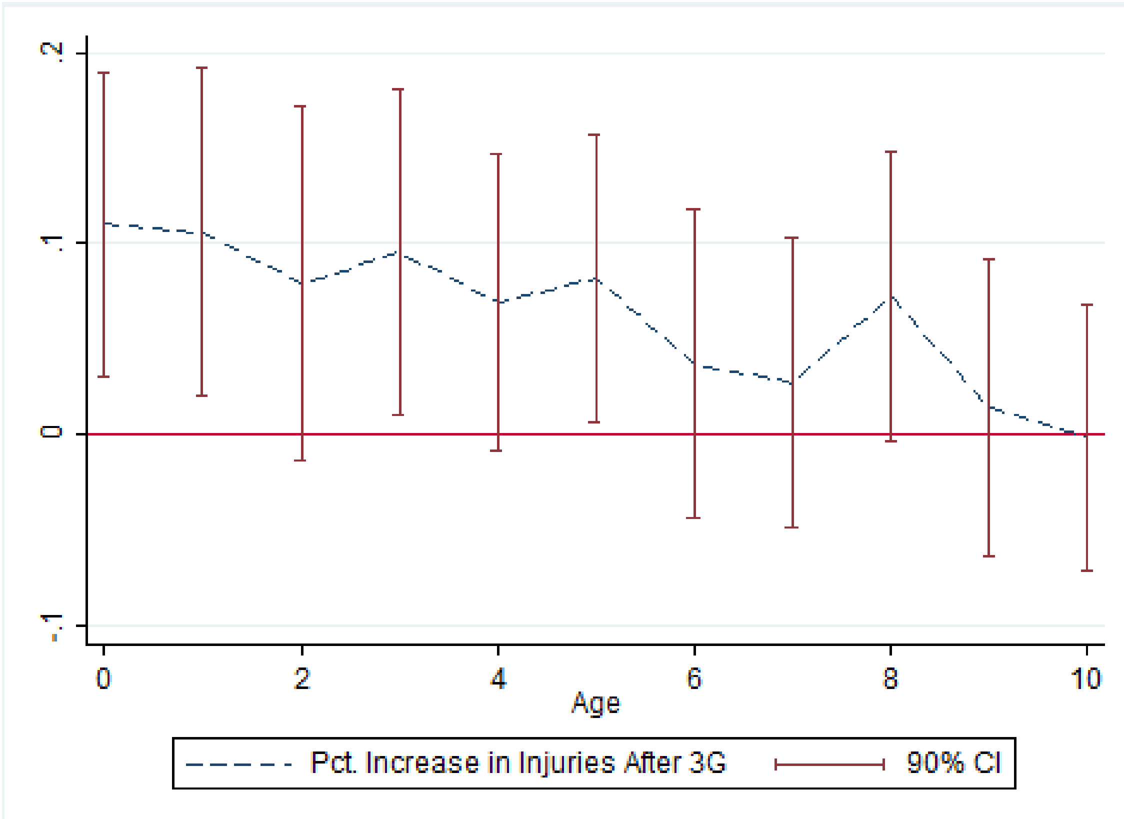

Figure 3: Effect of 3G On Child Injuries by Age Group

Notes: Coefficients are the β from the regression $\sinh^{-1}(y_{ht}) = \delta_h + \delta_t + \beta 3G_{ht} + u_{ht}$. All regressions have 11,089 observations. Standard errors are clustered at the hospital level.

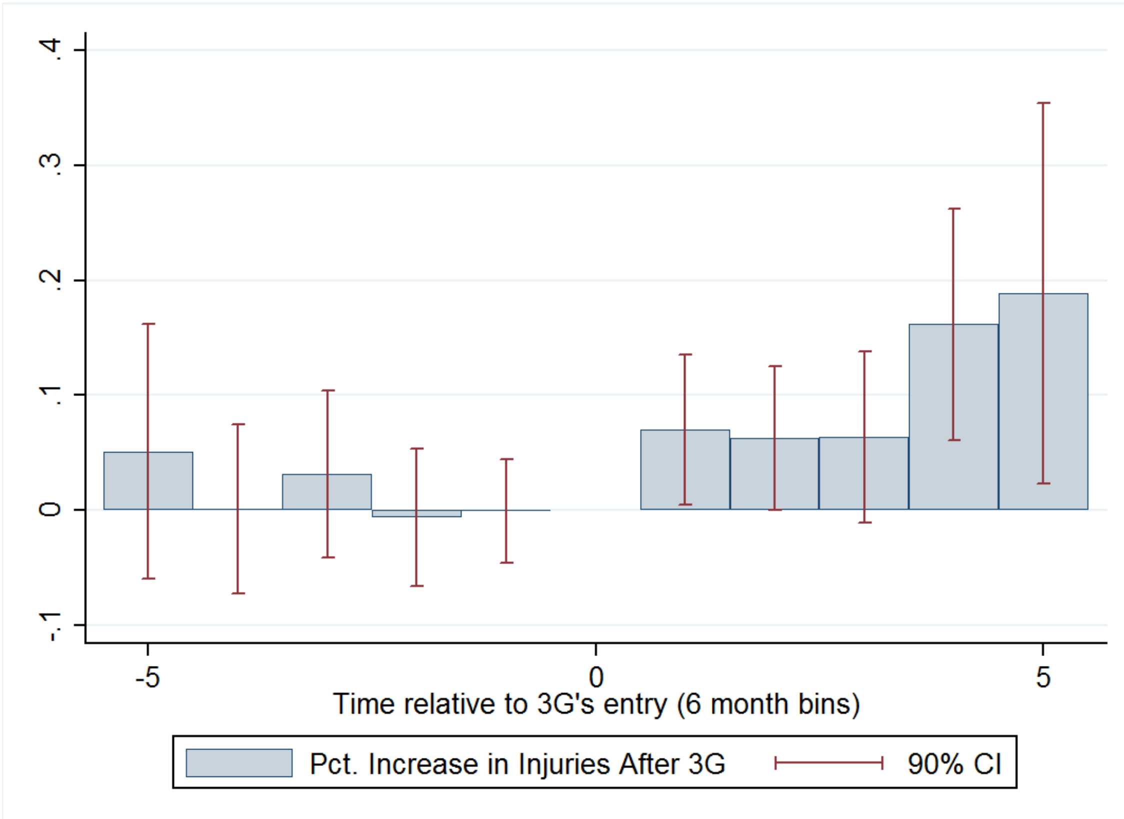

Figure 4: Checking Pre-existing Trends: The Effect of 3G Over Time on Injuries to Children 5 and Under

Notes: Coefficients come from a specification similar to Figure 3 (see notes) except instead of a 3G dummy the regression uses time dummies grouped in six-month bins. Positive values of T correspond to months after the market received 3G, and negative indicate before.

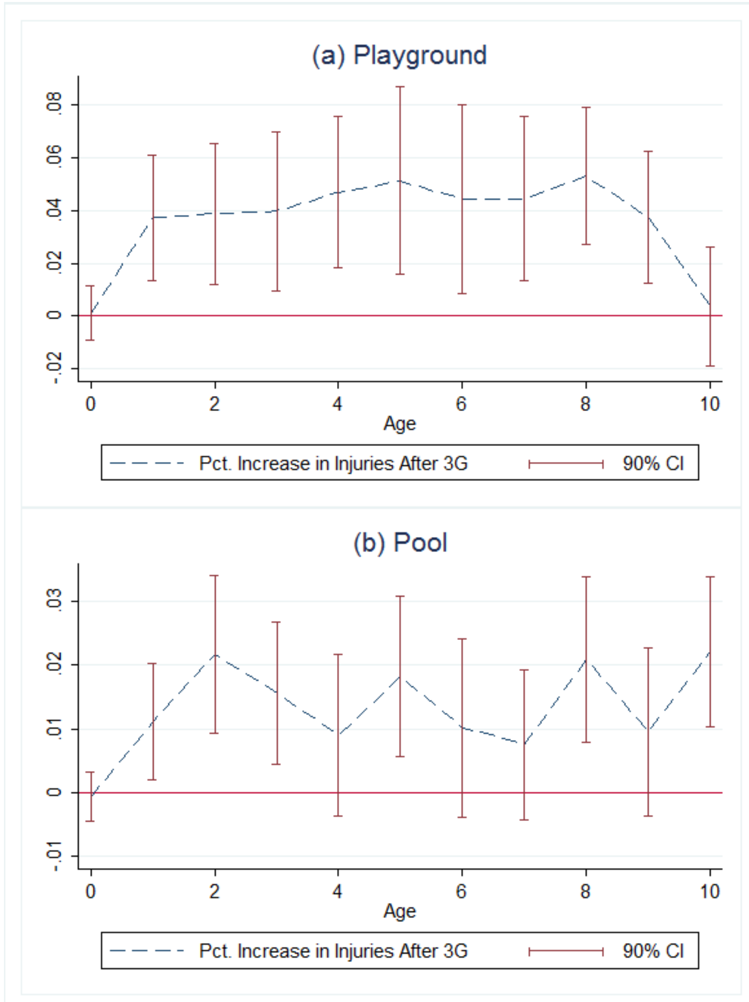

Figure 5: Effect of 3G on injuries in activities where participation and supervision might change

Notes: See Figure 3 notes for details on the regressions. Each panel uses a subset of the NEISS data where injuries were associated with the activity listed in the heading.

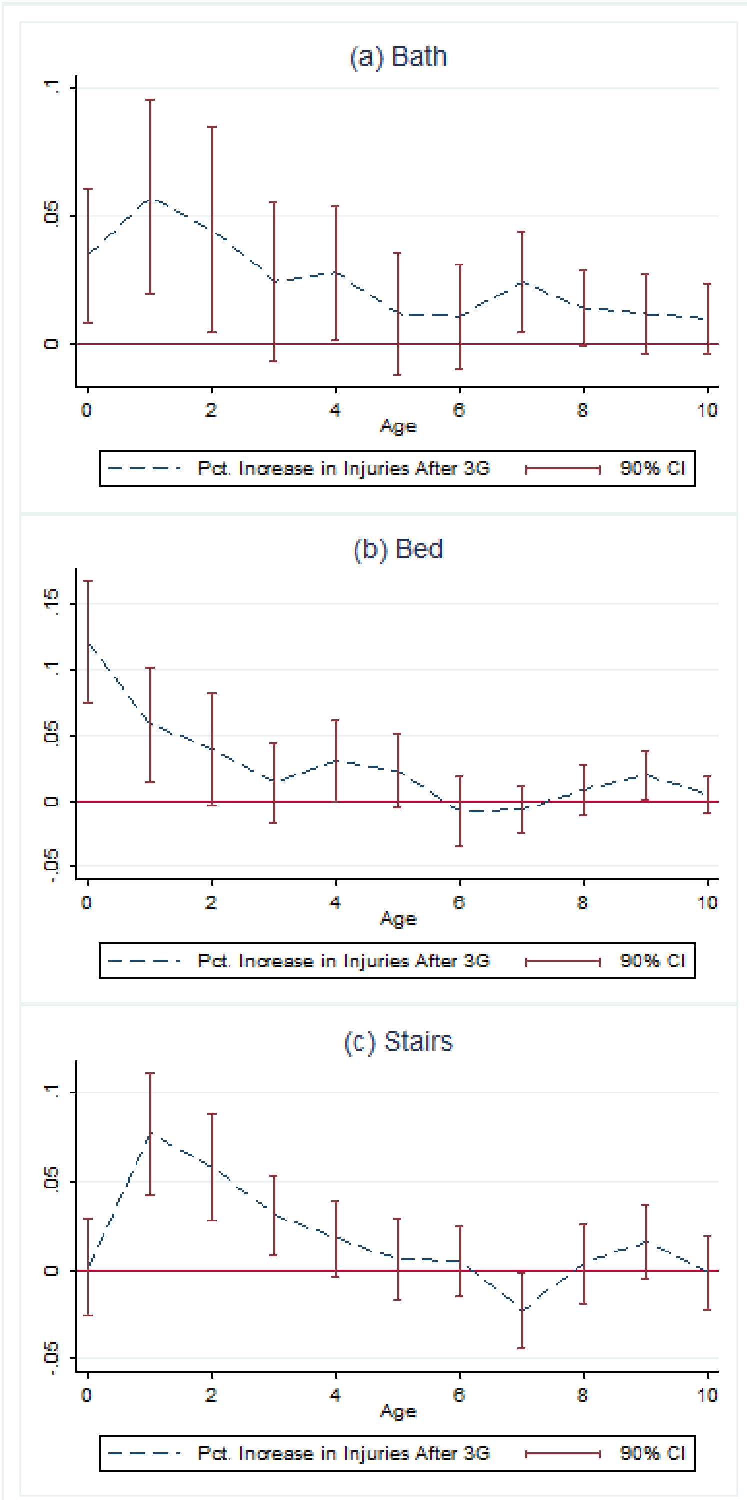

Figure 6: Effect of 3G in activities where participation should not change but supervision might

Notes: See Figure 5 notes.

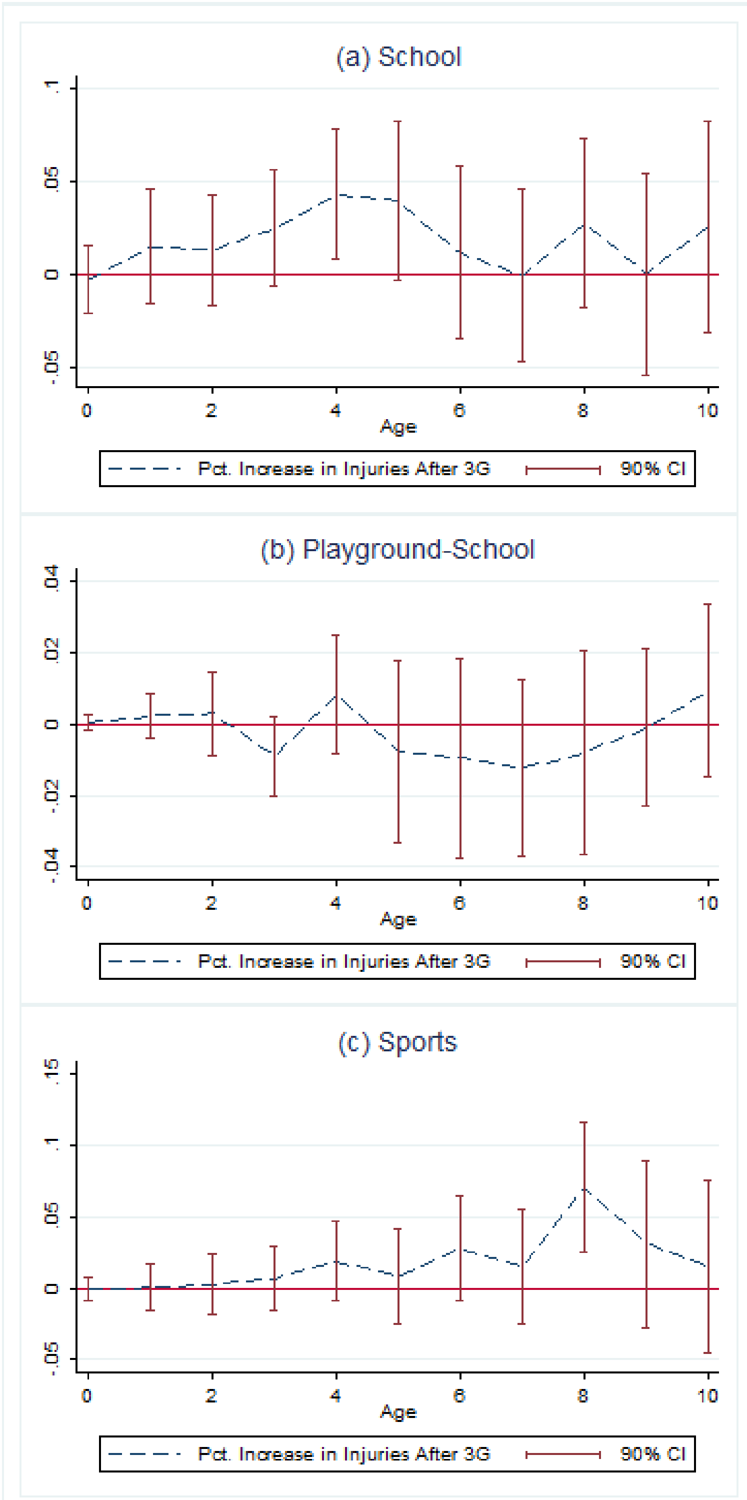

Figure 7: Effect of 3G in activities where parental supervision has little effect

Notes: See Figure 5 notes.

Table A1: Factors that predict 3G entry in a county where a NEISS hospital is located

	(1)	(2)	(3)	(4)	(5)
log(Population, 2010)	1.620***			1.344**	1.380**
	[0.130]			[0.182]	[0.179]
log(Population Density)		1.441***		1.198*	1.204*
		[0.0889]		[0.127]	[0.127]
log(Med. HH Income)			4.066***	1.534	
			[1.900]	[0.751]	
Under 5					0.863
					[0.107]

Notes: The reported coefficients are hazard ratios from Cox hazard models. All regressions have 97 observations. Data come from U.S. Census Bureau (2014). *** p< 0.01, ** p< 0.05, * p< 0.1.

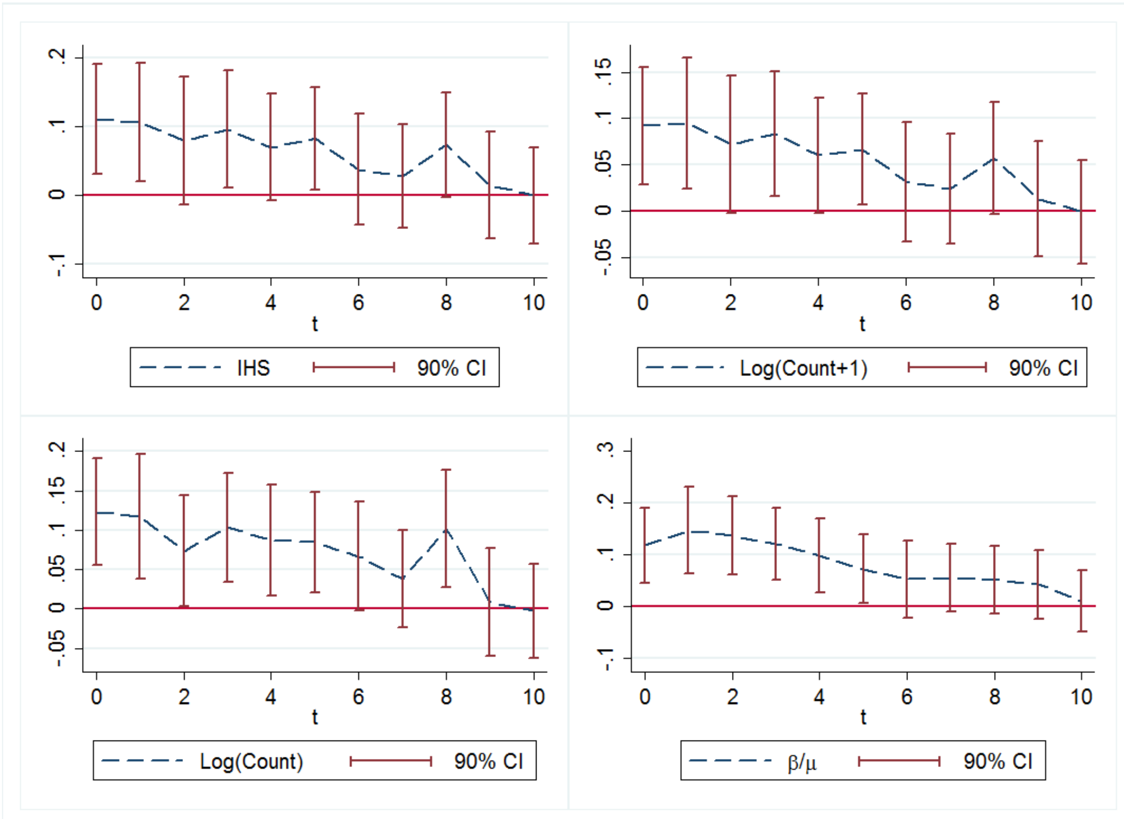

Figure A1: Robustness of 3G effects to different specifications

Notes: Each panel estimates $y_{ht} = \delta_h + \delta_t + \beta 3G_{ht} + u_{ht}$ for a different specification of y_{ht}. The definitions are: (a) inverse hyperbolic sine, same as in the text; (b) the log of one plus the count of injuries, to deal with months with zeros; (c) the log of the count of injuries, dropping months where no injury was recorded; (d) the count of injuries, and then each *beta* was divided by the age group's pre-2008 mean.

Table A2: Examples of reported injuries

Description	Location	Product Involved	Age	Sex
Slammed finger in bathroom door	Home	Door	7	F
Trampoline collission, cut lip	Place of recreation or sports	Trampoline	7	M
Crushed fingers in door	Not Recorded	Door	15 mo	M
Fell and hit mouth on hardwood floor	Not Recorded	Floor	14 mo	M
Fell skating and fractured forearm	Public Property	Skating	9	F
Fell off dresser and hit head	Public Property	Desks	7 mo	F
Crawling on hotel floor and grandma kicked face	Public Property	Floor	13 mo	F
Fell off monkey bars and fractured arm	Place of recreation or sports	Playground	6	F
Ran into dishwasher, cut forehead	Not Recorded	Dishwasher	4	M
TV fell on toe	Not Recorded	Television	7	M
Fell off monkey bars and hit head	School	Playground	7	F
Cut eyelid with clothes hanger	Home	Hanger	2	M
Fell off tricycle and fractured elbow	Home	Tricycle	8	M
Tripped on toy train and cut head	Home	Toy Vehicle	5	M

Notes: Examples come from descriptions in NEISS data.

Table A3: Coefficients for Figures

	Figure 3	Figure 5		Figure 6			Figure 7		
	All	Playground	Pools	Bath	Bed	Stairs	Playground-School	School	Sports
Age 0	0.110**	0.00089	-0.000665	0.0345**	0.121***	0.00193	-0.00282	0.000307	-0.00054
	[0.0486]	[0.00631]	[0.00236]	[0.0159]	[0.0286]	[0.0164]	[0.0110]	[0.00124]	[0.00478]
1	0.106**	0.0372**	0.0111*	0.0572**	0.0583**	0.0769***	0.0151	0.00221	0.000299
	[0.0523]	[0.0144]	[0.00558]	[0.0231]	[0.0265]	[0.0209]	[0.0187]	[0.00388]	[0.00986]
2	0.0787	0.0388**	0.0218***	0.0443*	0.0396	0.0580***	0.0129	0.00291	0.00242
	[0.0565]	[0.0164]	[0.00756]	[0.0245]	[0.0264]	[0.0181]	[0.0181]	[0.00711]	[0.0129]
3	0.0955*	0.0398**	0.0157**	0.0243	0.0137	0.0312**	0.0247	-0.00904	0.00639
	[0.0517]	[0.0184]	[0.00679]	[0.0190]	[0.0188]	[0.0136]	[0.0189]	[0.00677]	[0.0135]
4	0.0692	0.0470***	0.00907	0.0278*	0.0303	0.0181	0.0429**	0.00811	0.0185
	[0.0474]	[0.0176]	[0.00772]	[0.0160]	[0.0188]	[0.0130]	[0.0214]	[0.0100]	[0.0169]
5	0.0819*	0.0512**	0.0182**	0.0117	0.0228	0.00608	0.0393	-0.00762	0.00836
	[0.0457]	[0.0217]	[0.00771]	[0.0144]	[0.0170]	[0.0140]	[0.0259]	[0.0155]	[0.0204]
6	0.037	0.0443**	0.0102	0.0107	-0.00829	0.00519	0.0116	-0.00958	0.0275
	[0.0493]	[0.0219]	[0.00855]	[0.0125]	[0.0164]	[0.0122]	[0.0282]	[0.0170]	[0.0222]
7	0.0273	0.0444**	0.00757	0.0242**	-0.00658	-0.0228*	-0.000576	-0.0125	0.0149
	[0.0459]	[0.0190]	[0.00720]	[0.0119]	[0.0111]	[0.0127]	[0.0283]	[0.0150]	[0.0244]
8	0.0726	0.0530***	0.0209**	0.0139	0.00881	0.00392	0.0276	-0.00803	0.0702**
	[0.0462]	[0.0159]	[0.00794]	[0.00914]	[0.0117]	[0.0136]	[0.0278]	[0.0172]	[0.0277]
9	0.0139	0.0374**	0.00958	0.0117	0.0198*	0.0163	0.000429	-0.00118	0.0309
	[0.0473]	[0.0152]	[0.00805]	[0.00958]	[0.0113]	[0.0126]	[0.0330]	[0.0134]	[0.0355]
10	-0.00106	0.00351	0.0221***	0.00972	0.00487	-0.00133	0.0256	0.0092	0.0151
	[0.0424]	[0.0138]	[0.00719]	[0.00843]	[0.00828]	[0.0125]	[0.0344]	[0.0146]	[0.0368]

Notes: *** p< 0.01, ** p< 0.05, * p< 0.1.