The Impact of Quiet Zone Implementation on Accident Incidence at Highway-rail Grade Crossings

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Abstract

In the last five years, (2019-2023) there have been 10,704 accidents at highway-rail grade crossings (HRGCs) in the United States, resulting in 3,859 injuries and 1,233 fatalities. This paper seeks to address impact of quiet zones, where trains are not allowed to blow their horns before going through a crossing, on HRGC safety in the United States. Using a two-way fixed effects model, we find evidence of quiet zones increasing accident incidence and accident severity, in some instances at a level far higher than believed by the Federal Railroad Administration.

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1 Introduction

Railroad shipping has been an engine of American industry since the 1800s when the first transcontinental railroads were constructed. The need to transport vast quantities of goods and people great distances only increased with the expansion of the American economy throughout the following century. With this steadily increasing demand came an expansion of the railroad system, often in heavily populated areas with an abundance of highways. The result was the creation of the approximately 204,000 existing highway-rail grade crossings in the USA (USDOT, 2024). A highway-rail grade crossing (hereafter referred to as HRGC) is where rail tracks cross a road at the same level (not a tunnel or bridge for the road or tracks). Over the last 5 years (2019-2023), there have been 10,704 accidents at these crossings, resulting in 3,859 injuries and 1,233 fatalities (USDOT, 2024). These accidents occurred across the country, with certain major cities such as LA and Chicago being hot spots [2]. The scale of this issue warrants investigation into factors that could be impacting accident incidence rates. This paper will look at the impact of quiet zone designation on accident incidence rates at HRGCs.

Since the start of mandatory reporting requirements by railroads to the Federal Railroad Administration *(FRA)* in 1975, accidents and fatalities at crossings have decreased substantially (see Appendix A figures 1 and 2) due to improved oversight and safety measures implemented at crossings. The improvements in safety are due in no small part to an improved ability to predict accident incidence risk and accident severity risk at HRGCs. One step the FRA has taken, beyond improving safety measures, is closing as many crossings as possible, either by making them no longer grade crossings, or by closing the highway route. However, the number of accidents has leveled out in the last decade or

[2] The FRA has a visual aide to give an idea of the scale and distribution of accidents visitable on their safety data website under the Highway-Rail Grade Crossing landing page.

so indicating that there is still more work to be done in research of accidents at HRGCs. Fatalities have trended in a similar fashion over the same time period. Some have partially attributed the plateau and concerns over data showing a modern increase to the growing number of "long-trains" [3] and the increasing popularity of precision-schedule railroading (PSR), though the true impact of "long-trains" and PSR has yet to be fully researched.

HRGCs may be outfitted with several different safety features to reduce the chance of an accident occurring. These safety features fall under two types of classifications, active safety measures (ASMs) and passive safety features. Examples of active safety measures are descending gates that block off the crossings when a train is approaching, numerous types of lights meant to alert highway drivers of a train's approach, and bells that sound when a train is coming. In contrast, passive safety features include stop signs, crossbucks or pavement markings. After 2006, the FRA additionally mandated that all approaching trains should sound their horns at least 15 seconds and no more than 20 seconds before reaching a crossing (USDOT, 2025). In practice, train companies had been implementing this for some time already, and its impact was already well observed before the federal mandate was released. However, some localities find this last safety feature to be quite cumbersome on the surrounding area.

A quiet zone or whistle ban (hereafter referred to as QZ) is a crossing or group of crossings that is exempted from the mandate requiring trains to sound their horn upon approach to a crossing. There are three types of QZs: 24hr QZs, partial QZs, and Chicago Excused QZs[4]. Partial QZs restrict the sounding of horns between certain times of day.

[3] "long trains" refers to trains whose total length is over 7,500 feet, or 1.42 miles. For more information on the relevant research, refer to the FRA's publicly available long train report.

[4] Parts of northeastern Illinois are exempt from the CFR part 222 mandate, see CFR part 222.3c

Post-2003[5], QZs became regulated at the federal level. QZs established before 2003 had the opportunity to be grandfathered into the new regulation system. Public authorities such as townships or cities are the only entities with the ability to establish QZs (USDOT, 2024). As of 9/24/2024, there are 5469 crossings with a 24hr, partial or Chicago Excused quiet zone (USDOT GCIS). The large majority of these crossings are full 24hr QZs.

Since the implementation of a QZ removes a primary safety feature at HRGCs, liberal implementation of QZs had been observed to increase accident incidence at crossings. This effect was so large that, in 1991, the FRA intervened with local QZ administration in Florida with Emergency Order No.15, mandating that trains blow their horns at all crossings. Following the issue of Emergency Order No.15, the nighttime accident rate at affected crossings decreased by 68.6%, back to pre-QZ levels (USDOT, 1995). The FRA published a report in 1995 discussing the impact of QZ status on accident incidence rates. In both the before and after case studies and national risk analysis, QZ status was shown to significantly increase the accident incidence. The paper has no discussion of statistical significance, but the qualitative size of the difference in accident incidence at comparable crossings, up to a 204.99% increase for QZs of a certain assessed risk level, makes the findings compelling. Future studies by the FRA using a similar before and after analytical structure and focused on a limited sample of crossings found no significant difference in safety between QZ and non-QZ crossings (GAO, 2017).

It is likely due to the original findings that the modern criterion that must be met to create a QZ is quite stringent. The actual requirements are extremely long and can be accessed by viewing Appendix A or the USDOT Quiet Zone

[5]Although Congress passed a law mandating the sounding of horns at public grade crossings in 1994, quiet zones existed throughout the 90s and early 2000s without FRA approval. The FRA published the rule requiring trains sound their horns in December 2003, though it was not implemented for another year to allow for local governments to prepare for its implementation.

brochure (USDOT, 2013), but the most important requirement is that each public highway-rail crossing in a QZ must have active warning devices comprising of gates and flashing lights to be activated at intervals similar to that required by train horn mandates.

Despite the strict requirements, over the last five years, there were 938 accidents at QZ crossings, resulting in 163 fatalities and 297 injuries. Thus, accidents at QZ crossings account for 8.8% of all accidents, 13.2% of fatalities, and 8.7% of injuries occurring at accidents at all HRGCs in the last five years. It is worthwhile then to do an econometric-focused investigation into the true impact of QZ designation on safety at HRGCs.

In this paper, we will use a fixed effects panel model to test how being part of QZ impacts the occurrence and severity of accidents at HRGCs. The data we will use comes from FRA's public safety data website's HRGC accident reports and from the FRA's Grade Crossing Inventory System (GCIS). In the following section we will present a brief introduction to the broad literature regarding accidents and safety at HRGCs. Next, we will provide an introduction on the data and data sources we use and their potential limitations. Then we will describe our methodology and reasoning, and finally we will present our results and conclusions.

2 Literature Review

QZ designation is widely recognized to constitute an increased risk of accident incidence at HRGC. The foundational report on this area was published by the FRA in 1995. They used a before and after case study analysis to quantify the effect of being a QZ on HRGC safety, finding almost unilaterally that crossings were less safe when they are QZs. However, this report is limited in that its further analysis was based on a now antiquated model for accident and risk prediction at HRGCs, and there is no regression analysis.

More recently the FRA has done some analysis of the impact of QZ status on HRGC safety, occurring in 2011 and 2013 (Marquese Lewis, 2013). This 2013 internal report uses paired t-tests to investigate whether accidence incidence rates varies at QZ crossings before and after implementation of the QZ. In all but one group of QZs, they find no significant evidence that accident incidence rates increase after QZ implementation. However, the goal of this analysis was not to directly investigate whether QZ implementation decreases HRGC safety, but whether the implementation of QZs, in addition to the required SSMs and or ASMs, still results in a decrease in safety. Thus, the methodology used does not allow a distinction between a negative impact on safety due to the QZ and a positive impact on safety from the addition of additional safety features to the crossing. This 2013 analysis, and the previous analysis in 2011, were criticized by a 2017 Government Accountability Office report for several reasons. First, these analyses included only 203 and 359 crossings respectively, a far smaller scale of analysis than that which we undertake. In addition, the FRA relied on a before and after analysis, and as of the 2017 GAO report, did not plan on changing their methodology. The GAO report criticizes this method for being unable to control for other factors which may change during the sample period (GAO, 2017). We implement a panel dataset to allow our model to account for changes in crossing characteristics over time. This paper will improve upon past and current FRA research by using modern econometric methodology to study the same topic, as well as by adding a discussion of the impact of QZ status on accident severity.

One recurring issue that is a source of increased risk at HRGCs, and on railways in general, is the issue of trespassing. Ngamdung and daSilva (2020) investigated how QZ designation impacted the rate of incidents occurring as a result of trespassing at HRGCs and along a railroad's right of way (ROW). They use ArcGIS to do a spatial analysis of trepass casualties and determine whether they occurred within QZs. They found that QZs do not lead to a statistically significant increase in the amount of trespass casualties. Despite this result, the researchers noted that the small sample size of available trespass data limited their findings. This analysis is broader than ours in that it incorporates data from, and analyses the impact of QZs on, the entire railroad right of way, rather than just at HRGCs. Our analysis seeks to hone in on HRGCs in and focus on QZ's impact on highway users rather than trespassers.

There is some study of the negative effects of train horns on social welfare through property value decline. Cushing-Daniels and Murray (2005) provide evidence that the existing FRA mandate to sound train horns may actually have a higher social cost than benefit, especially from the point of view of the local residents. They studied the trade offs between increased safety levels and decreased property values due to the sounding of train horns. They came to the conclusion that the local costs of quiet zones exceeded the locally derived benefits of train horns being sounded.

In addition to research on train horns, Simons and El Jaouhari (2004) investigated how proximity to rail shipping lines affected property values or surrounding homes using a hedonic price model. They find mixed results, but some evidence indicating that proximity to rail shipping lines does have a statistically significant and negative effect of property values for small homes. Their proposed mechanism is the noise created by trains, primarily but not exclusively through train horns. We aim to build on this area of research by providing a more in-depth understanding of how QZs impact accident incidence and severity. By providing a more accurate understanding of the potentially negative impacts of QZs, we will inform future studies regarding the economic costs and benefits of QZs.

The discussion of QZs is only a small and relatively unexplored part of the literature surrounding HRGCs. There is a sound body of literature on how different crossing characteristics, including safety measures and traffic volume, affect the probability of an accident occurring. McCollister et al. (2007) use a logistic regression to estimate the impact of different crossing traits on the probability that an accident occurs. Their regression provides evidence to support the implementation of higher levels of safety measures at crossings and the statistical significance of several variables on accident incidence. They also find that several of the variables used in the FRA prediction model were not statistically significant in their regression. These variables included highway paving and number of tracks. They use their findings to build a model that, at the time, performed better than the one implemented by the FRA. Yan et al. (2010) used hierarchical tree-based regression to explore whether crossings exclusively outfitted with passive safety measures benefit from having a stop sign, finding that stop signs can be an effective measure to bolster safety at crossbuck only crossings. The FRA has also conducted extensive study on risk factors at HRGCs to inform their accident prediction model. Their model has been revised over time, with the most recent report in 2021. This report provides strong evidence of the importance of several factors toward HRGC safety, as well as presenting a new model for future projections. These studies provide insight into the factors which we will choose to control for in our varying specifications. We will extend this research by confirming the significance of some of these factors in a two-way fixed effects model setting.

Several researchers have published papers on the impact of different safety measures towards accident severity. Eluru et al. (2012) and Hao and Daniel (2016), using ordered probit and logit models with FRA data, found that several important measured factors could be seen to impact accident severity, including driver's age, the time of the accident, the presence of snow or rain, the vehicle's role in the crash, and motorist action. In another publication, Hao and Daniel (2016) studied the impact of inclement weather on accidents at HRGCs. They find that higher train and highway speed limits are associated with an increased rate of accidents, and that accidents are more severe at crossings lacking pavement and lighting. Hao and Kamga (2017) present related evidence that accidents at rural crossings are more likely to result in more severe injuries. Ma et al. (2018) show that riskier driving behavior and time of day are also important predictors of accident severity. We will build on research in this area by providing insight into how QZ designation affects accident severity.

Also comprehensively researched is how predictive models can be used to shed light on the most risky crossings in order to prioritize them for safety upgrades. Many such models have been developed by researchers and state DOTs (McCollister et al. (2007), Austin and Carson (2002), Saccomanno et al. (2004), Oh et al. (2006), Lu and Tolliver (2016), Khan et al. (2018), Pasha et al. (2020)) studied how accurately eleven existing models for accident and hazard prediction were able to predict hazard levels for 589 HRGCs in Florida for the year of 2017. They proposed a new model, a modified version of the Texas Priority Index Formula, to be used in Florida in the future. Their findings also show that the USDOT accident prediction formula at the time performed poorly against their sample relative to the other selected models. These articles do not discuss the impact of QZs and how they may best be factored into accident prediction models. Thus, our work will add to the literature by informing researchers about the size and direction of the effect of QZs on accident incidence rates.

Research has also been conducted on the impact of driver behavior on HRGC accidents. Yeh and Multer (2008) cite a 2004 report by the office of the Inspector General saying that 94% of accidents and 87% of fatalities were caused by risky driving behavior or poor judgement. They describe numerous reasons that a driver may make a poor decision at a HRGC, such as not expecting to encounter a train at the crossings because of prior experience around the crossing, not looking for a train, or simply generally dangerous driving behavior. This trend makes sense, especially at passively controlled crossings. We will be focusing more on the total impact of QZ designation on accident incidence, but we believe that the impact of QZ designation on driver behavior is another very worthy area of research.

Rapoza et al. (1999) on behalf of the USDOT investigate the factors that impact the effectiveness of train horns as a warning device, finding that factors such as train speed, highway speed, distance of train from the crossing, distance of the highway vehicle from the crossing, type of grade crossing warning device, the type of train horn and more impact effectiveness. Dolan and Rainey (2005) build on this analysis and their results suggest that the implementation of a lower-limit to the signal-to-noise ratio would improve the detection of train horns at HRGCs. Some researchers have gone beyond the existing arsenal of safety measures to investigate alternative options for increasing safety at crossings. In his dissertation, Landry (2016) discusses the potential for use of in vehicle auditory warnings to improve safety of HRGC with only passive protection measures. The implementation of this type of safety measure would reduce the need for train horns, while also bypassing geographic factors and background noise. In addition, in a possible near future where autonomously driving vehicles are widespread, new approaches to addressing highway safety at HRGCs will need to be addressed.

3 Theoretical Framework

It is already generally accepted that QZs have a detrimental impact on HRGC safety (hence the strict criterion to be met to become a QZ). Though this paper does not seek to address the mechanisms through which QZs have this impact, it is important to understand the proposed reasons for which QZs are believed to decrease HRGC safety. First, at crossings which themselves have no active safety measures, train horns may be the only active indication of an approaching train. According to Yeh and Multer (2008), risky driving behavior is the primary cause of accidents at HRGCs. While no amount of safety measures will ever be able to fully minimize the probability of risky driving behavior, a lack of active safety measures would certainly increase the probability of drivers not noticing an incoming train. At these crossings, the train horn serves as the only direct indicator for drivers of an incoming train.

In practice, however, public crossings in QZs are required to be equipped with active safety measures themselves. The mechanism through which a lack of a train horn being sounded impacts accident rates at these crossings is less clear, as drivers should be warned by the active safety measures at the crossing. One possible mechanism goes back to Yeh and Multer's (2008) conclusions on risky driving behavior. Drivers who are very familiar with crossings, potentially even being stopped at crossings equipped with active safety measures for several minutes waiting for a train to arrive and pass, may ignore the active safety measures. Examples of this type of behavior include going around gates or driving through a crossing despite bells and lights being activated. A crossing's safety measures do not give a clear indication of how soon a train may be arriving, and a driver may be tempted to believe that the crossing's safety measures are malfunctioning. In contrast, drivers know without a doubt that a train horn is indicative of an imminently arriving train. Our proposed mechanism through which the implementation of QZs causes increased risk at HRGCs is the elimination of the only safety measure that can be directly associated, in every case, with an incoming train.

While FRA studies provide evidence that QZs do not increase risk at HRGCs when taking into account the additional safety measures being implemented, they seem to tacitly acknowledge that QZs increase risk in some settings, such as adjusting risk at QZs upwards by 68% in the Quiet Zone Risk Index (QZRI)[6]. They seek to ensure that the average level of safety at crossings within a QZ, adjusted with the QZRI, is lower than the Nationwide Significant Risk Threshhold (NSRT). In other words, if, on average, the crossings within a QZ are judged to be safer than the average HRGC, then a possible increase in risk is considered to be acceptable. The FRA understands that QZ crossings are safer with horns sounded, but has judged the benefits of QZs to be worth the increase in risk (with stringent conditions for QZ adoption). With our new approach, we seek to add to the literature in such a way as to improve understanding of the degree of accident risk increase and accident severity increase to better inform policymaking in the future.

4 Data

In this paper, we will make use of FRA's HRGC accident data[7] and Grade Crossing Inventory System (GCIS)[8]. Both of the data sources are created and maintained by the Federal Railroad Administration. All data is publicly available. The HRGC accident data contains information on specific accidents, such as date, time of day, casualty breakdown, and the crossing ID number. GCIS contains several hundred fields of information on each crossing. Crossing infor-

[6]See Appendix A for definition of NSRT and QZRI
[7]This data is part of mandatory reporting by railroads on form 6180.57
[8]This data is reported through Form 6180.71.

mation will be taken from the GCIS and merged with HRGC accident data. These data are the primary resource used by investigators looking at HRGC safety in the United States. The HRGC data is robust, going back until 1975. The current GCIS contains all the information that the FRA has about the current state of crossings, but due to the large number of crossings and fields of data on the form, much of the data is incomplete. Farooq et al. (2023) compared a limited sample of GCIS data with verified crossing conditions in its use in accident prediction models. They found that there were statistically significant differences in the results of the accident prediction models and hazard prediction models when using the GCIS data versus the verified data. This study highlights the weakness of this dataset. The result is that our analysis will need to find a balance in choosing important control variables for which data is relatively complete and excluding crossings which do not have data for the variables we need. We exclude from our analysis a number of different variables used by other researchers, such as crossing surface type, crossing angle, the number of tracks, and the highway speed limit. Inclusion of these measures, even individually, heavily limits our sample availability.

While this dataset has its limitations, there is no other dataset with data spanning as wide of a region while also being able to satisfy our desire to compile a panel dataset.

Throughout our analysis we make the assumption that data missingness in the GCIS is random, and that excluding observations for data missingness will not bias our results. If data missingness and inaccuracy is randomly distributed, it will have no bias on our results. However, in order to minimize the impact of missing data, we selectively choose our control variables to maximize explanatory power and minimize data missingness.

The important variables we make use of in our analysis are described in

Appendix C figure 3. All of these variables are very commonly used in accident prediction formulae. Average annual daily traffic is a continuous measure of the amount of highway traffic that passes through a crossing on an average day. A limitation of this variable is that it is not updated very frequently. In some states, at 90% of crossings, AADT was most recently reported before 2000. Despite this, it is still an important indicator and is used in the calculation of an "exposure factor"[9] utilized by many other researchers in their models. As seen in the summary statistics table, the maximum value and standard deviation of AADT are quite high. We address this by including specifications that exclude the top 1% of values for AADT and other control variables.

On the other side of exposure factor is the number of trains that use the track at the crossing. There is a column in the dataset measuring the number of weekly trains. However, the majority of crossings are missing data for this variable. Therefore, we choose to use the Day Thru and Night Thru variables which are a continuous measure of the number of daytime and nighttime through trains. This data is far more complete and is a statistically significant predictor of accidents in a variety of specifications. One limitation of these variables is that they do not include trains that pass through a crossing that are operated by non-FRA regulated entities, such as regional light rail systems. Maximum speed is a continuous variable that measures the maximum speed at which a train is allowed to go through a highway grade crossing at. WdCode is a categorical variable that shows the highest level of safety device that is present at the crossing, with higher values indicating higher levels of safety measures. We also include a variable called Road at crossing code in the GCIS. This variable is a binary variable indicating whether a crossing lies in a rural or urban area. This variable is never significant in any models controlling for crossing fixed

[9] Exposure factor is a function of both the number of trains and the number of cars going through a crossing within a given time period.

effects (as this variable very rarely changes for individual crossings) but is always significant in models controlling for larger scale fixed effects.

We choose to use a fixed effects model to take advantage of our ability to compile a panel dataset. In order to compile the dataset necessary for this specification, we first collected accident data from 2014-2023. The yearly accident data is readily available through the FRA's public safety data website and presents data on each accident. In order to create crossing level observations, datasets are collapsed by CrossingID to make the transition from incident level to entity level observations, thus allowing it to be merged with entity level control variables. Prior to collapsing the data, specific identifier variables for fatal accidents, accidents with injuries, and accidents with casualties are generated, and these variables are included in the collapse to allow for an indication of accident severity post collapse. The resulting datasets contain the CrossingID, Accident, FatalAccident, InjuryAccident, and CasualtyAccident variables. Thus, there are no actual fatality, injury, or casualty counts from the accidents that do occur at a given crossing in a given year. These accident data collapsed by crossing are then saved for each individual year.

We then move to the management of the data on HRGC characteristics, or the Grade Crossing Inventory System (GCIS). The current GCIS is a dataset containing the most recently reported data on the crossing characteristics of every crossing in the US. There is also the historical GCIS, through which every past entry in the GCIS can be found. However, while the historical GCIS contains all entries into the GCIS, it is difficult to find the actual state of the GCIS at any given point in time using that dataset. In contrast, the FRA maintains internal snapshots of the GCIS at the end of every calendar year in our sample. We were given direct access to these datasets by Lindsay Peters-Dawson at the FRA, but these datasets should also be available upon submission of a FOIA request.

This version of the GCIS data is slightly different, both in content and form, than that which is publicly available on the FRA's public safety data website. In particular, several variables that we needed to be in integer form for continuous control variables needed to be destringed for use in the dataset. We also had to contend with different variable naming from the publicly available dataset. Following this, we dropped all crossings on private land (which face different rules) and all crossings closed to highway transport. Finally, we merge our yearly snapshots of the GCIS with the accident dataset from the same year. Our method results in a panel dataset spanning ten years with over 1.3 million individual observations and regressions that test across 130,000 public open crossings.

We decided to match 2015 accident data, occurring throughout 2015, with the snapshot of GCIS data from the end of 2015, instead of that from the end of 2014. This means that, if a crossing becomes a QZ near the end of 2014, but an accident occurred at the crossing before this update, that the accident would still be seen as occurring at a crossing with a QZ designation. Alternatively, we could have matched the previous year's snapshot with 2015's accident data, but this would have resulted in the opposite problem, where midyear changes in QZ designation would cause attribution of accidents occurring afterwards to crossings that are QZs but are not yet coded as such. We chose the first method since we believe accidents occurring in a close period before the adoption of QZ are likely to stymie or delay efforts to create a QZ, whereas accidents occurring after QZ designation would have no effect on the initial adoption. Since our chosen method could potentially attribute accidents that did not occur at active QZs to active QZs, we also tested the second method, and a third more nuanced matching method, and present their results in our robustness checks section.

Appendix C figure 4 shows the summary statistics for the dataset used in this specification. Figure 5 shows how the number of HRGCs designated as quiet zones changes throughout the sample.

5 Methodological Framework

Previous research on QZ safety from the FRA utilized a before and after framework. Researchers compared the number of accidents that occurred at crossings prior to and after the implementation of a QZ. This method has several shortcomings, namely that it fails to fully isolate the effect of QZ implementation since QZ implementation is almost always accompanied by the installation of new safety features or other changes to crossing characteristics. Since the FRA's goal was not to isolate the QZ effect, but rather to see the overall impact of QZ implementation, this was not an issue. However, the FRA's strategy also fails to account for changes in overall accident incidence rates over time, and the sample is conducted across a very narrow sample of crossings. In our analysis, we wanted to do several things differently. First, we wanted to isolate the effect of QZ implementation to gain a better idea of the qualitative significance of QZs on safety at HRGCs. Second, we sought to compile a larger sample, both in terms of crossings included in the analysis and the period of analysis, to increase our power to identify the effects of our different variables.

In pursuit of these goals, and due to the availability of year by year crossing level data, we decided to employ a two-way fixed effects model over our sample period from 2014-2023. The availability of a panel dataset would have also allowed us to use either a random effects of mixed effects model instead. However, random effects and mixed effects models would not be suitable in this situation as we are trying to use entity specific effects to control for unobserved characteristics that are correlated with our other independent variables. As such, we settled on a fixed effects model. Regional fixed effects, such as county level fixed effects, can control for unobserved geographic factors, and our preferred model controlling for entity specific fixed effects enabled us to control for unobserved crossing characteristics that do not regularly change for individual crossings. This model helps control for variables such as crossing angle and number of tracks as these variables are unlikely to change at individual crossings during our sample period. We were able to control for different levels of fixed effects, including state level fixed effects, county level fixed effects, and individual crossing fixed effects. Our basic model is as follows:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \lambda_{it} + \tau_i + \alpha_t + v_{it}$$

Where:

Y_{it} = Accident incidence rates

β_0 = The Y intercept

X_{it} = Quiet zone designation (binary variable equaling zero if a crossing is not a quiet zone and one if a crossing is any of the three types of quiet zone)

β_1 = The coefficient associated with quiet zone designation

λ_{it} = A vector of control variables

τ_i = Year fixed effects

α_t = Entity fixed effects

v_{it} = Error term

This model is adjusted in different specifications. In our basic model, QZ status is a binary variable, but almost all of the variation in QZ designation over the sample period results from full QZs. Thus, we tried a variety of different methods to isolate these crossings, including treating QZ designation as a categorical variable with values ranging from 0-3, thus allowing different coefficients to be attached to different types of QZ. We make further adjustments to the

QZ variable that are explained throughout the results and robustness checks sections.

The primary advantage of this model as opposed to those employed by the FRA in the past is that we are able distinguish between the effect of QZ implementation and the effects on safety due to changes in other crossing characteristics, namely improved safety measures. This capability allowed us to quantify the effect of QZ implementation on safety, all else held equal. We were also able to directly compare the effect of QZ implementation to the effects of improved safety measures. A second advantage of this model is that it is easily extended to look at the impacts of other types of crossing characteristics on safety at HRGCs. The biggest weakness of our approach is its reliance on FRA GCIS data which is often incomplete. We were forced to omit several potential control variables from our regressions due to high levels of data missingness. If, in the future, this dataset becomes more complete, it would allow for further analysis of the effects of more HRGC characteristics on HRGC safety.

6 Results

Appendix D figure 7 displays our main results from the fixed effects model. One asterisk represents significance at p = 0.05, two asterisks represents significance at p = 0.01, and three asterisks represents significance at p = 0.001. Each of our different measures for QZ designation are highly statistically significant in the base model using year and crossing fixed effects. In addition, the coefficient on QZ designation, ranges from 0.0152 to 0.0157 in columns 1-3. The mean for the accident variable is 0.012, meaning that the coefficient on QZ designation represents between 126-128% increase in accident incidence rates. The coefficient in column 4, which uses county fixed effects instead of crossing fixed effects, is smaller, but still accounts for a greater than 100% increase in accident incidence rates. [10] The majority of our included controls are also statistically significant predictors of accident severity, with the exception of Night Thru. This could be due to the very high correlation between the Day Thru and Night Thru variables (0.8659). This same idea is cited by McCollister et al. (2007), though in their case the number of night time trains was significant and the number of day trains was insignificant. Running the same regressions without Day Thru yields a positive and significant coefficient on Night Thru. In addition to statistical significance, we find that the direction of the relationship between accident incidence and our chosen controls matches that supposed by accident prediction formulae used by other researchers (McCollister et all, 2015) (Austin and Carson, 2002).

Although not in the table, each column in Main Results table additionally controls for WdCode. These results were not provided in the table as there are nine different categories which would have resulted in eight additional rows in the table. The base value in our regression is code 1: No signs or signals. In our chosen specification of column 4, Codes 3 and 4 (crossbucks and stop signs respectively) are statistically significant at 1% with a positive sign. Additionally, in almost every specification, codes 8 and 9 (All other gates and Four Quad Gates respectively) are statistically significant at 1% with a negative sign. The size of the negative coefficient associated with code 8 is -0.0152, a magnitude very similar to that of the estimated effect of full QZs. These results provide support for the FRA's emphasis on barrier gates and active safety measures for improving HRGC safety, as well as confirming previous research on the impact of different types of safety measures.

Appendix D figure 8, shows the results of our base severity regressions. In

[10] The meaning of the five different variables describing QZ designation is as follows: WhistleBanCodeBinary is 1 if a crossing is in any type of QZ and 0 otherwise, WhistleBanOne is 1 if a crossing is in full 24 hour QZ and 0 otherwise, WhistleBanCode is 1 if a crossing is in a full 24 hour QZ, 2 if a crossing is in a partial QZ, and 3 if a crossing is in a Chicago Excused QZ

these regressions, we substitute the Accident variable for the FatalAccident variable, a measure of the number of accidents in which at least one fatality occurred. We can see that the coefficients on the various different measures of QZ designation range from 0.00536 to 0.00549 for columns 1-3. The mean of the FatalAccident variable is 0.0012, meaning that these results imply that QZ designation is increasing fatal accident incidence rates by close to 500% of the mean. In contrast to our overall accident regressions, we see a lower level of overall statistical significance among our control variables in our models controlling for crossing fixed effects. However, Night Thru is statistically significant in columns 1-3 before the addition of clustered errors. This trend may have arisen due to a higher likelihood of more severe accidents at night time when visibility is decreased. This would support Hao and Daniels' (2016) conclusions on certain factors that affect accident severity at HRGCs.

A large portion of this increase could be attributed to a general increase in the accident incidence rate. We ran the same regressions but while also controlling for the overall accident rate. Appendix D figure 9 shows the output of these regressions. The three regressions which use crossing specific fixed effects have coefficients on their various QZ variables ranging from 0.00371 to 0.00385. Thus, even when controlling for accident incidence rates, QZ designation would lead to an over 300% increase in the probability that a crossing experiences a fatal accident. This result implies that QZs heavily increase the severity of accidents that occur at crossings within them.

In both the tables concerning accident severity, WdCode code 8 remains statistically significant with a negative sign in almost every regression, at a level between 30-40% of the magnitude of the positive effect on QZ designation. In comparison to the ratio of coefficients on QZ and WdCode 8 in the regression on accidents as a whole, this means that while higher levels of safety measures may be thought to offset the increase in accident incidence rates due to QZ implementation, they do not offset the increase in accident severity.

Finally, we test how weighting our regressions by AADT impacts our estimates. Since our preferred regression controls for crossing level fixed effects, we cannot use population weighting. As a substitute, we choose AADT as it is directly representative of a crossings usage rate by the surrounding population. The biggest issue with this method is with the AADT variable itself, as the age of the AADT estimate is over 10 years for many crossings. AADT weighting reduces both the estimated effect of QZ designation on accident rates and the estimated effect of QZ designation on fatal accident rates (controlling for accident rates) by about 50%, suggesting large results are partially driven by high traffic crossings.

7 Robustness Checks

This section will cover alternative specifications we used to check the robustness of the results from our main model. The most important check we do is compile an alternative dataset based on the second merging method mentioned in the data section. Our primary dataset merges 2015 accident data, occurring throughout 2015, with a snapshot of the GCIS at the end of 2015. This GCIS snapshot contains the most recent entry into the GCIS for each crossing as of the 2015. This method has one large problem. If a crossing becomes a QZ in 2015, but an accident occurred in the same year before the crossing became a QZ, the accident will be mistakenly attributed to a QZ crossing. Given that more crossings are becoming QZs than stop being QZs throughout or sample period, this will bias our estimates up.

In order to address this issue, we use an alternative method to compile our sample. Instead of matching 2015 accident data with the GCIS snapshot from the end of 2015, we match 2015 accident data with the GCIS snapshot from the end of 2014. Using this method results in the opposite problem as the first method. If a crossing becomes a QZ in the middle of the year, any accident occurring after a crossing becomes a QZ will be mistakenly coded as having occurred at a non-QZ crossing. Given that more crossings are becoming QZs than stop being QZs throughout or sample period, estimates from this method will be biased down. It is also notable that, since 2024 accident data is not yet fully completed as of the writing of this paper, this dataset only contains 9 years of data (2015-2023 accidents matched with 2014-2022 GCIS).

We use the same two-way fixed effects methodology as in our main methodology. The results are presented in Appendix E figure 10. The substantive and statistical significance of the coefficients on QZ designation are both diminished from the main regressions. Coefficients ranging from 0.00612-0.00653 represent effects around 40% of the estimated effects from the primary dataset. These effects are still statistically significant in columns 1-3, but become insignificant after the inclusion of clustered standard errors. While these estimates are significantly less than those from our primary dataset, the fact that these estimates are likely smaller than the true effect gives us a high level confidence of a positive true effect of QZ designation on accident incidence rates, the true level of which likely lies somewhere between the estimates of the two models.

We also tested our severity regressions on this alternative dataset. The results of these regressions are seen in Appendix E figure 11. While the effect size in the main regressions shrunk by around 60% and retained statistical significance, the estimates in the severity regressions shrunk in magnitude by as much to 98% and flipped signs. The only specification which for which the estimates remained positive and statistically significant was the specification controlling for county specific fixed effects rather than crossing specific fixed effects. The specifications controlling for Accident, seen in Appendix E figure 12 provide similar results.

These results decrease our overall level of confidence in our findings regarding the impact of QZ designation on accident severity. However, the fact that we still find significant effects of QZ implementation on accident rates in this model, despite its structure, support the idea that QZs increase accident rates.

We also used a third matching method to test our results (Alternative Sample 2). In this method, we match accidents occurring from July 1st of 2014 to June 30th of 2015 to the GCIS snapshot from the end of 2014. In contrast to both previous matching methods, in this method the date issue is creating bias in both directions. In addition, this method ensures that the farthest accident observation from the date of the GCIS entry is 6 months, as opposed to a whole year in the first two methods. Similar to the first alternative dataset, this sample has only 9 whole years of data (omitting the first and final 6 months of the main dataset). The results from this method are very similar, in statistical significance and substantive magnitude, to those from our base regression (see Appendix E Figure 13). Notably, column 4 of figure 14, the regression model equivalent to that in Figure 12, gives a coefficient on 24 hour QZs of 0.485 (4X the mean number of fatal accidents) with a t-value of 2.42. However, unlike our base regression, where the coefficient on WdCode = 8 represented an around 30% offset relative to the coefficient on 24 hour QZs, the coefficient on WdCode = 8 in this regression in not statistically significant. This result bolsters our confidence that QZ implementation is associated with an increase in accident severity rates. It also provides further support for the conclusion that ASMs and SSMs installed as a precondition for QZ implementation are less effective at mitigating increases in accident severity than they are at mitigating overall accident incidence rates.

Between the three data set merging methods we used, our chosen method which is expected to bias result slightly up and the method we expect to be the most neutral in terms of bias, are very similar. Both of these datasets lead to similar conclusions with respect to the impact of QZ implementation on accident incidence and accident severity rates.

Next, we decided to run an event study (Appendix E figure 15) to test the parallel trends assumption. We find no significant pre-trend from 5-2 years before QZ implementation. However, there is a significant jump in accident rates from 2-1 years before QZ implementation, a fact which is difficult to explain given the structure of our study. It is unlikely that drivers change their behavior simply due to the knowledge that a crossing will be a QZ in the future. The dataset used to compile this event study graph was the same utilized in a results section, that being that if a crossing becomes a QZ anytime during the year, it is represented as a QZ for the entire year. Thus, it is not possible that this rise is due to some crossings actually having QZs implemented in year before the dataset has recorded. The event study looks very similar when using the 2nd alternative dataset. Despite this inexplicable trend, the absence of any sustained pre-trend lends some evidence to the parallel trends assumption.

For further robustness checks, we also decided to check how narrowing our experimental group would effect the output of the regressions. Since estimated effects of partial QZs (WhistleBanCode = 2) are not significantly different from for our base regressions, we wanted to test how including partial QZs within the control group would effect the model. In this specification, the independent variable in question is a binary variable equal to 1 if a crossing is within either a full QZ or Chicago excused QZ and 0 otherwise. As expected, given the small number of partial QZs relative to full QZs, the results of this test provide estimates very similar in substantive size and statistical significance as our main regressions on both accident and fatal accident incidence rates.

Next, we narrowed our sample by restricting the WdCode to only that greater than or equal to 5. This method eliminates all crossings with only passive safety measures from the control group. Despite the sample size shrinking to just over 700,000 (around 77,000 crossings), estimates on QZ implementation remain substantively similar and statistically significant at 1%. However, the magnitude of the coefficients on higher levels of safety measures increase significantly (by around 100% for WdCodes 8 and 9). Even when further restricting the sample to those crossings with WdCode greater than or equal to 8 (effectively restricting the sample to exclude any crossings without descending gates), the estimates remain virtually unchanged and statistically significant at 1% (N=510000).

Finally, we remove from our sample all crossings that are designated as being in a QZ through the entire 10 year sample. We do this to address the concern that including these observations will contaminate our control and experimental groups. To accomplish this, we generated an alternative experimental variable. Where the full dataset contains crossings coded as QZs that are QZs through the entire sample, the new variable equals 1 for any crossing that becomes a full QZ during the sample, and 0 otherwise. We then use this variable in our base regression. The resulting estimate is statistically significant at 1% and 20% larger (0.0181) in magnitude than the estimate from column 1 of figure 7. This strategy also increases the magnitude of the estimates in the regressions on fatal accidents. This same trend is present in the third matching method dataset and across nearly every specification.

8 Discussion

Our results provide several avenues for discussion with previous research undertaken by the FRA and academics on factors influencing accident incidence and severity at HRGCs.

First, our results generally affirm several relationships observed in previous research on HRGC accidents. Previous literature relies heavily on exposure factor, a function of the number of cars going through a crossing (in our dataset as AADT) and the number of trains going through a crossing (Night Thru and Day Thru). Higher values of exposure factor are taken to indicate higher accident incidence risk. Both AADT and the number of trains going through a crossings are seen to be statistically significant, or approaching statistical significance, with positive coefficients in most specifications. Although certain specifications depart from the norm, every model that utilizes county-fixed effects affirms this relationship. We also find evidence supporting Hao and Daniel's (2016) conclusion that higher speed limits for trains increase accident incidence rates.

Second, we find strong evidence supporting the emphasis of the FRA on gate installation to reduce the risk of injury incidence in HRGCs. Codes 8 and 9 (All Other gates and Four quad barrier gates respectively) are consistently statistically significant with negative coefficients. In some cases, the negative coefficient associated with either gate code is of similar magnitude to that of the positive coefficient on QZ designation. If the FRA maintains the goal of ensuring that QZ crossings are no more unsafe than the average HRGC (using the NSRT), then these findings support the idea that installation of higher-level active safety measures can offset the increased risk of accidents resulting from being in a QZ. Furthermore, this finding makes sense given that the FRAs own reports find that QZ implementation, after accounting for additional safety features, does not increase accident incidence rates (Marquese Lewis, 2013).

Finally, our panel model produces convincing evidence that the FRA's decision to focus on a before-and-after analytical model using a limited number of crossings may be concealing the true impact of QZs on HRGC safety. Our fixed effects model provides strong evidence that QZs increase accident incidence rates of crossings as well as some evidence that QZs increase accident severity at affected crossings. The coefficients on our different measures of QZ designation are not only highly statistically significant but are extremely substantively significant. Our panel model suggests that QZ designation may be increasing accident incidence rates for affected crossings by 120% of mean accident rates. This value is close to double the rate at which the FRA adjusts risk within the QZRI. Furthermore, these results are robust to our various different specifications. We also find evidence that QZs may contribute to an increased incidence of severe accidents. This increase in the number severe accidents is not simply because of a general increase in accident rates, but because any given accident is more likely to be severe. Despite our findings that improved safety features may be able to offset the increase in accident incidence rates after QZ implementation, we find that they are insufficient to mitigate higher accident severity rates.

Ultimately though, any serious discussion focusing on QZ policy must weigh both the costs and benefits of quiet zones. While our research provides strong evidence that previous studies have underestimated the safety risks associated with QZs, the economic benefits—such as property value preservation and noise reduction—may still justify their implementation in certain cases. Future research should focus on quantifying these trade-offs more precisely, particularly through cost-benefit analyses that compare the financial savings of QZs to the potential social costs of increased accident rates. Our findings suggest that policymakers should carefully consider whether current safety requirements for QZs are sufficient or whether additional risk mitigation strategies, such as enhanced active warning systems or taking away QZ status from certain crossings, should be mandated. By providing a more accurate assessment of QZ risks, we hope to contribute to a more informed policy discussion on costs of QZs.

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10 Appendix A

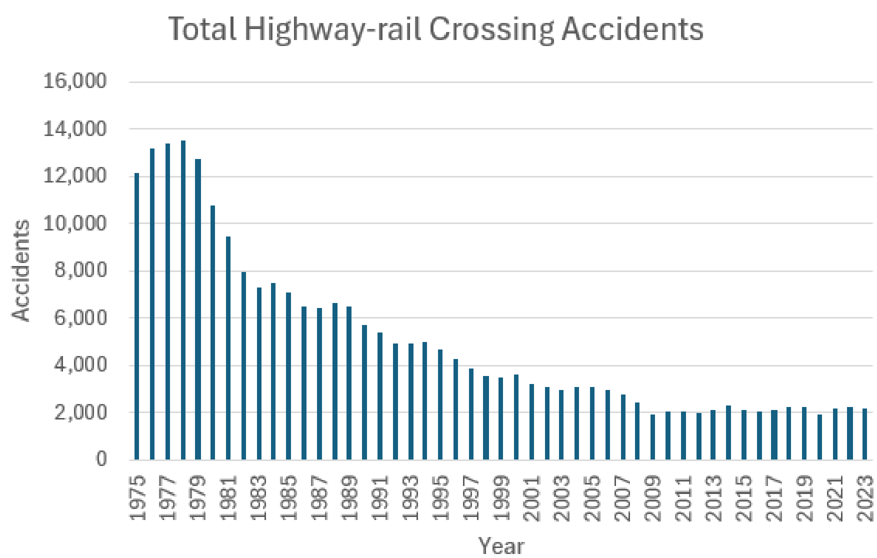

Figure 1: Total Highway-Rail Crossing Accidents. Data from FRA form 57

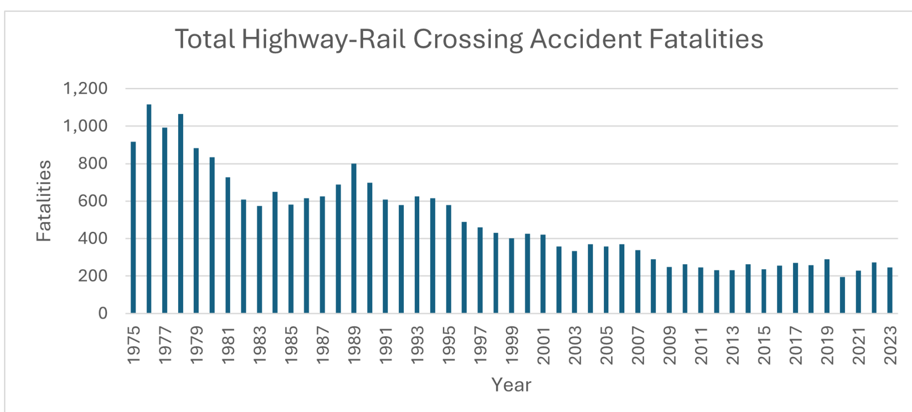

Figure 2: Total Highway-Rail Crossing Fatalities. Data from FRA form 57

11 Appendix B

Requirements for Quiet Zone creation:

- Each public highway-rail crossing in a QZ must have active warning devices comprising of gates and flashing lights to be activated at intervals similar to that required by train horn mandates.

- All crossings must be equipped with an advance warning sign that warns drivers that crossing is in a QZ. There are no signage requirements for non-QZ crossings.

- All pedestrian crossings must be equipped with a bell . In addition to these basic requirements, public authorities must also show one of the following:

- The Quiet Zone Risk Index (QZRI) is less than or equal to the Nationwide Significant Risk Threshold[11] (NSRT)[12] before or after implementation of supplementary safety measures (SSMs) or alternative safety measures (ASMs).The current NSRT is 15,488 (Federal Register).

- The Quiet Zone Risk Index (QZRI) is less than or equal to the Risk Index With Horns (RIWH)[13] with additional safety measures such as SSMs or ASMs. The QZRI uses the same risk formula, but multiplies risk by 1.668 to account for increased risk without horns being sounded.

- Install SSMs[14] at every public highway-rail crossing It is notable that the accident prediction formula currently implemented in calculation of risk indices uses the accident history of a crossing for the last five years (US Government Publishing Office, 2025).

[11] Risk Index is the predicted cost to society of the casualties expected to occur at the predicted accidents at a crossing. Please see Appendix D to CFR part 222 (US Government Publishing Office, 2025) for more information on FRA risk indices.

[12] These are two models for risk maintained by the USDOT. The NSRT is the average risk index for all crossings equipped with flashing lights and gates where horns are sounded.

[13] The RIWH is a measure of the average risk index of crossings in the proposed QZ if horns are still sounded

[14] An example of an SSM is a wayside horn. Wayside horns are installed at the HRGC and are sounded instead of train horns in quiet zones. Wayside horns are viewed by the FRA as a 1-1 replacement of train horns.

12 Appendix C

Variable Name	Variable Type	Variable Description
WhistleBanCodeBinary	Binary	A binary variable equaling 1 if a crossing is any of the three types of QZ and 0 otherwise
WhistleBanCodeOne	Binary	A binary variable equaling 1 if a crossing is a full 24 hour QZ and 0 otherwise
WhistleBanCode	Categorical	Equals 1 if a crossing is within a full 24 hour QZ, 2 if a crossing is within a partial QZ, 3 if a crossing is in a Chicago Excused QZ, and 0 otherwise
Accident	Continuous	A measure of the number of accidents occuring at a crossing within a give time frame.
FatalAccident	Continuous	A measure of the number of accidents with at least one fatality occuring at a crossing within a give time frame.
InjuryAccident	Continuous	A measure of the number of accidents with at least one injury occuring at a crossing within a give time frame.
CasualtyAccident	Continuous	A measure of the number of accidents with at least one injury or fatality occuring at a crossing within a give time frame.
DayThru	Continuous	A measure of the number of through trains going through a crossing during daylight hours (6am - 6pm)
NghtThru	Continuous	A measure of the number of through trains going through a crossing during nightitme hours (6pm - 6am)
MaxTrainSpeed	Continuous	The speed limit of trains on the section of track upon which a crossing is located
WdCode	Categorical	A measure of the highest level of safety measure present at a crossing.
AverageAnnualDailyTraffic (AADT)	Continuous	A measure of the average number of highway users going through a crossing everyday
RoadAtCrossingCode	Binary	A measure of the rural vs urban status of a crossing location equaling 0 if a crossing is considered rural and 1 if a crossing is considered urban
CrossingID	Categorical	An identifier variable unique to each individual crossing
CountyCode	Categorical	An identifier variable unique to each individual county (FIPS code)

Figure 3: This table presents variable descriptions. WdCode has nine different categories defined as such:

9 - Four Quad (full barrier) Gates

8 - All other Gates

7 - Flashing lights

6 - Highway signals, wigwags, bells, other activated

5 - Special Active Warning Devices

4 - Stop signs

3 - Crossbucks

2 - Other signs or signals

1 - No signs or signals

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Accident	148902	.012	.117	0	7
FatalAccident	148902	.001	.037	0	2
InjuryAccident	148902	.003	.059	0	3
CasualtyAccident	148902	.004	.069	0	3
DayThru	147918	5.106	10.269	0	443
NghtThru	147906	4.239	8.174	0	376
MaxTrainSpeed	147612	30.353	22.123	0	110
AverageAnnualDaily~c	125885	3003.3	9601.425	0	999999
RoadAtCrossingCode	119747	.412	.492	0	1

Figure 4: Summary Statistics

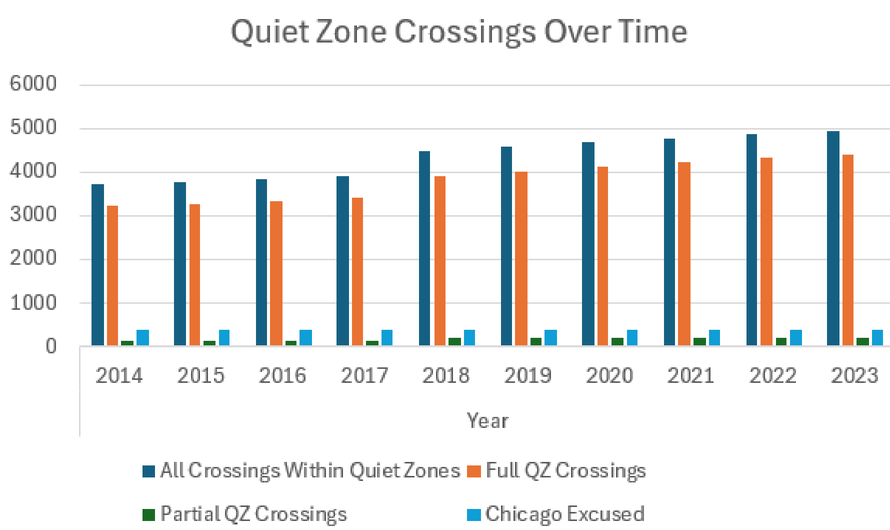

Figure 5: Shows the number of crossings within quiet zones in our sample over the sample years (2014-2023)

	WhisBan	NghtThru	DayThru	AADT	MinSpee	MaxSpee	RurUrb
WhisBan	1						
NghtThru	0.1676	1					
DayThru	0.2115	0.8500	1				
AADT	0.0700	0.0100	0.0288	1			
MinSpee	0.0103	0.2092	0.1947	-0.0235	1		
Max Spee	0.0585	0.5064	0.4686	-0.0798	0.5061	1	
RurUrb	0.1732	0.0117	0.0498	0.2553	-0.0973	-0.2224	1

Figure 6: Correlation Matrix (excluding WdCode)

13 Appendix D

	(1) Accident	(2) Accident	(3) Accident	(4) Accident	(5) Accident
WhistleBanCodeBinary	0.0152***				
	(6.71)				
WhistleBanOne		0.0154***			
		(6.71)			
1.WhistleBanCode			0.0157***	0.0157**	0.0136***
			(6.90)	(3.25)	(16.70)
2.WhistleBanCode			-0.00568	-0.00568	0.00360
			(-0.62)	(-0.57)	(0.95)
3.WhistleBanCode			0.0200	0.0200	0.0118***
			(1.14)	(0.58)	(4.68)
NghtThru	-0.0000890	-0.0000701	-0.0000836	-0.0000836	0.000190***
	(-1.46)	(-1.13)	(-1.40)	(-0.73)	(6.08)
DayThru	0.000264***	0.000246***	0.000254***	0.000254**	0.000480***
	(5.14)	(4.74)	(5.06)	(2.82)	(18.14)
MinTrainSpeed	0.0000218	0.0000212	0.0000219	0.0000219	0.000143***
	(1.13)	(1.10)	(1.13)	(0.86)	(13.12)
MaxTrainSpeed	0.0000629**	0.0000672**	0.0000620**	0.0000620*	0.000346***
	(2.74)	(2.93)	(2.71)	(2.20)	(38.26)
AADT	0.000000146*	0.000000152*	0.000000142*	0.000000142	0.000000524***
	(2.07)	(2.16)	(2.04)	(1.21)	(31.75)
RoadAtCrossingCode	0.000562	0.000586	0.000595	0.000595	0.00684***
	(0.53)	(0.55)	(0.56)	(0.55)	(22.57)
cons	0.0139***	0.0137***	0.0139***	0.0139***	-0.0155***
	(7.58)	(7.51)	(7.70)	(9.65)	(-22.57)
Crossing Fixed Effects	Yes	Yes	Yes	Yes	
County Fixed Effects					Yes
Clustered Standard Errors				Yes	
N	1269774	1264609	1282298	1282298	1283256

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 7: Main Results

	(1) FatalAccident	(2) FatalAccident	(3) FatalAccident	(4) FatalAccident	(5) FatalAccident
WhistleBanCodeBinary	0.00536***				
	(7.22)				
WhistleBanOne		0.00549***			
		(7.35)			
1.WhistleBanCode			0.00546***	0.00546**	0.00258***
			(7.33)	(2.70)	(9.92)
2.WhistleBanCode			0.000609	0.000609	0.00163
			(0.20)	(0.13)	(1.34)
3.WhistleBanCode			0.00207	0.00207	0.00597***
			(0.36)	(0.13)	(7.40)
NghtThru	0.0000402*	0.0000482*	0.0000393*	0.0000393	0.0000353***
	(2.01)	(2.39)	(2.01)	(1.09)	(3.53)
DayThru	0.0000139	0.0000180	0.0000134	0.0000134	0.000100***
	(0.82)	(1.06)	(0.81)	(0.39)	(11.85)
MinTrainSpeed	-0.0000149*	-0.0000157*	-0.0000148*	-0.0000148	0.00000801*
	(-2.35)	(-2.50)	(-2.35)	(-1.61)	(2.31)
MaxTrainSpeed	0.0000195**	0.0000194**	0.0000193**	0.0000193*	0.0000756***
	(2.59)	(2.60)	(2.58)	(2.02)	(26.17)
AADT	2.74e-08	3.01e-08	2.70e-08	2.70e-08	6.87e-08***
	(1.19)	(1.32)	(1.18)	(0.99)	(13.05)
RoadAtCrossingCode	-0.00000791	-0.00000506	-0.0000127	-0.0000127	0.00111***
	(-0.02)	(-0.01)	(-0.04)	(-0.04)	(11.46)
_cons	0.00184**	0.00178**	0.00184**	0.00184***	-0.00259***
	(3.06)	(3.00)	(3.11)	(4.27)	(-11.79)
Crossing Fixed Effects	Yes	Yes	Yes	Yes	
County Fixed Effects					Yes
Clustered Standard Errors				Yes	
N	1269774	1264609	1282298	1282298	1283256

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 8: Severity Regression Results

	(1) FatalAccident	(2) FatalAccident	(3) FatalAccident	(4) FatalAccident	(5) FatalAccident
WhistleBanCodeBinary	0.00371***				
	(5.30)				
WhistleBanOne		0.00385***			
		(5.45)			
1.WhistleBanCode			0.00376***	0.00376*	0.00111***
			(5.35)	(2.09)	(4.54)
2.WhistleBanCode			0.00122	0.00122	0.00124
			(0.43)	(0.30)	(1.08)
3.WhistleBanCode			-0.0000880	-0.0000880	0.00469***
			(-0.02)	(-0.01)	(6.18)
NghtThru	0.0000498**	0.0000557**	0.0000483**	0.0000483	0.0000148
	(2.64)	(2.93)	(2.61)	(1.41)	(1.57)
DayThru	-0.0000147	-0.00000831	-0.0000140	-0.0000140	0.0000483***
	(-0.92)	(-0.52)	(-0.90)	(-0.44)	(6.08)
MinTrainSpeed	-0.0000173**	-0.0000180**	-0.0000172**	-0.0000172*	-0.00000739*
	(-2.88)	(-3.03)	(-2.88)	(-2.00)	(-2.26)
MaxTrainSpeed	0.0000127	0.0000123	0.0000126	0.0000126	0.0000382***
	(1.79)	(1.73)	(1.79)	(1.43)	(14.05)
AADT	1.16e-08	1.39e-08	1.16e-08	1.16e-08	1.22e-08*
	(0.53)	(0.64)	(0.54)	(0.43)	(2.46)
RoadAtCrossingCode	-0.0000687	-0.0000678	-0.0000770	-0.0000770	0.000371***
	(-0.21)	(-0.21)	(-0.24)	(-0.23)	(4.07)
Accident	0.108***	0.107***	0.108***	0.108***	0.108***
	(372.33)	(369.13)	(373.59)	(40.74)	(406.49)
_cons	0.000335	0.000317	0.000338	0.000338	-0.000916***
	(0.59)	(0.56)	(0.60)	(0.82)	(-4.42)
Crossing Fixed Effects	Yes	Yes	Yes	Yes	
County Fixed Effects					Yes
Clustered Standard Errors				Yes	
N	1269774	1264609	1282298	1282298	1283256

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 9: Fatal Accident Controlling for Accident Rates

14 Appendix E

	(1) Accident	(2) Accident	(3) Accident	(4) Accident	(5) Accident
WhistleBanCodeBinary	0.00653**				
	(2.71)				
WhistleBanOne		0.00612*			
		(2.51)			
1.WhistleBanCode			0.00642**	0.00642	0.0114***
			(2.64)	(1.28)	(13.19)
2.WhistleBanCode			-0.0209*	-0.0209	0.00195
			(-2.14)	(-1.26)	(0.48)
3.WhistleBanCode			0.0415*	0.0415	0.0110***
			(2.07)	(1.01)	(4.14)
NghtThru	-0.000147*	-0.000108	-0.000147*	-0.000147	0.000219***
	(-2.33)	(-1.69)	(-2.33)	(-1.16)	(6.67)
DayThru	0.000260***	0.000236***	0.000260***	0.000260*	0.000585***
	(4.85)	(4.38)	(4.86)	(2.50)	(20.60)
MinTrainSpeed	-0.00000906	-0.00000896	-0.00000870	-0.00000870	0.000150***
	(-0.47)	(-0.46)	(-0.45)	(-0.34)	(13.02)
MaxTrainSpeed	0.0000327*	0.0000317*	0.0000321*	0.0000321	0.000289***
	(2.08)	(2.03)	(2.05)	(1.75)	(30.48)
AADT	0.000000153*	0.000000154*	0.000000153*	0.000000153	0.000000593***
	(2.04)	(2.06)	(2.03)	(1.23)	(31.29)
RoadAtCrossingCode	0.00258*	0.00261*	0.00255*	0.00255*	0.00640***
	(2.16)	(2.19)	(2.13)	(2.03)	(19.96)
_cons	0.0165***	0.0163***	0.0164***	0.0164***	-0.0145***
	(8.79)	(8.78)	(8.77)	(10.66)	(-20.19)
Crossing Fixed Effects	Yes	Yes	Yes	Yes	
County Fixed Effects					Yes
Clustered Standard Errors				Yes	
N	1147563	1142932	1147563	1147563	1148380

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 10: Alternative Sample Main Regressions

	(1) FatalAccident	(2) FatalAccident	(3) FatalAccident	(4) FatalAccident	(5) FatalAccident
WhistleBanCodeBinary	-0.000122				
	(-0.15)				
WhistleBanOne		-0.000169			
		(-0.21)			
1.WhistleBanCode			-0.000214	-0.000214	0.00150***
			(-0.27)	(-0.10)	(5.41)
2.WhistleBanCode			0.00273	0.00273	0.00299*
			(0.85)	(0.46)	(2.31)
3.WhistleBanCode			0.00305	0.00305	0.00616***
			(0.46)	(0.15)	(7.24)
NghtThru	0.0000444*	0.0000394	0.0000442*	0.0000442	0.0000466***
	(2.14)	(1.89)	(2.13)	(0.77)	(4.44)
DayThru	0.00000518	0.0000105	0.00000535	0.00000535	0.000121***
	(0.29)	(0.60)	(0.30)	(0.11)	(13.33)
MinTrainSpeed	-0.0000103	-0.0000107	-0.0000103	-0.0000103	0.0000127***
	(-1.61)	(-1.70)	(-1.61)	(-1.08)	(3.44)
MaxTrainSpeed	0.0000118*	0.0000115*	0.0000119*	0.0000119	0.0000627***
	(2.29)	(2.25)	(2.30)	(1.88)	(20.64)
AADT	4.87e-08*	4.70e-08	4.87e-08*	4.87e-08	7.56e-08***
	(1.97)	(1.92)	(1.97)	(1.46)	(12.47)
RoadAtCrossingCode	0.0000532	0.0000588	0.0000560	0.0000560	0.00104***
	(0.14)	(0.15)	(0.14)	(0.12)	(10.18)
_cons	0.00136*	0.00134*	0.00135*	0.00135***	-0.00250***
	(2.21)	(2.21)	(2.19)	(3.97)	(-10.87)
Crossing Fixed Effects	Yes	Yes	Yes	Yes	
County Fixed Effects					Yes
Clustered Standard Errors				Yes	
N	1147563	1142932	1147563	1147563	1148380

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 11: Alternative Sample Severity Regressions

	(1) FatalAccident	(2) FatalAccident	(3) FatalAccident	(4) FatalAccident	(5) FatalAccident
WhistleBanCodeBinary	-0.000829				
	(-1.11)				
WhistleBanOne		-0.000823			
		(-1.10)			
1.WhistleBanCode			-0.000909	-0.000909	0.000260
			(-1.20)	(-0.48)	(1.00)
2.WhistleBanCode			0.00500	0.00500	0.00278*
			(1.65)	(0.94)	(2.28)
3.WhistleBanCode			-0.00145	-0.00145	0.00497***
			(-0.23)	(-0.07)	(6.21)
NghtThru	0.0000604**	0.0000509**	0.0000601**	0.0000601	0.0000229*
	(3.09)	(2.59)	(3.07)	(1.15)	(2.31)
DayThru	-0.0000229	-0.0000147	-0.0000228	-0.0000228	0.0000577***
	(-1.38)	(-0.89)	(-1.38)	(-0.49)	(6.76)
MinTrainSpeed	-0.00000929	-0.00000979	-0.00000934	-0.00000934	-0.00000358
	(-1.54)	(-1.64)	(-1.55)	(-1.05)	(-1.03)
MaxTrainSpeed	0.00000827	0.00000806	0.00000839	0.00000839	0.0000313***
	(1.70)	(1.67)	(1.73)	(1.43)	(10.96)
AADT	3.21e-08	3.05e-08	3.22e-08	3.22e-08	1.14e-08*
	(1.38)	(1.32)	(1.38)	(1.00)	(1.99)
RoadAtCrossingCode	-0.000226	-0.000220	-0.000220	-0.000220	0.000351***
	(-0.61)	(-0.60)	(-0.59)	(-0.52)	(3.64)
Accident	0.108***	0.107***	0.108***	0.108***	0.108***
	(351.35)	(347.95)	(351.35)	(38.50)	(385.07)
_cons	-0.000424	-0.000405	-0.000432	-0.000432	-0.000928***
	(-0.73)	(-0.71)	(-0.74)	(-1.25)	(-4.28)
Crossing Fixed Effects	Yes	Yes	Yes	Yes	
County Fixed Effects					Yes
Clustered Standard Errors				Yes	
N	1147563	1142932	1147563	1147563	1148380

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 12: Alternative Sample Severity Regressions Controlling for Accident

	(1) Accident	(2) Accident	(3) Accident	(4) Accident	(5) Accident
WhistleBanCodeBinary	0.0128***				
	(5.28)				
WhistleBanOne		0.0129***			
		(5.24)			
1.WhistleBanCode			0.0132***	0.0132*	0.0130***
			(5.43)	(2.44)	(15.07)
2.WhistleBanCode			-0.00433	-0.00433	0.00214
			(-0.44)	(-0.37)	(0.53)
3.WhistleBanCode			0.0259	0.0259	0.0121***
			(1.29)	(0.60)	(4.57)
NghtThru	-0.000210***	-0.000151*	-0.000200**	-0.000200	0.000165***
	(-3.31)	(-2.34)	(-3.21)	(-1.66)	(5.09)
DayThru	0.000364***	0.000327***	0.000351***	0.000351***	0.000522***
	(6.75)	(6.02)	(6.65)	(3.55)	(18.96)
MinTrainSpeed	0.0000181	0.0000188	0.0000179	0.0000179	0.000134***
	(0.90)	(0.94)	(0.89)	(0.68)	(11.75)
MaxTrainSpeed	0.0000192	0.0000188	0.0000190	0.0000190	0.000340***
	(0.80)	(0.78)	(0.79)	(0.65)	(35.67)
AADT	0.000000149*	0.000000160*	0.000000144	0.000000144	0.000000493***
	(1.97)	(2.11)	(1.92)	(1.13)	(29.15)
RoadAtCrossingCode	0.000668	0.000702	0.000655	0.000655	0.00702***
	(0.55)	(0.58)	(0.55)	(0.53)	(21.96)
_cons	0.0168***	0.0166***	0.0168***	0.0168***	-0.0154***
	(8.60)	(8.55)	(8.69)	(10.31)	(-21.58)
Crossing Fixed Effects	Yes	Yes	Yes	Yes	
County Fixed Effects					Yes
Clustered Standard Errors				Yes	
N	1147563	1142932	1157969	1157969	1158997

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 13: Alternative Sample 2 Main Regressions

	(1) FatalAccident	(2) FatalAccident	(3) FatalAccident	(4) FatalAccident	(5) FatalAccident
WhistleBanCodeBinary	0.00468***				
	(6.20)				
WhistleBanOne		0.00507***			
		(6.67)			
1.WhistleBanCode			0.00485***	0.00485*	0.000996***
			(6.42)	(2.42)	(3.81)
2.WhistleBanCode			0.00814**	0.00814	0.00239
			(2.67)	(1.57)	(1.96)
3.WhistleBanCode			-0.0154*	-0.0154	0.00423***
			(-2.46)	(-1.34)	(5.26)
NghtThru	0.0000276	0.0000342	0.0000269	0.0000269	0.00000927
	(1.40)	(1.72)	(1.39)	(0.65)	(0.95)
DayThru	0.00000830	0.0000126	0.00000785	0.00000785	0.0000534***
	(0.50)	(0.75)	(0.48)	(0.19)	(6.43)
MinTrainSpeed	-0.0000167**	-0.0000173**	-0.0000167**	-0.0000167	-0.00000779*
	(-2.67)	(-2.80)	(-2.69)	(-1.84)	(-2.27)
MaxTrainSpeed	0.000000894	0.000000774	0.000000963	0.000000963	0.0000366***
	(0.12)	(0.10)	(0.13)	(0.10)	(12.70)
AADT	8.05e-09	7.28e-09	8.50e-09	8.50e-09	1.17e-08*
	(0.34)	(0.31)	(0.37)	(0.24)	(2.29)
RoadAtCrossingCode	-0.000567	-0.000563	-0.000560	-0.000560	0.000328***
	(-1.51)	(-1.52)	(-1.51)	(-1.27)	(3.39)
Accident	0.110***	0.109***	0.110***	0.110***	0.110***
	(357.46)	(354.37)	(358.27)	(37.73)	(391.88)
_cons	0.000257	0.000235	0.000305	0.000305	-0.000924***
	(0.42)	(0.39)	(0.51)	(0.72)	(-4.29)
Crossing Fixed Effects	Yes	Yes	Yes	Yes	
County Fixed Effects					Yes
Clustered Standard Errors				Yes	
N	1147563	1142932	1157969	1157969	1158997

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 14: Alternative Sample 3 Fatality Accident Controlled Regressions

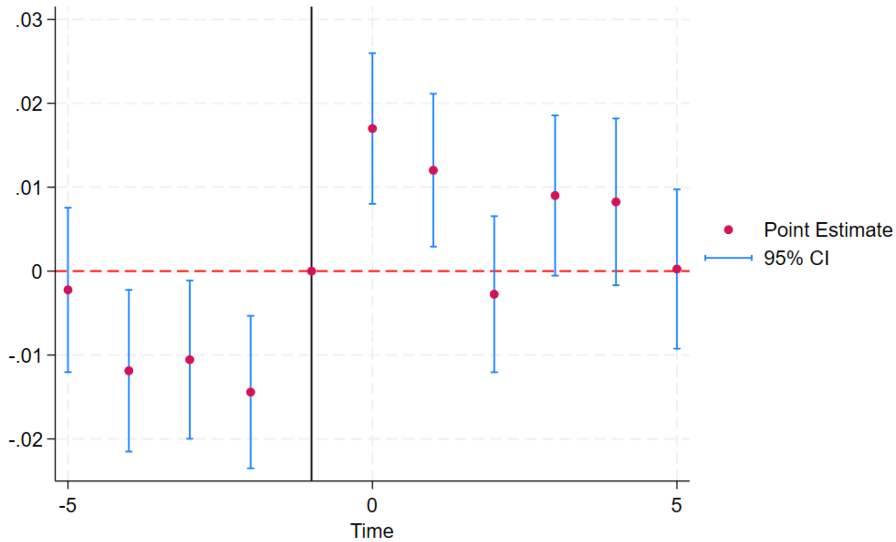

Figure 15: Event Study