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Examining The Impact of Florida's Non-Economic Damage Cap on Elderly Populations

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Abstract

In this paper, I use data from the Florida Closed Claims Database to investigate how Florida's 2003 non-economic damage cap legislation impacted elderly malpractice claimants. More specifically, I measure whether or not non-economic damage caps adversely impact claimants in counties with high elderly densities. To measure the effect of Florida's non-economic damage caps, I look at multiple metrics that measure both elderly claimants' monetary gains and their access to the justice system after the reform is passed. I find mildly conclusive evidence that counties with higher elderly density, and assumedly more elderly claimants, are more likely to settle cases before reaching a jury trial and are less likely to file a medical malpractice claim. Conversely, though, I find limited evidence supporting the idea that elderly claimants receive less monetary damage payments or drop cases more. Overall, then, my findings are not consistent with the view that non-economic damage caps significantly discriminate against elderly claimants.

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1: Introduction

The state of medical malpractice liability legislation has been debated extensively and fluctuated between heavy and light regulation at a state level since the liability insurance crisis of the 1970's and 1980's. With liability insurance premiums rising due to a seemingly excessive increase in lawsuits and jury payouts to plaintiffs, Hyman et al. (2009) notes that many states have adopted medical malpractice damage caps to prevent plaintiffs from filing frivolous lawsuits and to encourage doctors to work in a particular state and to not practice "defensive medicine", as put by Kessler and McClellan (1996). One particular type of damage cap, known as a non-economic damage cap, attempts to limit the money that can be awarded at trial for non-economic injuries in medical malpractice cases. Non-economic damages seek to award plaintiffs for non-physical, non-wage related damages such as pain, suffering, and emotional distress. As claimed in a study by Fort et al. (1986), "noneconomic losses make up the largest portion of jury awards." One estimate, provided by the Congressional Budget Office in 2013 in an attempt to provide solutions for lowering the federal deficit, asserts that a series of national tort reforms which includes capping non-economic damage caps at $250 thousand per claimant could reduce total healthcare spending by .5%,[1] and in turn could reduce federal healthcare expenditures by as much as $57 billion between 2014 and 2023. The tradeoff to installing non-economic damage caps, though, is that some valid medical malpractice cases will not be brought to trial because malpractice claims have a lower potential payout, and hence lawyers will be less willing to take on the case. The balance between decreasing healthcare costs and incentivizing individuals to seek justice is an

[1] Other aspects of the proposed reform would cap punitive damages, limit the statute of limitations, and expand permissible evidence standards at trial.

imperative issue to examining tort reform, and in particular to examining non-economic damage caps. While some studies, such as one conducted by Paik et al. (2010), have found that non-economic damage caps generally decrease both the number of cases that reach a jury award and also the total payout by insurance companies in settled cases. The motivation for this paper is to take this generalized analysis one step further and focus on how different demographics are impacted by non-economic damage caps.

The purpose of my study is to analyze data from the Florida Closed Claims Database between the years 1999 and 2009 in order to assess whether or not elderly populations are negatively impacted by legislation imposing non-economic damage caps. Florida is an excellent state to examine the impact of non-economic damage caps on elderly patients due to both the availability of their medical malpractice database as well as the general belief that many elderly people move to Florida for retirement. I investigate this question by examining whether non-economic damage caps produce an effect on the probability of filing a claim, the probability of settlement, the probability of dropping a claim, and the total insurance payout in settled claims for county and year combinations with high elderly densities. I examine these three probability measures because they act as a proxy for elderly citizens' access, or at the least their expected access, to the court system. In a more applicative sense, if elderly patients are settling more cases, filing fewer claims, and dropping more cases, it would suggest that elderly claimants' ability to access the medical malpractice system has declined. My fourth measure of fairness of non-economic damage caps, the total insurance payout in settled claims, is crucial to analyze because it highlights whether or not elderly claimants actually receive less money in medical malpractice cases when non-economic damage caps are in place. I choose the years 1999 to 2009 because Florida enacted non-economic damage caps in late 2003.

If non-economic damages statistically impact elderly claimants, then this may be motivation for Florida to adjust their medical malpractice laws to treat elderly patients more fairly to encourage healthy practices. As noted by several scholarly papers such as Paik et al. (2010) and Sager et al. (1990), medical spending is disproportionally spent on elderly patients, so the investigation of non-economic damage caps is imperative to understanding the complex dynamic between physicians, elderly patients, and the decision to seek medical help. Furthermore, the impact of non-economic damage caps on elderly patients, or even across all age cohorts, is important because tort law aims to treat all individuals fairly. Non-economic damage caps are an especially pertinent issue for the elderly, though, because older individuals are less likely to receive wages so non-economic damages likely form a larger portion of their malpractice award. As such, the non-economic damage caps likely hit elderly claimants proportionally harder than those typically specified as working age. If specific reforms such as non-economic damage caps are unintentionally discriminating against elderly claimants, then the medical liability system is doing a poor job representing and protecting more illness-prone, not-working individuals from medical harm. Interestingly, relatively little research has been conducted solely examining how the elderly have been impacted by various tort reforms.

As noted above, because elderly people, which I define as individuals over the age of 65, are usually retired and do not have an income stream from an employer, they typically rely more heavily on non-economic damages in medical malpractice suits. Given the reputation of Florida as a retirement state for many elderly individuals and couples, the population of Florida is an extremely intriguing state to investigate because of its elderly density and high frequency of patients who will not be eligible for economic damages at trial. Considering that elderly claimants are, theoretically, limited in the amount of money that they can recover by filing a claim and have less incentive to enter the medical malpractice claim legal procedure, I have a four-part hypothesis regarding each of my important parameters. Firstly, I hypothesize that, due to the imposition of economic damage caps in 2003, claims filed in county and year combinations with higher elderly densities will more be more likely to settle claims out of court because basic settlement theory predicts that lower potential awards will result in fewer settlements. Second, I predict that high elderly densities, again in a particular county and year, will less lower the likelihood of filing medical liability claims, which indicates the elderly are more likely to avoid the justice system. Likewise, my third hypothesis is that claims filed in county and year combinations with higher elderly densities will more frequently drop claims because they have a limit to their potential compensation. Finally, these three hypotheses lead me to predict that high elderly density will result in lower damage payments in settled cases because the institution of non-economic damage caps has changed the feasible settlement amount by capping a crucial part of elderly damage packages. After analyzing my data, though, I find that the imposition of Florida's 2003 non-economic damage cap only shows a moderate negative effect on the probability of settlement and filing a claim. Numerically, the partial effect of elderly density in the post-reform period lowers the probability of settlement by roughly 8.5% to 12%,[2] and lowers

[2] As I will mention in my robustness testing results, this 8.5% to 12% figure only represents elderly densities within two elderly age cohorts, 65-75 and 75-85. Thus, elderly density for those above 85 is not represented in these figures.

the probability of filing a case by between .5% and .8%. Contrarily, the imposition of non-economic damage caps does not seem to have a partial effect on the size of indemnity payments to elderly claimants or the probability of the elderly dropping a claim. Considering these mixed results, I find that the evidence presented throughout this paper is not consistent with the theory that non-economic damage caps are systematically discriminating against the elderly populations' access to, or monetary compensation in, the tort system.

The rest of this paper is as follows. Section 2 outlines a brief history of Florida's medical malpractice legislation in regards to non-economic damages. Section 3 discusses basic settlement theory and how introducing non-economic damage caps changes the settlement model. Section 4 outlines my data source, data limitations, and provides summary statistics. Section 5 displays my full model, the results of my regressions, several robustness tests for my results, and limitations to my regression analysis. Section 6 consists of my concluding remarks.

2: Florida's Tort Reform and Relevant Literature

2.1: Florida Tort Reform

Before diving into the relevant literature studying the impact of non-economic damage caps, it is valuable to get a firm understanding of the evolution of tort reform in Florida given that my analysis focuses on the effects of medical malpractice claims in Florida. As noted by Black et al. (2005), Amidst the medical malpractice crisis of the 1970's and 1980's, many states sought to reform their medical malpractice systems to limit damages that could be awarded at trial, which would act towards decreasing problematically high insurance carrier premiums charged to physicians and hospitals. Decreasing the burden on physicians and hospitals would in turn incentivize physicians to practice in a particular state. While many pieces of relevant tort reform legislation have been passed, the success of non-economic damage caps in Florida has been underwhelming, as noted by the relevant and recent history of Florida's non-economic damage caps provided in Appendix A.

According to Fort et al. (1986), prior to Florida's 1986 tort reform legislation there was no cap on non-economic damages. As a result of the 1986 legislation, though, Fort et al. (1986) explained that Florida imposed a fairly stringent punitive damage cap as well as a non-economic damage cap of $450 thousand per plaintiff. This reform was short-lived, however. As noted by Cline and Pepine (2004), in 1987 the Florida Supreme Court ruled the non-economic damage cap unconstitutional. Moving forward in time, Cline and Pepine (2004) asserted that by 2002 Florida was in a medical malpractice crisis as medical malpractice liability claim payouts had increased over 3000% since 1975.[3] In an attempt to address this crisis, Cline and Pepine (2004) discuss how Florida passed a fairly comprehensive set of tort reforms, and one of the byproducts of this 2003 reform was a $500 thousand cap per claimant on non-economic damages. Under egregious circumstances, the non-economic damage cap could be bumped up to $1 million, though. The normal non-economic cap for emergency rooms was set at $150 thousand, but could rise to $300 thousand in devastating cases. Kaminski (2004) also explained that the 2003

[3] In addition to Florida, Cline and Pepine (2004) adds that Georgia, Mississippi, Nevada, New Jersey, New York, Ohio, Oregon, Pennsylvania, Texas, Washington, and West Virginia were also considered at crisis levels.

reform stated that in claims against non-physician entities, the cap for non-economic damages was bumped up to $750 thousand and in egregious cases $1.5 million. In 2014, the Florida Supreme Court again struck down the cap on non-economic damages, reasoning that the cap was unfair to plaintiffs.[4] Thus, the period from 1987 to 2003 is a period where Florida had no economic damage caps, and 2004 to 2014 is a period with acting non-economic damage caps, which gives me the ability to compare differences in claimant behavior and claim payouts across these two time periods for elderly claimants. See Appendix A for a more concise, condensed summary of the history and success of Florida tort reform.

2.2: Relevant Literature Review

There is an abundance of relevant literature examining the aggregate effects of tort reform and non-economic damage caps in medical malpractice. For example, a multitude of papers have been written predominantly by the trio of Bernard Black, Charles Silver, and David Hyman on Texas' non-economic damage caps passed in 2003. Some of the key findings of papers written about the Texas non-economic damage cap will be discussed more deeply below. More generally, however, very few papers focus explicitly on how the elderly are impacted by such reforms. Below I will discuss the findings of these Texas studies, as well as other pieces of relevant literature to my focused investigation on elderly populations.

The most relevant study investigating the effect of tort reform, and more specifically the impact of non-economic damage caps on the elderly, is Paik et al. (2010)

[4] Mary Ellen Klas, "Fla. Supreme Court rejects damage caps on medical malpractice," *Miami Herald* (Miami, FL), March 13th, 2014.

and their study using data from the Texas Closed Claims Database (1988 to 2007).[5] Paik et al. (2010) measure if paid claim rates changed for the elderly after 2003, when Texas adopted a cap on non-economic damages. They find that prior to the non-economic damage cap legislation; elderly aggregate payout had steadily increased since 1988, but was still considerably low compared to the percentage of total medical spending allocated to the elderly. Post-reform, though, they find that there is a 63% decline in elderly claim filings and a 33% decline in payout per claim. The results from Paik et al. (2010) led them to predict a 60% drop in total claims and a roughly 33% drop in payout per claim for the elderly population of Texas.[6] Thus, Paik et al (2010) provide strong evidence that non-economic damage caps have a very significant effect on reducing claims and payout per claim. Pertaining more explicitly to the elderly, they find that non-elderly and elderly claimants experience similar drops in filed claims and payout per claim. In their analysis, when non-economic damages are imposed, the decline in payout per claim between elderly and non-elderly claimants is statistically insignificant.

The noted decline in filed claims from Paik et al. (2010) is similar to the findings of Burstin et al. (1993), which used data from 51 New York hospitals and found that elderly claimants are less likely to file medical malpractice claims. Additionally, Sager et al. (1990) used malpractice data from Wisconsin in 1983 and 1984 to investigate the likelihood of potential claimants actually filing medical malpractice claims, and found that the elderly file malpractice claims much less frequently than the non-elderly. Burstin

[5] Paik et al. (2010) acknowledge that they only use the Texas Closed Claims Database for medical malpractice cases where payout is at least $25,000 in 1988 inflation-adjusted dollars, which means that insurers have to file a “Long Form,” which contains more expansive information about the claim.
[6] Due to the fact that the data only was available up to 2007, Paik et al. (2010) are uncertain as to whether Florida’s tort reform is fully integrated into their models. Thus, they use their data to predict the real impact of the cap.

(1993) theorizes the elderly may file fewer medical malpractice cases because they typically have longer and more established relationship with their physicians, and also because they have lower expectations of doctors as they have a shorter life expectancy than younger patients.

Preceding Paik et al. (2010), Hyman et al. (2009) and Silver et al. (2008) also investigate the general effect of Texas's non-economic damage cap on medical malpractice claims and payouts using the Texas Closed Claims Database. In contrast, Finley (2004) more broadly studied non-economic damage caps in California, Florida, and Maryland by examining how damage caps impacted gender, race, and age demographics. Interestingly, Hyman et al. (2009) identify that the non-economic damage cap altered 47% of jury awards and 18% of settled cases. In jury cases, the mean feasible verdict declines 37%, and in settled cases payout declines 18%.[7] With regards to elderly plaintiffs, Hyman et al. (2009) indicate that elderly plaintiffs see a 51% drop in feasible verdicts, a 38% drop in aggregate payout, and a 19% decline in payout per case. Silver et al. (2008), likewise, finds the same decline for elderly populations. Consistent with the other studies that used the Texas Closed Claims Database, the difference in the decrease in payouts for the elderly is not significant when compared to other age demographics.[8] Unlike the Texas Closed Claims Database studies, however, Finley (2004) finds that non-economic damage caps hit both women and the elderly, and in particular elderly women,

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[7] Hyman et al acknowledge that a feasible verdict, or an "allowed verdict", totals the allowable portion of jury awards plus interest.

[8] These payout decreases are calculated using data from 1988 to 2004, with the same inflation-adjusted method used by Paik et al. (2010).

hardest.[9] Furthermore, Finley (2004) puts forth the belief mentioned earlier that lower possible payments makes lawyers less likely to accept medical malpractice cases for the elderly and for women. Thus, aside from the significance of their findings, Hyman et al. (2009), Silver et al. (2008), and Finley (2004) have similar results to those dictated in Paik et al. (2010). Most notably, these critical pieces of literature identify that non-economic damages lower payouts in settled and trial cases for elderly claimants, and they also indicate that non-economic damage caps deter elderly people from filing medical malpractice claims and entering the legal system.

Finally, Kessler and McClellan (1996) and Shepherd and Rubin (2008) take more unconventional, and applicative, means to studying non-economic damages. Kessler and McClellan (1996) study elderly Medicare patients to measure whether or not doctors tend to practice defensive medicine in the face of large potential malpractice payouts. Specifically using data from 1984 to 1990 and looking just at one particular treatment for heart attacks,[10] they conclude that medical spending could drop between 5% and 9% once damage caps are fully implemented. More important to my topic at hand, though, this indicates that capping non-economic damages is likely beneficial in increasing physician efficiency but may detract from elderly patients' ability to recover damages for medical liability cases. In addition to damage recovery, though, elderly patients may be less likely to even seek medical attention if non-economic damages inhibit their ability to receive just compensation. Shepherd and Rubin (2008), likewise, examined state-level death rates

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[9] Although Finley (2004) acknowledges that elderly men actually had a lower post-reform recovery in sample of California malpractice cases, the proportional effect was worse for women.
[10] This treatment is formally called "acute myocardial infarction".

for differing demographics,[11] and discovered that non-economic damage caps tend to decrease non-accidental deaths in a given state, but non-economic damage caps have a lesser effect on decreasing death rates for the elderly. This negative partial effect of non-economic damages on death rates for the elderly indicates that non-economic damage caps, be it medical malpractice or other torts, discriminate against the elderly in more than just monetary terms, as the caps are not as beneficial to protecting their lives. These two articles indicate, again, that non-economic damage caps may adversely affect a particular demographic, in my case the elderly, from taking necessary medical action or suing physicians in medical malpractice cases.

My study branches out from the existing literature in several important ways. First, I am using data from the state of Florida between 1999 and 2009. Within this time frame, Florida has one distinct period with no non-economic damage caps imposed and another distinct period with a non-economic damage cap. Unlike the cases using the Texas Closed Claims Database, I have substantially more data on the time frame with non-economic damage caps and do not need to worry as much about the full implementation of tort reform. For example, Hyman et al (2009) use a very detailed simulation to estimate the effect of Texas' tort reform passed in 2003 because they only have Texas data from 1988 to 2004. Furthermore, the Texas studies only utilize cases that have an indemnity payment over $25 thousand when inflation adjusted. In my study I use all indemnity payments provided within my dataset. Another difference between my study and the Texas literature is that I also have gender data for filed claims, so I have the ability to control for gender when examining how elderly claimants are impacted.

[11] Sheperd and Rubin (2008) only consider non-vehicle related deaths.

Although Finley (2004) emphasizes non-economic damage caps with respect to gender discrimination, I put a lesser emphasis on gender and treat it as a control. She is primarily concerned with gender and views age demographics as a secondary concern. Additionally, I control for several other economic factors, such as per capita income and the percentage of individuals not currently receiving a paycheck at the county and year level to determine whether particular counties are more prone to settlement or smaller awards in settled cases. Finally, since I do not have individual ages for claimants, I use age bins at the county and year-specific level, which allows me to draw inferences about the likelihood of settlement at broader level than for a particular age.[12] Although this is a drawback to my study because I would ideally use individual claimant age, my approach to analyzing the impact of non-economic data using county and year level age cohorts separates my study from the existing literature quite substantially.

3: Theory and Model of Non-Economic Damages

3.1: Settlement and Payout Theory

Before discussing the intricacies of my data and my models, it is appropriate to first discuss motivations for applying settlement theory to this paper. Essentially, because medical malpractice claims do not follow a random selection process, we can effectively compare elderly claimants against non-elderly claimants. The fact that individuals have to conscientiously, not randomly, choose to enter the claim process means that claimants

[12] As I will address in Section 4, the current archive from the Florida Closed Claims Database stopped providing the age of claimants sometime between 2004 and 2014. I have an outdated version of the FCCD extending through 2004 with claimant age, but the 2014 version had age redacted.

do not have identical assumptions about their chances of winning compensation, and thus we can break down claimants into the categories of elderly and non-elderly.

In basic settlement theory between one plaintiff and one defendant, the important parameters that determine feasible settlement regions are the expected reward at trial, each side's respective belief about victory in court, and each side's respective costs of litigation. The relationship that determines if settlement is feasible can subsequently be written as:

(Eq. 1) $$\left(P_p - P_D\right) * J \leq C_P + C_D$$

where the subscripts p and D stand for plaintiff and defendant, P is expected probability of the plaintiff winning the case, J is the award at trial, and C is the cost of litigation. In other words, a settlement is reachable if the combined legal costs of the two parties are greater than the trial award multiplied by the difference in victory expectations. If the two parties have the same exact opinion about the probability of the plaintiff winning the case, then theoretically settlement should always be attainable. This settlement theory is outlined in more detail by Hay and Spier (1997). One crucial point that Hay and Spier (1997) make is that there is a range of settlement values for which both sides should theoretically be willing to settle, but bargaining problems may occur over how to distribute the gains from settling. Hay and Spier (1997) indicate that the settlement range in a basic trial model is:

(Eq. 2) $$P_p * J - C_p \leq S \leq P_D + C_D$$

This indicates that settlement is possible if the settlement amount is greater than the expected gain of the plaintiff and less than the expected loss of the defendant. For the sake of simplicity, and remaining focused on non-economic damage caps in Florida, I will not consider asymmetric information models detailed by Hay and Spier (1997) and Sieg (2000) as to why settlement may break down or not be reached when the above equation holds.[13]

Some important takeaways from the basic settlement model are that holding all else equal, a lower potential award at trial, J, makes settlement more likely. Thus, when Florida imposed non-economic damage caps in 2003, they artificially lowered the value that J could attain. For potential elderly claimants in particular, who cannot easily recover economic damages because they are not losing wages, the value of J can be significantly diminished, thus making settlement more likely for elderly claimants. This argument hinges on the fact that imposing non-economic damages should theoretically not change the probability of victory in medical malpractice cases, and should not change the costs of litigation either.

3.2: Application of Settlement Theory

Understanding that settlement is more likely with non-economic damage caps, lowering the potential award at trial, J, confounds a multivariate linear regression on the

[13] The general intuition of asymmetric information models is that litigating parties do not go have equal information. Defendants or plaintiffs may have information that the other does not, which makes potentially breaks down the settlement in a variety of ways. One such way dictated by Hay and Spier (1997) is that willingness to settle may be a sign of weakness, so parties may hold out to try and trick the other side into believing they have a stronger case.

awards paid in settled cases. Due to reverse causality between awards and settlement likelihood, a simple regression will ineffectively estimate the effect of non-economic damages on payouts to elderly claimants. Essentially, because settlement is more likely when non-economic damage caps are in place, we cannot accurately attribute decreasing settlement payouts to the limits imposed by non-economic damage caps or the fact that settlement is simply more likely and thus the average settlement amount will be lower. Problematically, neither relevant scholarly sources nor I found an effective instrument that only explained claim payout via the probability of settlement.[14] Because I do not have an instrument, though, I will use a heavily interacted model to test only whether or not areas with higher elderly densities in Florida see significantly smaller awards in settled cases when non-economic damage caps have been imposed. I cannot, however, firmly attribute any subsequent declines to the non-economic damage law itself. I also will construct three linear probability models to measure the degree to which non-economic damage caps make settlement, filing a case, or dropping a case more likely. These three models, which will be discussed in further detail in Section 5, will be the basis by which I evaluate the extent to which elderly populations access to the justice system is impacted by Florida's non-economic damage. These three regressions also have similar reverse causality issues. For example, if the probability of settlement increases, I cannot firmly attribute this change to the non-economic damages or the fact that indemnity damage payments are lower.

[14] Paik et al. (2010) acknowledged that settlement becomes more likely, but does not provide a remedy for eliminating this reverse causality effect. Other papers, such as the work of Silver et al. (2008), are not as concerned with the likelihood of settlement, but also acknowledge that settlement is more likely with the non-economic damage cap in place.

4: Data Description, Limitations, and Summary Statistics

4.1: Data Description

I use data from the Florida Closed Claims Database, which has been compiled by the Florida Office of Insurance Regulation and is publicly available for purchase. The Florida dataset is ideal for my purposes because it contains all medical malpractice liability claims from 1975 to the present. Helland and Showalter (2003) note, importantly, that insurance companies began supplying more information to the state of Florida in 1980, such as the physicians' specialty in a given case. The Florida Closed Claims Database actually is divided into two archives. The first contains data from 1975 to roughly 1997, and the second holds data from predominantly 1997 to the present. The second, more recent archive from 1997 to present contains 93,203 cases. There is, however, a considerable degree of overlap between the two files of claims, as the more current archive contains some claims stretching as far back as 1992, and some of these claim observations are actually in both databases. Given that many cases are duplicate cases within the database, assumedly due to the fact multiple plaintiffs can sue for the same malpractice, the actual number of cases for the purpose of my study is substantially less than 90,000. Numerically, the number of raw duplicates in the dataset is 42,439 observations. Whittling the useable observations down even more, I only examine data from the second archive when the both injury date and the date the case is disposed of are both between the years 1999 and 2009, which leaves me with a total of 24,883 observations for the purpose of my study.

The archived claims contain key variables such as date of injury occurrence, date that a claim was disposed, the severity of the injury, whether or not the case was settled,[15] and the gender of the plaintiff. In regards to payments, the database delineates between types of damage payment, such as economic, non-economic, and punitive damages. Also, as noted by Vidmar et al. (2005), the database records deductible payments and excess payments by insurers. Considering that non-economic damage caps were only instituted in Florida in 2003, this rich dataset provides ample information to compare pre-cap awards in medical malpractice cases to post-cap awards. Even more notably, Florida has a reputation as a prime destination for retired, elderly Americans. Thus, having the complete closed claims database for Florida makes my findings on the elderly especially relevant. If there are significant effects of non-economic damage caps on counties with high elderly densities in Florida, where the sample size of elderly Americans is likely quite large, then making extrapolations outside of Florida may be more prudent because there is a large enough sample of elderly claimants to draw conclusions beyond the state of Florida.

Other pieces of data that I use within this paper come from the Federal Reserve Economic Data of the St. Louis Federal Reserve and the United States Census. Specifically, the Federal Reserve Economic Data (FRED) is used to provide per capita income levels for individual counties in Florida dating between 1999 and 2009. I also used the County and City Data Book provided by the U.S. Census to gather data on the size of the civilian labor force, civilian labor force unemployment, and age demographics at both the county and year level from 1999 to 2009. Using this data that I gathered, I am

[15] And, if the case was settled, the database also records at what stage of the litigation process the case was settled

able to construct a series of explanatory variables for my model in Section 5. The full description of explanatory and control variables can found in Appendix B.

4.2: Data Limitations

Despite the rich amount of data and information the Florida Closed Claims Database provides, it does have several notable limitations that should be addressed. First and foremost, the Florida Closed Claims Database has now redacted claimant age, likely due to privacy issues. In a previous dataset from the Florida Office of Insurance Regulation spanning cases closed through the year 2004, age was provided. I opted not to use this data source for my direct analysis because the non-economic damage cap was enacted in late 2003, which means too few claims would have occurred, and proceeded through the legal system, to effectively analyze the effect of the non-economic damage cap. Using this older dataset would make me encounter the same problem that Hyman et al. (2009) encounters by having a long enough sample period after the non-economic damage cap has been imposed in Florida. As such, I had to reconstruct age demographics at the county and year level using the County and City Data Book for the more expansive dataset. The age demographic data from the County and City Data Book only provided distinct age demographic figures for each county between 2000 and 2009, so I used the compound growth rate over this period to extrapolate the age demographic figures for the year 1999. The fact that the database no longer provides the plaintiff’s age restricts my ability to make exact judgments on whether or not elderly populations are statistically impacted by non-economic damage caps.

Furthermore, as indicated by both Sieg (2000) and Hay and Spier (1997) in Section 3, above, of my paper, standard settlement models indicate that when the amount of damages that can be claimed at trial are lower, settlement is more likely. I cannot be positive that the changes in payout per claim in trial or settlement are due strictly to non-economic damage caps. Understanding this source of bias, my results will likely overestimate the effect of non-economic damage caps. This dataset does not provide me with an instrument to effectively diminish the reverse causality between settlement likelihood and claim payout in settled cases, and thus non-economic damage caps will likely account for variation in settlement probability and payout size that should be attributed to this reverse causality. There remains a distinct possibility that elderly payouts dropped simply because settlement is more likely. Another potential limitation of this data source is that it does not provide the lawyer or law firm that represents the claimant. It would be interesting to examine if different law firms were less likely to take on elderly cases as a result of the non-economic damage cap. Finally, the Florida Closed Claims database does not explicitly claim whether or not the non-economic damage law is in effect at any point of the data. This makes determining exactly what cases apply under the non-economic damage cap difficult. For simplicity, because the law went into effect September 15th, 2003, I consider all cases in 2003 to be exempt from non-economic damages, and all cases after 2004 to have the damage cap imposed.

4.3: Summary Statistics

Table 1, presented in Appendix C, presents general summary statistics for my sample. Column 1 summarizes my entire dataset from 1999 to 2009. In order to give a better perspective of the era prior to non-economic damage caps being instituted in Florida, Column 2 presents the same set of summary statistics for claims where the injury happened in the period 1999-2003 (pre-reform). Column 3, subsequently, presents summary statistics for claims where the injury happened in the period 2004-2009 (post-reform).The significance stars in Column 3 are individual t-test's for a difference of means between the sample of cases occurring before 2004 and the sample occurring after 2004. The bottom of Table 1 displays the significance level of the t-test for each respective variable.

In particular, Column 1 of Table 1 demonstrates that the average indemnity payment by an insurance company to a claimant, adjusted for inflation, in settled cases is well over $200 thousand. This gives a quantitative measure for the significance of these medical malpractice liability claims; the payout per claim is a sizeable sum of money. Furthermore, the weighted average through the sample at the county and year level illustrates that roughly 17% of the population is over 65. This is the primary sample of people I am focused on throughout this study, and the more defined age bins are employed as a means of robustness testing for the impact of non-economic damages with finer age distinctions. Additionally, it is important to note that within these summary statistics, per capita income, no paycheck ratio, and age demographics are weighted towards more frequently cited counties in the database. For example, large counties like Miami-Dade likely have a larger influence on the mean and standard deviation of the sample because there are more medical malpractice claims from these more populated areas. Considering this weighting, it is interesting that Column 2 and Column 3 show that the inflation adjusted weighted per capita income in Florida is actually lower post-reform, and the no paycheck ratio is higher. This signals that the claims made in Florida after 2003 came from areas with lower average incomes and higher no paycheck ratios. Intuitively, this may indicate that a worsening economic condition or that poor medical care in less thriving counties in Florida will have a significant effect on medical malpractice liability claims and payouts.

Interestingly, the inflation adjusted indemnity in the second sample period is significantly lower by roughly $63 thousand on average. More prudently, the difference in means t-test implies that this discrepancy is very significant, which in turn indicates that post-reform indemnity payments have certainly shrunk. This could be because the severity of injuries is statistically smaller between 2004 and 2009, but could also be partially attributable to the effect of non-economic damage caps. Conversely, Column 3 indicates that fewer cases are settled in the post-reform sample. In fact, Columns 2 and Column 3 display that only 52% of post-reform claims, compared to 59% of pre-reform claims, were settled. This opposes my initial hypothesis, and my theory section, advocating for a higher percentage of settled cases due to lower payment possibilities. This does not mean, however, that the non-economic damage caps result in more settlements. In all likelihood, more cases involving predominantly economic damages were claimed during the post-reform era. This may indicate that, although we have no direct means of testing it with this dataset, fewer cases heavily dependent upon non-economic damages even have claims made because potential claimants have lower payout potential. Another interesting comparison between Column 2 and Column 3 shows that many more cases are filed in the post-reform period. Similar to settlement theory, more stringent non-economic damage caps would expectedly lower the likelihood of filing a claim with the insurance company. Again, since potential payouts have decreased, the small cost of filing a claim becomes less attractive, which would indicate that filing a claim becomes less likely after non-economic damage caps are instituted.

More in line with expectations, almost twice as many cases are dropped in the post-reform sample, and about twice as many cases actually go to trial in the pre-reform period. Both of these differences are significant at the 1% level. Non-economic damage caps were put into effect partially to lower the number of frivolous lawsuits, so I expect that fewer cases actually make it to trial since claims of lesser merit will not progress as far in the legal system. Likewise, I expect cases that are dropped, which implies that the case never went to trial and the plaintiff didn’t get paid, to be higher after 2004 because insurance companies will more easily discard low quality claims. Unlike the pre-reform period, where potential questionable lawsuits could progress through the legal system unhindered, non-economic damage caps make it more likely for less deserving claims to be discarded with little to no payment. The final aspect of Column 2 and Column 3 to note is that while the finer age demographics of Florida are quite significantly different in the pre-reform and post-reform era, the percentage of the population over 65 has an insignificant t-value, implying that the weighted elderly density of Florida was likely static in my two sample periods. This is likely attributable to the fact that most elderly people in Florida are within the elderly1 age bracket, which also has no statistical evidence of being different in the two sample periods. elderly2 and elderly3 are smaller age cohorts, so they did not have enough influence to effectively demonstrate the elderly density was significantly changed. For reference, all summary statistic tables and regression outputs are located in Appendix C.

4.4: Demographic Statistics and Maps

Because much of the data I gathered was at the county and year level for the individual counties of Florida in years 1999-2009, the summary statistics for variables such as no paycheck, per capita income, and elderly density (labeled Over 65) simply provide a weighted average of each variable, depending on how frequently a particular county or year is seen within the dataset. In other words, the summary statistics do not provide a balanced picture of these economic or demographic variables. To give a better sense of county differences in my key variables, Figure 1, in Appendix D, color-coordinates the average percentage of elderly people within a particular county. To calculate the proportion of elderly population by county, I took the average proportion of elderly citizens over my designated time frame of 1999-2009. As expected, southern and central Florida have the highest average proportion of elderly people. These are the areas that are typically coveted as retirement locations for their warm weather. Correspondingly, the Florida panhandle, which is not typically viewed as a desirable location for elderly individuals, has relatively few elderly people as a percentage of their total population. For reference, all future figures can also be found in Appendix D.

Additionally, Figure 2 displays the average, inflation-adjusted, per capita income by county on a similar map. Notably, many of the areas with high densities of elderly people also appear to be wealthier counties. This is not shocking for two reasons. First, I assume that, similar to common sentiments, many elderly citizens who chose to move to Florida are fairly wealthy. Secondly, since these counties with higher elderly densities are typically seen as having attractive weather conditions, I also assume that wealthy individuals are likely to reside in these areas which spur more lucrative businesses to locate in these areas. As such, I would expect per capita income to be higher in these areas. Many of the low income counties in Florida, most notably in north Florida, have a low proportion of elderly individuals. There is likely no external flow of elderly people to these low-income areas because they do not provide the amenities, weather, or community that the affluent areas of central and southern Florida offer.

Finally, Figure 3 presents the average percentage of county residents that do not regularly receive a paycheck. As indicated in Appendix B, the no paycheck ratio variable attempts to measure what percentage of individuals would be ineligible for economic damages in a medical malpractice lawsuit. Since these individuals are unemployed in the civilian labor force or not even in the labor force, they assumedly are not receiving paychecks from an employer. Figure 3 highlights that, as expected, the majority of counties with a high no paycheck ratio tends to have lower per capita income. Counties with high no paycheck ratios are usually the result of a lower employment rate. In essence then, Figure 3 shows a noticeable correlation with Figure 2, which indicates that both variables appear to be indicators of economic well-being at the county level in Florida. Interestingly, most counties with high ratios of people not receiving a paycheck have a low elderly population density. Although this may seem counterintuitive, it is important to note that the no paycheck ratio essentially seeks to merge economic health with elderly density. In this case, Figure 3 simply shows that economic health is a better indicator of the percentage of people not receiving a paycheck than the proportion of elderly individuals. In addition, considering that many people over the age of 65 remain in the workplace, this no paycheck map is useful mainly for indicating that elderly people typically live in wealthier areas where a higher percentage of the population is employed in the civilian labor force.

The main takeaway from Figure 1, Figure 2, and Figure 3 is to demonstrate there is substantial demographic and economic variation between counties within Florida. Notably, the average elderly density per county spans from 8% to 33%, whereas the average per capita income per county ranges between roughly $14 thousand to $48 thousand. Clearly, within Florida alone, there is substantial variation that validates my decision to examine county level data as an alternative to actual age data. Additionally, the substantial county level variation in my key demographic and economic variables indicates that the panel data I utilize comes from a very diverse population, thus diminishing the likelihood my data does not come from a homogeneous population. This heterogeneous population in Florida allows me to effectively utilize my synthetic panel, which I will discuss further in Section 5.

My final portion of data analysis regards how well my county and year level age cohorts align with the actual age distributions seen in a fraction of the Florida Closed Claims Database. As mentioned in Section 4.1, I have a dated version of the Florida Closed Claims Database that contains roughly 8,700 claims that were disposed between the years 1999 and 2004, which conveniently fits into the time frame of my sample. Importantly, this dataset has the age of the claimant when the medical malpractice occurred. Thus, to measure whether or not my age demographic findings from the County and City Data Book closely correlate to the actual ages of claimants filing cases in Florida, I broke down the abridged Florida Closed Claims Database by the percentage of claimants over the age of 65 by county and year. I then compared each subsequent proportion[16] to the elderly density I created from the City and County Data Book between 1999 and 2004. Figure 4 displays the scatterplot of these two ratios with a 45 degree line imposed on it to demonstrate how the two would ideally correlate. Figure 4 shows that while my probability-based approximation for the age of a claimant in my dataset is not a perfect solution, the relationship is clearly positive, with a correlation coefficient of roughly .4877 and an R-squared value of roughly .237. This low R-squared value, though, indicates that my regression results will likely contain lots of noise and not be perfectly representative of the population in Florida. One reason for this discrepancy between the age cohort data and the actual age breakdown seen in the old database could be that I have limited the timeframe of my sample. Perhaps with a larger timeframe the county and year level elderly density would better correlate with actual claimant age. Additionally, the relatively low R-squared could be attributable to smaller counties having a small number of claims, and thus proportion of elderly claimants are quite volatile. I tried to account for this by excluding county and year combinations with no elderly cases or more than 50% elderly cases, but this still leaves a fair amount of possible variation. Contrarily, my age cohort data is concerned with elderly density, so it does not account for some counties only providing a few cases to the claims database in a given county and year. To account for the relative representation of each county within the dataset, I also ran a simple linear regression at the claim level of elderly density at the county level on the observed probability of an individual claim being elderly. Although this regression effectively accounts for larger counties more than smaller counties, the R-

[16] I did exclude these proportions when they equaled 0 or were greater than 50, though, because of the scarcity of samples stratified by county and year. With so few cases in some county and year combinations, I only considered combinations I felt were more representative of the true population.

squared value for this regression was only .2469.[17] This again validates my belief that my approximation for the elderly population is not perfect, and thus my regressions and takeaways will be impacted by the noise of my imperfect representation of Florida's demographics.

5: Methodology, Model, and Results

5.1: Methodology for Regressions

Following Paik et al. (2010), my model analyzes whether or not the elderly are negatively impacted by the imposition of non-economic damage caps in medical malpractice cases by estimating models of the following form using Ordinary Least Squares (OLS):

(Eq. 3) $$y_{ikt} = \beta_0 + \beta_1(x_{ikt}) + \beta_2(x_{ikt} \times \delta_{it}) + \beta_3(\delta_{it}) + \theta_i + \alpha_t + \varepsilon_{ikt}$$

where y_{ikt} represents the dependent variable at time t and in county k. β_0 is a constant term, x_{ikt} is one of my three major independent variables, δ_{it} is a dummy variable for whether or not non-economic damages are present in this year, θ_i is a vector of control variables encompassing a gender dummy variable and nine injury severity dummy

[17] This R-Squared value still excludes county and year combinations where there were no elderly claimants or where over 50% of the claimants were elderly. I keep this criterion to stay consistent with the data I use in Figure 4.

variables,[18] and α_t is a vector of time-fixed effects. As I will elaborate on later, I use clustered standard errors to account for with county variation over time periods.

In order to comprehensively analyze the effect of non-economic damage caps on the elderly, y_{ikt} will be different in subsequent regressions. In my first set of OLS regressions, y_{ikt} will be the natural log of the inflation adjusted total paid indemnity by the insurance company in settled claims. This variable is crucial to measure because it will directly predict how much more an individual from a county with many elderly people will receive in settled claims. I use the natural log of this variable due to the positive skew of the total paid indemnity data, and as mentioned in Appendix B, I inflation adjust the indemnity payments using 1999 as the base year. The next three fundamental regressions employ y_{ikt} as linear probability models referencing the likelihood that a case is settled, that a case is filed, and that a case is dropped.

Additionally, because I am interested in the partial effect of the elderly density (Over 65), no paycheck ratio, and per capita income within a particular county and year, the coefficient β_1 and the independent variable x_{ikt} refer to three possible variables in each regression on my four dependent variables, y_{ikt}.[19] The first case for x_{ikt} is the proportion of the population that is elderly in a particular county and year. The second rendition of x_{ikt} is the no paycheck ratio, and the third value that x_{ikt} takes is the natural log of inflation adjusted per capita income. Although the per capita income distribution is not too heavily skewed, I chose to use the natural log of this value in order to interpret my regression coefficients as elasticity measures when compared to natural log of

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[18] As mentioned in the data descriptions in Appendix A, injury severity has a value between 1 and 10, so I consider nine injury severity dummy variables to avoid perfect multicollinearity.

[19] The four OLS regression of y_{ikt}, as stated before, are natural log of total paid indemnity, probability of settling a claim, probability of filing a claim, and probability of dropping a claim.

indemnity payments. These models will hereafter be referred to as the "basic model(s)". Each of the four basic models for different y_{ikt} have three individual regressions for each independent variable x_{ikt}.

The term β_2 references the coefficient of the interaction of x_{ikt} with the non-economic damage cap dummy, denoted δ_{it}. As referenced in Appendix B, this dummy variable equals 1 between the years 2004 and 2009, and equals 0 before 2004. The term β_3 references the coefficient given strictly to the non-economic damage cap dummy variable. Because my model includes x_{ikt}, δ_{it}, and the interaction of these two variables, I am chiefly concerned with the coefficient of β_2 as the partial effect of the non-economic damage cap on my independent variable of interest. As mentioned above, the term θ_i references a vector of control variables, specifically controlling for gender of the claimant and the severity of the individual injury that is sustained[20]. Finally, α_t references time-fixed effects between 1999 and 2009 based on the year that the case was disposed of.

After running a series of basic models, I run a fourth regression of each y_{ikt} using all three independent variables and their respective interactions. The reasoning for running an OLS regression combining all three of these independent variables is to truly isolate the effect that elderly claimants experience due to non-economic damage caps. I will, henceforth, refer to this model as the "complex model," which takes the following form:

(Eq. 4) $$y_{ikt} = \beta_0 + \beta_m(\tau_{ikt}) + \beta_n(\tau_{ikt} \times \delta_{it}) + \beta_3(\delta_{it}) + \theta_i + \alpha_t + \varepsilon_{ikt}$$

[20] Injury severity ranges from 1-10, and I chose to make injury severity act as a state-fixed effect.

where all variables have the same meaning except for τ_{ikt}, which now is a vector of the elderly density, no paycheck ratio, and natural log of per capita income with regression coefficients equaling β_m for the variable itself and β_n for the interaction term. As in the basic model, I also use clustered standard errors in the complex model. My chief concern in this model is the coefficient β_n when τ_{ikt} refers to the elderly density. Again, this coefficient highlights the partial effect of the non-economic damage cap for the elderly density of a given county and year.

The complex model is crucial to the greater understanding the effect of non-economic damage caps on the elderly because this complex model effectively controls for attributes that I could falsely attribute to age demographics. Thus, in the complex model, the no paycheck ratio and natural log of per capita income become crucial control variables rather than key explanatory variables.

One intricacy of my data and my model is that I use a synthetic panel to make my model as representative as possible of the Florida population. The basic idea around a synthetic panel, as indicated by Dang and Lanjouw (2013), is that one can develop panel data out of a series of cross-sectional data sources.[21] Since I do not have individual claimant age in our panel data, I use a synthetic panel to mimic the demographics of residents of Florida at a county and year level. Thus, while I cannot determine whether a claimant is elderly or not, I can use the relative proportion of elderly people in a specific county, in a specific year, to estimate the effects of noneconomic damage caps on the elderly. Likewise, I can use other control variables at both a county and year level to

[21] Dang and Lanjouw (2013) comment that synthetic panels are most widely used for poverty investigations, mainly due to the difficulty of following individuals through time. Essentially, synthetic panels allow one to follow age cohorts through time rather than focusing on individuals.

make the synthetic panel representative of the Florida population on a year-over-year basis. The benefit of my synthetic panel is that it allows me to examine age bins rather than individual claimant age, which I do not have, in order to measure the effect of non-economic damage caps on said age bins. Thus, while not having an actual age variable is still a sizeable drawback, my use of a synthetic panel is an appropriate solution given the nature of my data.

Another issue worthy of addressing is the potential for my model to violate OLS assumptions. Most notably, OLS regressions typically assume that error terms are independent of each other. Because many of my variables are at a county level,[22] the errors in my regressions are likely not independent due to the correlation between values in the same county. This has the potential to be fairly substantial problem because Florida has 67 counties, and my subset of data specifically has claims filed in 65 counties. My use of a synthetic panel at the county level to approximate for the age profiles of Florida citizens prompts me to accurately account for the fact that county level data points are likely highly related. To remedy this issue, I use clustered regressions by county, which effectively remedies the problem with having data points based at the county level. Essentially, clustering my regressions utilizes heteroskedasticity-robust standard errors with the additional benefit of accounting for inter-relatedness of variables within a particular county, which diminishes sources of possible homoscedasticity within my data. My use of the synthetic panel and clustered regressions both seek to reduce the noise in my analysis due to the imperfections of my dataset.

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[22] Three crucial independent variables, proportion of the population over 65, No Paycheck ratio, and per capita income, all are gathered at the county level.

5.2: Regressions Results

Reiterating my general hypotheses of the regressions, I hypothesize that, similar to the expectations of literature like Paik et al. (2010) and Finley (2004), a higher proportion of elderly people at a county and year level will receive lower indemnity payments at settlement, be more likely to settle claims, be less likely to file claims, and be more likely to drop claims. Considering the general settlement theory discussed in Section 3, claimants should be wary of filing claims, which would lead to more cases being dropped before going to trial or contending seriously to go to trial. Similarly, I expect that county and year combinations with a higher no paycheck ratio will register the same partial effects as having a high proportion of elderly people; having no paycheck indicates that economic damages are much less likely to be a major percentage of the possible damages in a claim. With regards to per capita income at a county and year level, medical malpractice cases in wealthier areas are likely to see higher payouts due to higher economic losses awarded, and thus also see fewer settlements, more cases filed, and fewer cases dropped. This hypothesis is grounded in the fact that those areas with higher per capita income, as seen in Figure 2 and Figure 3, typically have higher employment rates as well. Thus, areas with lower per capita income and higher no paycheck ratios likely will correspond to areas that rely more heavily on the benefits of non-economic damages in medical malpractice cases.

Table 2 presents coefficients and t-statistic (in parentheticals) based on Equation 3 when the dependent variable is the size of the inflation-adjusted indemnity that insurance companies pay out in settled cases. For simplicity, I have omitted two control variables, the severity of the injury and the year the case was disposed, from the regression table.

Because I considered severity code and year disposed as state and time-fixed effects, respectively, I do not feel it is imperative to report the coefficients and standard errors for these terms.

It can be seen that, when examining the three basic models in Columns 1-3 of Table 2, only per capita income has a statistically significant effect on the size of the insurance company's indemnity payment in these settled cases. Because both terms are in natural logs, the coefficient for per capita income implies that a 1% increase in per capita income (for a given county and year where the medical malpractice occurred) results in a .391% larger indemnity. This result is not surprising, considering that these claimants with a higher per capita income likely have more economic damage claims and are less impacted by the non-economic damage caps enacted in 2003. In the more complex regression in Column 4, though, the effect of living in a wealthier county is even more pronounced and more significant, as a 1% increase in adjusted per capita income results in a predicted .691% larger indemnity. More notably, though, the no paycheck ratio and the proportion of the population over 65, as well as their interaction terms, appear to have statistically insignificant coefficients, with the exception of the elderly density in the complex model, which shows a fairly strongly significant negative coefficient at the 1% level. This coefficient implies that a 1 percentage point increase in the proportion of elderly people in a given county and year tends to drop the indemnity payment by 1.39%. The interpretation of this coefficient shows that areas with higher elderly densities tend to receive smaller payouts, and considering that the average indemnity size over 1999-2009 was over $240 thousand, a 1.39% decrease is a substantial sum of money. Interestingly, the effect of having a higher elderly density in a county and year combination is insignificant when interacted with the non-economic damage cap dummy variable. This seemingly implies that, controlling for all other variables within the complex model, a higher elderly density results in smaller indemnity payments regardless of non-economic damage caps being in place.

The findings of both Column 1 and Column 3 of Table 2 are in line with the findings of Silver et al. (2008), Hyman et al. (2009), and Paik et al. (2010) that the difference in indemnity payment is insignificant between elderly and non-elderly claimants. This could be a sign that Florida's medical malpractice law is discriminating against the elderly in a means not related to the size of the indemnity payment, such as the probability of even entering the medical malpractice legal system. The general takeaway from Table 2, though, indicates that non-economic damages do not significantly enhance the deleterious effect of elderly density on the size of the settled payout, as the interaction term is still insignificant. To show the degree of insignificance in the complex model, the F-Test testing whether or not Nonecon * Over 65, Nonecon * No Paycheck, and Nonecon * Ln Per Capita Income adj all are simultaneously equal to zero is 1.87, which implies a 14.37% chance all are equal to zero. This seemingly shows that the non-economic damage cap does not impact the size of insurance company indemnity payments. This opposes my hypothesis, but this finding may be the result of the non-economic damage cap effectively filtering worthy cases into the medical malpractice system. If this were the case, then the size of indemnity payments rightly is unaffected.

Moving on, the first linear probability model displayed in Table 3, which examines the probability of a given claim being settled, displays rather puzzling results.

Whereas per capita income was significant for the indemnity size, Column 3 highlights that per capita income, and the interaction of per capita income and non-economic damage caps being in place, in a given county and year has no statistically significant effect on the likelihood of an individual claimant settling their case out of court. Similar to Table 2, the no paycheck ratio is again insignificant in estimating the probability of settlement in both the basic and complex models in Column 2 and 4, respectively. Most puzzling, though, both the basic model looking at just elderly density in Column 1 and the complex model in Column 4 indicate that high-density elderly counties are statistically significantly less likely to settle claims.[23] Similar to the findings of Table 2, this significance indicates that the higher elderly density typically corresponds to fewer settlements. However, since the interaction between non-economic damage caps and my three independent variables of interest are statistically insignificant and provide no useful insight, it appears that settlement likelihood does not change as elderly density increases due to the imposition of the non-economic damage cap. One aspect of such a finding to consider is that, assuming elderly people typically have a lower likelihood of still working and receiving a paycheck, they likely have amassed greater wealth by working for a long period of time in the past. This may mean that incurring the legal costs of a trial and not settling a case may be more acceptable since legal costs are not cutting into actual income, but rather pre-existing wealth.

One final interesting aspect of Table 3 is the impact of gender. In all regressions the gender control coefficient is significant at the 1% level and consistently indicates that males are about 3 to 4 percentage points less likely to settle medical malpractice cases.

[23] Although, as Table 3 displays, this figure is weakly significant at the 5% level.

This indicates that males are much less likely to settle claims. This may be a function of males typically suffering worse injuries in the dataset[24] or could be more psychologically based in that men are typically believed to be more competitive, and thus may act less rationally in a settlement situation. Despite the gender peculiarity, though, the F-statistic for whether all three interaction terms in the complex model equal zero is .78, with a probability of almost 51% that all simultaneously equal zero.

Some explanations for the results in Table 3 are that counties with higher elderly density may be less likely to settle cases because elderly patients have less to lose by going avoiding a settlement. As elderly life expectancy decreases, the litigation costs of trial may not be as much of a burden, especially if the medical malpractice shortened their life expectancy even further. Another possible reason that counties with more elderly people may see fewer settlements is that these claimants are deterred from even filing a medical malpractice claim. Harkening back to Section 3, if settlement becomes more likely due to lower expected, or feasible, payouts, then we would expect fewer elderly people to even bother filing a claim with the insurance company. Rationally speaking, if elderly individuals know that the gains from potentially costly litigation are low and are aware that they do not have a solid claim under the restrictions of the non-economic damage cap, filing a claim may be an avoidable expense. Or, likewise, non-economic damage caps may promote insurance companies to pay feasible claims made by the elderly before they can ever be filed. Since non-economic damage caps should theoretically flush out some of the less deserving claims, insurance companies have

[24] Within the data, the severity code average for males is 5.99, while the severity code average for females is 5.35. A t-test of means indicates that this difference in injury severity is very significant, which may account for why men are less likely to settle.

incentive to compensate the elderly claims that are in fact brought to their attention. As such, elderly claimants could witness fewer settlements because the cases that are filed are, in all likelihood, quite disputed cases that will not be settled easily.[25] One final piece of reasoning for the noted increase in settlement likelihood is that the threat of potentially massive non-economic damage awards, whether by jury or in settlement, is what incentivizes insurance companies to take medical malpractice cases more seriously. Thus, when the potential threat of non-economic damages are reduced due to caps, insurance companies may dig their heels in more and refuse to settle. If this speculation were accurate, we could feasibly see settlements as less likely to occur due to the relaxation of risk aversion angst by insurance companies.

Examining Table 4, which is a summary of the linear probability model measuring the likelihood of filing a claim, my theorized situation appears to be very likely. Columns 1 and Column 4 indicate that the interaction between elderly proportion and the non-economic dummy is significant at the 1% level and the 5% level in the basic model and the complex model, respectively. The fact that counties with higher elderly densities appear to file fewer claims due to non-economic damages being imposed seems to support the findings of both Burstin et al. (1993) and Sager et al. (1990). The complex model in Column 4 of Table 4 happens to show the most significant results, as the F-statistic for all three interaction terms equaling zero in the complex model is 6.47, with a virtually 0% chance that all are equal to zero. In the basic model, a higher density of elderly people during the period with non-economic damages implies that a 1 percentage

[25] By "disputed" I imply that non-economic damage caps may flush out frivolous medical malpractice cases, which indicates that filing a claim is less likely to begin with. Of the claims that get filed, then, they are less likely to be settled because they are stronger cases.

point increase in elderly proportion leads to a .5 percentage point decrease in the chance of filing a claim, and this same coefficient implies a .8 percentage point decrease in the complex model. This appears to confirm the idea that non-economic damage caps made claims made in counties with a higher elderly density less likely to even file claims. This also bolsters the theory that settlement in high elderly density areas is less likely because claims are less likely to be filed, especially during the post-reform period. Additionally, the basic regression in Column 2 regarding the no paycheck ratio demonstrates that after the non-economic damage cap was imposed, the higher proportion of individuals in a given county and a given year without a paycheck will result in a lower probability, roughly .5 percentage points, of claims being filed.

The findings from Table 4 are generally consistent with my hypothesis and the relevant literature, considering that people without an income stream would have less incentive to file claims when they cannot recover as much at trial or in a settlement. Notably, Column 2 indicates that the general effect of having a higher no paycheck ratio leads to more cases being filed at a very significant .1% level, although the likelihood of filing a claim only drops by about .3 percentage points for a 1 percentage point increase in the proportion of people not getting a paycheck in county and year combination. This may be a result of areas with fewer employed individuals experiencing worse healthcare due to their lower income levels, and likely worse medical expertise in the area which would encourage individuals to file more claims. Furthermore, as hypothesized, the complex model indicates that during the non-economic damage period, a higher per capita income at the county and year level results in a higher likelihood of cases being filed. While this term is significant, a 1% increase in per capita income only results in a

.001 percentage point increase in the likelihood of filing a claim. This trend can likely be attributed to the fact that wealthier counties are more likely to have individuals with disposable income streams, so filing a claim is a fairly insubstantial cost to them. During the non-economic damage cap period specifically, though, a higher income may allow claimants to re-classify their damage claim as economic damages rather than non-economic damages, which would encourage claim filing for wealthier people.

A final important figure to recognize in Table 4 is the significance of the non-economic damage cap dummy in Column 1 and Column 2. The positive coefficient on this term means that the non-economic damage caps correlate to a higher probability of filing a claim. The magnitude of this coefficient is especially shocking, as claims are roughly 57 percentage points (Column 1) and 76 percentage points (Column 2) more likely to be filed between 2004 and 2009 than 1999-2003. My summary statistics from Table 1 showed that many more cases were filed post-reform, and thus this positive correlation is crucial to compare to the elderly density interaction coefficient discussed earlier; non-economic damage caps generally imply that filing a claim is more likely, but for areas with higher densities of elderly individuals, the probability of filing a claim actually decreases. Importantly, the complex model seems to dull the effects of non-economic damage caps on the likelihood of filing, which may indicate that including all three county and year level data series is crucial to identifying the negative, or even null, effect of non-economic damage caps on the likelihood of filing a claim.[26]

[26] Column 4 indicates that when controlling for all three county/year variables the partial, effect of the non-economic damage cap is actually negative and insignificant. Therefore the complex model seems to refute the takeaway from two basic models.

The final OLS linear probability model that I ran was on the likelihood of a claim being dropped in Table 5. As more descriptively defined in Appendix B, a claim is considered dropped when a claim did not go to trial and resulted in no indemnity payment by the insurance company. Table 5 highlights that fairly few of my important independent variables are significant in changing the likelihood of dropping a claim. In fact, the density of elderly populations appears completely insignificant in both the basic and the complex model. Somewhat expectedly, a higher no paycheck ratio showed a significant positive effect on the likelihood of dropping a case. This coefficient seems to indicate that regardless of non-economic damages, the higher proportion of those not in the civilian labor force and those unemployed peoples in the civilian labor force corresponds to more dropped claims, although a 1 percentage point increase in the no paycheck ratio corresponds to just a .2 percentage point drop in the likelihood of dropping the claim. This may be attributable to the fact that these areas are typically poorer and may not be able to withstand the costly litigation process in order to receive payment for a claim. Areas with a high density of people not receiving a paycheck could also be more likely to file, and subsequently drop, frivolous claims. I should note, however, that in the complex model the no paycheck ratio is seemingly insignificant, which shows that the true effect of not earning a paycheck on the likelihood of filing a claim is likely insignificant.

Moving forward, it appears that the per capita income coefficient is highly significant.[27] Both coefficients from Column 3 and Column 4 strongly imply that county and year combinations with a higher per capita income are substantially less likely to

[27] This coefficient is significant at the .1% level and 1% level in the basic model and complex model, respectively.

drop a claim, where a 1 percentage point increase corresponds to a probability decrease by 8 percentage points and 6 percentage points, respectively. This may be attributable to the fact that counties with richer individuals are more willing to incur the costs of litigation to settle a claim or fight in court. Also, as established in Table 2, since richer areas tend to get larger payouts in settlements, dropping a case has a higher opportunity cost for individuals in these wealthier counties. Importantly, though, the effect of per capita income on dropping a case does not depend on non-economic damage caps being in place, as displayed by the insignificant coefficient of the interaction term in Column 3 and Column 4. Furthermore, similar to the results of Table 4, the non-economic damage cap dummy has a highly significant effect in the basic models for elderly proportion and for the no paycheck ratio. In both cases, non-economic damage caps are expected to increase the likelihood of dropping a case by well over 15 percentage points. Intriguingly, though, in the complex model the sign on the non-economic damage caps coefficient is again negative and insignificant, indicating that the true effect of the non-economic damage cap is not clear. Finally, the F-test for the interaction variables in this case indicate that all three have a 14.3% chance of simultaneously equaling zero, which thrusts doubt into whether or not the proportion of elderly people, or any explanatory variables of interest for that matter, have any effect on the probability of dropping a claim.

Overall, the results of my four primary regressions do not show exceedingly convincing results that non-economic damage caps negatively impact counties with more elderly populations. In fact, only the results of the linear probability model predicting the likelihood of filing a case demonstrated that the interaction of the elderly density and the non-economic damage period had a statistically significant impact. I did identify, however, that elderly people, regardless of the economic damage cap, were statistically less likely to settle cases and typically received smaller indemnity payments in settlements. These results do not give insight into the effect of the non-economic damage cap, though. In fact, the per capita income at the county and year level actually appeared to be the most consistently significant term throughout my regression analysis. Claims filed in areas and years with a higher per capita income resulted in statistically significant larger settlements, and when interacted with the non-economic damage cap showed significantly higher probability of filing a case and lower probability of dropping a case. Furthermore, in the complex model, the non-economic damage cap term was never significant which shrouds the impact of imposing the cap on changing medical malpractice behavior.

5.3: Robustness Testing

My method of testing the robustness of my results is primarily concerned with breaking down my age variable into a handful of age demographic bins. Rather than strictly consider the proportion of a counties population in a particular year over the age of 65, I instead broke down this term into 10 age bins, with most measuring the proportion of the population within a 10-year age bin. As mentioned earlier, Appendix B contains the definition and range of each age bin. The more intense stratification of age demographic densities are useful because it allows me to see whether the expected effect of non-economic damages is corresponds to the life cycle of wages. Since both the very young and the elderly do not receive a paycheck, and hence should rely more heavily on non-economic damages, the partial effect of non-economic damage caps on these age cohorts should more extreme values than the coefficients of age cohorts within the typical wage-earning age spectrum. As such, I expect that age cohorts between the ages of roughly 25 and 65 should not see very significant changes to their payouts or access to the justice system when non-economic damage caps are instituted in 2003. The functional form of this model is as follows:

(Eq 5.) $$y_{ikt} = \beta_0 + \beta_m(\rho_{ikt}) + \beta_n(\rho_{ikt} \times \delta_{it}) + \beta_3(\delta_{it}) + \theta_i + \alpha_t + \varepsilon_{ikt}$$

where all variables have the same definition except for ρ_{ikt}, which now is a vector of nine age bins with coefficient β_m for the non-interaction term and β_n for the interaction term.[28] This is where I further utilize the synthetic panel that I discussed in Section 5, as I am following age cohorts throughout time. Each age bin spans 10 years with two exceptions; the Young variable only measures density of people younger than 5 years old and the Elderly3 variable measures the proportion of the population over 85 years old.

Table 6, shown in Appendix C, displays the four basic models for my four dependent variables while omitting the proportion of the population over 65 and instead including the nine of the age bin variables. Some crucial takeaways from this robustness test are that no terms predicting indemnity payout are significant for a single age bracket or age bracket interacted with the non-economic damage period. In terms of settlement, though, the interaction terms of non-economic damage with elderly1 and elderly2both

[28] I only include nine age bin references because the sum of all of these terms equals 1. Including all of these terms would lead to collinearity issues. I excluded the variable “young”, so all terms are assuming that a particular age bin increases by 1 percentage point and the proportion of those aged 0-5 decreases by the same amount.

indicate that county and year combinations with more people in these two age bins are more likely to settle by 10 percentage points and 8.5 percentage points, respectively. As opposed to my model discussed in Section 5, and specifically in Table 3, the values in Column 2 of Table 6 now indicate that higher proportions of people in two of the three elderly age bins show a statistically significant positive effect on the probability of settlement when the non-economic damage caps are applied. This seemingly gives strong support to my initial hypothesis that areas with higher elderly densities would experience higher likelihoods of settlement. Since counties with more elderly claimants likely have a lower feasible award at trial or in settlement, they are more likely to settle rather than incur unnecessary legal costs.

Moving on to the linear probability of filing a case, Column 3 of Table 6 highlights that the proportion of people in a county and year combination aged 65-75 has a statistically negative impact on the probability of filing a case. In line with the takeaways from Table 3, this coefficient indicates a 1 percentage point increase in the proportion of the population results in a roughly 7 percentage point decline in the likelihood of filing a claim. Interestingly, though, the general term elderly1 is positive and significant at the 5% level, implying that the non-economic damage cap lowers the probability for an age cohort that is usually more likely to file claims. The other two elderly age cohorts show no significant coefficients. Finally, in regards to the probability of dropping a claim, both elderly1 and elderly2 indicate that counties and years with more people in these age cohorts are more likely to drop claims. Shockingly, however, the interaction between the non-economic damage cap dummy and elderly1 shows a strongly negative impact on the probability of dropping a case, while the interaction between the non-economic damage cap dummy and elderly2 has a negative and insignificant coefficient. This seemingly states that the partial effect of the non-economic damage cap on the proportion of the population between 65 and 75 decreased the likelihood they dropped a claim. This goes against my hypothesis, and may signify that only serious non-economic damage caps entice only very serious claimants to even enter the legal system, so counties with higher densities of people between 65 and 75 won't file a case unless they have an intention of seeing the case be resolved.

Although most of the interaction terms between non-economic damage caps and individual age bins returned insignificant results, there is still value to comparing the sign and magnitude of the coefficients of these terms. As such, Figure 5, Figure 6, Figure 7, and Figure 8, which are found in Appendix D, visually show the coefficients of the interaction term of non-economic damage caps and each age bin for the natural log of total paid indemnity, probability of settling, probability of filing, and probability of dropping, respectively. Reiterating analysis from above, because the age bin densities sum to one I make the assumption that any changes in one age bin come at the expense of the youngest age bin.[29] Based on my discussion of settlement theory and the incentives entering of the medical malpractice liability system when non-economic damages are imposed, I expect that coefficients should be more extreme for young, non-working age bins and elderly age bins. This would signify that, although the regression results displayed insignificance, that non-economic damage caps appear to be behaving as expected.

[29] Or, more appropriately, sum to 100 because I multiplied the age bin density by 100 to more easily interpret the regression coefficients.

Figure 5 displays fairly erratic results, as the coefficient measuring the partial effect on the size of indemnity payment does not show a noticeable pattern in either the size or magnitude. In fact, within the three elderly age bins alone there is a noticeable difference in the sign of the coefficients. On the younger end of the spectrum, it does not appear that density of these age bins have coefficients more extreme than standard working age adult bins, young adult through old adult. As such, Figure 5 does not display the expected coefficient trend, which bolsters my findings that the indemnity payment is not significantly impacted by either the elderly density or specific age bin densities.

Figure 6, contrarily, displays slightly be encouraging results than those of Figure 5. While the coefficient for the adult age bin is larger than any other coefficient, the three younger age bin density coefficients, and even the three elderly age bins, appear to weakly display more extreme partial effects on the size of settlement. Although I would expect that the probability of settlement was closer to zero for typical working age bins because most of their damage payments could be classified as economic damages, the fact that all age bin coefficients are positive indicates that non-economic damage caps seem to cause all age bins to increase the odds of settlement.

The visual display of coefficients in Figure 7 shows some encouraging, as well as some puzzling, results. The three youngest age bin densities seem to generally show a substantial negative partial effect on the likelihood of filing a claim. In the middle age bins of working-age individuals, two of the three coefficients hover close to zero as I would expect. The coefficient for mid adults between 45 and 55, though, displays an extreme partial effect. Furthermore, two of the three elderly age bin densities display extreme results as expected, but the elderly2 age bin shows has a coefficient very close to zero. In general, though, Figure 7 seems to indicate that the three younger and the three elderly age bin densities seem to have a more substantial effect on the probability of filing a claim.

Similar to the visual findings in Figure 6, Figure 8 displays that with the imposition of non-economic damage caps all age bins are less likely to drop a case, although Table 6 does display that some of these coefficients are insignificant. The general trend, though, indicates that filing is universally lower once non-economic damage caps are imposed. Additionally, it appears that the three middle age bin densities, which are likely to be predominantly employed individuals, generally have the least extreme coefficients on the probability of dropping a case. These coefficient results meet my expectations, and seem to imply that, although I initially expected dropped cases to increase due to non-economic damage caps, age bin densities of typically employed individuals respond less to non-economic damage caps. Interestingly, the difference between the lowest coefficient and the largest coefficient on the probability of dropping represents roughly 6 percentage point difference in the chance of dropping a case.

The second part of my robustness test involves re-running the complex model with my age cohort proportions rather than my individual variable, Over 65, measuring the elderly density. Table 7, also located in Appendix C, displays the new regression results. Table 7 illustrates a few interesting changes from my initial basic model. Column 1 shows that the coefficient for elderly2 is now positive and significant; meaning that when adding additional control variables, a 1 percentage point increase in the proportion of people aged 75 to 85 expects to raise the total indemnity payment by a staggering 23.7%. Furthermore, unlike the results from Table 2, the no paycheck ratio now has a slightly positive and significant effect on the total indemnity paid out in settled cases. This may be a result of cases occurring before 2003, which do not apply under the non-economic damage cap, having large payouts at trial due to fewer restrictions on the damages.

Some of the most valuable results from this robustness test are found in Column 2. In this regression on the probability of settling, we see that the elderly1 and elderly2 coefficients are negative, implying these parties are less likely to settle claims. When elderly1 and elderly2 are interacted with the non-economic damage cap dummy, though, we see that these coefficients are very significantly positive, implying that the damage cap promotes counties and years with many elderly people to settle cases more despite their general propensity to be less likely to settle. This stands in fairly stark contrast to the findings in Table 3, and is much more in line with my initial hypothesis that higher proportions of elderly people would result in many more settlements, and it corresponds fairly well to the findings in Table 6. Additionally, the county and year level still retains a significantly negative impact on the likelihood of settlement. The results of Column 3 show very little, as only one age bin has a statistically significant partial effect, and the no paycheck ratio has a positive effect on the probability of filing a case, which is consistent with the results discussed in Table 4. Finally, Column 4 displays one very intriguing result; the elderly2 variable[30] is, at the 1% significance level, more likely to drop cases. When interacted with the non-economic damage dummy, however, there is no discernible effect. Thus, my robustness tests again provide little insight onto the probability of dropping a case, which leads me to believe that the decision to drop a case is likely

[30] But, coincidentally, not the elderly1 or elderly3 variable.

independent of the elderly density in a given county. To further bolster this independence theory for dropping a case, the interaction between the no paycheck ratio and non-economic damage cap shows a significant negative relationship, which again goes against my general intuition.

My final robustness test seeks to mimic the Texas Closed Claims Database model by only examining claims with an inflation adjusted indemnity payment over $25 thousand. Considering that both the basic and complex models of my initial model and my robustness age bin models have shown that the density of elderly people in a given county insignificantly effects indemnity payments, I restrict my sample similarly to the Texas studies to examine if small indemnity payment claims are skewing my results. Table 8 displays the new output for the basic and complex model regression on the natural log of total paid indemnity. Roughly 4,000 observations have been dropped, but the coefficients on both the elderly density and the elderly density interaction term remain insignificant, further bolstering the idea that cases filed in counties with higher elderly densities do not statistically impact insurance indemnity payments. And, by approximation, non-economic damage caps do not appear to negatively impact elderly claimants' payments in settled medical malpractice cases. However, the interaction term of non-economic damage caps and per capita income is now significant and negative in Column 3 and Column 4, implying that indemnity payments declined in high income areas due to the imposition of non-economic damage caps. A final interesting aspect of Table 8 is that all coefficients for being a male are statistically significant, and all columns of Table 8 seem to display that men typically have 5% to 6% higher indemnity payouts in settled cases. This strengthens the argument Finley (2004) who theorized that non-economic damage caps discriminated against women more than men.

Merging the results of my model with the findings of my robustness testing, the only major additional evidence I find of non-economic damage caps discriminating against the elderly is that the breakdown of my age data into cohorts showed a very significant positive effect on the likelihood of settlement. Overall then, I only find moderate evidence to support my hypothesis that non-economic damage caps would negatively impact the elderly's payout in settled claims and provide disincentive to enter the medical malpractice claim legal process.

5.4: Regression Limitations

I have already discussed the limitations of my data sources in Section 4.3, but my regression analysis also leads me to acknowledge some limitations to my findings. Firstly, since I do not have specific age data, the interpretation of my regressions relies heavily on the existing demographics of the individual counties in Florida. I cannot make accurate predictions for individual claimants, so my interpretations are less personal and more oriented towards age cohorts. The fact that my interpretations are focused on age cohorts rather than individuals naturally limits my study to a broader view of the effect of non-economic damage caps. Furthermore, I only acknowledged a handful of control variables throughout my regressions. Other control variables, such as the type of operation conducted where the malpractice occurred, the specialty of the physician, and many other variables that were not attainable could be important in more finely investigating how elderly populations are impacted by non-economic damage caps. And, finally, the elderly population of Florida may not be truly indicative of the elderly across the United States. Many elderly people move to Florida because they have the necessary wealth to live a comfortable life in Florida, which means that a higher percentage of elderly individuals may be well off enough that pursuing a medical malpractice liability case is not as much of a burden as in other states. Additionally, physicians in Florida are likely attuned to the fact that elderly people flock to Florida, and could be better suited to provide services to the elderly.

6: Conclusions

The purpose of this study was to investigate the impact of Florida's non-economic damage caps on the elderly population using the publicly available Florida Closed Claims Database. While various sources of scholarly writing indicate that non-economic damages lower payout per claim and commonly result in fewer claims being filed, I wanted to see how the elderly in particular were affected by this particular damage cap. Due to several data limitations, but most notably the absence of medical malpractice claimant age, I used the portion of elderly citizens in the particular county and the particular year of a claim filing as an approximation for the elderly population. This is commonly called a synthetic panel.

While I theorized that county and year combinations with higher elderly densities would see lower payouts in settled cases, higher probability of settlement, lower probability of dropping a claim, and a higher probability of dropping a case, I found only weak evidence for my beliefs. Surprisingly, my basic model, my more heavily controlled model, and my robustness tests indicated that a higher elderly density during times with non-economic damage caps had no significant effect on indemnity payments or the probability of filing a case. Furthermore, my results indicated that some portions of the elderly community, notably those between 65 and 85, were much more likely to settle after the imposition of non-economic damage caps. My robustness test model indicated that a one percentage point increase in the elderly density, between 65 and 85 years old, increased settlement likelihood between 8 percentage points and 12 percentage points. Higher elderly density during the period 2004-2009 also signified a lower likelihood, albeit a small marginal decrease, in the likelihood of filing a claim. Both my basic and complex model indicated that a one percentage point increase in the elderly proportion for a given county and year decreased the likelihood of the elderly filing a claim by between .5 percentage points and .8 percentage points. Finally, my analysis displayed that neither non-economic damages nor higher elderly proportions impacted the likelihood of a claimant to drop his or her claim. As such, I consider my study as finding mildly conclusive results, especially with regard to the probability of filing or settling a claim.

The rather inconclusive results from my study make it difficult for me to assess whether or not non-economic damage caps discriminate against the elderly. Considering the limitations of my data source, though, the fact that I still identify areas with higher elderly densities as being less likely to file claims and more likely to settle highlights that non-economic damage caps appear to have a more substantial effect on limiting the elderly's access to the legal system rather than discriminating against in the form of indemnity payments them once they enter the system. A natural extension of this theory is to investigate the quality of claims that are now entering the tort system, and to likewise look into an incentive program or piece of legislation that propels elderly claimants into the medical malpractice legal system rather than avoiding the system.

Appendix A: Relevant History of Non-Economic Damage Caps in Florida[31]

Year	Description of Reform
1986	Non-Economic Damage Caps capped at $450 thousand per plaintiff. Overturned in 1987 by the Florida Supreme Court.
1988	Limited non-economic damage caps in arbitration ($250 thousand) and cases where the plaintiff rejects arbitration ($350 thousand). Still in effect to date.
2003	Imposed non-economic damage caps against emergency-room practitioners ($150 thousand per claimant), emergency room facilities ($750 thousand per claimant), non-practitioners ($750 thousand per claimant), and practitioners ($500 thousand per claimant). In especially bad occurrences, though, the practitioner limit could be bumped up to $1 million per claimant (such as wrongful death), and emergency-room practitioner limit could be bumped to $300 thousand. This set of non-economic damage caps was repealed in 2013.

[31] I Referenced the American Tort Reform Association site on Noneconomic Damages Reform for the description of these relevant reforms.

Appendix B: Variable Descriptions

Variable Name	Description
Nonecon (Non-Economic Damage Cap)	Equals 1 when the injury date is between 2004 and 2009. Equals 0 in year injury 1999-2003 when Florida did not have non-economic damage caps. Notably, any variables with the subscript Nonecon * "variablename", is the interaction of that variable with the Non-Economic Damage Cap dummy.
County	Denotes the county that the physician (insured party) is from. 65 counties are represented in the dataset.
Total Paid Indemnity	Amount the insurance company pays to the plaintiff either by trial or by settlement.
Ln Total Paid Indemnity Adj	Natural Log of Total Paid Indemnity, adjusted for inflation with 1999 as the base year.
Year	Year in which a claim was disposed against the insured physician or medical institution. Used to control for potential time fixed effects in medical malpractice cases.
Year Injury	Year in which the actual malpractice occurred. Injuries occurring before 2003 are not applicable under non-economic damage cap. If injury occurred between 2004 and 2009 then non-economic damage cap applies.
Settle	Equals 1 if the two parties settle before a jury verdict and the

	payment to plaintiff is greater than zero. Equals 0 if the case reaches a jury verdict or there is no payment at settlement.
Drop	Equals 1 if case is dropped or case is settled with no insurance indemnity payment to the plaintiff.
Trial	Equals 1 if there are court proceedings or a summary judgment for the plaintiff. Equals 0 otherwise. Measures the number of cases that actually proceed to trial to be heard by a judge or jury.
File	Equals 1 if a claimant has filed a medical malpractice claim and there is no suit date. Equals if 0 if a lawsuit date is reported. Filing a claim is a costly step in the litigation process, and essentially measures if a plaintiff can get his/her lawyer to proceed further than simply calling the insurer to report alleged malpractice.
Male	Equals 1 if the injured party (plaintiff) is a male. Equals 0 if female. Used to control for discrepancies between male and female claimants.
Severity Code	Equals a value within the range 1 to 9, where lower values are less severe malpractice injures. For example, a severity code of 1 denotes “Emotional Only” damage. A severity code of 9 denotes “Permanent, Death”. Used to control for disparities in indemnity payouts and probability of entering the tort system based on how serious the injury is in a medical malpractice case.
Per Capita Income	Per capita income in the county and year where the insured

Adj.	operates. Per capita income is inflation adjusted with 1999 as the base year. Calculated at a county-year level.
Ln Per Capita Income Adj	Natural log of per capita income adjusted for inflation with 1999 as base year. Calculated at the county-year level. Used as an approximation for individual claimant's income.
No Paycheck	Equals the number of individuals not in the civilian labor force plus the unemployed members of the civilian labor force, divided by the total population. Calculated at the county-year level. Used as an approximation for the likelihood that a claimant does not have an income stream from an employer.
Young	Equals the percentage of a county's population, in a given year, of individuals under the age of 5, multiplied by 100.
Kid	Equals the percentage of a county's population, in a given year, of individuals between the ages of 5 and 14, multiplied by 100.
Student	Equals the percentage of a county's population, in a given year, of individuals between the ages of 15 and 24, multiplied by 100.
Young Adult	Equals the percentage of a county's population, in a given year, of individuals between the ages of 25 and 34, multiplied by 100.
Adult	Equals the percentage of a county's population, in a given year, of individuals between the ages of 35 and 44, multiplied by 100.
Mid Adult	Equals the percentage of a county's population, in a given year, of individuals between the ages of 45 and 54, multiplied by 100.

Old Adult	Equals the percentage of a county's population, in a given year, of individuals between the ages of 55 and 64, multiplied by 100.
Elderly1	Equals the percentage of a county's population, in a given year, of individuals between the ages of 65 and 74, multiplied by 100.
Elderly2	Equals the percentage of a county's population, in a given year, of individuals between the ages of 75 and 84, multiplied by 100.
Elderly3	Equals the percentage of a county's population, in a given year, of individuals over the age of 85, multiplied by 100.
Over_65	Equals the percentage of a county's population, in a given year, over the age of 65, multiplied by 100. Also referred to as "Elderly density" throughout the paper. Used as an approximation for the likelihood that a particular claimant is elderly in a given county and year.

Appendix C: Summary Statistics Regression Tables

Table 1 – Summary Statistics

Variable	(1) Mean - Total (24,883 obs.)	(2) Mean: Pre-Reform (16,530 obs.)	(3) Mean: Post-Reform (8,353 obs.)
Settle	0.567	0.590	0.522***
File	0.422	0.324	0.615***
Drop	0.226	0.174	0.329***
Trial	0.156	0.187	0.095***
Nonecon	0.336	0.000	1.000
Male	0.475	0.482	0.461***
Severity Code	5.655	5.818	5.332***
Per Capita Income adj	32349.490	32781.730	31494.120***
No Paycheck	53.232	0.531	0.535***
Over 65	17.051	17.035	17.085
Young	6.227	6.200	6.283***
Kid	12.204	12.337	11.941***
Student	12.720	12.671	12.818***
Young Adult	12.585	12.587	12.581
Adult	14.240	14.532	13.661***
Mid Adult	13.926	13.805	14.165***
Old Adult	11.046	10.834	11.467***
Elderly1	8.093	8.101	8.076
Elderly2	6.390	6.460	6.25***
Elderly3	2.569	2.473	2.758***
Total Paid Indemnity adj	$243764.6	$263055.2	$200637.5***
N (Indemnity Payments) [32]	14101	9743	4358
	*** = 1%	** = 5%	* = 10%

[32] Appendix B explained that indemnity payments are defined as payments made by insurance companies in settled cases, and that a case is settled if the plaintiff payout is greater than zero. In some cases, indemnity payments were 0 and other compensatory payments were made to the defendant, so these cases were not included in the summary statistics or regression of Total Paid Indemnity. This explains why the number of cases with indemnity payments is not the same as the number of settled cases.

Table 2 – OLS Regression on Natural Log Total Indemnity Payment

	Ln Total Paid Indemnity adj			
Variable	(1)	(2)	(3)	(4)
Over 65	-0.0000723			-0.0139**
	(-0.01)			(-2.67)
Nonecon * Over 65	-0.00263			0.00328
	(-0.49)			(0.38)
No Paycheck		-0.000421		0.0203
		(-0.04)		(1.74)
Nonecon * No Paycheck		0.000455		-0.00858
		(0.06)		(-0.86)
Ln Per Capita Income adj			0.391**	0.622***
			(3.34)	(6.08)
Nonecon * Ln Per Capita Income adj			-0.296	-0.369
			(-1.31)	(-1.52)
Nonecon	-0.0779	-0.146	2.941	4.094
	(-0.80)	(-0.38)	(1.25)	(1.60)
Male	0.0111	0.0108	0.00920	0.00843
	(0.40)	(0.37)	(0.35)	(0.31)
Constant	8.654***	8.675***	4.612***	1.421
	(42.06)	(15.22)	(3.73)	(0.93)
N	14101	14101	14101	14101
	* p<0.05	** p<0.01	*** p<0.001	
	omitted controls : Severity Code and Year			

Table 3 – OLS Linear Probability Model of Likelihood of Settlement

	Settle			
Variable	(1)	(2)	(3)	(4)
Over 65	-0.00339*			-0.00469*
	(-2.03)			(-2.04)
Nonecon * Over 65	0.00282			0.00114
	(1.48)			(0.44)
No Paycheck		-0.000548		0.00344
		(-0.38)		(1.19)
Nonecon * No Paycheck		0.00283		0.00200
		(1.68)		(0.61)
Ln Per Capita Income adj			-0.0727	-0.0135
			(-1.19)	(-0.22)
Nonecon * Ln Per Capita Income adj			0.0223	0.0242
			(0.30)	(0.26)
Nonecon	-0.0468	-0.149	-0.232	-0.376
	(-1.32)	(-1.61)	(-0.30)	(-0.36)
Male	-0.0373***	-0.0385***	-0.0378***	-0.0372***
	(-4.30)	(-4.14)	(-4.21)	(-4.30)
Constant	0.838***	0.805***	1.527*	0.821
	(22.45)	(9.10)	(2.40)	(1.12)
N	24883	24883	24883	24883

* p<0.05 ** p<0.01 *** p<0.001

omitted controls : Severity Code and Year

Table 4 – OLS Linear Probability of the Likelihood of Filing a Claim

	File			
Variable	(1)	(2)	(3)	(4)
Over 65	0.00132			0.000762
	(1.15)			(0.46)
Nonecon * Over 65	-0.00544**			-0.00830*
	(-3.34)			(-2.30)
No Paycheck		0.00395***		0.00263
		(3.59)		(1.43)
Nonecon * No Paycheck		-0.00529**		0.00291
		(-2.95)		(0.77)
Ln Per Capita Income adj			-0.0621	-0.0541
			(-1.89)	(-1.38)
Nonecon * Ln Per Capita Income adj			0.0305	0.114*
			(0.65)	(2.22)
Nonecon	0.575***	0.762***	0.167	-0.708
	(16.24)	(8.29)	(0.34)	(-1.11)
Male	0.000627	0.000324	0.00141	0.000922
	(0.08)	(0.04)	(0.17)	(0.11)
Constant	1.003***	0.820***	1.670***	1.433**
	(29.87)	(12.73)	(4.81)	(3.17)
N	24883	24883	24883	24883

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

omitted controls : Severity Code and Year

Table 5 – OLS Linear Probability Model of Likelihood of Dropping a Claim

	Drop			
Variable	(1)	(2)	(3)	(4)
Over 65	0.000155			-0.0000132
	(0.16)			(-0.01)
Nonecon * Over 65	-0.00000742			-0.000323
	(-0.00)			(-0.14)
No Paycheck		0.00293**		0.00204
		(2.81)		(0.95)
Nonecon * No Paycheck		-0.00272		-0.00137
		(-1.60)		(-0.59)
Ln Per Capita Income adj			-0.0805***	-0.0694**
			(-3.79)	(-2.69)
Nonecon * Ln Per Capita Income adj			0.0902	0.0857
			(1.92)	(1.83)
Nonecon	0.164***	0.306**	-0.772	-0.648
	(4.98)	(3.35)	(-1.60)	(-1.23)
Male	0.00268	0.00235	0.00340	0.00304
	(0.35)	(0.30)	(0.46)	(0.41)
Constant	0.166***	0.0144	1.000***	0.777*
	(6.91)	(0.25)	(4.58)	(2.42)
N	24883	24883	24883	24883

* p<0.05 ** p<0.01 *** p<0.001

omitted controls : Severity Code and Year

Table 6 – Robustness Testing Basic Model with Age Bins

Variable	**Ln Total_Paid_Indemnity_adj** (1)	**Settle** (2)	**File** (3)	**Drop** (4)
Kid	-0.0608	-0.0236	0.0338	0.0813**
	(-0.42)	(-0.58)	(1.62)	(2.97)
Student	0.0109	-0.0313	0.0306*	0.0613**
	(0.11)	(-1.09)	(2.16)	(2.87)
Young Adult	0.0260	-0.0212	0.0464*	0.0669**
	(0.20)	(-0.60)	(2.44)	(2.75)
Adult	0.0688	-0.0576	0.0252	0.0669*
	(0.72)	(-1.68)	(1.40)	(2.25)
Mid Adult	-0.0536	-0.0241	0.0338*	0.0589**
	(-0.50)	(-0.88)	(2.09)	(3.26)
Old Adult	0.0609	-0.0369	0.0246	0.0644**
	(0.57)	(-1.15)	(1.43)	(2.99)
Elderly1	-0.124	-0.0238	0.0533*	0.0608*
	(-1.01)	(-0.81)	(2.46)	(2.52)
Elderly2	0.185	-0.0576	0.0159	0.0741**
	(1.47)	(-1.51)	(0.84)	(3.17)
Elderly3	-0.183	0.0384	0.0323	0.0121
	(-0.94)	(0.93)	(1.07)	(0.41)
Nonecon * Kid	-0.0782	0.0837	-0.0608	-0.0936
	(-0.39)	(1.50)	(-1.36)	(-1.72)
Nonecon * Student	0.00860	0.0903*	-0.0319	-0.0933*
	(0.07)	(2.51)	(-1.08)	(-2.43)
Nonecon * Youngadult	0.0688	0.107*	-0.0527	-0.113*
	(0.45)	(2.51)	(-1.48)	(-2.43)

Nonecon * Adult	-0.102	0.127***	0.00672	-0.104**
	(-0.70)	(3.78)	(0.21)	(-2.83)
Nonecon * Midadult	0.200	0.0682	-0.0559*	-0.0885*
	(1.27)	(1.91)	(-2.39)	(-2.14)
Nonecon * Oldadult	-0.239	0.0887*	-0.0217	-0.0696
	(-1.62)	(2.30)	(-0.60)	(-1.78)
Nonecon * Elderly1	0.240	0.100*	-0.0697*	-0.120**
	(1.62)	(2.19)	(-2.02)	(-2.86)
Nonecon * Elderly2	-0.157	0.0850*	0.00510	-0.0657
	(-0.96)	(2.34)	(0.18)	(-1.60)
Nonecon * Elderly3	0.126	0.0792	-0.0819	-0.0973
	(0.63)	(1.31)	(-1.52)	(-1.96)
Nonecon	-0.123	-8.787*	3.969	9.024*
	(-0.01)	(-2.54)	(1.40)	(2.41)
Male	0.00801	-0.0379***	0.000442	0.00344
	(0.30)	(-4.32)	(0.06)	(0.45)
Constant	8.282	3.816	-2.109	-5.986**
	(0.84)	(1.36)	(-1.52)	(-2.89)
N	14101	24883	24883	24883
	* p<0.05	** p<0.01	*** p<0.001	

omitted controls : Severity Code and Year

Table 7 - Robustness Testing Complex Model with Age Bins

Variable	**Ln Total_Paid_Indemnity_adj** (1)	**Settle** (2)	**File** (3)	**Drop** (4)
Kid	0.172	-0.0839*	0.0290	0.0606*
	(1.14)	(-2.33)	(1.03)	(2.10)
Student	0.166	-0.0692**	0.0287	0.0505*
	(1.59)	(-2.75)	(1.50)	(2.53)
Young Adult	0.221	-0.0679*	0.0441	0.0529*
	(1.64)	(-2.23)	(1.77)	(2.31)
Adult	0.165	-0.0843**	0.0231	0.0611*
	(1.69)	(-2.68)	(1.16)	(2.32)
Mid Adult	0.130	-0.0518*	0.0386*	0.0560**
	(1.25)	(-2.60)	(2.06)	(3.18)
Old Adult	0.182	-0.0712*	0.0213	0.0545**
	(1.67)	(-2.45)	(0.99)	(2.85)
Elderly1	0.0936	-0.0831**	0.0471	0.0373
	(0.75)	(-2.77)	(1.62)	(1.47)
Elderly2	0.237*	-0.0697*	0.0155	0.0749***
	(2.20)	(-2.20)	(0.91)	(3.79)
Elderly3	0.0234	-0.0162	0.0278	-0.0114
	(0.14)	(-0.40)	(0.72)	(-0.35)
Nonecon * Kid	-0.138	0.108	-0.0537	-0.0523
	(-0.60)	(1.82)	(-0.97)	(-0.81)
Nonecon * Student	-0.0260	0.109**	-0.0258	-0.0695
	(-0.16)	(2.78)	(-0.71)	(-1.57)
Nonecon * Youngadult	0.0184	0.127**	-0.0470	-0.0823
	(0.09)	(2.76)	(-1.10)	(-1.53)

Nonecon * Adult	-0.112	0.140***	0.0120	-0.0887*
	(-0.65)	(3.87)	(0.31)	(-2.22)
Nonecon * Midadult	0.143	0.0914*	-0.0501	-0.0760
	(0.77)	(2.31)	(-1.79)	(-1.73)
Nonecon * Oldadult	-0.270	0.103**	-0.0179	-0.0484
	(-1.68)	(2.73)	(-0.43)	(-1.17)
Nonecon * Elderly1	0.193	0.124*	-0.0608	-0.0761
	(0.98)	(2.35)	(-1.40)	(-1.32)
Nonecon * Elderly2	-0.186	0.0858*	0.00239	-0.0616
	(-1.08)	(2.45)	(0.09)	(-1.67)
Nonecon * Elderly3	0.0905	0.106	-0.0718	-0.0562
	(0.43)	(1.77)	(-1.16)	(-0.92)
No Paycheck	0.0236*	0.00311	0.00383*	0.00509**
	(2.32)	(1.10)	(2.12)	(2.71)
Nonecon * No Paycheck	-0.00610	0.00565	0.00149	-0.00626*
	(-0.70)	(1.52)	(0.40)	(-2.10)
Ln Per Capita Income adj	0.692***	-0.128*	0.00637	-0.0234
	(4.82)	(-2.33)	(0.14)	(-0.82)
Nonecon * Per Capita Income adj	-0.198	0.0845	0.0272	0.0685
	(-0.65)	(1.01)	(0.38)	(0.78)
Nonecon	5.985	-11.70**	3.093	6.338
	(0.34)	(-2.71)	(0.76)	(1.28)
Male	0.00667	-0.0375***	0.000519	0.00332
	(0.25)	(-4.34)	(0.06)	(0.44)
Constant	-15.32	8.656**	-2.191	-4.952*
	(-1.35)	(3.23)	(-0.98)	(-2.37)
N	14101	24883	24883	24883

* p<0.05 ** p<0.01 *** p<0.001

omitted controls : Severity Code and Year

Table 8: OLS Regression on Natural Log Total Indemnity Payment > $25,000

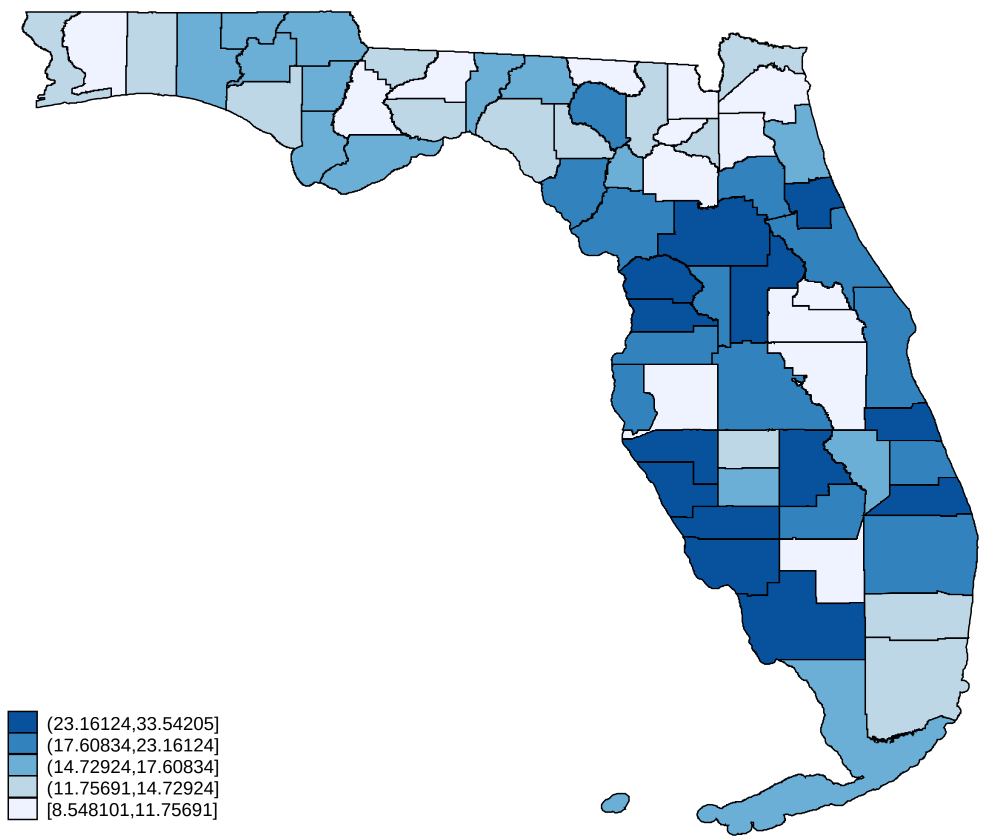
	Ln Total Paid Indemnity adj			
Variable	(1)	(2)	(3)	(4)
Over 65	-0.00289			-0.00854
	(-0.72)			(-1.91)
Nonecon * Over 65	-0.00123			-0.00456
	(-0.30)			(-0.74)
No Paycheck		-0.00307		0.00794
		(-0.51)		(1.14)
Nonecon * No Paycheck		0.00871*		0.00933
		(2.22)		(1.34)
Ln Per Capita Income adj			0.143	0.258*
			(1.54)	(2.17)
Nonecon * Ln Per Capita Income adj			-0.329***	-0.242*
			(-3.46)	(-2.14)
Nonecon	0.0338	-0.450*	3.413**	2.103
	(0.38)	(-2.22)	(3.44)	(1.59)
Male	0.0564***	0.0552**	0.0543**	0.0558***
	(3.46)	(3.30)	(3.44)	(3.50)
Constant	11.44***	11.55***	9.920***	8.472***
	(46.59)	(32.20)	(10.07)	(5.86)
N	10816	10816	10816	10816

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

omitted controls : Severity Code and Year

Appendix D: Figures

Figure 1: Average Percent Elderly Population by County (1999-2009)[33]



[33] In Figure 1, Figure 2, and Figure 3, two counties (Glades and Liberty) were initially omitted because there are no malpractice claims from either county in my sample. However, using the raw data I found the average elderly percentage, per capita income, and No Paycheck ratio for these two counties to simplify the map.

Figure 2: Average Adjusted Per Capita Income by county (1999-2009)

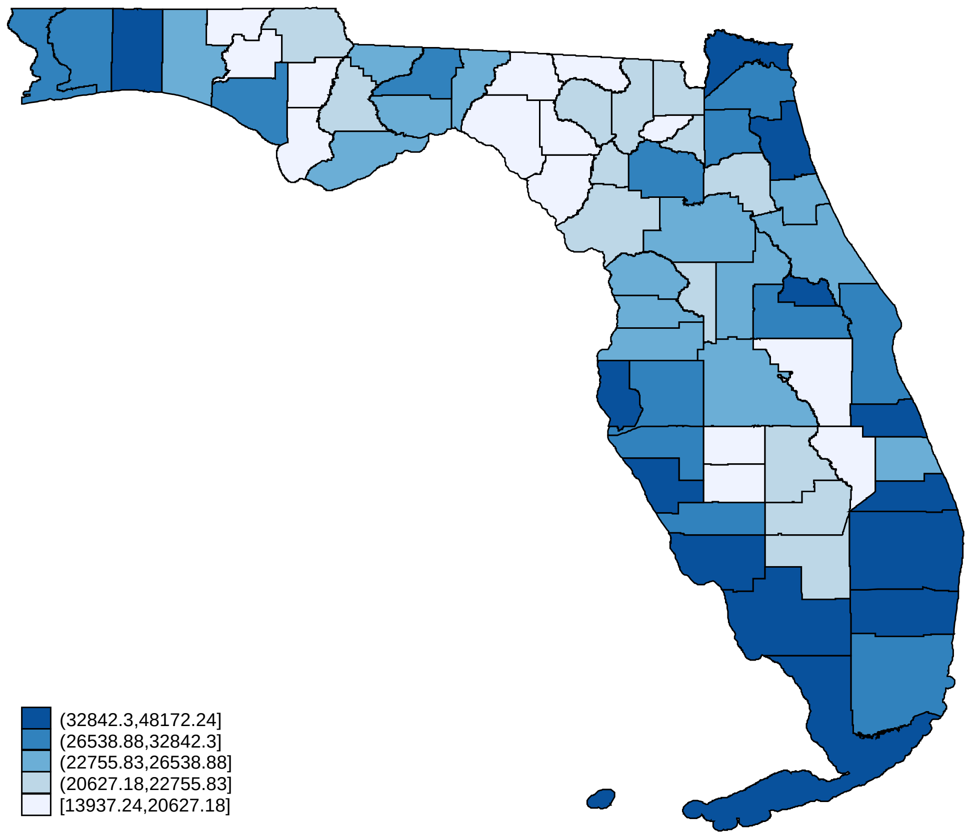


Figure 3 – Average Percent with No Paycheck by County (1999-2009)

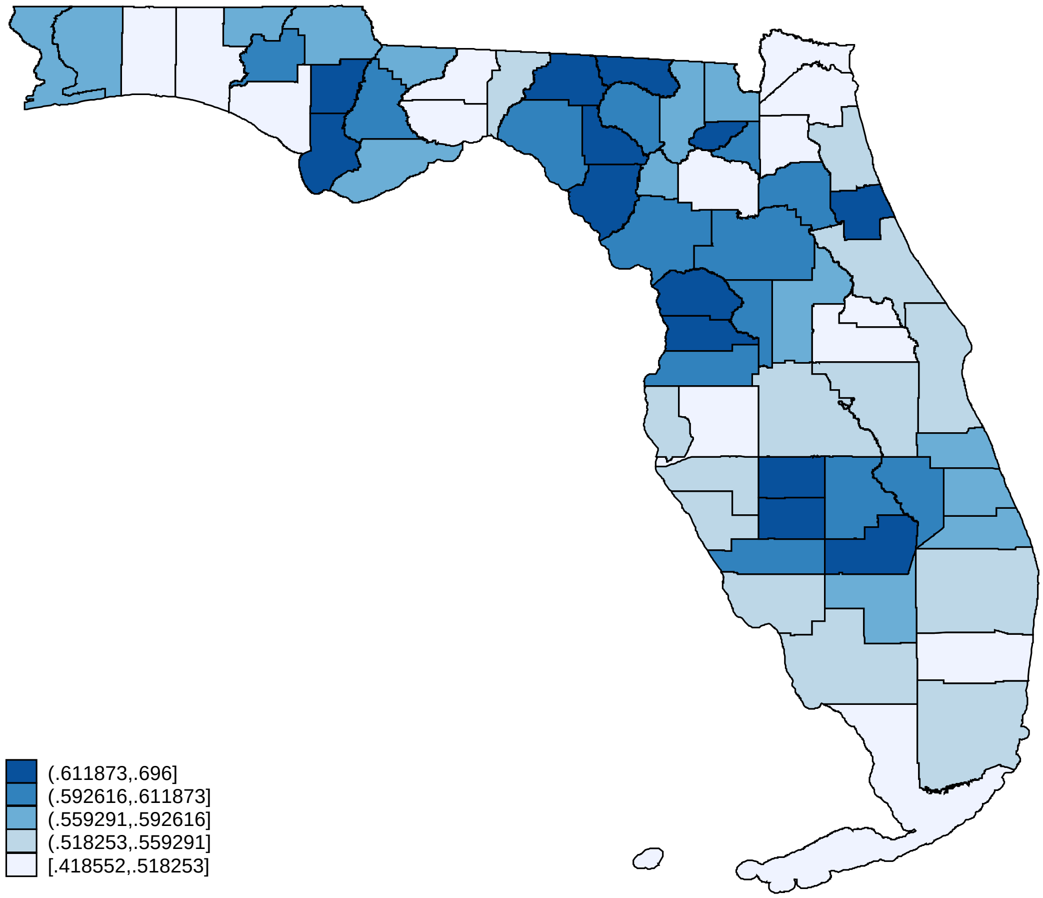


Figure 4 –Observed Elderly Claim Percentage vs. County/Year Elderly Proportion

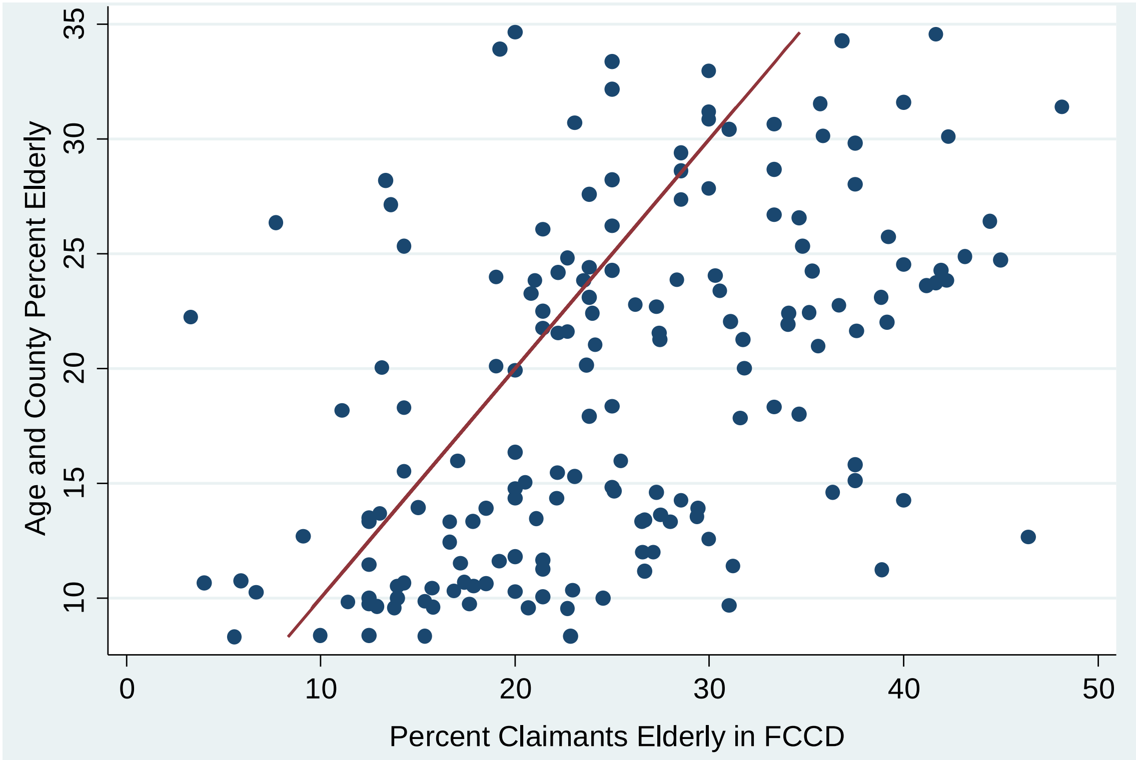


Figure 5: Age Bin Interaction Coefficients for Natural Log Indemnity Payment

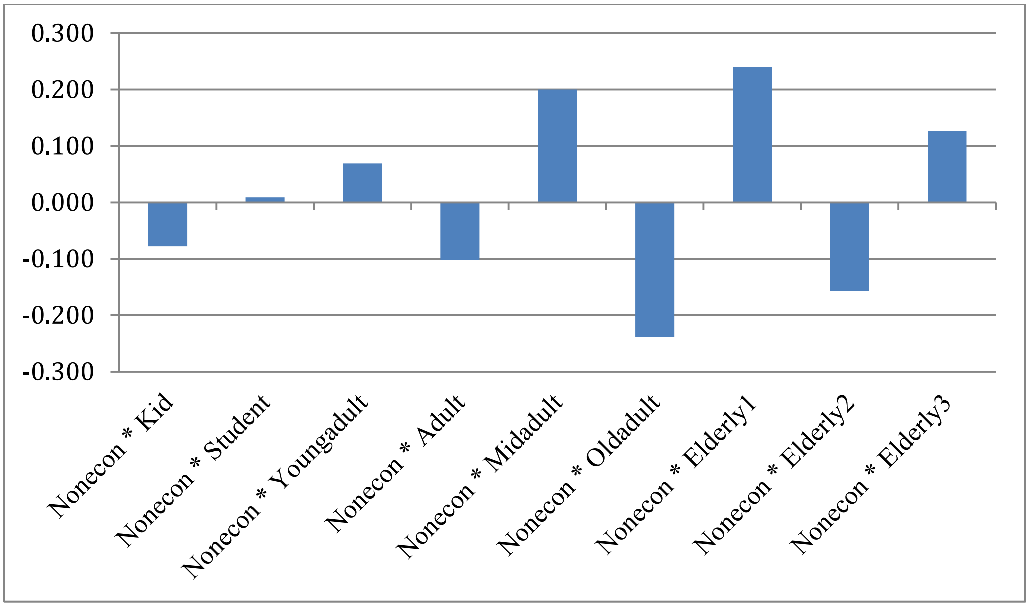


Figure 6: Age Bin Interaction Coefficients for Probability of Settlement

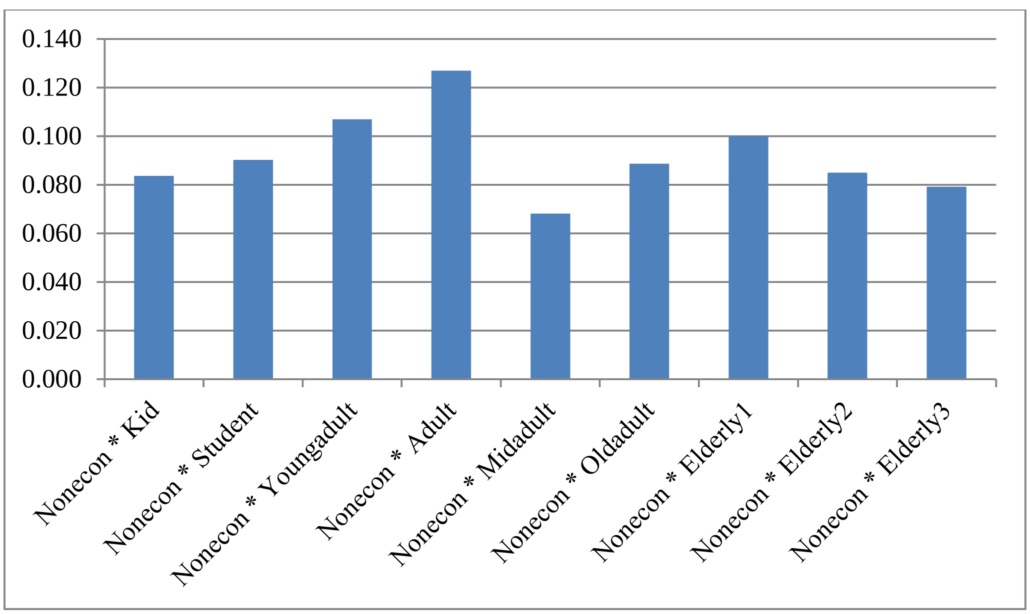


Figure 7: Age Bin Interaction Coefficients for Probability of Filing

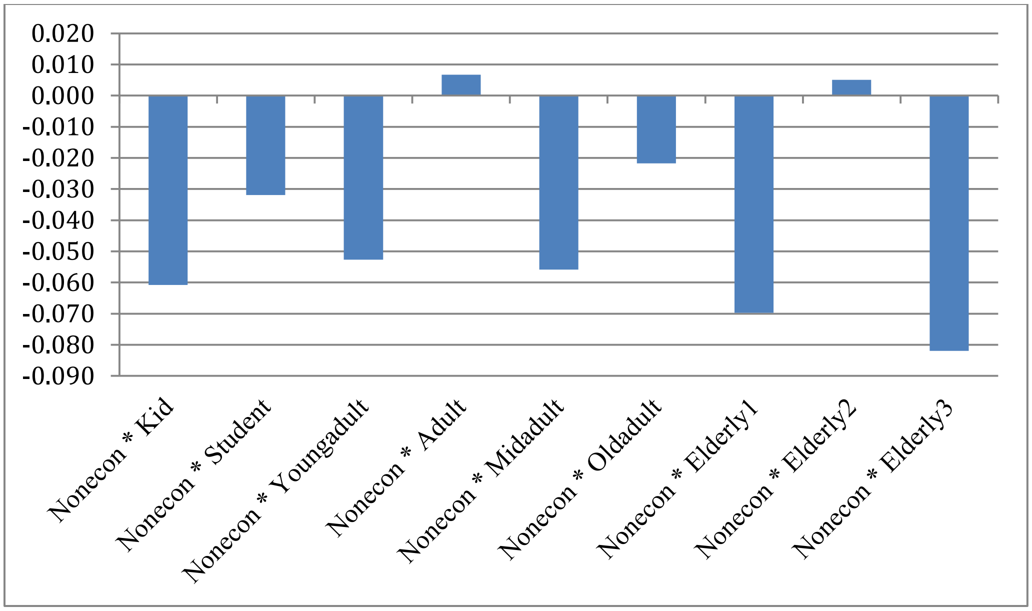
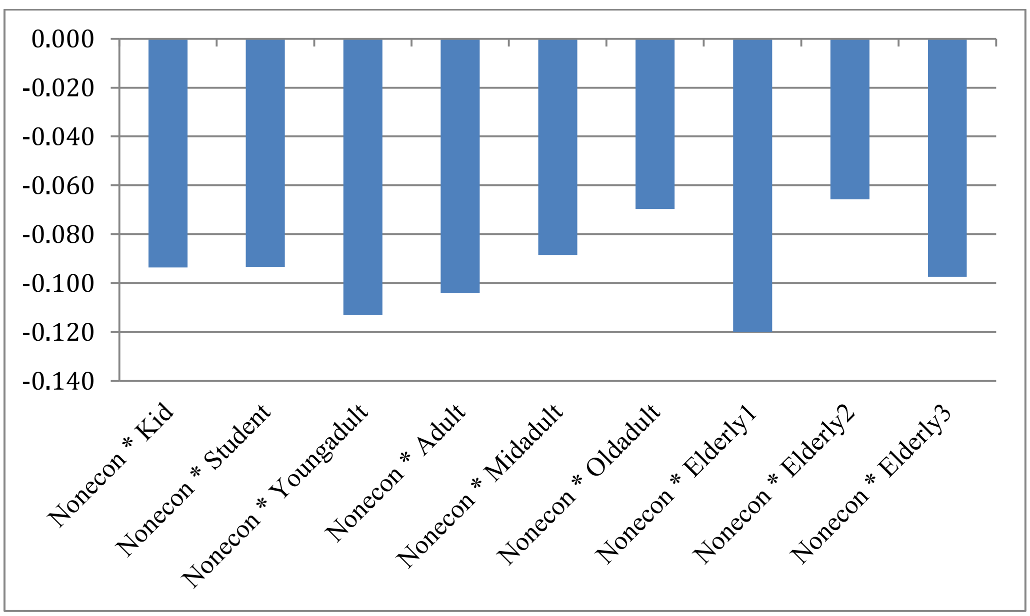


Figure 8: Age Bin Interaction Coefficients for Probability of Dropping



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