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Abstract

We show that natural disasters affect a region's aggregate human capital through at least four channels. In addition to causing out-migration, natural disasters reduce student achievement, lower high school graduation rates, and decrease post-secondary attendance. We estimate that disasters that cause at least $500 in per capita property damage reduce the net present value (NPV) of an affected county's human capital by an average of $505 per person. These negative effects on human capital are not restricted to large disasters: less severe events – disasters with property damages of $100-$500 per capita – also cause significant and persistent reductions in student achievement and post-secondary attendance.

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I Introduction

In the immediate aftermath of Hurricane Katrina, the destruction of physical capital was apparent; buildings were destroyed, bridges impassable, and factories devastated. Yet Hurricane Katrina's impact on the human capital of the region was just as catastrophic. Nearly 1 million people, close to half of the population of New Orleans, fled the city, many of whom never returned. In addition, affected students missed 5 weeks of school on average, leading to significant disruptions to learning and reductions in student test scores (Sacerdote, 2012; Pane et al., 2006). Post-secondary enrollment in Louisiana also dropped significantly, indicating that the damage that Hurricane Katrina did to the region's human capital extended beyond the impact it had on out-migration.[1] Strikingly, while more than $120 billion flowed into Louisiana and Mississippi to rebuild the region's infrastructure and housing – more than 3 times the annual budget of Louisiana alone – almost no Federal money was allocated to directly rebuild the region's human capital.[2] [3]

In this paper, we show that Hurricane Katrina was not unique. While the scale of its damages remains an outlier, we demonstrate that much smaller natural disasters have measurable negative impacts on an area's human capital. We do so by constructing a detailed dataset of all recent Presidential Disaster Declarations merged with a number of newly available datasets tracking county-level human capital indicators. We use this data to estimate the causal effect of natural disasters on four measures of human capital: net migration, average test scores, high school graduation rates, and post-secondary enrollment rates.

We begin with tax filer data from the IRS to estimate disaster-induced migration flows, building on the work of Boustan et al. (2012, 2020). We show that very large disasters reduce a region's human capital by leading to increased out-migration, but that smaller disasters do not appear to cause a meaningful migration response. This disaster-induced out-migration is not a slow-moving process; families flee immediately after storms with little evidence that they return. The richness of the data also allows us to provide some evidence on the characteristics of movers, which has implications for a county's human capital base.

This disaster-induced migration has important implications for the long-term effect of disasters on the local economy. Most notably, it suggests that even if the Federal or state government provides enough funding to fully rebuild the region's physical capital, local GDP will not fully recover. This, in turn, has implications for both the equity and efficiency of post-disaster recovery operations. That said, while increased out-migration does reduce the local stock of human capital, it has no

[1] Interestingly, while Katrina reduced test scores by approximately 18 percent of a standard deviation due to its initial disruption, it appears to have had a larger positive effect on learning for those who relocated to better schools (Sacerdote, 2012). In addition, some of the drop in post-secondary enrollment was surely due to out-migration.

[2] The estimated relief amount comes from a New Orleans Times-Picayune/NOLA.com article, linked here and accessed on August 30, 2021.

[3] Of course, it is possible that re-building physical capital helps re-build human capital; for instance, if damaged schools are reconstructed with improved air quality, climate control, or acoustics, which have been shown to improve performance Stafford (2015); Lafortune and Schonholzer (2019); Park et al. (2020). On the other hand, stimulus to help re-build physical capital may have additional negative spillovers on human capital if it reduces the incentives to stay in school or attend college, due for instance to increased low-skilled labor demand.

impact on the global stock of human capital.[4] To shed light on this, we next turn our attention to the effects that disasters have on educational achievement and attainment.

Specifically, we start by using nation-wide data on average test scores to explore the impact that disasters have on student achievement. Importantly, we show that although increased out-migration only occurs after very large disasters (i.e., disasters with more than \$500 in per capita property damage), the negative impact of disasters on students' achievement occurs for a wider range of disaster magnitudes (i.e., disasters anywhere from \$10-\$500 in per capita property damage). This suggests that the impact on average test scores is not solely driven by the increase in out-migration observed. Using the prior year's scores as a counterfactual outcome variable, we show that these results are not spurious.

We next study the effects of disasters on educational attainment, as measured by high school graduation rates and college enrollment. We find strong evidence that college enrollment decreases in the years following a natural disaster and suggestive evidence that high school graduation rates fall for individuals who were in 11^{th} grade when the disaster struck.[5] As is the case with test scores, the reduction in educational attainment occurs not only after the largest disasters but also after disaster with less than \$500 in per capita property damage. Again, this is in stark contrast to the migration effects, which only occur after the very largest disasters, suggesting that the results indeed reflect global reductions in educational attainment.

Collectively, these findings imply that disasters reduce an affected region's human capital. How do these effects compare to the damages to physical capital? To provide a sense of the relative magnitude of human vs. physical capital effects, we engage in a simple back-of-the envelope calculation that monetizes the effects we document by aggregating the implied net present value (NPV) of human capital losses in a disaster-stricken location, using a modified version of the Jorgensen-Fraumini method. While we caution against interpreting our estimates too literally, we believe that they are instructive. We find that a natural disaster that causes at least \$500 per person in assessed property damages reduces the NPV of a region's stock of human capital by approximately \$505 per person. While this does not account for the potential improvement in welfare arising from out-migrants who move to locations featuring better school- or job-match quality, it also ignores a range of other (potentially large) human capital costs. Therefore, this likely represents a conservative estimate of the impacts of such events on the affected region's human capital. On a per-student – rather than per-person – basis, the costs are even higher: students who live in a county hit by a disaster that causes at least \$100 per person in assessed property damages see reductions in the NPV of their lifetime earnings of at least \$750.

These findings are important in light of work which shows that existing social safety net programs, while effective at offsetting many of the health and labor market damages from natural disasters, do not appear to remediate potential human capital impacts. For instance, Deryugina (2017) finds that, whereas hurricanes lead to significant increases in unemployment insurance,

[4] This statement assumes that the act of migration itself has no impact on an individual's human capital.

[5] As we explain below, there is reason to believe that the effects on students in 12^{th} grade are ambiguous due to endogenous responses on the part of school administrators.

disability insurance, and medicare payments, educational assistance transfers actually appear to decline. In addition, understanding how natural disasters affect human capital is important for our understanding of the determinants of economic growth (Acemoglu et al., 2001; Rodrik et al., 2004), as well as in estimating the social cost of carbon and magnitude of the climate externality (Greenstone et al., 2013; Carleton et al., 2018). It is also of relevance from the standpoint of public finance given geographic variation in natural disasters and social insurance in the form of risk pooling across time and space, as many such insurance schemes have almost exclusively focused on physical damages when it comes to assessing damages and allocating disaster relief (Jerch et al., 2020; Wagner, Forthcoming).

Our findings contribute to multiple literatures, including the literature on the economic impacts of natural disasters, the determinants of migration, and the environmental determinants of human capital outcomes. We build on a growing body of work examining the economic consequences of natural disasters, including work that estimates effects on local economic growth (Strobl, 2011; Hsiang et al., 2013), wages and employment (Belasen and Polachek, 2008; Groen et al., 2020), health (Deryugina and Molitor, forthcoming), and fiscal transfers (Deryugina, 2017; Barrage, 2020). We also build on a growing literature that examines the environmental determinants of educational outcomes (Graff-Zivin and Neidell, 2012), by studying the effects of a wide range of natural disasters on human capital outcomes across the age spectrum, including primary and secondary achievement, high school graduation, and college enrollment. This is in contrast to existing related work that tends to focus on the effect of a single large natural disaster or on one measure of human capital (e.g. McIntosh (2008); De Silva et al. (2010); Sacerdote (2012); Deryugina et al. (2018); Ortega and Taşpınar (2018); Özek (2021)).

II Disasters, Disaster Relief, and Human Capital

II.A Disasters and Disaster Relief

While a handful of large storms like Hurricane Katrina stand out in the public mind, there have been over 3,000 federally-declared disasters since 1953; these include hurricanes, as well as fires, snow storms, tornadoes, and other severe storms. In the United States, natural disasters often receive federal relief funds and there exists a highly structured process for a disaster declaration to take place. Once the declaration has taken place, however, there is no statutory limit on the number of people that can be helped following a disaster nor is there a cap on the amount of funds that can be expended to make repairs or accomplish a replacement. Generally speaking, local governments must demonstrate that they are unable to pay for repairs themselves. Damage assessments are made at the time of the disaster, and if they exceed a nominal threshold – around \$1.50 per capita at the state-level and \$3.50 per capita at the county-level for included counties – the storm qualifies for federal relief.

Since the passage of the Stafford Act of 1988, the Federal Emergency Management Agency (FEMA) is the first and largest federal agency to respond with funding after a disaster, controlling a budget of around $14 billion annually.[6] Roughly 50% of FEMA spending is through Public Assistance (PA) grants which provide eligible state and local grantees funding to rebuild infrastructure back to the existing status quo. An additional 25% of FEMA spending provides Individual Assistance (IA) in the form of cash grants directly to homeowners and businesses; however, this amount is capped at around $30,000 per household, and is meant to serve as a supplement to regular insurance claims, or for the uninsured. Moreover, IA funding is only made available in particularly damaged areas, and much of it funds temporary relocation expenses. The remaining budget is for overhead and hazard mitigation, which helps prepare for future storms.

When catastrophic storms, like Hurricanes Katrina, Sandy, or Harvey strike, the federal government spends far greater sums on relief than is accounted for in the yearly FEMA budget. Over fiscal years 2011-2013 alone the federal government spent $136 billion through a variety of federal agencies, which made up approximately 1% of the federal budget during that time frame.[7] As an example, Hurricane Sandy, which struck the United States in late 2012, resulted in the Disaster Relief Appropriations Act and the Sandy Recovery Improvement Act. This provided an additional roughly $60 billion in funding for disaster relief agencies. Natural disasters of this scale are expected to increase in both frequency and cost in coming decades as a result of climate change and urban development in disaster-prone areas.

We mention disaster relief here for two reasons. First, while FEMA does provide some individual assistance (IA), the vast majority of the relief funding is aimed at rebuilding the physical capital of the area. FEMA spending, for example, tracks recorded damages for municipal buildings nearly 1:1.[8] Second, it emphasizes that the results found in this paper should be considered to be net-of-disaster relief spending. Considering disaster relief blunts the impacts of natural disasters by propping up labor markets, rebuilding the physical capital stock of an area, and providing some cash transfers and loans to victims, any negative consequences of disasters that we find on human capital are likely a lower bound estimate of the effects absent relief spending.

II.B Human Capital

Human capital, in the words of Goldin (2016), is “the stock of skills that the labor force possesses.” While difficult to define precisely, historically human capital was initially used to capture the important fact that as a country’s labor force increases, becomes more healthy, and more educated, the country will experience economic growth even if their physical capital does not increase (Goldin and Katz, 2020). In this paper we are using the term “human capital" in its original sense, to capture the idea that a region will potentially experience a decrease in output after a natural disaster even if the physical capital of the region is rebuilt completely, or even upgraded. We highlight this

[6] In practice, the Federal government replenishes FEMAs budget in response to catastrophic storms, so it is a misconception to think of this as a fixed budget. Other federal aid programs include subsidized loans from the Small Business Administration and community grants through the Department of Housing and Urban Development.

[7] This number comes from the Center for American Progress.

[8] This is despite the the fact that the damages are assessed at the time of the storm, and the spending is done over a multi-year window through individual grant applications. We show this empirically in our data in Figure A2.

to distinguish our use of the term "human capital" from another sense in which the term "human capital" is commonly used, that in which "human capital" is used to capture other components of individuals' subjective well-being that are not easily captured by a country's GDP.

These two definitions partly reflect the fact that there are two main approaches to measuring human capital: monetary based measures and indicator-based measures (Liu and Fraumeni, 2020). Indicator-based methods combine a range of components that are generally aimed at capturing a broad sense of the determinants of an individuals' quality of life. A notable example is the United Nation's Human Development Index (UN HDI), which is meant to serve as a "summary measure of average achievement in key dimensions of human development: a long and healthy life, being knowledgeable and hav[ing] a decent standard of living."[9]

In contrast, monetary based measures generally follow in the footsteps of Jorgenson and Pachon (1983) by combining estimated and assumed age-earnings and education-earnings functions to compute monetized estimates of country-level human capital stocks. The so-called Jorgenson-Fraumeni lifetime income approach can more easily be incorporated into comprehensive wealth accounting (e.g. Lange et al. (2018)). In addition, by monetizing the value of each component, such measures more closely reflect the definition of human capital as being related to the skills of the labor market, rather than the definition of human capital as being a more general "well-being" measure.

In this paper, we use a monetary-based measure to provide our back-of-the-envelope calculations of how disasters affect the aggregate human capital of the impacted counties. We emphasize that we do so not because we think that it is a better method or that "human capital" is only about individuals' ability to earn income. Instead, we use a monetary-based method for two reasons. First, it better reflects the empirical results in Section IV; simply put, we do not have data to estimate the effect on a number of important components that often appear in the indicator-based measures, such as measures of individuals' health status. Second, it allows us to quantify the scope of human capital losses on a similar scale as the physical capital destruction.[10]

With that in mind, we can write county C's aggregate stock of human capital in year t as:

$$H_{C,t} = \sum_{\forall i \in C_t} h_{i,t} \tag{1}$$

where $h_{i,t}$ is individual i's human capital in year t and C_t is the set of individuals in county C in year t. We discuss the specific measures of each individual's human capital measure in Section V,

[9]Quote is from the United Nations Development Programme description of their HDI found at this link, which was accessed on July 22, 2021.

[10]For example, suppose that a disaster causes damages of \$500 per person in a region's physical capital and \$250 per person in a region's human capital, as quantified by the Jorgenson-Fraumeni lifetime income approach. The government could then, in theory, give each individual a lump sum payment of \$500 to compensate individuals for the property damage and \$250 to compensate for the human capital damage and restore individuals' financial situation to what it was prior to the disaster. In this way, we can conclude that the damages to human capital were in fact half that of the damages to physical capital, highlighting that the damages are on the same scale. This hypothetical also highlights the fact that our computations are focused on economic outcomes and although the lump sum payments may restore the individuals' financial situation to what it was prior to the disaster, it would not compensate them for the stress caused by the disaster.

but note here that it can be conceptually thought of as the net present value (NPV), as of time t, of an individuals' lifetime earnings.

In Section V, we use this framework to combine the effects we estimate in Section IV into a single back-of-the-envelope calculation of the overall impact that disasters have on human capital. Here, we can use the potential outcome framework and define $H_{C,t}(D = 1)$ to be the hypothetical aggregate human capital measure in county C in year t if it was affected by a disaster in the previous year and $H_{C,t}(D = 0)$ to be the same measure if it was not affected by a disaster. The effect of a disaster is then defined as $H_{C,t}(D = 1) - H_{C,t}(D = 0)$.[11]

While straightforward, this simple formulation highlights two important conceptual points about our computations. First, a county's aggregate human capital stock may change due to a disaster both because it can cause individuals to exit and/or enter the county, thereby changing the set of individuals who are summed over, and because it can cause a change in the human capital of individuals who remain in the county. Second, while the human capital components themselves are measured in net present values and therefore implicitly incorporate some dynamic considerations, the calculation of a change in the aggregate human capital stock is itself a static calculation. Thus, our calculations would not incorporate, for example, the slow deterioration of a county's education system due to decreased fiscal revenue (Jerch et al., 2020).

III Empirical Strategy and Data

III.A Data Sources

Damage and spending data on disasters come from the Federal Emergency Management Agency (FEMA) and Spatial Hazard Events and Losses Database for the United States (SHELDUS). We compile spending on storms from FEMA itself using their detailed list of presidentially declared disasters. FEMA makes available spending data at the county- or state-level for the near universe of declared disasters since 1998, with coverage of both Public Assistance (PA) and Individual Assistance (IA) spending. We combine this spending data with Preliminary Damage Assessment (PDA) data, also available from FEMA. A PDA is a summary document of initial cost estimates of a disaster used as a critical portion of any (modern) disaster assistance request. A "PDA team" is assembled at the request of the governor in the wake of a storm and includes both federal representatives and state, tribal, and local officials. These teams go door-to-door to assess damage done to households and damage to public use space and infrastructure (here utilizing cars or planes if the damage is particularly severe). This assessment is turned over to the governor who then reviews the information found and decides whether to make a formal request for federal disaster relief. In Section A.1 we provide an example of a PDA for a typical disaster.

[11] There is a lot of subtlety in this simple expression, as it begs the question of what exactly is meant by $H_{C,t}(D = 1)$ and $H_{C,t}(D = 0)$. While Rubin's causal model is always easy to denote and difficult to interpret, in this case it is especially subtle given that there is not a single treatment/control and instead multiple disasters. The subtlety makes for fun philosophical discussions, but is not particularly important for the points we are aiming to make in this paper.

Since these documents are only available starting in 2008, have missing entries due to expedited requests, and may not survey the full extent of damages, we combine this with data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) which contains assessed physical damage by major declared disaster over the full length of the sample of all of our outcome variables interest. The advantage of SHELDUS is that they contain not only the damage to (local) government capital, but also assessments of private property. Unsurprisingly, the damage and spending data from all the sources are highly correlated. Our process for combining the data is as follows: where we have listed damage estimates from FEMA damage assessments, we use these. Otherwise, we fill in missing values for declared storms from SHELDUS. If damage estimates are missing from both sources, we impute the damages from the spending data itself.[12]

Data on in- and out-migration come from the US IRS county-to-county migration data. They are based on year-to-year address changes reported on individual income tax returns. These data are available for filing years 1991 through 2018 and include the number of returns filed – approximating households – the number of exemptions claimed – approximating individuals – and the total adjusted gross income, which gives the exact capital flows from county-to-county in migration patterns.

Data on educational outcomes come from the Stanford Education Data Archive (SEDA), Integrated Postsecondary Education Data System (IPEDS), and EDFacts. SEDA provides information on average test scores for each year from SY2008-2009 through SY2017-2018 (Reardon et al., 2021). In addition to the county-level averages, which we use as our main measure, SEDA includes county-by-ethnicity/race averages as well as average test scores for economically disadvantaged students (ECD).[13] IPEDS is run by the National Center for Education Statistics (NCES) within the U.S. Department of Education and contains, among other data, enrollment information for each post-secondary institute in the United States in each year.[14] All colleges, universities, and technical/vocational institutions that receive Title IV federal student final aid funds, such as Perkins Loans and Pell Grants, are required to report their enrollment yearly to IPEDS, which is the main measure we use. The EDFacts Initiative is a program run by the U.S. Department of Education that collects K-12 performance data from state education agencies, centralizes the data repository, and makes available the data to researchers and policymakers. Among the measures they collect is the adjusted cohort graduation rate, which corresponds to the percent of high school freshmen who graduate within four years with a regular high school diploma.[15]

For our outcomes $\Delta y_{i,t}$, we use the following four measures. To measure migration we start

[12]We run a panel regression model of damages on spending with year and disaster category fixed effects, and take the predicted damage estimates from the resulting spending. The appendix illustrates that all three measures are highly correlated. Results do not change with the damage measure used; however, we lose statistical power when only using one measure or another due to a loss in sample size.

[13]They also provide test score averages at different levels than the county, such as at the school or metro area. We opted for the county-level averages since these contain less noise than the school-level averages and are the level of the disaster data.

[14]Much of the other information data in IPEDS, such as financial information, graduation rates, and admissions information are only reported every other year, which limits its usefulness for our purposes.

[15]In fact, the SEDA data we use for average test scores is itself derived from EdFacts data. We downloaded the EDFacts graduation data from the Urban Institute's Education Data Portal.

by computing the difference between the number of individuals migrating into the county minus the number of individuals migrating out of the county and then normalize net-migration rates by dividing this number by the total number of individuals in the county and then multiplying by 100,000.[16] This gives us the net-migration rate per 100,000 individuals, which we use as our main outcome for migration.[17] For academic achievement, we use the school-grade average end-of-year test scores, normalized such that the overall average is zero and standard deviation (across students) is one for each school-grade-year.[18] We then calculate the difference in the school-by-grade average test scores between two subsequent years, which is our main measure of academic achievement. Similarly, our measure of graduation rates is computed by simply taking the difference in the adjusted cohort graduation rate between two subsequent cohorts of students in the same school and our measure of post-secondary attendance is the difference in the log full time enrollment population between two subsequent years in the same post-secondary institution.[19]

Figure 1 shows the distributions of all four outcomes. As can be seen, the distributions are all relatively symmetric around zero and appear approximately normal. However, all four distributions have fatter tails than a normal distribution with the same mean and standard deviation. Note also the jumps in the distribution of high school graduation rate changes at zero, five, and ten percentage points. This is because our data coarsens the graduation rate in high schools with too few individuals as a way to preserve anonymity. While this adds noise to the measure, it is unlikely to impact the results beyond increasing the uncertainty of the estimates.

III.B Empirical Strategy

Our empirical strategy aims to estimate the effect of natural disasters on year-to-year changes in the human capital outcomes of interest described in detail above. As such, the first step is to define the year-to-year change in our outcome of interest from year $t-1$ to year t in place i as: $\Delta y_{i,t} = y_{i,t} - y_{i,t-1}$. Similarly, let $D_{c,t}$ be the per capita property damage caused by natural disasters in county c in year t, which is equal to zero if county i is not affected by a disaster in year t. While we index by t for all outcomes, we measure the year differently depending on the outcome, most notably in the education context where school years span two calendar years. We always ensure that we define the disaster year and the outcome year in the same way, be it calendar year when the outcome is migration or school year when the outcome is test scores, high school graduation,

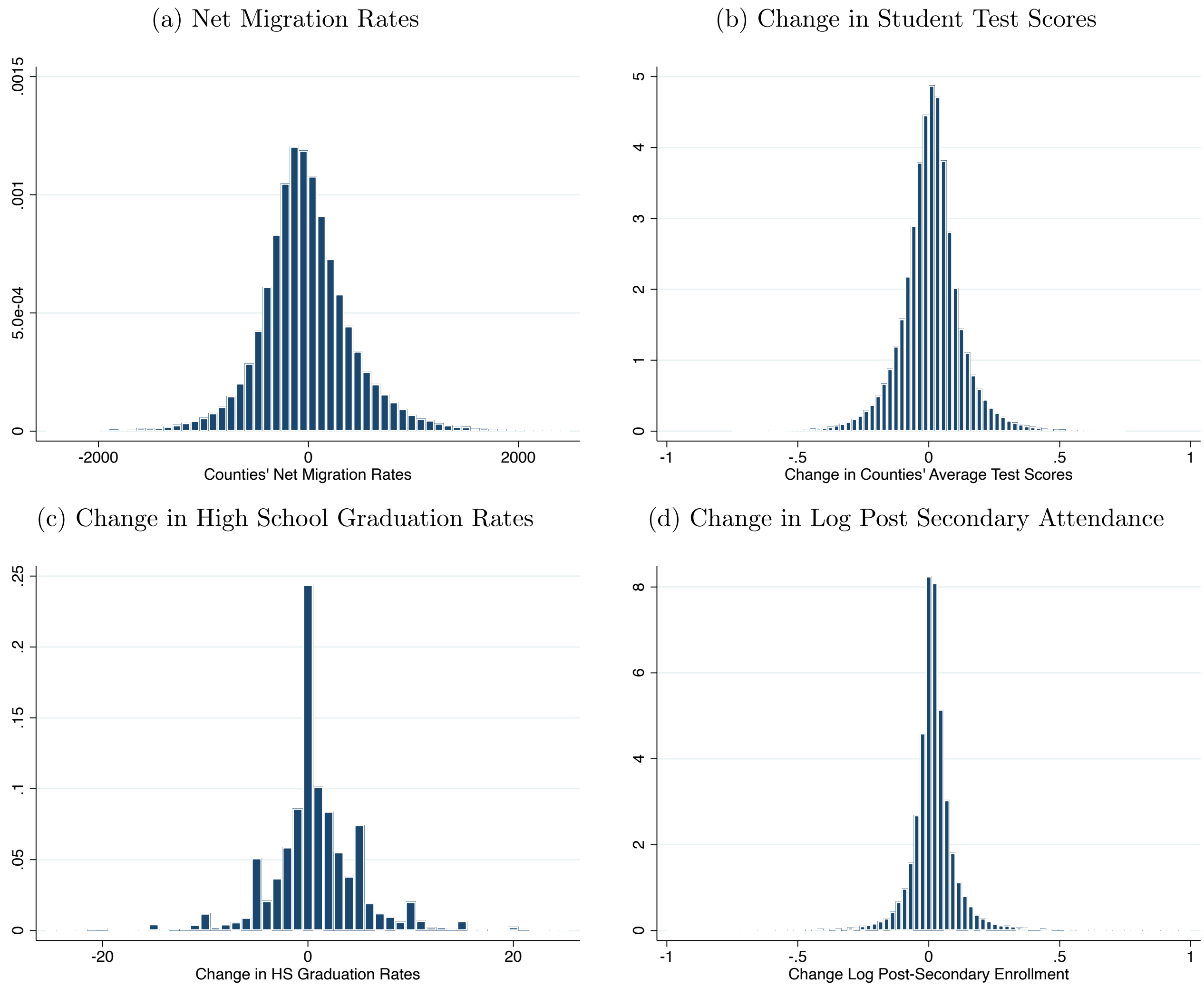
[16] To be explicit, the number of individuals we measure as moving is the number of “dependents" as reported on the IRS data.

[17] Note that since migration is itself a change in population, we do not measure the change in migration rates. The results are quite similar if we use the change in migration rate as our outcome. We also Winsorize the measure by replacing net migration rates with 10,000 if the rate is over 10,000 and -10,000 if the rate is less than -10,000. Since two of the three counties that experience large disasters have net migration rates of less than -10,000, doing so reduces our estimated effect but ensures that the results are not solely driven by these two counties.

[18] Specifically, we use the SEDA data that makes these assumptions when turning the coarse proficiency scores reported by EDFacts into continuous estimates of average test scores.

[19] Here, we Winsorize by replacing populations that increased or decreased by a factor of 4 with either 2 or -2, depending on whether it is an increase or decrease. Doing so does not change the results, but does decrease the standard errors. If a school closes, we replace the log-enrollment change with -2.

Figure 1: Outcome Distributions Across All Observations



Note: The figure shows the histograms for the four main outcomes.

or college attendance.[20] We also index the outcome by (i, t) rather than (c, t) to acknowledge that not all outcomes are at the county-level and instead at the school or school-grade level, which are nested within counties.

Given these measures, we employ two identification strategies. In the first, we focus exclusively on county-years which experience a disaster and ask whether counties that experienced larger disasters, as measured by per capita property damage, saw larger changes in the outcome than counties that experienced a smaller disaster. To do so, we run the following regression:

[20] Doing so is possible since we have the county-specific per capita property damage that occurs in each quarter of the year. In the education outcomes, we ignore disasters that occur in the summer, when schools are generally not in session. We also omit disasters that occur in the second or third quarter when estimating the effect of disasters on test scores or graduation, since it is unclear which school year the second quarter should be identified with and schools are generally not in session during the third quarter. Since the majority of large and very large disasters occur in the first quarter, our results are similar when include these quarters.

$$\Delta y_{i,t} = \alpha + \tau log\big(D_{c,t}\big) + \theta_t + \epsilon_{i,t} \quad (2)$$

where $log\big(D_{c,t}\big)$ is the log (base 10) of per-capita property damage in county c in year t and θ_t are year fixed effects. We focus only on counties with more than 1 in per capita property damage and so $log\big(D_{c,t}\big) > 0$ for every observation in the regression. We weight the regressions by a measure of the school or county population in order to ensure that small schools or counties are not overrepresented in the results or that the results are driven by a handful of small schools/counties.[21] We present the results in binned-means as a graphical illustration of the result and report the specific coefficient estimates in Table A1 in the Appendix.[22] For the migration and post-secondary results, we allow the relationship between $log\big(D_{c,t}\big)$ and $\Delta y_{i,t}$ to be a cubic function, rather than a linear one; we restrict the relationship to be linear for test scores and graduation rates due to fewer years of data being available for those outcomes. We also run placebo tests in which we use $\Delta y_{i,t-1}$ as the outcome, which ensures that there is no relationship between disaster size and the previous year-to-year changes and provides evidence that the main relationships estimated are indeed the causal effect of disasters on the human capital components.

While the figures from the regressions provide visual evidence that natural disasters do impact human capital measures, the specification in Equation 2 is lacking in two ways. First, it puts a strong functional form assumption on how the effects scale with the size of the disaster, namely that it scales with the log of per-capita property damage. This makes it difficult to disentangle, for example, whether a small coefficient means that even small disasters have a negative impact on the outcome or whether it means that disasters simply do not impact the outcome. Relatedly, the second issue is that it omits all counties in which disasters do not occur, which removes a potentially valuable source of identification.[23]

To more flexibly estimate how the effect of a disaster scales with the size of the disaster and to leverage the full panel, we first assign disasters to one of five bins. The five bins are “No Disasters” in which per capita property damage is less than \$1 per person, “Small Disasters” in which $D_{i,t} \geq \$1$ and $D_{i,t} < \$10$, “Medium Disasters” in which $D_{i,t} \geq \$10$ and $D_{i,t} < \$100$, “Large Disasters” in which $D_{i,t} \geq \$100$ and $D_{i,t} < \$500$, and “Very Large Disasters” in which $D_{i,t} \geq \$500$.[24] As we show more in Appendix B, although hurricanes and tropical storms often dominate the public perception, they make up less than one-quarter of the Very Large Disasters’ and less than 15% of the Large, Medium, and Small disasters. This means disasters of all sizes occur throughout the United States and in every year of our sample.

[21]Specifically, we weight by the county’s population in the migration results and the school’s enrollment for the education outcomes. All populations are measured by averaging over the entire sample, so that the weights are fixed over the course of the panel.

[22]For the regression results in the table, we cluster the standard errors at the county-level. The graphs are done using the *binsreg* command of Stata.

[23]For example, focusing only on counties in which disasters occurred makes it difficult to precisely account for year-on-year trend in the outcomes.

[24]Note here that we group counties that experience a disaster with per capita property damage of less than \$1 per person in with counties that did not experience a disaster to construct the control or “No Disasters” group. This is to limit the number of parameters shown and does not materially impact the effect estimates.

Using these binned outcomes, our main regression specification then estimates the following equation:

$$\Delta y_{i,t} = \alpha + \sum \tau_k D^k_{c,t} + \theta_t + \epsilon_{i,t} \tag{3}$$

where $D^k_{c,t}$ is an indicator function that designates whether county c in year t is in bin k, θ_t denotes year fixed effects, and ϵ is an error term. Note that the outcome we have is generally defined as a change, which implies that time-invariant level-differences in outcomes across counties will not impact the coefficient estimates and is what county fixed-effects account for when the outcome is in levels. Even so, we also run specifications that include county fixed-effects, which allow for some counties to consistently have larger or smaller changes in outcomes than other counties. The results are generally consistent regardless of whether we include county-fixed effects or not, which suggests that the specification is appropriate and the results robust. We cluster our standard errors at the county-level for all specifications to account for potential serial correlation in disaster realization within counties over time and weight the regressions by population in the same way as in the specification above.[25]

This specification allows us to flexibly explore the relationship between disaster size and impact.[26] As before, we also run placebo tests in which we use $\Delta y_{i,t-1}$ as the outcome, to test whether there is a relationship between disaster size and the previous year-to-year changes in the county. While we focus on the immediate effect of the disaster in the main paper, we provide evidence on the medium-term effects in Appendix C as well as showing traditional event studies as further support of our identification assumption.

IV Impact on Human Capital Components

IV.A Impact on In- and Out-Migration

We begin with an analysis of the effects on migration. In Figure 2 the blue dots show the average county net migration rates post-disaster in ten bins of disaster size and the blue line represents the fitted cubic function on the underlying data, while the red triangles and dashed line represent the equivalent measures using the pre-disaster migration rate. As can be seen, Figure 2 suggests that large disasters lead to significant out-migration rates, but that this effect only occurs after the largest disasters and is absent from disasters with less than $1,000 in per capita property damage. This is consistent with other recent work, such as McIntosh (2008); De Silva et al. (2010); Bohra-Mishra et al. (2014); Boustan et al. (2012, 2020).[27]

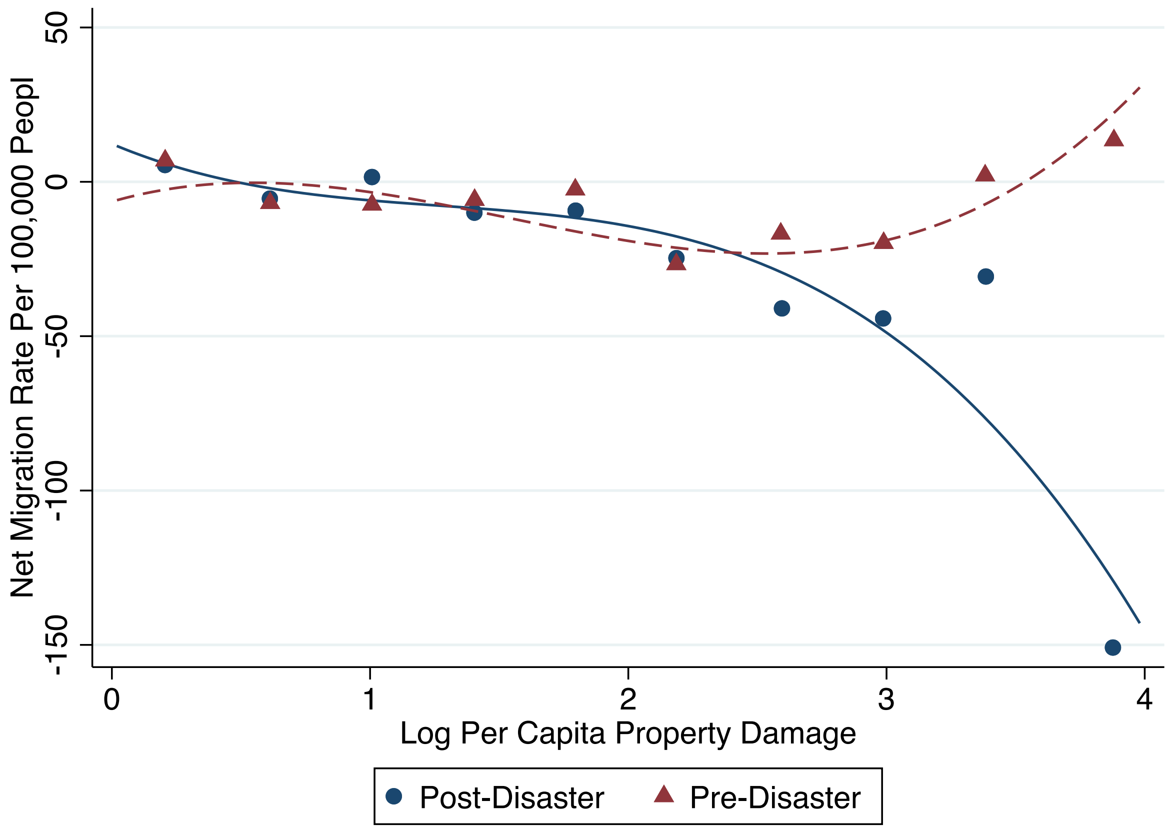
That only sizable disasters cause out-migration can also be seen in the regression coefficients

[25]Clustering at the state-level to allow for possible spatial correlation in the error term gives similar results.

[26]A specification in which property damages enter linearly, in contrast, would mean that the coefficient estimates were largely determined by the response to a small handful of larger disasters, while a specification in which property damages enter via their log-value would mean that the coefficient estimates were largely determined by the response to small disasters.

[27]Boustan et al. (2020) show that the long-term migration response occurs mainly after “severe" disasters, as measured by the fatality rate.

Figure 2: Impact of Disasters on Net Migration Rates



Note: The dots represent the average outcome in one of ten bins, spaced equally throughout the distribution. The lines represents the prediction from a cubic regression.

presented in Table 1. In this specification, which also includes counties without a disaster to serve as controls, we find that only very large disasters, those with with >\$500 in per capita property damage, cause a significant decrease in net migration rates (i.e. an outflow of individuals from the county). In fact, the estimates even suggest that small and medium disasters, those with less than \$100 in per capita property damage, if anything lead to increases in net migration rates (i.e. an inflow of individuals to the county). In many ways, this result is unsurprising and, for example, is consistent with there being a relatively large fixed-cost of moving. As we discuss below, however, this result is in stark contrast to other measures of human capital, which are impacted by disasters with less than \$500 in per capita property damage.

As we show in the Appendix, and Figure A6 specifically, these effects are also isolated in time. Specifically, those that do move because of the disaster do so in the year following the disaster. Furthermore there is no evidence that the reduction in net migration is offset by increased in-migration or decreased out-migration in subsequent years. This suggests both that those that did move were not planning on moving and, consistent with Boustan et al. (2020) and others, that

Table 1: Impact of Disasters on Net Migration Rates

	(1) Net Migration Rate	(2) Net Migration Rate	(3) Net Migration Rate (Lagged)	(4) Net Migration Rate) Lagged)
Small Disaster	17.53**	-5.705	16.74**	-5.444
	(8.171)	(5.561)	(8.499)	(5.772)
Medium Disaster	16.25**	11.21**	12.52	9.136
	(7.569)	(5.063)	(7.860)	(5.874)
Large Disaster	-8.148	-7.263	-3.566	-1.138
	(10.90)	(7.503)	(11.08)	(7.365)
Very Large Disaster	-53.22***	-37.09**	2.484	5.922
	(18.77)	(15.07)	(16.16)	(10.53)
County FE		X		X
Observations	76163	76162	76203	76202
Number of Clusters	3142	3141	3143	3142

$***p < 1\%, **p < 5\%, *p < 10\%$. Each observation is a county-year. Standard errors, in parenthesis, are clustered at the county-level. All regressions include time fixed effects. “Small Disaster" consist of counties with per capita property damage of $1-$10 per capita in a year; “Medium Disasters" have per capita property damage of $10- $100; “Large Disasters" have per capita property damage of $100-$500, and “Very Large Disasters" have more than $500 per capita property damage. County-years with less than $1 in per capita property damage, including those with no property damage, are the omitted category.

disasters lead to long-term decreases in the affected area's population.

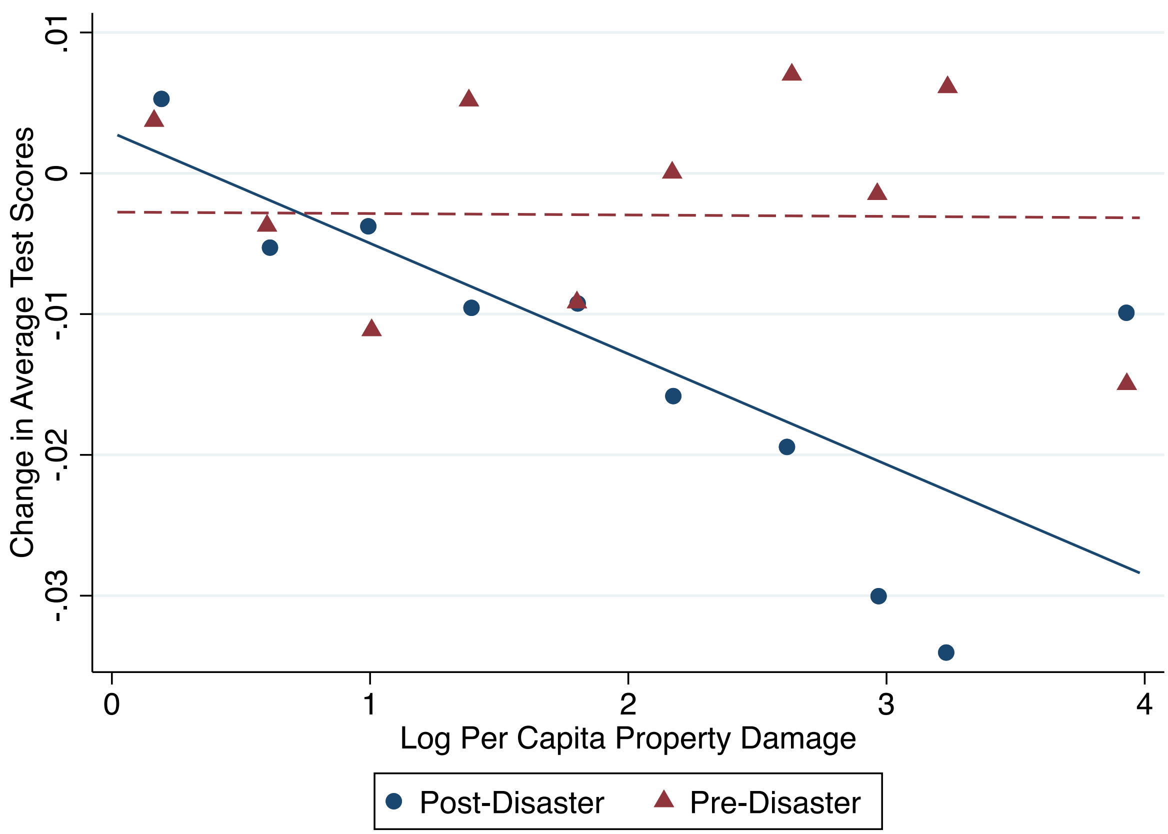
Finally, we also show in the Appendix that the decrease in net migration stems largely from an increase in out-migration, rather than from a decrease in in-migration. Interestingly, and quite relevant to this study, we also find that although disasters increase the out-migration rates, they do not change the average adjusted gross income (AGI) of the out-migrants nor do they change the average AGI of the in-migrants. In other words, those that leave a county due to the disaster are, on average, neither more nor less wealthy than those who leave in any other year. The exact results are shown in Appendix Table A3.

IV.B Impact on Student Test Scores

Figure 3 provides a stylized visual representation of the impact that disasters have on student test scores. Again, the blue dots show the average change in average test scores post-disaster in ten bins and the red triangles show the corresponding average change in the year before the disaster. As shown, it appears that average test scores in an affected county drop in the year following a natural disaster. Furthermore, unlike the year after the disaster, the red triangles and dotted line illustrate that is no significant relationship between the change in average test scores in the year before a disaster hits a given county and the disaster size. This suggests that the relationship illustrated by the blue dots and solid line represent a causal relationship between disaster size and average test scores.

Note that in contrast to the effect of a disaster on migration – where the effects only occur

Figure 3: Impact of Disasters on Average Student Test Scores



Note: The dots represent the average outcome in one of ten bins, spaced equally throughout the distribution. The lines represents the prediction from a linear regression.

after very large disasters – the magnitude of the impact appears to roughly scale with disaster size, as measured by the log of per-capita property damage.[28] This is also reflected in the coefficient estimates, presented in Table 2. These results, reflecting the estimates resulting from Equation 3, suggest that average test scores decrease by around 0.015σ in the year following a disaster with \$100-\$500 in per capita property damage, and by around 0.023σ in the year following a disaster with $>$\$500 in property damage per capita. Even medium-sized disasters, those with per capita property damage of between \$10 and \$100 in per-capita property damage, cause a decrease in test scores of around 0.006σ. These results are consistent whether or not county fixed-effects are included and, notably, the relationship between test score changes and disasters is absent in the year before a disaster strikes.

While we leave the exact dynamic impact of disasters on test scores to the Appendix, we briefly note that the results suggest that the decrease in average student test scores is persistent. Figure

[28]Since we have a shorter panel of test scores than migration rates, the line in Figure 3 shows the linear relationship between the variables rather than the cubic relationship. However, the conclusion that the effects are not isolated to the larger disasters is also apparent when the line represents a cubic function.

Table 2: Impact of Disasters on Average Test Scores

	(1) Avg. Test Scores	(2) Avg. Test Scores	(3) Avg. Test Scores (Lagged)	(4) Avg. Test Scores (Lagged)
Small Disaster	-0.00167	-0.000754	-0.00504	-0.00346
	(0.00299)	(0.00337)	(0.00315)	(0.00343)
Medium Disaster	-0.00620**	-0.00565**	0.000954	0.00119
	(0.00262)	(0.00286)	(0.00298)	(0.00342)
Large Disaster	-0.0140**	-0.0153**	0.00755	0.00501
	(0.00559)	(0.00612)	(0.00585)	(0.00683)
Very Large Disaster	-0.0219***	-0.0228***	-0.00383	-0.00400
	(0.00625)	(0.00648)	(0.00661)	(0.00781)
County FE		X		X
Observations	209450	209448	168453	168448
Number of Clusters	3074	3072	3052	3047

$***p < 1\%, **p < 5\%, *p < 10\%$. Each observation is the change in average test scores at the school-grade-year level. Standard errors, in parenthesis, are clustered at the county-level. All regressions include time fixed effects. "Small Disaster" consist of counties with per capita property damage of \$1-\$10 per capita in a year; "Medium Disasters" have per capita property damage of \$10- \$100; "Large Disasters" have per capita property damage of \$100-\$500, and "Very Large Disasters" have more than \$500 per capita property damage. County-years with less than \$1 in per capita property damage are the omitted category.

3 and Table 2 show that there is a negative change in test scores in the year of the disaster. If this was a transitory shock, as opposed to a persistent change, we would observe a positive year-to-year change in test scores in the year following the disaster – as individuals returned to their pre-disaster level – either by engaging in make-up classes or some other form of remedial investment in learning. There is no evidence that this occurs, regardless of the disaster size and, in fact, there is even some suggestive evidence that average test scores continue to decrease in the years following a large disaster, suggesting that, if anything, the coefficients in Table 2 understate the long-term impact of very large disasters on test scores.

One might be concerned by the possibility that these changes in average test scores are driven by the effects on out-migration documented in Section IV.A, particularly in light of the findings in Sacerdote (2012), who find Hurricane Katrina to have displaced a non-trivial number of students. If out-migrants include relatively high-achieving students, selection could drive some or all of the achievement effects, leading our estimates in Table 2 to overstate the effect of natural disasters on stayers' achievement. If, on the other hand, out-migrants tend to be relatively low-achieving, our estimates may understate the effect of natural disasters on the achievement of those who remain.

There are two reasons to suspect that the results in Figure 3 and Table 2 are not driven by migration. First, as we discussed above, only very large disasters cause changes in net-migration rates, while the medium, large, and very large disasters all cause reductions in average test scores.

Second, although our data do not allow us to answer this question definitively, we can provide suggestive evidence the selective migration is not biasing the estimates reported in Table 2. While we do not observe individual test scores, the data includes subgroup-specific averages. For example, our data includes average test scores separately for each racial group (in addition to gender, grade, and year), groups that vary significantly in baseline achievement. If our effects are driven by high achieving students leaving the district, it is likely that the effects would be reflected, at least in part, by the racial makeup of the schools. As consequence, we would observe larger impacts on achievement when averaging over all racial groups than when looking within racial groups. To test this, we re-estimate the year-to-year change in average test scores holding the racial makeup of a school fixed.[29] The results, shown in Appendix Table A4, are nearly identical to those in Table 2. While we cannot rule out the possibility that differential migration within the racial groups is driving the result, the fact that there is little evidence of such selection across the racial groups makes it less likely.

Finally, in Appendix Table A4 we also show that the effect of natural disasters on average test scores of economically disadvantaged (ECD) students is large, and in fact larger than the effect on all individuals in the school. This result is particularly striking, as there are likely some students who are re-classified as ECD students after the disaster. This re-classification would likely lead to increases in the average test scores of ECD students holding all individual test scores and the population constant, since non-ECD students generally have higher test scores than economically disadvantaged students. For the large negative effects on ECD students to be explained solely by differential migration, we would therefore need larger compositional changes within the ECD students than across the ECD/non-ECD groups. We find this to be unlikely.

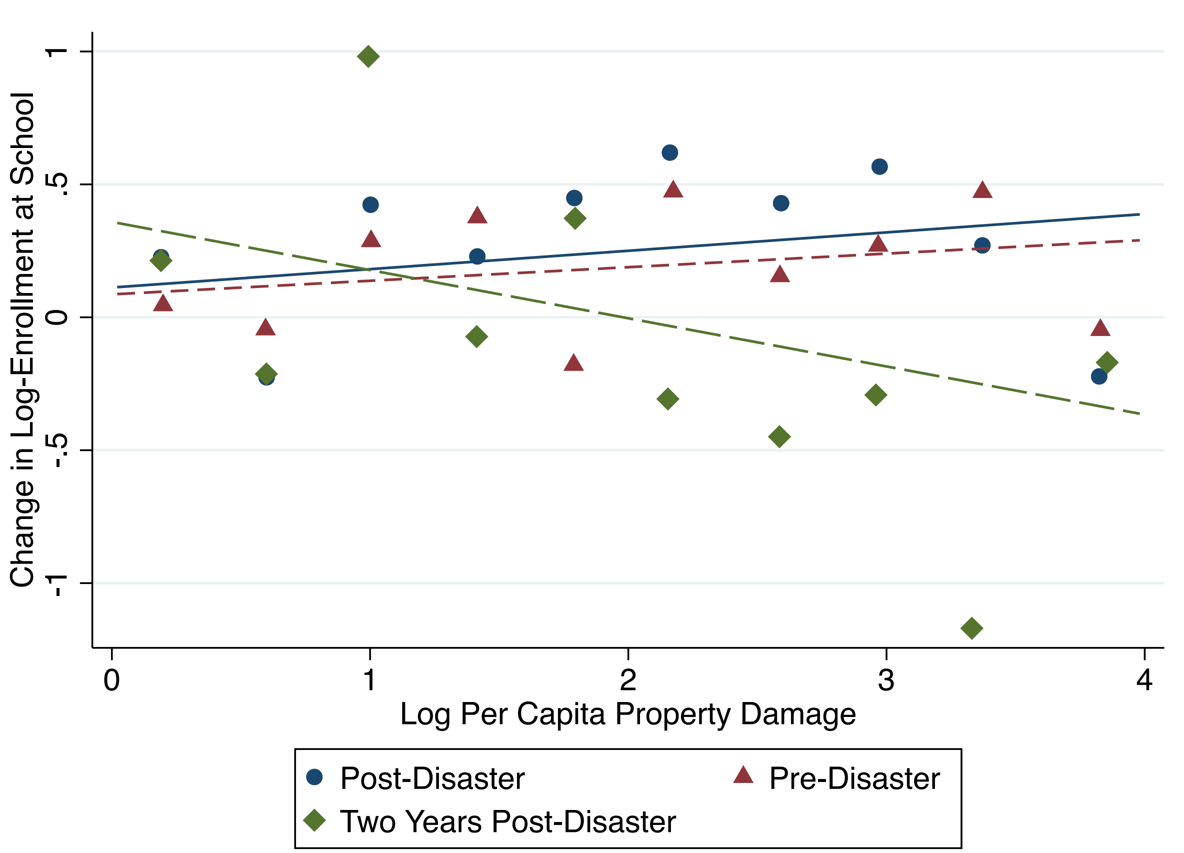
IV.C Impact on High School Graduation Rates

We next turn our attention to the effect of disasters on high school graduation rates. Note first that the direction of the expected effect of disasters on high school graduation rates is less clear than the effect on test scores. On the one hand, disasters that occur during the school year are likely to disrupt instruction and cause difficulty for students in receiving their high school diploma. Conversely, disasters may create a behavioral response from school/county administrators who, recognizing the added burden faced by the students in their districts, may lower standards for completing degrees, and in fact may graduate more students than they otherwise would.[30] For instance, Park et al. (2020) finds that teachers in New York City public schools engage in selective grade manipulation at significantly higher rates for exams taken under extreme temperature conditions, shielding some students from adverse consequences on high school graduation. Such endogenous responses to

[29] Concretely, we define the year-to-year change instead as $\Delta y_{i,t} = \sum \alpha^g_{i,t-1} \Delta y^g_{i,t}$, where $\Delta y^g_{i,t}$ denotes the year-to-year change of subgroup g in school i in year t, and $\alpha^g_{i,t-1}$ is the fraction of students in subgroup g in school i in year t-1.

[30] This phenomena was anecdotally reported during the novel SARS CoV-2 pandemic, with states giving students greater flexibility in completing their degrees. A cursory summary of these changes can be found at the following URL. To the best of our knowledge, no similar documented evidence of this phenomena exists for disasters, however, it is probable that administrators respond to disasters with the interest of affected students in mind.

Figure 4: Impact of Disasters on High School Graduation Rates



Note: The dots represent the average outcome in one of ten bins, spaced equally throughout the distribution. The lines represents the prediction from a linear regression.

disasters could actually raise graduation rates.[31]

Figure 4 illustrates evidence that is at least consistent with these different mechanisms. Notably, it shows that there is no evidence that high school graduation rates are lower in the year after a disaster than in the year before a disaster; the relationship between the year-to-year graduation rates and disaster size is nearly identical in the year following the disaster than the year preceding the disaster. However, Figure 4 also shows some evidence that larger disasters do cause high school graduation rates to decrease two years after a disaster. In other words, students who are Seniors in high school when the disaster strikes are no less likely to graduate that the previous cohort of students, but students are who were Juniors in high school when the disaster hit are less likely to graduate than the preceding two cohorts of students. Like the effect on test scores, this effect is not isolated to very large disasters and, as shown in Table 3 the only statistically significant effect occurs for disasters with \$100-\$500 per capita property damage than for disasters with >\$500.

[31] However, in Park et al. (2020), hotter temperature on exam day nevertheless has a persistent negative effect on high school graduation status, despite some fraction of students being protected by such adaptive grading.

Table 3: Impact of Disasters on High School Graduation Rates

	(1) HS Graduation Rate	(2) HS Graduation Rate	(3) HS Graduation Rate (Lagged)	(4) HS Graduation Rate (Lagged)	(5) HS Graduation Rate (Lead)	(6) HS Graduation Rate (Lead)
Small Disaster	-0.0682	-0.215	0.0218	-0.0569	0.0765	-0.0850
	(0.121)	(0.143)	(0.182)	(0.195)	(0.250)	(0.316)
Medium Disaster	0.0974	-0.0353	-0.0533	-0.288	0.158	0.0427
	(0.127)	(0.128)	(0.257)	(0.255)	(0.237)	(0.244)
Large Disaster	0.379	0.187	0.374	0.101	-0.465	-0.724**
	(0.260)	(0.275)	(0.346)	(0.373)	(0.310)	(0.335)
Very Large Disaster	0.176	0.106	-0.0615	-0.172	-0.347	-0.411
	(0.177)	(0.186)	(0.211)	(0.215)	(0.248)	(0.280)
County FE		X		X		X
Observations	140267	139028	116791	115487	116482	115132
Number of Clusters	3127	3126	3126	3123	3127	3123

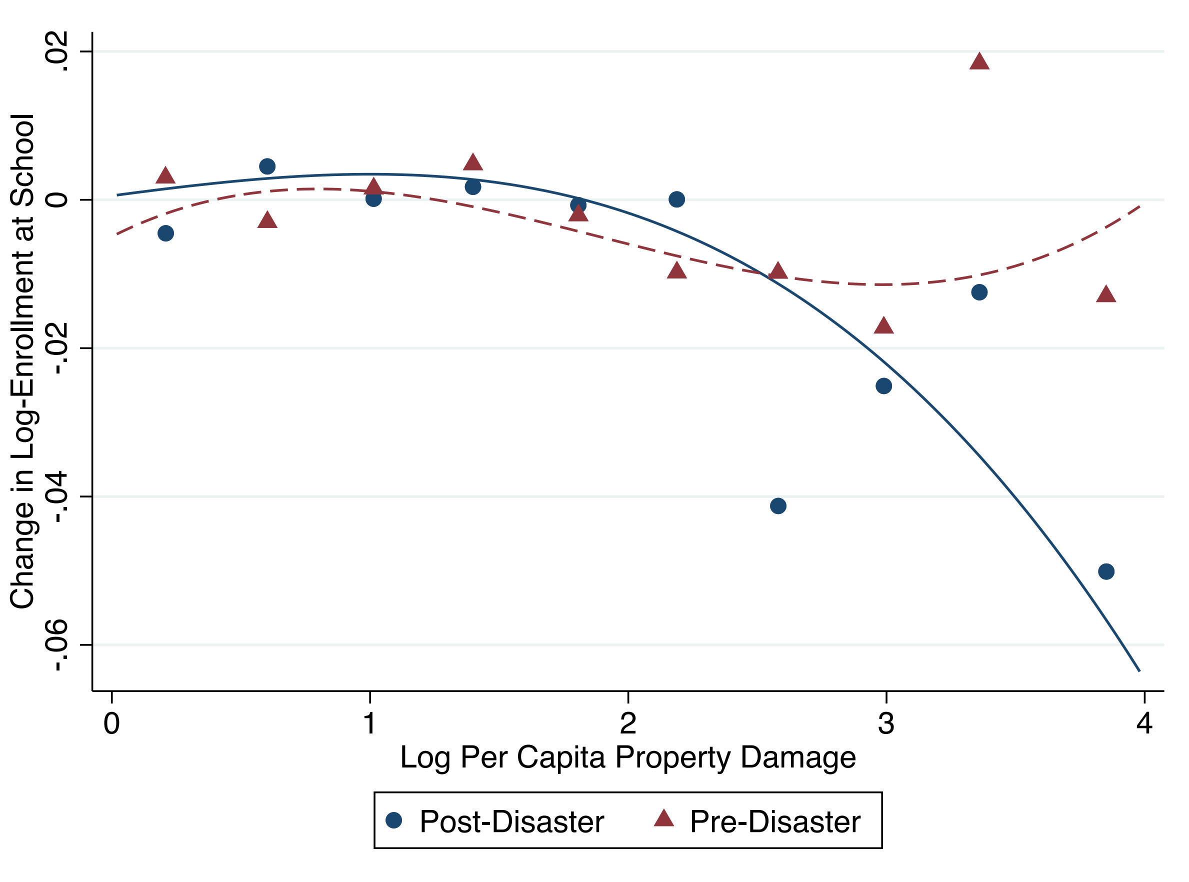
$***p < 1\%, **p < 5\%, *p < 10\%$. Each observation is the change in high school graduation rates at the school-year level. Standard errors, in parenthesis, are clustered at the county-level. All regressions include time fixed effects. "Small Disaster" consist of counties with per capita property damage of \$1-\$10 per capita in a year; "Medium Disasters" have per capita property damage of \$10- \$100; "Large Disasters" have per capita property damage of \$100-\$500, and "Very Large Disasters" have more than \$500 per capita property damage. County-years with less than \$1 in per capita property damage are the omitted category.

IV.D Impact on Post-Secondary Enrollment

We next turn to the impact of natural disasters on college attendance. Natural disasters are a major life disruption for many, which may be reflected in increased college dropout and reduced enrollment among affected student populations. On the other hand, disasters may lead to structural changes in the economy, such as increasing demand for construction workers, which could increase the incentives for individuals to obtain formal training. It is also well documented that college enrollment is countercyclical, increasing when jobs are scarce and decreasing when jobs are plentiful (Dellas and Sakellaris, 2003); depending on how the disaster impacts the local economy, this too could lead to either increased or decreased post-secondary enrollment.

As before, figure 5 illustrates the results by plotting the average change in post-secondary attendance post-disaster and pre-disaster in ten bins, along with the fitted cubic functions of the relationship between disaster size and change in post-secondary attendance. As can be seen, there does appear to be significant decreases in the post-secondary attendance after large disasters, a relationship that does not exist in the year before the disaster hit. This is also apparent in the estimates reported in Table 4, which shows that post-secondary enrollment drops by approximately 2.5% after disasters with more than \$500 in per capita property damage. Again, this result is unlikely to be caused only by individuals moving out of the county, as disasters with \$100-\$500 in per capita property damage also cause a 1.8% decrease in enrollment even though we find no evidence that disasters of that size increase migration. While the magnitudes and statistical significance differ slightly, the reduction appears to occur for all major race/ethnicity groups: White, Black, Hispanic, and Asian; see Appendix Table A5 for results of this analysis. In contrast, while disasters reduce the number of individuals enrolling in post-secondary schools full-time, there is little evidence that they reduce (or increase) the number individuals enrolling part-time. Whether this is because they

Figure 5: Impact on College Enrollment



Note: The dots represent the average outcome in one of ten bins, spaced equally throughout the distribution. The lines represents the prediction from a cubic regression.

cause individuals enrolled full-time to enroll part-time and those enrolled part-time to drop out, or whether disasters do not have a large impact on part-time students is, unfortunately, unanswerable with our data.

We again leave the dynamic effects to Appendix C. However, we note here that there is no evidence that individuals are simply delaying going to college, as enrollment does not increase in any of the three years following a disaster. This suggests that individuals who are in high schools when the disaster strikes are also less likely to enroll in post-secondary institutions after high school. If that is the case, the relatively limited negative impact on high school graduation masks a larger impact on high schoolers' human capital. As discussed below, this would lead us to underestimate the overall impact that disasters have on a regions' human capital.

Table 4: Impact on Post-Secondary Enrollment

	(1) College Enrollment	(2) College Enrollment	(3) College Enrollment (Lagged)	(4) College Enrollment (Lagged)
Small Disaster	0.00324	0.00200	0.00506*	0.00382
	(0.00293)	(0.00314)	(0.00304)	(0.00301)
Medium Disaster	-0.000173	-0.00174	0.00565	0.00384
	(0.00318)	(0.00320)	(0.00350)	(0.00368)
Large Disaster	-0.0185**	-0.0192***	-0.00866*	-0.00866*
	(0.00739)	(0.00737)	(0.00476)	(0.00500)
Very Large Disaster	-0.0262**	-0.0264**	-0.00362	-0.00318
	(0.0118)	(0.0119)	(0.00830)	(0.00812)
County FE		X		X
Observations	105606	105532	101481	101299
Number of Clusters	5584	5510	5579	5397

$***p < 1\%, **p < 5\%, *p < 10\%$. Each observation is the change in log-college enrollment at the college-year level. Standard errors, in parenthesis, are clustered at the county-level. All regressions include time fixed effects. Small Disaster consist of counties with per capita property damage of \$1-\$10 per capita in a year; "Medium Disasters" have per capita property damage of \$10- \$100; "Large Disasters" have per capita property damage of \$100-\$500, and "Very Large Disasters" have more than \$500 per capita property damage. Counties with less than \$1 in per capita property damage are the omitted category.

V Overall Impact on Human Capital

In the previous section, we provided evidence that natural disasters negatively affect a range of human capital measures: workforce size, post-secondary attendance, high school graduation, and elementary and middle school test scores. These findings imply that disasters reduce the affected regions' human capital; however, the magnitude of the various impacts are difficult to interpret in piecemeal form. To aid in this interpretation, we conduct a series of back of the envelope calculations that allow us to characterize the effect in NPV terms.

V.A Aggregation Approach

As discussed in Section II.B, our general model of human capital begins with equation 1, which aggregates $h_{i,t}$ over individuals in county C. We begin by extending this framework to better understand the channels through which disasters can impact a county's aggregate human capital. We start by making a distinction between individuals in four "life-stages": working, attending post-secondary school, attending high school, and attending elementary/middle school. We distinguish the stage individual i is in as of year t with a superscript, where $h^w_{i,t}$ reflects a worker, $h^p_{i,t}$ reflects an individual in a post-secondary school, $h^h_{i,t}$ reflects an individual in high school, and $h^{em}_{i,t}$ reflects a student in elementary/middle school.[32]

[32] Of course, already we have made some strong assumptions, such as assuming that an individual is not both working and in post-secondary school and ignoring all children not yet in elementary school.

Using this partitioning, we can re-write the change in human capital as:

$$\Delta = \sum_{\forall k \in \{w,p,h,em\}} \left[\sum_{\forall i \in C^k(1)} h_i^k(1) - \sum_{\forall i \in C^k(0)} h_i^k(0) \right] \tag{4}$$

where $C^k(l)$ denotes the set of individuals in life-stage k under $D = l$, i.e., $C^k(1)$ is the set of individuals in a state of the world where a disaster hits and $C^k(0)$ is the set of individuals when the disaster does not hit. Similarly, $h_i^k(1)$ denotes the human capital on individual i in life-stage k under $D = l$.[33]

We engage in one further partition for each of the four life-stages, by noting that the change in human capital for all four stages can be written as the human capital of the individuals who exit due to the disaster plus the change in average human capital of those who stay.[34] Denoting the set of individuals who leave as $L^k = \{i | i \in C_i^k(0) \ \& \ i \notin C_i^k(1)\}$, we can write this as:

$$\begin{aligned}
\sum_{\forall i \in C^k(1)} h_i^k(1) - \sum_{\forall i \in C^k(0)} h_i^k(0) &= -\left(\sum_{\forall i \in L^k} h_i^k(0) \right) + \left(\sum_{\forall i \in C^k(1)} h_i^k(1) - h_i^k(0) \right) \\
&= -\left(N_L^k \cdot \mathbb{E}\Big[h_i^k(0) \Big| i \in L^k \Big] \right) + \left(N_S^k \cdot \mathbb{E}\Big[\Delta h_i^k \Big| i \in C^k(1) \Big] \right)
\end{aligned}$$

where N_L^k is the number of individuals who leave due to the disaster, N_S^k is the number of individuals who stay, and $\Delta h_i^k \equiv h_i^k(1) - h_i^k(0)$ is the change in individual i's human capital due to the disaster. This captures the idea that disasters can potentially impact a county's human capital because they cause individuals to leave the county, noted by $N_L^k \cdot \mathbb{E}[h_i^k(0) | i \in L^k]$, and because they can affect the human capital of individuals who stay, noted by $N_S^k \cdot \mathbb{E}[\Delta h_i^k | i \in C^k(1)]$.

Combining this information with Equation (4), the overall effect of the disaster on county C's human capital can be written as:

$$\Delta = \sum_{\forall k \in \{w,p,h,em\}} \left[-\left(N_L^k \cdot \mathbb{E}\big[h_i^k(0) \big| i \in L^k \big] \right) + \left(N_S^k \cdot \mathbb{E}\big[\Delta h_i^k \big| i \in C^k(1) \big] \right) \right] \tag{5}$$

To make the computations more tractable, we next make two simplifying assumptions. First, while we use the IRS Migration Data to estimate the number of workers who leave the county due to the disaster (as discussed in Section IV.A), we ignore any out-migration that occurs for anyone in the post-secondary, high school, or elementary/middle school life-stage (i.e. we set $N_L^p = N_L^h = N_L^{em} = 0$). Of course, if disasters also cause non-workers to leave the county, this simplification would mean that we underestimate the overall effect of disasters on the county's human capital. Second,

[33] Note that henceforth to simplify notation we will stop indexing by t here and denote the world as 1 or 0, rather than $D = 1$ or $D = 0$.

[34] This partitioning assumes that no one enters due to the disaster or that anyone who would have left stays due to the disaster. Formally, it assumes that $\{i | i \in C_i^k(1) \ \& \ i \notin C_i^k(0)\} = \emptyset$. Relaxing that assumption would require a third term in the partition. Not also that this assumption means that $i \in C^k(1)$ implies that $i \in C^k(0)$, i.e., that $C^k(1)$ corresponds to the set of individuals that stay.

while we allow for the disaster to impact the human capital of individuals in the elementary/middle school, high school, and post-secondary life-stages, we ignore any human capital changes that occur for the worker life-stage (i.e. we set $\mathbb{E}\big[\Delta h_i^w \big| i \in C^w(1)\big] = 0$). This means that we ignore, for example, changes in a county's sectoral composition due to the disaster, as well as the impact that they would have on workers' human capital such as inducing inferior job match quality or reducing opportunities for dynamic complementarities in on the job training. We acknowledge, however, that there are plausible arguments for why the disaster could increase some individuals' human capital, and so it is not clear that this simplification necessarily leads us to an over- or under-estimate of the overall effect.

Given these two assumptions, we can write the overall effect of the disaster on county C's human capital as consisting of four terms, which correspond to the objects we estimate in our data:

$$\Delta = -N_L^w \cdot \mathbb{E}\big[h_i^w(0)\big| i \in L^w\big] + N_S^{em} \cdot \mathbb{E}\big[\Delta h_i^{em}\big| i \in C^{em}(1)\big] + N_S^h \cdot \mathbb{E}\big[\Delta h_i^h\big| i \in C^h(1)\big] + N_S^p \cdot \mathbb{E}\big[\Delta h_i^p\big| i \in C^p(1)\big] \tag{6}$$

It is worth noting that this expression highlights that we are taking a county's perspective on aggregate human capital here, rather than an individual's perspective. Notably, if an individual leaves the county, by this measure her entire human capital is "lost," regardless of what happens to the individual's own human capital. The chief rationale here is that this informs societal decisions regarding the composition and magnitude of disaster aid, as well as decisions regarding social insurance, particularly schemes that spread disaster-related consumption risk across space and time. In addition, there is the practical constraint that we would otherwise have to approximate how an individual's human capital changes when a disaster causes them to move. That said, in the results we separately present both the "local" loss of human capital, given by Equation 6, and the "global" loss of human capital, which excludes $N_L^w \cdot \mathbb{E}[h_i^w(0)|i \in L^w]$ from the calculation. In this "global" measure, we implicitly assume that an individual moving does not impact her or his human capital.

To compute Δ, we start by using the IRS Migration Data to find that the average gross income (AGI) per person who moved counties in 2018 is approximately \$36,000.[35] We therefore use this yearly income as the benchmark to compute the net present value of lost future income, since that is the benchmark used to measure human capital. We simplify by assuming that each worker is 40 years old, which corresponds to the median age of workers in the United States, and stays in the labor market until 65, at which point they retire.[36] If those who migrate skew younger than the average age we would underestimate $\mathbb{E}\big[h_i^w(0)\big| i \in L^w\big]$ and vice versa. Discounting each future period by a rate of β, and ignoring individuals' wage growth, we obtain the following expression:

$$\mathbb{E}\big[h_i^w(0)\big| i \in L^w\big] = \sum_{l=1}^{25} \beta^l X = \frac{1-\beta^{25}}{1-\beta} 36,000 \tag{7}$$

Following Krueger (1999), Chetty et al. (2011), and Chetty et al. (2014), we discount the future at

[35] Note that this is the AGI per person, or more precisely per exemption on the tax return, not AGI per household.

[36] The fact that the median age of workers in the United States comes from the Bureau of Labor Statistics (BLS), and was found here on July 22, 2021.

a 3% (real) rate, which means that we estimate $\mathbb{E}\left[h_i^w(0) \middle| i \in L^w\right]$ to be approximately $640,000.

Next, we estimate the effects of present lost learning on later life earnings, in order to monetize the effects on student achievement estimated in Section IV.B. To do so, we use estimates from Chetty et al. (2014), who study the effect of learning on later life outcomes, including income as adults. There, they find that a 0.10 standard deviation increase in achievement due to higher value-added teachers leads to an approximate increase in income of 1 percent at age 28. We further use Chetty et al. (2014)'s estimate of the mean NPV of earnings in the United States population, making two small adjustments. We inflate their estimate to reflect 2018 dollars and increase the discounting so it reflects the mean ten year old rather than twelve year old; doing so gives us an estimate of the mean NPV of $565,000.[37] This suggests that a 0.10σ reduction in test scores corresponds to an NPV of $5,650 of lost future earnings, which corresponds to 1% of $565,000.[38] It should be noted explicitly, that using the Chetty et al. (2014) estimates to monetize the student achievement effects requires us to assume that the effects of natural disasters on skills not assessed in standardized tests (e.g. non-cognitive skills) are similar to those associated with worse teachers, as measured by value-added. If natural disasters have a larger effect on these skills our computations will result in an underestimate, and vice versa.

Third, we similarly monetize the estimated effects on high school graduation and post-secondary attendance. To do so, we use estimates of the causal effects of an extra year of schooling provided in a recent review by Gunderson and Oreopolous (2020), who estimate that an extra year of schooling increases an individual's earnings by approximately 10%. We consider both changes in high school graduation rates and changes in post-secondary attendance to be equivalent to a changes of a single year of schooling, which means that again we may be underestimating the effect if it actually reduces their schooling by more than a single year or if there is an added graduation bonus in the form of sheepskin effects (Jaeger and Page, 1996). Similarly, given well-documented convexification of the returns to schooling, particularly for college and beyond, this approach may underestimate the true earnings losses. On the other hand, if the effects we document are merely delays in high school graduation or college attendance, then this approach may overstate the lifetime earnings impacts. We see no evidence of this occurring in the medium-term results, however, and the reductions in post-secondary enrollment persist through the three years post-disaster that we explore. As in the student achievement context above, we use Chetty et al. (2014)'s estimate of the mean NPV of earnings in the United States population, this time adjusting the measures to correspond to the NPV for 18 and 20 year olds, depending on whether we are measuring high school graduation changes or post-secondary attendance changes. This corresponds to NPVs of $720,000 and $765,000 per student respectively. This suggests that a 1-year reduction in high school or post-secondary education has an NPV of approximately $72,000 and $76,500 for each age group, respectively.[39]

[37] We derive this number by multiplying their estimate of $522,000 by 1.15, to reflect the 15% inflation from 2010 to 2018, and then by 0.97^2 to reflect the mean earnings of a ten year old rather than a twelve year old.

[38] More generally, a decrease in test scores of xσ corresponds to an NPV of $\$565,000 \cdot \frac{0.01}{0.10} \cdot x$, where $\frac{.01}{.1}$ reflects a 1% drop in NPV of earnings for every 0.1σ decrease in test scores.

[39] As a comparison, assuming a similar quarterly increase in wages during their entire career as he finds during years 8 to 14 post-high school graduation, Zimmerman (2014) finds that a marginal admission to the Florida State

Finally, to compute the size of each life stage, we use data from the National Center for Education Statistics, which suggests that in 2020, of the roughly 300 million individuals in the U.S., there were approximately 35.3 million students in elementary and middle schools, 15.4 million students in high school, and 19.7 million students in colleges and universities.[40]

V.B Results

The results of our calculations are presented in Table 5. Human capital impacts are nontrivial in magnitude, across many sizes of disaster. Disasters that cause more than $500 in property damage lead to the largest decrease in NPV of their human capital, with a decrease of approximately $505 NPV per person. This decrease comes approximately equally from excess migration out of the county and from decreases in academic outcomes of individuals within the county. If we ignore any changes in the human capital of those who move, this means that very large disasters cause "global" loss in human capital (i.e. the human capital cost measure that does not consider migration as a decrease in human capital) of approximately $268 per person. Note, however, that this number is lessened by the fact that only 10% of individuals are in elementary and middle schools, 5% in high school, and another 5% in post-secondary schools. On a per student basis – as opposed to a per-person basis – the effect is much larger, suggesting important inter-generational distributional consequences of relief efforts focused on rebuilding physical capital or remunerating lost wage income for working adults.

As shown in Table 5, living in an area hit by a disaster with >$500 in per capita property damage reduces the NPV of earnings by around $1,288 per elementary and middle school student, $184 per high school student, and $1,950 per post-secondary enrollee. Note further that the low estimated effect per high school student are quite likely in part due to our lack of appropriate measures for students of that age. We find, for example, no indication that post-secondary enrollment reverts to its initial levels in the post-disaster years, suggesting that high school students who are affected by a disaster are less likely to enroll in post-secondary institutions post-disaster. This decline, however, is not captured in our static estimates. In addition, it is plausible that disasters decrease high school achievement, since decreases are observed in elementary and middle school data; however, we simply do not have good nationwide achievement data for high school students, and so these hypothetical decreases are not included in our human capital loss calculations.

As implied by the results in Section IV, the negative effect on students' NPV of earnings are not isolated to very large disasters. Disasters with $100-$500 in per capita property damage also see large decreases in the NPV of earnings for students. In particular, disasters of that size decrease students' NPV of earnings by approximately $865 per elementary and middle school student and

University System increases an individuals' NPV of earnings by over $150,000. Bahr et al. (2015) compare earnings of those who graduate community college to those who enroll but do not graduate, to show that graduation is associated with NPV of earnings by between $72,000 and $180,000 depending on which degree they earned. Our numbers for the NPV are therefore aligned with other numbers estimated in the literature.

[40]Population estimate according the U.S. Census's Population Clock, found here. All student estimates come from the following URL, accessed on July 22, 2021.

Table 5: Changes In Human Capital Post Disaster

Size	"Local" Human Capital Change	"Global" Human Capital Change	Migration	Student Achievement	High School Graduation	Post-Secondary Attendance
Small	-$30	-$7	$37	-$43	$34	$166
Medium	$30	-$41	$71	-$319	-$14	-$110
Large	-$231	-$185	-$46	-$865	-$128	-$1,400
Very Large	-$505	-$268	-$237	-$1,288	-$184	-$1,950
Normalization	Per Person	Per Person	Per Person	Per Person	Per Student	Per Student
Weight	–	–	1.0	0.11	0.05	0.06

Numbers reflect changes in individuals' net present value (NPV) of earnings. "Local" Human Capital Change counts out-migration as a loss to human capital, while "Global" Human Capital Change does not. Small Disaster consist of counties with per capita property damage of $1-$10 per capita in a year; "Medium Disasters" have per capita property damage of $10-$100; "Large Disasters" have per capita property damage of $100-$500, and "Very Large Disasters" have more than $500 per capita property damage. Counties with less than $1 in per capita property damage are the omitted category. Non-statistically significant effects have been rounded to zero. The "Normalization" row reflects the who the dollar value is normalized to. The student achievement is per elementary and middle school student, the high school graduation column is per high school student, and the post-secondary attendance column is per college and university attendee. The "Weight" is the re-normalization value which with we multiple the dollar amount to turn it from a "Per Student" value to a "Per Person" value; this is simple the fraction of people who are, for example, an elementary or middle school student.

$1,400 pre post-secondary enrollee. These make up the majority of the $231 per person decrease in the local human capital, since few people migrate due to disasters of that size.

VI Conclusion

Natural disasters such as hurricanes and floods can have large impacts on local economies. Understanding the economic consequences of natural disasters is important for understanding potential damages from climate change (Greenstone et al., 2013), as well as in designing policies that help societies insure against, and cope with, the consumption shocks that arise from them (Kahn, 2016). While a growing literature documents the consequences of such disasters for physical capital and their attendant effects on economic growth (Hsiang and Jina, 2014; Deryugina, 2017; Barrage, 2020), relatively little is known regarding their impacts on human capital, which may be just as important in determining longer-run economic outcomes.

In this paper, we compile what is – to our knowledge – the most comprehensive dataset assembled to date to assess the human capital consequences of natural disasters. Exploiting within-county variation in disaster timing and intensity, we estimate the causal impact of a wide range of natural disasters on human capital outcomes. We find that natural disasters diminish a region's stock of human capital along multiple dimensions, including out-migration of productive labor, reduction of student achievement and learning, and postponement or permanent reduction of higher levels of educational attainment. Because our disaster data includes harmonized estimates of assessed per-capita property damages, we are able to provide what is, to our knowledge, the first comparison of the relative magnitude of human versus physical capital impacts of natural disasters. We find that large natural disasters that cause at least $500 in per-capita physical damages may reduce a region's human capital by approximately \$505, approximately half of which is driven by increased out-migration and the other half due to decreases in student achievement and attainment. For smaller natural disasters, the effect is driven primarily by reductions in student achievement and college attendance: disasters with per capita physical damages of \$100 to \$500 result in human capital losses valued at approximately \$231 per person; all but \$46 is due to decreases in student achievement and attainment.

We stress that these numbers should be viewed as indicative of the impact that disasters have on human capital, rather than definitive estimates of their effects. The relatively small impact on high school attendees, for example, is most likely due to the limits of our data on high school outcomes rather than disasters having a smaller impact on high school students than on either elementary/middle school students or college attendees. In addition, while the use of nation-wide data on average test scores and college attendance means that we can explore the effects of national disasters of all sizes and types, the lack of individual-level data means that we cannot rule out that some of the results on educational achievement and attainment are due to composition changes rather than individual-level impacts. Our numbers also do not include any changes due to shifts in the region's sectoral composition caused by the disaster and we assume that migration itself has no impact on an individuals' human capital. We therefore view our calculations as a starting point and indicative of the fact that natural disasters may cause as much, if not more, of an impact on a county's human capital as on its physical capital.

This finding has implications for our understanding of local economic growth. A long-standing macro-development literature consistently finds human capital to be a primary driver of economic growth and to explain a large proportion of differences in per-capita incomes (Mankiw et al., 1992; Hanushek and Woessmann, 2012). Whether, and to what extent, geographic/climatic factors play a role in these relationships remains debated. Our findings suggest that the subtle but persistent effects of natural disasters on human capital may be an important mechanism by which geographic factors affect long-run economic growth and the attendant differences in living standards.

The findings also have implications for policy. We build on a growing literature that explores the fiscal implications of natural disasters, including work by Deryugina (2017), who finds that hurricanes lead to significant federal transfers. In addition to disaster aid, existing social safety net programs including Medicare, Unemployment Insurance, and Disability Insurance increase significantly following hurricane landfall, but actually lead to a small reduction in educational assistance transfers. Disaster-relief currently focuses largely on rebuilding the region's physical capital. Our paper suggests that this is not enough and that fully alleviating the damage caused by a disaster also requires rebuilding the region's human capital.

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A Disaster Data

A.1 Example of Preliminary Damage Assessment

Figure A1 contains a representative Preliminary Damage Assessment (PDA) from a FEMA declared disaster. This storm was located in Georgia and featured severe storms and tornadoes. The total amount requested is \$14.5 million for Public Assistance (PA) requests. No money was requested for Individual Assistance (IA) – funds that go directly to individual households through an application process. PA requests include the affected counties, as well as a damage estimate (per capita). A Python script was used to do the initial scrape of the publicly available PDFs, and all the results were manually corrected for errors.

Figure A1: PDA for FEMA Disaster Number 4259

Georgia – Severe Storms and Flooding
FEMA-4259-DR

Declared February 26, 2016

On February 10, 2016, Governor Nathan Deal requested a major disaster declaration due to severe storms and flooding during the period of December 22, 2015 to January 13, 2016. The Governor requested a declaration for Public Assistance for 33 counties and Hazard Mitigation statewide. During the period of January 20 to February 9, 2016, joint federal, state, and local government Preliminary Damage Assessments (PDAs) were conducted in the requested counties and are summarized below. PDAs estimate damages immediately after an event and are considered, along with several other factors, in determining whether a disaster is of such severity and magnitude that effective response is beyond the capabilities of the state and the affected local governments, and that Federal assistance is necessary.[1]

On February 26, 2016, President Obama declared that a major disaster exists in the State of Georgia. This declaration made Public Assistance requested by the Governor available to state and eligible local governments and certain private nonprofit organizations on a cost-sharing basis for emergency work and the repair or replacement of facilities damaged by the severe storms and flooding in Baker, Carroll, Chattahoochee, Crawford, Dade, Decatur, Douglas, Fannin, Fayette, Gilmer, Greene, Haralson, Harris, Jeff Davis, Lamar, Macon, Marion, Meriwether, Montgomery, Morgan, Muscogee, Newton, Oglethorpe, Pickens, Stewart, Talbot, Taliaferro, Taylor, Towns, Troup, Upson, Webster, and Wilkes Counties. This declaration also made Hazard Mitigation Grant Program assistance requested by the Governor available for hazard mitigation measures statewide.[2]

Summary of Damage Assessment Information Used in Determining Whether to Declare a Major Disaster

Individual Assistance - *(Not requested)*

- Total Number of Residences Impacted:[3] -

  Destroyed - -
  Major Damage - -
  Minor Damage - -
  Affected - -

- Percentage of insured residences:[4] -
- Percentage of low income households:[5] -
- Percentage of elderly households:[6] -
- Total Individual Assistance cost estimate: N/A

Public Assistance

- Primary Impact: Damage to roads and bridges
- Total Public Assistance cost estimate: \$14,507,757

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- Statewide per capita impact:[7] \$1.50
- Statewide per capita impact indicator:[8] \$1.41
- Countywide per capita impact: Baker County (\$8.32), Carroll County (\$7.84), Chattahoochee County (\$4.97), Crawford County (\$6.65), Dade County (\$110.44), Decatur County (\$10.78), Douglas County (\$3.76), Fannin County (\$9.90), Fayette County (\$10.04), Gilmer County (\$52.09), Greene County (\$9.44), Haralson County (\$4.62), Harris County (\$4.22), Jeff Davis County (\$4.98), Lamar County (\$11.47), Macon County (\$16.67), Marion County (\$22.88), Meriwether County (\$24.78), Montgomery County (\$5.86), Morgan County (\$18.71), Muscogee County (\$4.66), Newton County (\$10.43), Oglethorpe County (\$8.22), Pickens County (\$11.67), Stewart County (\$66.03), Talbot County (\$18.79), Taliaferro County (\$34.92), Taylor County (\$28.07), Towns County (\$9.36), Troup County (\$28.06), Upson County (\$4.95), Webster County (\$30.37), and Wilkes County (\$51.45).
- Countywide per capita impact indicator:[9] \$3.57

[1] The Preliminary Damage Assessment (PDA) process is a mechanism used to determine the impact and magnitude of damage and resulting needs of individuals, businesses, public sector, and community as a whole. Information collected is used by the State as a basis for the Governor's request for a major disaster or emergency declaration, and by the President in determining a response to the Governor's request (44 CFR § 206.33).
[2] When a Governor's request for major disaster assistance under the Robert T. Stafford Disaster Relief and Emergency Assistance Act, as amended (Stafford Act) is under review, a number of primary factors are considered to determine whether assistance is warranted. These factors are outlined in FEMA's regulations (44 CFR § 206.48). The President has ultimate discretion and decision making authority to declare major disasters and emergencies under the Stafford Act (42 U.S.C. § 5170 and § 5191).
[3] Degree of damage to impacted residences:
  - Destroyed – total loss of structure, structure is not economically feasible to repair, or complete failure to major structural components (e.g., collapse of basement walls/foundation, walls or roof);
  - Major Damage – substantial failure to structural elements of residence (e.g., walls, floors, foundation), or damage that will take more than 30 days to repair;
  - Minor Damage – home is damaged and uninhabitable, but may be made habitable in short period of time with repairs; and
  - Affected – some damage to the structure and contents, but still habitable.

[4] By law, Federal disaster assistance cannot duplicate insurance coverage (44 CFR § 206.48(b)(5)).
[5] Special populations, such as low-income, the elderly, or the unemployed may indicate a greater need for assistance (44 CFR § 206.48(b)(3)).
[6] Ibid (44 CFR § 206.48(b)(3)).
[7] Based on State population in the 2010 Census.
[8] Statewide Per Capita Impact Indicator for FY16, *Federal Register*, October 1, 2015.
[9] Countywide Per Capita Impact Indicator for FY16, *Federal Register*, October 1, 2015.

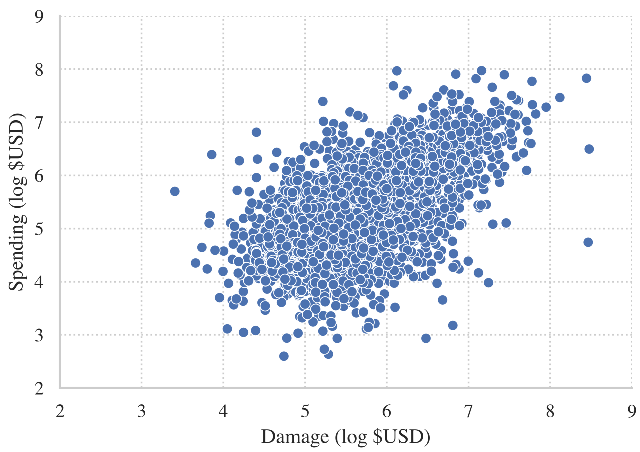
3

A.2 Combining Damage Data From Various Sources

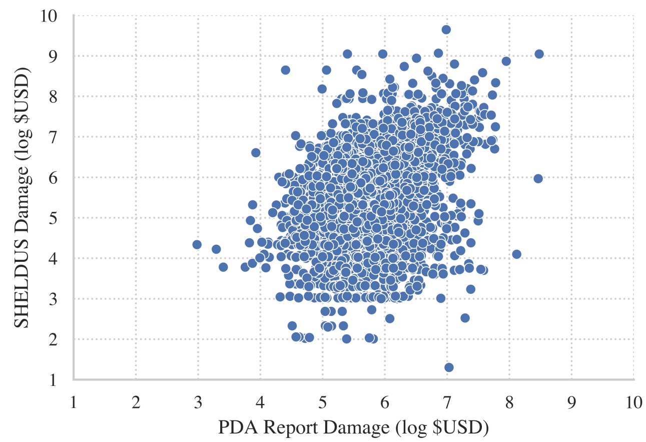
There is no one reliable source for disaster damage data. Some data are based on surveys, others are based on insurance claims, and others are done by FEMA itself and relate to the physical capital stock of the municipalities that they are planning to rebuild. In practice, however, all of these measures are highly correlated. Figure A2 shows the full comparison of the data from all the various sources. Panel (a) compares the preliminary damage assessment data to the resulting FEMA spending done in that county for that particular storm, where both observations are available. While the results may not be sur prising, it is interesting that FEMA spends – over years and through a patchwork of individual grant applications – approximately what they estimate the total damages from a storm are in a particular county. Panel (b) compares the SHELDUS data to the FEMA PDA assessments. These are also highly related, even though they are based on different criteria. When SHELDUS data is compared directly to FEMA spending in panel (c), we see that spending tends to fall short of total damages. This is understandable, since FEMA spending is on municipally owned buildings as opposed to total damages which also contain the claims of individual property owners.

Figure A2: Scatterplots of Disaster Data From All Sources

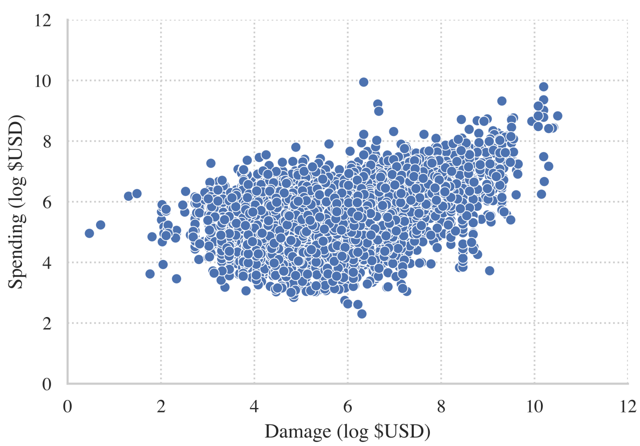
(a) PDA Damage and FEMA Spending



(b) SHELDUS Damage and PDA Damage



(c) SHELDUS Damage and FEMA Spending



In this study, since we are considering the effects of the damages themselves and the decisions of households in human capital development, we favor the SHELDUS data. However, given that some storms are missing for this dataset, we add in damages using FEMA data by regressing the log of per capita SHELDUS damage data on the log per capita PDA damages and log per capita spending data, respectively. We include disaster type fixed effects. We take the fitted values from this regression and if two potentially fitted values are available average them. We fill in the missing

SHELDUS values with this averaged value coming from FEMA. The main results in this paper are robust to ignoring these additional storms.

B Disaster Types, Frequencies, and Locations

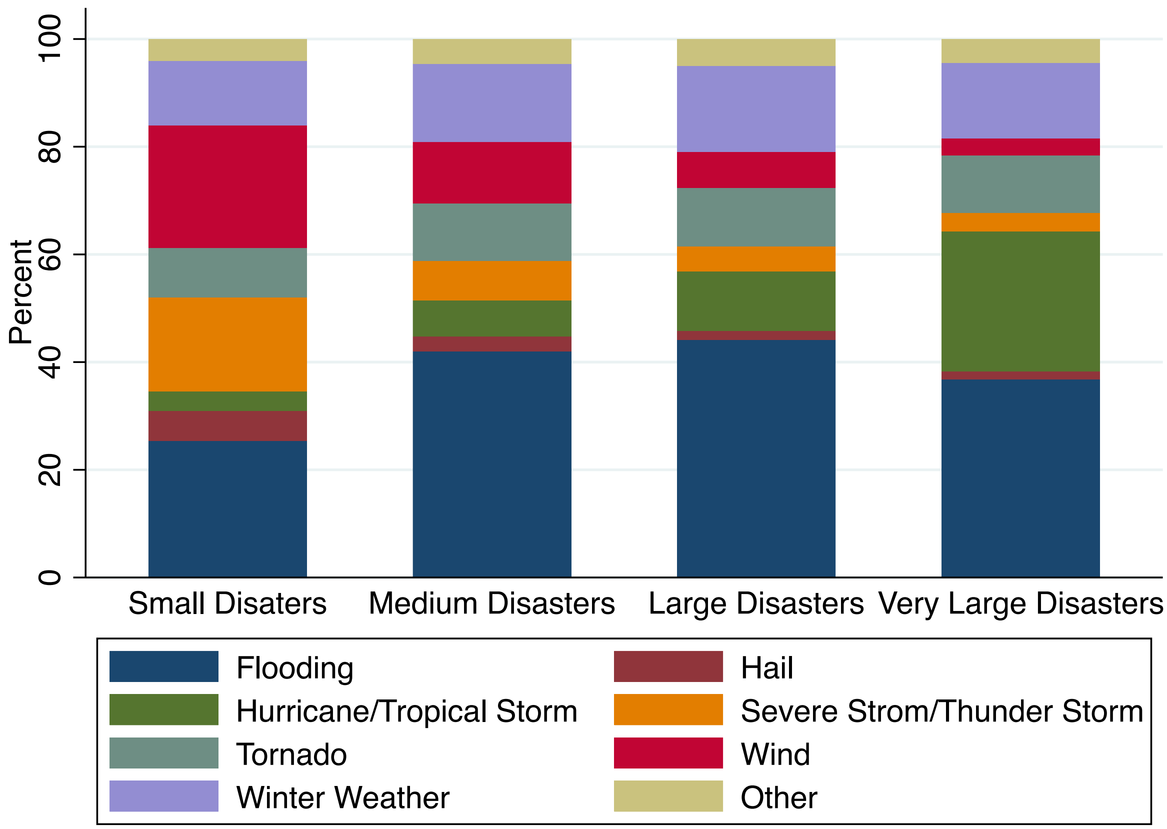
Hurricanes and tropical often dominate the discussion of large disasters in the United States, and admittedly at least one of the co-authors initially assumed that the vast majority of disasters with $>$ \$500 in per capita damage would be hurricanes, those that we call Very Large Disasters.[41] However, as shown in Figure A3 hurricanes and tropical storms together only make up 26% of all Very Large Disasters, with floods, tornados, and "winter weather" also causing a number of Very Large Disasters.

Among other things, the diversity of disaster types means that although the Gulf Coast is indeed a hot-spot for Very Large Disasters, counties in a variety of locations across the country are affected. Other common types of disasters that cause $>$ \$500 in per capita property damage are floods in the Great Plains and winter weather in New England. Four maps showing how many times a particular county was impacted by Small, Medium, Large, and Very Large disasters are shown in Figure A4, which also illustrate the number of counties impacted by a disaster with at least \$100 in per capita property damage. In fact, more than two-thirds of the counties in the contiguous United States (CONUS) - approximately 2,100 of the roughly 3,100 counties in CONUS - were impacted by at least one disaster that caused at least \$100 in the county during the roughly 20 years of our sample.

Finally, Figure A5 show that disasters of all sizes occurred in every year in the sample and although there are spikes in some years, the are no major increases or decreases over time in the number of impacted counties. As mentioned above, although we show disasters from 1990-2018, the results that rely on SEDA or EdFacts data are restricted to a much more recent sample.

[41] For those curious, that naive author was Isaac.

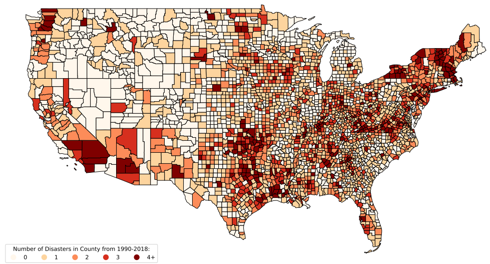
Figure A3: Disaster Types



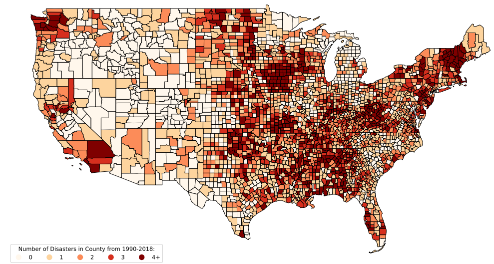
Note: This figure illustrates how many disasters of a given category were classified as a particular disaster type by SHELDUS. Small Disaster consist of counties with per capita property damage of \$1-\$10 per capita in a year; “Medium Disasters" have per capita property damage of \$10- \$100; “Large Disasters" have per capita property damage of \$100-\$500, and “Very Large Disasters" have more than \$500 per capita property damage.

Figure A4: Disaster Locations

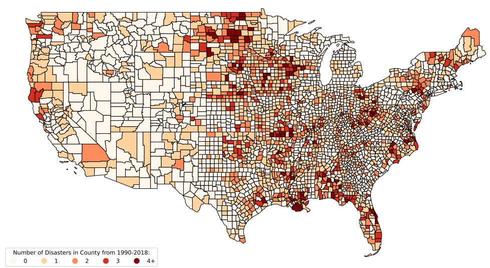
(a) Small Disasters



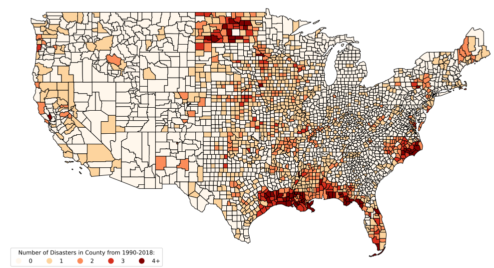
(b) Medium Disasters



(c) Large Disasters

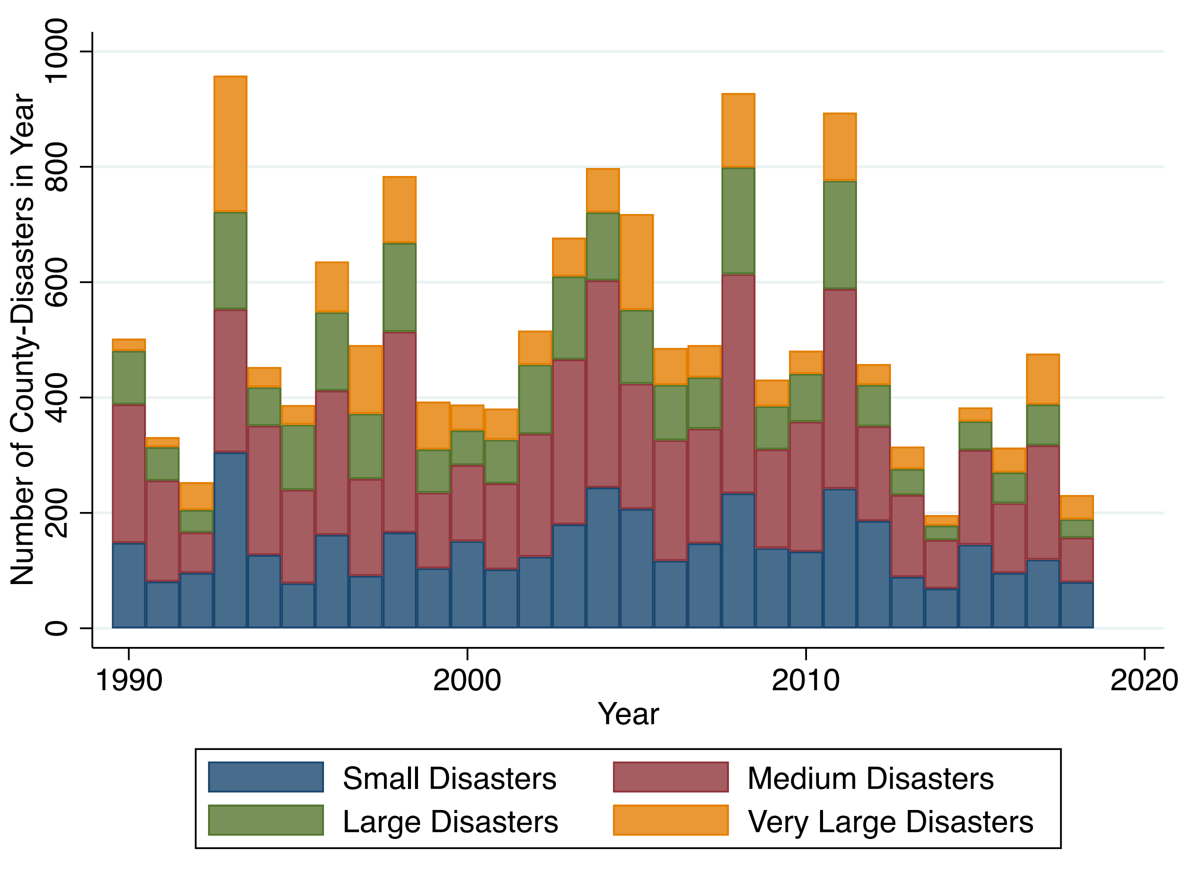


(d) Very Large Disasters



Note: These maps show how many times a county was impacted by disasters from the period 1990-2018. Small Disaster consist of counties with per capita property damage of \$1-\$10 per capita in a year; “Medium Disasters" have per capita property damage of \$10- \$100; “Large Disasters" have per capita property damage of \$100-\$500, and “Very Large Disasters" have more than \$500 per capita property damage.

Figure A5: Disasters Over Time



Note: This figure illustrates how many disasters of a given category occurred in each year of the data. Small Disaster consist of counties with per capita property damage of \$1-\$10 per capita in a year; "Medium Disasters" have per capita property damage of \$10- \$100; "Large Disasters" have per capita property damage of \$100-\$500, and "Very Large Disasters" have more than \$500 per capita property damage.

C Dynamic Effects

In Section IV, we present results on the effect of disasters in the year following the disaster. Here, we provide evidence on the impact that disasters have on outcomes in the four years following a disaster. To do so, we estimate dynamic effects by running versions of equation 3 in which we include not only $D^k_{i,t}$ but also $D^k_{i,t+l}$ for $l \in \{0, 1, 2, 3\}$. Formally, these regressions are of the form:

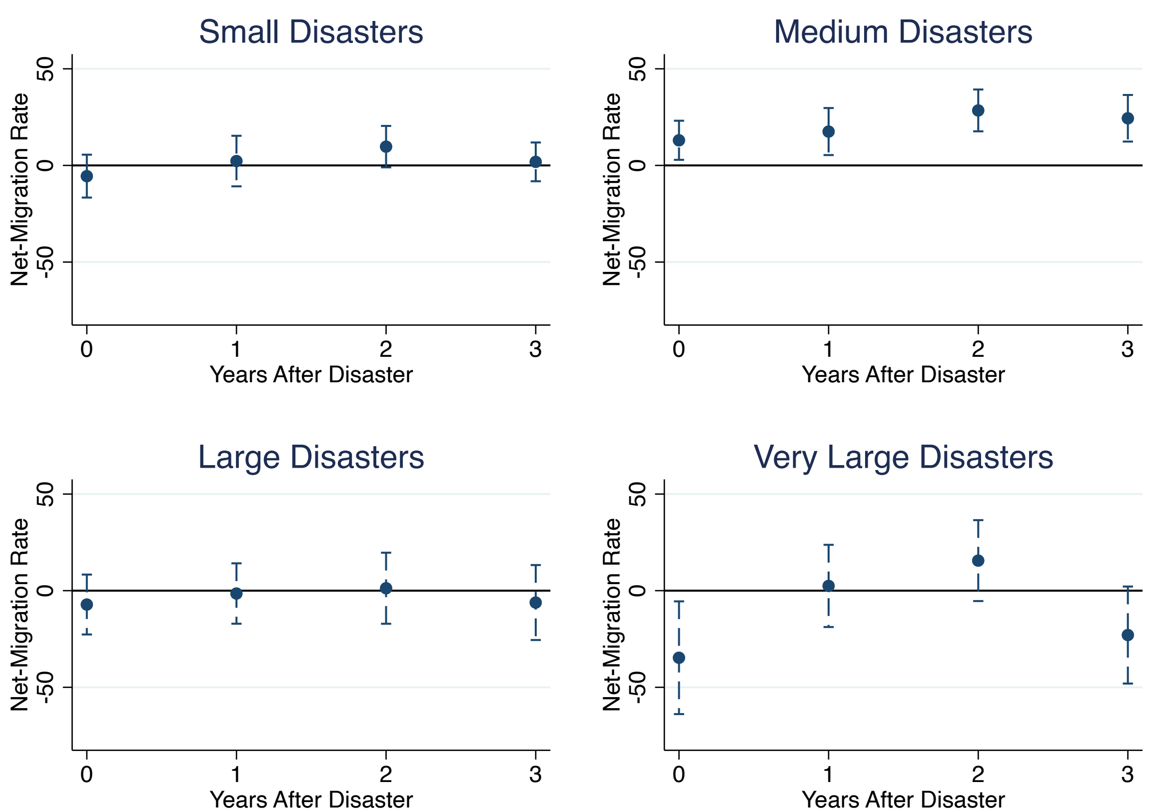
$$\Delta y_{i,t} = \alpha + \sum_{l=0}^{3} \sum_{\forall k} \tau_{k,l} D^k_{i,t-l} + \mu_i + \theta_t + \epsilon_{i,t} \tag{8}$$

Thus $\tau_{k,l}$ here would estimate the average effect of a disaster of size k hitting a county in year $t - l$ on the change in outcomes in year t. Equivalently, we could think of $\tau_{k,l}$ as being the average effect of a disaster of size k hitting a county in year t on the change in outcome in that county in year $t+l$.

In our main specification, we do not include measures $l \in \{-1,-2,-3\}$ as is often done in an event study because of our relatively short panel of outcomes. Since we have historical data on whether counties were impacted by a disaster, we can add measures of $D^k_{c,t-l}$ without dropping observations; however, since we do not know in advance which counties will be impacted in the future, we cannot add measures of $D^k_{c,t+l}$ without dropping observations. For transparency, however, we also illustrate more traditional event study results which estimates Equation 8 using both leads and lags.

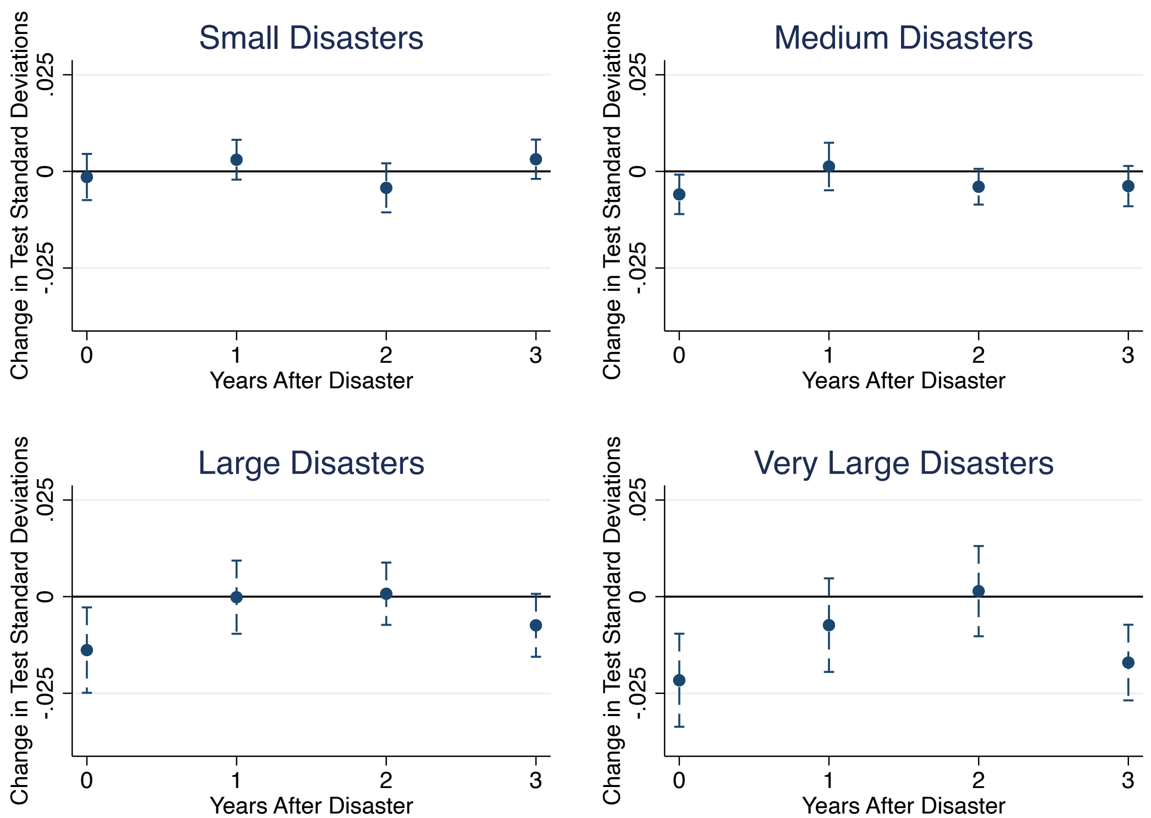
The results on dynamic effects are shown in the following four figures, which illustrate the results for the four outcomes we discuss in Section III.A.

Figure A6: Dynamic Impact on Net Migration Rates



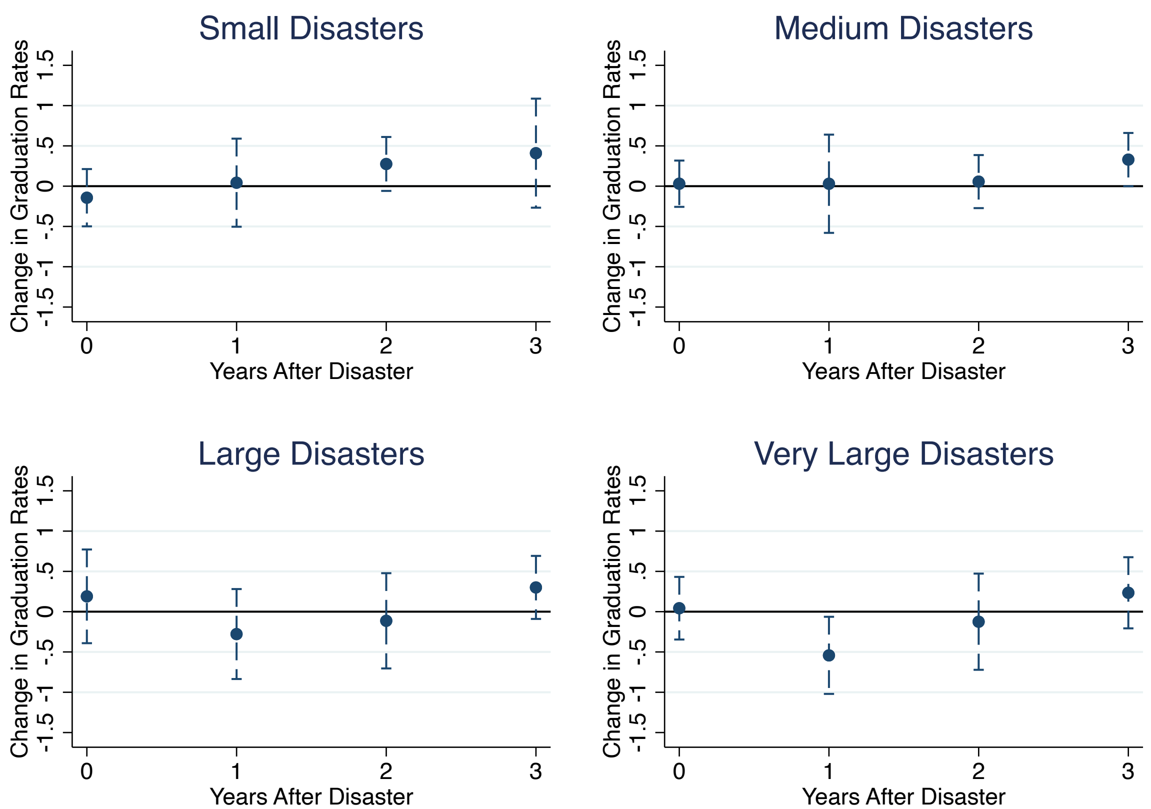
Note: This figure illustrates the point estimate and 95% confidence internals of the dynamic effects of disasters on average test scores. Small Disaster consist of counties with per capita property damage of \$1-\$10 per capita in a year; “Medium Disasters" have per capita property damage of \$10-\$100; “Large Disasters" have per capita property damage of \$100-\$500, and “Very Large Disasters" have more than \$500 per capita property damage. Counties with less than \$1 in per capita property damage are the omitted category.

Figure A7: Dynamic Impact on Average Student Test Scores



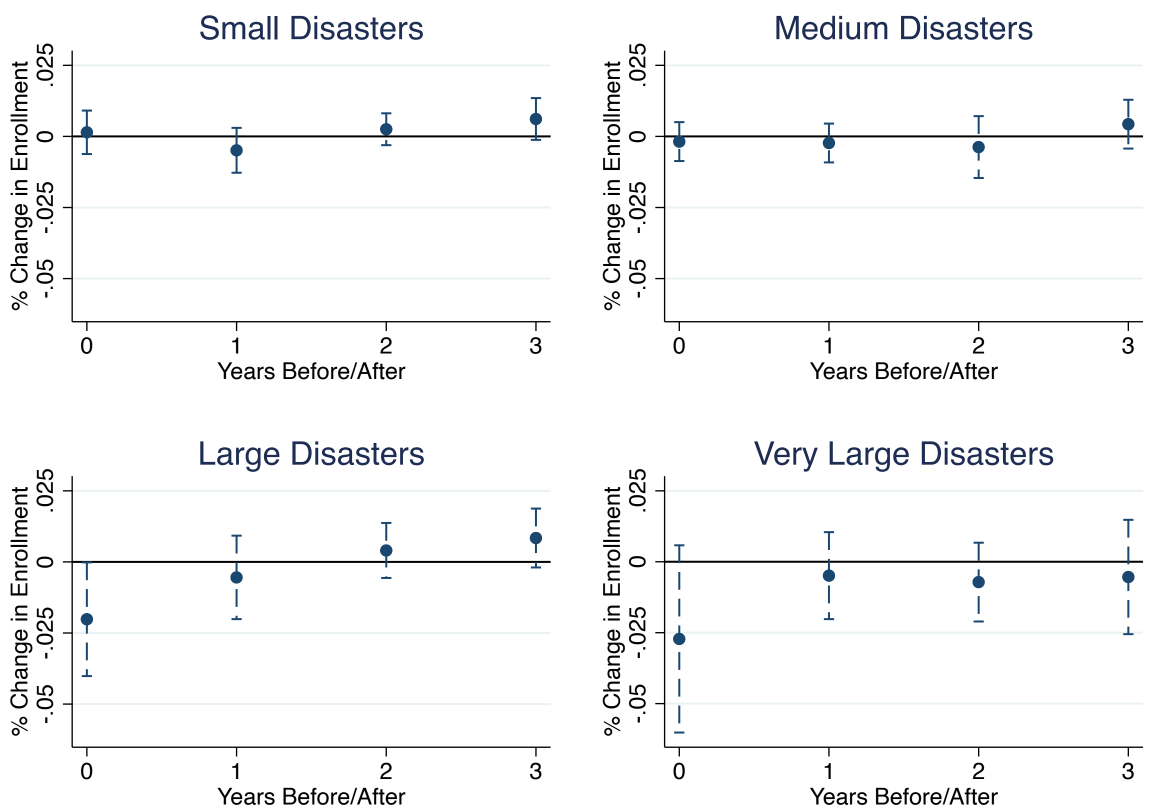
Note: This figure illustrates the point estimate and 95% confidence internals of the dynamic effects of disasters on average test scores. “Small Disaster" consist of counties with per capita property damage of \$1-\$10 per capita in a year; “Medium Disasters" have per capita property damage of \$10-\$100; “Large Disasters" have per capita property damage of \$100-\$500, and “Very Large Disasters" have more than \$500 per capita property damage. County-years with less than \$1 in per capita property damage are the omitted category.

Figure A8: Dynamic Impact on High School Graduation Rates



Note: This figure illustrates the point estimate and 95% confidence internals of the dynamic effects of disasters on average test scores. Small Disaster consist of counties with per capita property damage of $1-$10 per capita in a year; “Medium Disasters" have per capita property damage of $10-$100; “Large Disasters" have per capita property damage of $100-$500, and “Very Large Disasters" have more than $500 per capita property damage. Counties with less than $1 in per capita property damage are the omitted category.

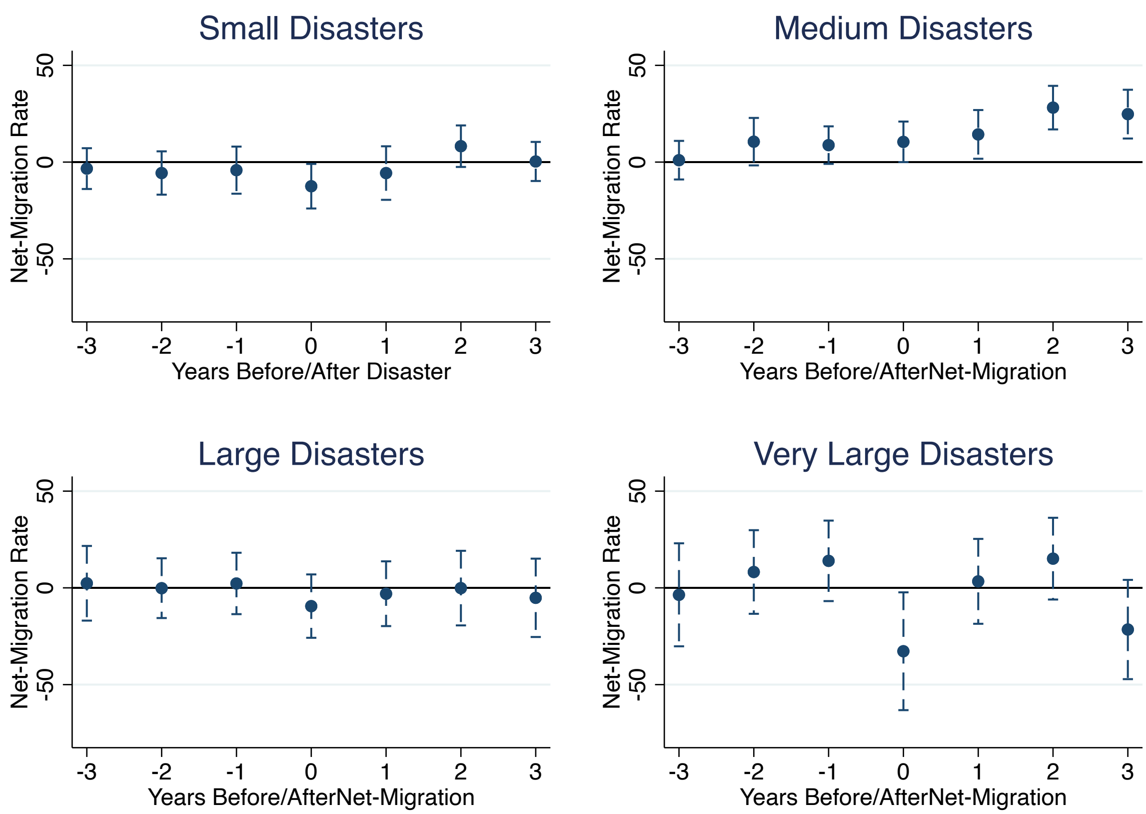
Figure A9: Dynamic Impact on Post-Secondary Enrollment



Note: This figure illustrates the point estimate and 95% confidence internals of the dynamic effects of disasters on average test scores. Small Disaster consist of counties with per capita property damage of \$1-\$10 per capita in a year; “Medium Disasters" have per capita property damage of \$10-\$100; “Large Disasters" have per capita property damage of \$100-\$500, and “Very Large Disasters" have more than \$500 per capita property damage. Counties with less than \$1 in per capita property damage are the omitted category.

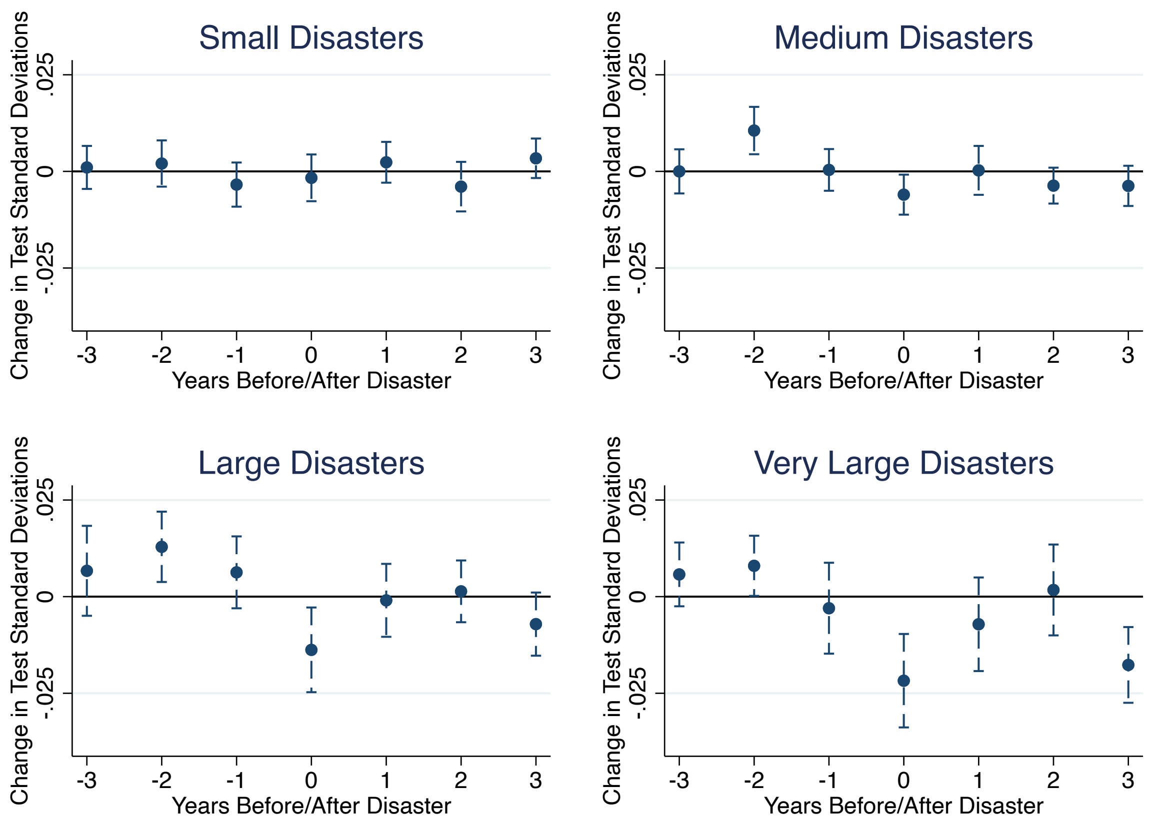
In all of the measures, the results are generally isolated to the year or two after after the disaster and for larger or very large disasters. The results are generally similar when we include lags as well as leads, as shown in the four figures below. Notably, for none of the outcomes in which we find large effects is there any evidence of strong pre-tends, suggesting that focusing on year-to-year changes is sufficient.

Figure A10: Event-Study on Net-Migration



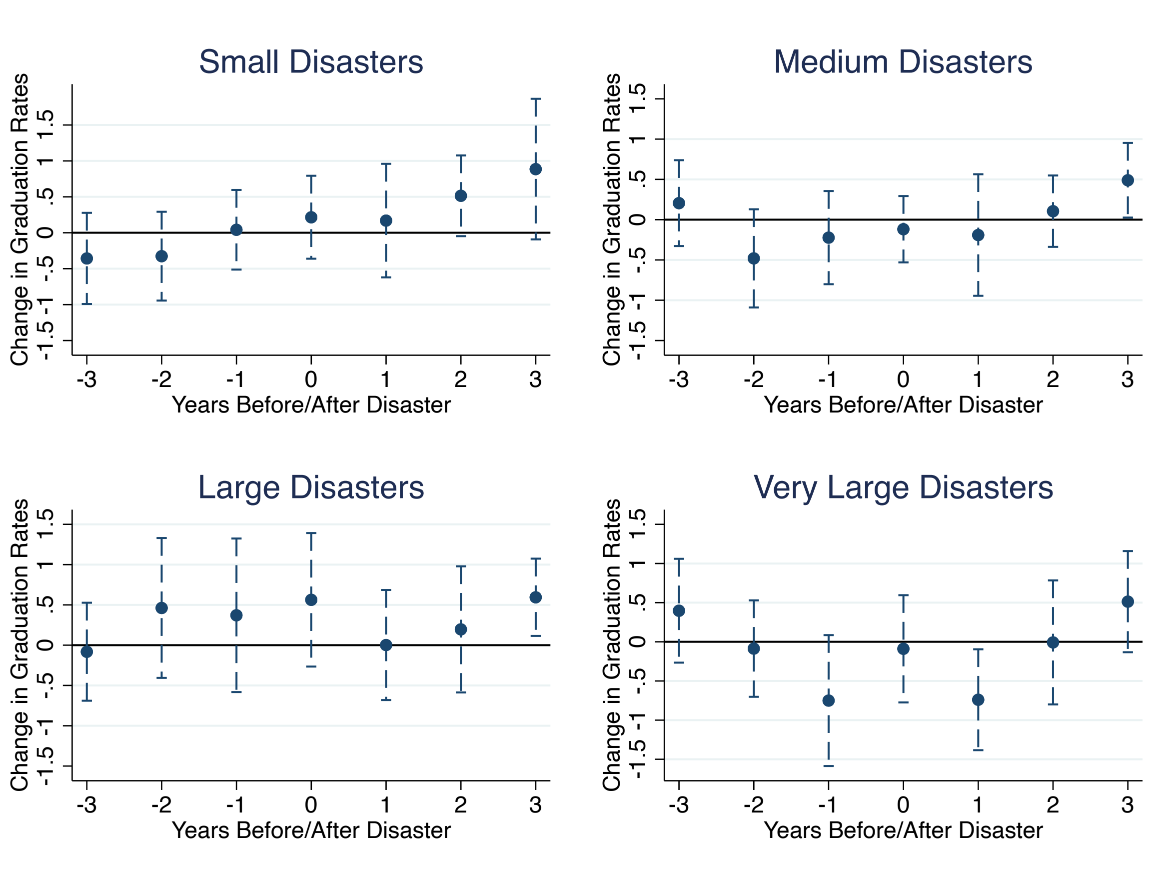
Note: This figure illustrates the point estimate and 95% confidence internals of the dynamic effects of disasters on net-migration. Small Disaster consist of counties with per capita property damage of \$1-\$10 per capita in a year; "Medium Disasters" have per capita property damage of \$10- \$100; "Large Disasters" have per capita property damage of \$100-\$500, and "Very Large Disasters" have more than \$500 per capita property damage. Counties with less than \$1 in per capita property damage are the omitted category.

Figure A11: Event-Study for Student Test Scores



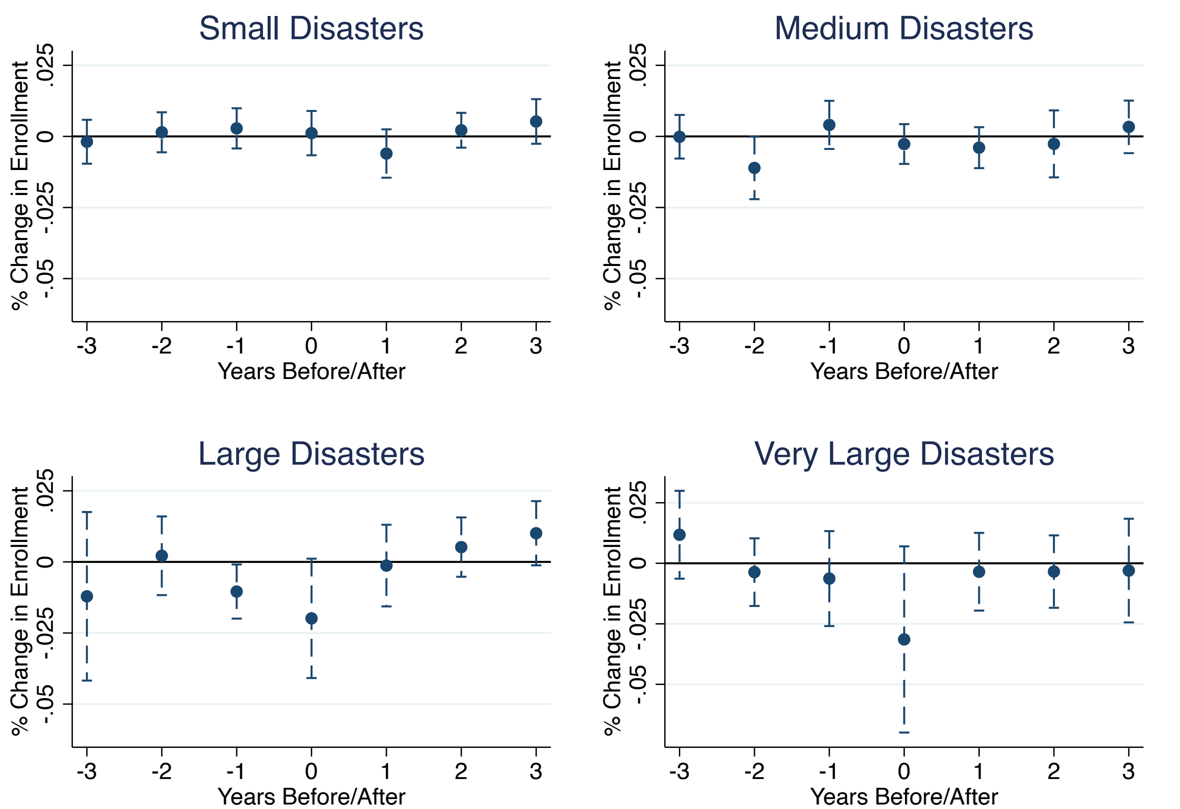
Note: This figure illustrates the point estimate and 95% confidence internals of the dynamic effects of disasters on average test scores. Small Disaster consist of counties with per capita property damage of $1-$10 per capita in a year; “Medium Disasters" have per capita property damage of $10-$100; “Large Disasters" have per capita property damage of $100-$500, and “Very Large Disasters" have more than $500 per capita property damage. Counties with less than $1 in per capita property damage are the omitted category.

Figure A12: Event Study for High-School Graduation



Note: This figure illustrates the point estimate and 95% confidence internals of the dynamic effects of disasters on high school graduation rates. Small Disaster consist of counties with per capita property damage of $1-$10 per capita in a year; “Medium Disasters" have per capita property damage of $10- $100; “Large Disasters" have per capita property damage of $100-$500, and “Very Large Disasters" have more than $500 per capita property damage. Counties with less than $1 in per capita property damage are the omitted category.

Figure A13: Event Study for Post-Secondary Enrollment



Note: This figure illustrates the point estimate and 95% confidence internals of the dynamic effects of disasters on log post-secondary enrollment. Small Disaster consist of counties with per capita property damage of \$1-\$10 per capita in a year; “Medium Disasters" have per capita property damage of \$10- \$100; “Large Disasters" have per capita property damage of \$100-\$500, and “Very Large Disasters" have more than \$500 per capita property damage. Counties with less than \$1 in per capita property damage are the omitted category.

D Additional Results

Table A1: Log Disaster Size

(a) Post-Disaster

	(1)	(2)	(3)	(4)	(5)
	netmig_rate	d_all	d_grad_rate	f_d_grad_rate	Change in College Enrollment
Log Property Damage Per Capita	-23.74***	-0.00592**	0.0690	-0.186	-0.00988**
	(6.834)	(0.00230)	(0.0738)	(0.127)	(0.00479)
Observations	13002	9115	12518	10364	18362
Number of Clusters	2928	704	1253	1070	1091

(b) Pre-Disaster

	(1)	(2)	(3)	(4)
	l_netmig_rate	l_d_all	l_d_grad_rate	Change in College Enrollment (Lagged)
Log Property Damage Per Capita	-3.380	0.00115	0.0412	-0.00295
	(5.548)	(0.00226)	(0.103)	(0.00262)
Observations	12109	6450	9518	17693
Number of Clusters	2904	569	1053	1085

$***p < 1\%, **p < 5\%, *p < 10\%$. Each observation is a county-year. Standard errors, in parenthesis, are clustered at the county-level. All regressions include time fixed effects. We restrict the sample to counties with more than $1 in per capita damages.

Table A2: Impact of Disasters on Out- and In- Migration Rates

	(1)	(2)	(3)	(4)
	Out Migration Rate	In Migration Rate	Out Migration Rate (Lagged)	In Migration Rate (Lagged)
Small Disaster	0.602	-3.860	7.285	2.021
	(6.480)	(6.728)	(8.485)	(7.481)
Medium Disaster	-28.64***	-10.59	-20.01***	-16.23***
	(5.743)	(8.212)	(7.264)	(6.100)
Large Disaster	-14.91	-4.739	7.088	3.066
	(10.13)	(14.50)	(9.089)	(8.769)
Very Large Disaster	77.33***	11.34	-2.190	8.452
	(29.17)	(11.79)	(12.81)	(11.52)
County FE	X	X	X	X
Observations	76250	78055	76273	78089
Number of Clusters	3141	3141	3142	3142

$***p < 1\%, **p < 5\%, *p < 10\%$. Each observation is a county-year. Standard errors, in parenthesis, are clustered at the county-level. All regressions include time fixed effects. "Small Disaster" consist of counties with per capita property damage of $1-$10 per capita in a year; "Medium Disasters" have per capita property damage of $10- $100; "Large Disasters" have per capita property damage of $100-$500, and "Very Large Disasters" have more than $500 per capita property damage. County-years with less than $1 in per capita property damage, including those with no property damage, are the omitted category.

Table A3: Impact of Disasters on Average AGI of Migrants

	(1) AGI per Out-Migration Household	(2) AGI per Out-Migration Household	(3) AGI per In-Migration Household	(4) AGI per In-Migration Household
Small Disaster	554.3**	576.0**	97.91	62.28
	(267.8)	(286.7)	(135.9)	(145.1)
Medium Disaster	-928.0	-907.8	-295.2	-285.7
	(1002.9)	(1029.5)	(468.5)	(499.2)
Large Disaster	-55.62	185.5	-316.8	-259.8
	(162.3)	(193.5)	(492.8)	(521.6)
Very Large Disaster	-194.5	-229.6	-63.06	-80.55
	(204.2)	(240.4)	(196.8)	(208.7)
County FE		X		X
Observations	71136	71134	74768	74767
Number of Clusters	3140	3138	3140	3139

$***p < 1\%, **p < 5\%, *p < 10\%$. Each observation is a county-year. Standard errors, in parenthesis, are clustered at the county-level. All regressions include time fixed effects. "Small Disaster" consist of counties with per capita property damage of $1-$10 per capita in a year; "Medium Disasters" have per capita property damage of $10- $100; "Large Disasters" have per capita property damage of $100-$500, and "Very Large Disasters" have more than $500 per capita property damage. County-years with less than $1 in per capita property damage, including those with no property damage, are the omitted category.

Table A4: Robustness of the Estimated Impact of Natural Disasters on Average Test Scores

	(1) Change in Avg. Test Scores	(2) Change in Avg. Test Scores	(3) Change in Avg. Test Scores	(4) Change in Avg. Test Scores
Small Disaster	-0.00187	-0.00132	-0.00155	0.000383
	(0.00306)	(0.00355)	(0.00343)	(0.00396)
Medium Disaster	-0.00681**	-0.00751**	-0.00636*	-0.00661*
	(0.00279)	(0.00303)	(0.00342)	(0.00385)
Large Disaster	-0.0133**	-0.0132**	-0.0151**	-0.0177**
	(0.00549)	(0.00575)	(0.00693)	(0.00744)
Very Large Disaster	-0.0219***	-0.0218***	-0.0267***	-0.0244***
	(0.00657)	(0.00657)	(0.00766)	(0.00857)
County FE		X		X
Outcome	Fixed Race/Ethnicity Weights	Fixed Race/Ethnicity Weights	Economically Disadvantaged	Economically Disadvantaged
Observations	189788	189783	190768	190768
Number of Clusters	2914	2909	2966	2966

$***p < 1\%, **p < 5\%, *p < 10\%$. Each observation is a school-grade-year. Standard errors, in parenthesis, are clustered at the county-level. The "Fixed Race/Ethnicity Weights" specifications define the average test score as a weighted average of the race/ethnicity specific average test scores, with the weights on the race/ethnicity equal held fixed. The "Economically Disadvantaged" specification focused only on the average test scores of economically disadvantaged individuals. All regressions include time fixed effects. Small Disaster consist of counties with per capita property damage of $1-$10 per capita in a year; "Medium Disasters" have per capita property damage of $10- $100; "Large Disasters" have per capita property damage of $100-$500, and "Very Large Disasters" have more than $500 per capita property damage. Counties with less than $1 in per capita property damage are the omitted category.

Table A5: Reductions in Post-Secondary Enrollment by Race

	(1) Change in College Enrollment	(2) Change in College Enrollment	(3) Change in College Enrollment	(4) Change in College Enrollment
Small Disaster	-0.00897**	-0.00141	0.00241	-0.0000599
	(0.00382)	(0.00469)	(0.00620)	(0.00538)
Medium Disaster	-0.00874**	-0.00498	-0.00464	-0.00252
	(0.00372)	(0.00429)	(0.00432)	(0.00521)
Large Disaster	-0.0203***	-0.0232**	-0.0295**	-0.0172
	(0.00747)	(0.00950)	(0.0139)	(0.0133)
Very Large Disaster	-0.0337***	-0.0159	-0.0147	-0.0159
	(0.0115)	(0.0134)	(0.0132)	(0.0138)
Race/Ethnicity	X	X	X	X
County FE	White	Black	Hispanic	Asian
Observations	93718	86686	83174	68823
Number of Clusters	5332	5175	5251	4590

$* * *p < 1\%, * * p < 5\%, *p < 10\%$. Each observation is a college-year. Standard errors, in parenthesis, are clustered at the county-level. All regressions include time fixed effects. Small Disaster consist of counties with per capita property damage of \$1-\$10 per capita in a year; "Medium Disasters" have per capita property damage of \$10- \$100; "Large Disasters" have per capita property damage of \$100-\$500, and "Very Large Disasters" have more than \$500 per capita property damage. Counties with less than \$1 in per capita property damage are the omitted category.