THE EFFECTS OF ANTI-PRICE GOUGING LAWS

IN THE WAKE OF A HURRICANE

by

Michael Steven Tarrant

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TABLE OF CONTENTS

TABLE OF CONTENTS - CONTINUED

LIST OF TABLES

LIST OF TABLES – CONTINUED

Table Page

LIST OF FIGURES

ABSTRACT

The southeastern coast of the United States is vulnerable to hurricanes and the destruction they cause. Previous literature has explored hurricanes' impacts on growth in coastal counties of the United States, but not the inherently linked effects of anti-price gouging (APG) laws, which prohibit firms from significantly increasing prices during a declared state of emergency. The relationship between APG laws and economic growth following a hurricane is estimated with a fixed effect model and county-level quarterly wage data for the period 1990-2012. Results suggest that hurricane-stricken counties are worse off in the presence of APG laws, with the most pronounced negative effects in the accommodations industry. The deleterious effects of APG laws, however, are short-lived; affected counties appear to rebound once the laws are no longer in effect. As the first paper to empirically examine the economic effects of APG laws, these results counter common political thinking and provide empirical support of standard economic theory regarding price ceilings.

INTRODUCTION

Hurricanes garner particular attention in the United States, especially since the devastation of Hurricane Katrina in 2005. In their wake, discussion often turns to the potential presence of "price gouging," or pricing by firms in the affected areas at levels higher than is considered "fair."[1] Among the North Atlantic United States, every state but Delaware, Maryland, and New Hampshire has adopted an anti-price gouging (APG) law.[2] These laws generally prohibit firms from significantly increasing prices during a declared state of emergency. While the economic effects of a hurricane strike have been examined, the effects of APG laws have only been discussed theoretically. This thesis exploits the spatial and temporal variation of hurricane strikes and APG laws in the North Atlantic United States to estimate the relationship between APG laws and economic growth.

Standard economic theory predicts that states with APG laws will be worse off if the imposed price ceiling binds. Among the 21 states that border the North Atlantic Basin, 18 passed APG laws between 1979 and 2012. During this period, 75 hurricanes impacted the United States along the North Atlantic Basin. Annual per capita income and quarterly per-worker wages were collected to estimate the relationship between APG laws and growth. In the initial econometric specification, using a fixed effect model and annual per capita income data, the results appear to suggest that APG laws are beneficial to hurricane-stricken counties within states that pass them. These results are spurious,

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[1] This is a normative claim so its merit cannot be judged using economics. Standard economic theory would suggest prices increase due to market forces and not consider whether the increase is fair.
[2] The North Atlantic United States region includes Alabama, Arkansas, Connecticut, Delaware, Florida, Georgia, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Texas, Vermont, and Virginia.

however, due to industry-specific effects, the annual time frame for analysis, and the construction of the income data.

Using a second econometric specification that employs quarterly firm-reported per-worker wages and a fixed effect model that allows for observation of heterogeneous effects across industries, results indicate that hurricane-stricken counties are worse off in the presence of APG laws. Negative effects are pronounced among industries commonly cited for supposed price gouging, such as accommodations, although the detrimental effect generally does not linger beyond the quarter of the declared state of emergency when the laws are in effect. Rather, counties appear to experience a lagged rebound after the declared state of emergency is lifted and the APG law is no longer in effect, suggesting the initial annual results are partially driven by this lagged rebound.

To my knowledge, this is the first paper to empirically examine the economic effects of APG laws. The results counter common political thinking and provide further evidence of standard economic theory regarding price ceilings. While politicians pitch APG laws as beneficial protection to consumers, that conclusion may be incorrect.[3] The deleterious effects of APG laws, however, are short-lived, as affected counties appear to fully rebound once the laws are no longer in effect.

The remainder of this thesis is organized as follows. Chapter 2 presents background information on APG laws and hurricanes, including the link between the two. Chapter 3 explores the economic literature on price controls, including APG laws, natural disasters, and price controls in natural disasters. Chapter 4 discusses the theoretical

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[3] For example, following Hurricane Katrina, acting New Jersey Governor Richard J. Codey said, “Companies that prey on hard-working families through fraudulent practices should feel the full force of the law. Katrina was a devastating hurricane, not a financial windfall for the shameless” (Smothers 2005).

framework for APG laws and hurricanes. Chapter 5 presents annual per capita income data and the empirical methodology used to examine these data, while Chapter 6 discusses results when using annual per capita income data. Chapter 7 presents quarterly per-worker wage data and the corresponding empirical methodology, and Chapter 8 reports quarterly county-level results, including examination of specific industries. The thesis concludes with Chapter 9, which discusses results and limitations of this thesis.

BACKGROUND

Anti-Price Gouging Law Background

Anti-price gouging (APG) laws, which are a form of a price ceiling, have been adopted by 33 states since 1979. These laws prevent prices from rising above a specified level during a declared state of emergency, including natural disasters such as hurricanes. In the absence of APG laws, supply shocks, such as to oil infrastructure following a hurricane, and demand shocks, such as a sudden increase in consumers looking to purchase gas and hotel rooms, cause prices to rise following a natural disaster. APG laws prohibit firms from raising prices in these markets unless the price increase is demonstrably due to an increase in input costs. For example, following a hurricane, it is illegal for a gas station owner to raise prices in response to an increase in consumers purchasing gas, yet the same gas station owner is not prohibited from raising prices if the price from the wholesaler or refinery has increased due to a supply shock, such as from damaged pipelines. This is not true in Missouri, Texas, and Wisconsin, as APG laws in these states do not include "increased cost" provisions (Davis 2008). Therefore, the gas station owner in these states may not increase prices in any circumstance. Table 1 details APG laws by state, and table 2 chronologically lists the passage of each law.

APG laws vary in specifics from state to state, but many prevent prices from rising above "pre-emergency prices," although APG laws in a few states prevent prices from rising beyond a small range, such as 10 percent. This price ceiling applies to broadly defined "general goods and services" for 26 states. APG laws in Illinois, Indiana, Massachusetts, and Vermont only apply to petroleum products, while a few other states have different specifications.[4] Offenders most often face fines of $1,000-$10,000 per violation, although eight states also specify face jail time as a possible penalty (Davis 2008). These penalties only apply, however, for violations when the laws are in effect. APG laws in most states are triggered by a state of emergency declaration by that state's Governor or the U.S. President (Davis 2008).[5] Louisiana's APG law is unique in that it is also triggered when any named tropical storm or hurricane is in or threatening the Gulf of Mexico.

Therefore, in most cases, suppliers can still adjust their prices for sudden increases in demand outside of a declared state of emergency. For example, the gas station owner may raise prices to adjust for an increase in consumers during the tourist season, but not during a declared state of emergency such as during a hurricane. An important distinction is that the law is triggered when the emergency is declared, which does not necessarily correspond to when a natural disaster occurs. A state of emergency is often declared when a state is expecting a hurricane to strike in the next few days. Therefore, the APG law may go into effect slightly before the hurricane strike has actually occurred.

Most APG laws were passed by state legislatures.[6] Iowa, Massachusetts, and Missouri have APG laws that are included in the administrative codes for those states, so these measures were not enacted by state legislatures. All of these APG laws have

[4] Connecticut's law applies to "goods and energy," Idaho's law applies to "food, fuel, pharmaceuticals," and Missouri's law applies to "necessities."

[5] Twenty-five have APG laws triggered by a declared state of emergency. APG laws in Maine, Vermont, and Wisconsin are triggered by "abnormal market disruptions," while Oregon and Pennsylvania's laws are triggered by either a declared state of emergency or "abnormal market disruptions." For the remaining states, Iowa's law is triggered by a "disaster," APG laws in Illinois and Massachusetts are triggered by a "market emergency," and the trigger for Missouri's law is not clearly specified.

[6] State legislatures passed APG laws in 29 of the 33 states with the laws (Davis 2008).

withstood the test of time, as no state has yet repealed the passage of an APG law. Therefore, APG laws are not unpopular measures. One might expect these laws to be repealed if they resulted in unpopular waiting lines, as Barzel suggests would be the case (1974). Davis argues that widespread lines do not develop because of the increased cost provisions in most APG laws, making the laws less stringent and allowing suppliers to ignore the laws in practice (Davis 2008).[7]

Davis further argues that APG laws are passed in ignorance of how markets actually work. The lack of repeals suggests that either the laws have no effect, if the increased cost provisions render laws punch-less popularity measures, or the laws create some benefit that outweighs possible waiting lines. Yet it seems that APG laws are not solely symbolic measures. Davis argues that APG laws are not without effect, finding many examples of prosecution of "gougers" under the laws, as evidenced by fines, settlements, refunds, and reputation costs (Davis 2008). Furthermore, Davis argues that APG laws are not symbolic measures; state legislatures do not always pass APG laws unanimously, and some states have failed to pass APG measures.[8] Some states have later amended their laws to expand their reach, especially in California, Mississippi, New York, North Carolina, and South Carolina. Louisiana also passed an amendment allowing the APG law to be enforced when any named tropical storm or hurricane is threatening or in the Gulf of Mexico.

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[7] There is some evidence to the contrary that lines do indeed develop, especially at gas stations and most notably following Hurricane Katrina. For example, see http://www.washingtonpost.com/wp-dyn/content/article/2005/09/01/AR2005090101072.html and http://www.nytimes.com/2008/09/30/us/30gas.html.

[8] However, voting records reflect that many states do indeed pass APG laws unanimously or very nearly so. This is the case in Alabama (1996), Arkansas (1997), Connecticut (1986), Georgia (1995), Indiana (2002), Kansas (2002), Kentucky (2004), Louisiana (2005), New Jersey (2001), New York (1979), North Carolina (2003), Oklahoma (1999), and South Carolina (2002).

Davis points out that that later amendments to APG laws do not more clearly assign property rights, nor do the laws become more efficient over time (Davis 2008). Rather, it appears passage and amendments of many APG laws have been in response to disasters. This has been more pronounced in the past decade, with many states passing APG laws in 2002 following the 9/11 terrorist attack, and in 2006 in response to Hurricane Katrina the previous year, suggesting that states that more frequently experience seasonal disasters such as hurricanes are more likely to adopt APG laws in response to previous disasters.[9]

The first state to pass an APG law was New York, in response to high heating oil prices in the winter of 1978-1979 (Davis 2008). Since passage of the law, complaints for price gouging in New York have involved tree removal following Hurricane Gloria in 1985; generators, food, and batteries following an ice storm in 1998; ice, generators, home repairs, hotel rooms, and tree cleanup services after a wind storm in 1998; hotel rooms following the 9/11 attacks in 2001; snowplow services after a snowstorm in 2001; hotel rooms following an ice storm in 2003; gas prices after Hurricane Katrina in 2005; and hotel rooms following a flood in 2006. Among other states, complaints generally involve similar goods and services, where the most common complaints concern prices for gas, hotel rooms, and contracted debris cleanup.

Davis claims that some states appear to have adopted APG laws in response to a disaster (2008). These states, marked in table 2, include Florida, which adopted an APG

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[9] Almost every state that has experienced a hurricane strike has passed an APG law. The exceptions in the North Atlantic United States are Delaware, Maryland, and New Hampshire. These states, however, tend to experience fewer hurricanes than many other Atlantic States (for more information on hurricane strikes by state, see http://www.nhc.noaa.gov/paststate.shtml).

law in 1992 in response to Hurricane Andrew; California, following the Northridge earthquake in 1994; Georgia, after widespread flooding in 1994; Alabama, in response to Hurricane Opal in 1995; Arkansas, after large storms in 1997; Oklahoma, following tornados in 1999; and Virginia, in response to Hurricane Isabel in 2003. Although Hurricane Katrina did not strike these states, APG laws were also adopted in 2006 in Pennsylvania, Vermont, and Wisconsin. Other states appear to have adopted APG laws in direct response to the 9/11 terrorist attacks: Idaho, Indiana, Kansas, New Jersey, South Carolina, Tennessee, and West Virginia.

Enforcement of APG laws varies by state. A few states are known to devote many resources to enforce the measure, such as Florida, Georgia, Mississippi, and Missouri.[10] Other states appear to rarely enforce the measure, if it all. For example, neither Louisiana nor Texas pursued any reports of price gouging following Hurricane Katrina (Davis 2008).[11] Instances of price gouging are generally reported through consumer hotlines, where citizens can report suspected price gouging to the office of the Attorney General. The Attorney General decides whether to pursue charges against the alleged gougers. Some states, such as Florida, are known to investigate many of these claims and often level charges. Other states, such as Louisiana, especially following Hurricane Katrina, do not have a reputation for following up on consumers' claims of price gouging. Differences in enforcement levels of APG laws, which could be due to differences among

[10] In Florida, the APG law was especially enforced under Attorney General Charlie Crist, who encouraged consumers to report instances of price gouging and then later used his record of strong enforcement of APG laws to successfully run for governor. In Missouri, Attorney General Jay Nixon followed a similar approach.

[11] Louisiana's lack of enforcement following Hurricane Katrina could be due to great strain on available resources.

states or Attorneys General, complicate analysis. A particular state may have passed the law but is not known to enforce it, effectively rendering the law symbolic.

Hurricanes and their Relationship to APG Laws

APG laws require a disaster, or at least an "abnormal market disruption," in order to go into effect. This disaster can come in many forms – earthquakes, floods, ice storms, or a terrorist attack. The disaster most common in the North Atlantic United States is a hurricane. Hurricanes that develop in the North Atlantic Basin can strike anywhere along the eastern and southeastern United States coastline, from Texas to Maine. These states' commonality in hurricanes presents a good natural experiment to examine the economic effects of APG laws; a hurricane strike triggers the APG law in the impacted state. States passed APG laws at different times since 1979, allowing the opportunity to examine outcomes within and between states with and without APG laws when hit by a hurricane.

Hurricanes have generated much fascination, especially following Hurricane Katrina in 2005. Ranging in intensity by diameter and wind speed, these large storm systems can develop in the North Atlantic Basin and, spinning counterclockwise, travel to the U.S. coast, making landfall and progressing inland until dissipating or spinning back off into the ocean. Hurricanes in the North Atlantic Basic occur seasonally, usually from May through November. To be classified as a hurricane, the storm must exhibit wind speeds great enough to fall into one of the Saffir-Simpson scale categories, which range from 1 to 5.[12] A hurricane consists of a low pressure center (the "eye"), the surrounding

[12] The Saffir-Simpson scale categories, which are determined by wind speed, in kilometers per hour, are (1) 119-153, (2) 154-177, (3) 178-209, (4) 210-249, and (5) 250 and higher.

"eyewall," where the highest speed winds can be found, and the rest of the storm, where wind speeds slowly and unevenly dissipate further away from the eyewall. Hurricanes can also generate damaging storm surges, or the temporary rise in coastal sea levels created by the low-pressure hurricane eye. When a hurricane makes landfall, these strong winds, heavy rainfall, and storm surges can inflict extensive physical damages.

Damages from a hurricane depend on wind speed and storm surge, but also on the hurricane's size. Yet a storm's size is not necessarily determined only by top wind speeds and therefore, its Saffir-Simpson categorization. Strobl states that hurricane-strength storms are generally 500 km wide yet can vary considerably (2011). A hurricane with very high wind speeds and a rather small diameter may inflict intense damages, but the damages may occur only in a very localized area. Another hurricane with lower wind speeds and a much larger diameter may inflict greater overall damages due to a wider area of impact.[13] The impact of a hurricane also depends on the characteristics of the area affected. An area with high population or large physical capital stock, such as New Orleans or New York City, may suffer much larger damages than an area with lower population or fewer resources. In either case, the hurricane creates a negative impact through destruction of property and disruption in production (Strobl 2011).

While hurricanes are more seasonally predictable than other disasters such as earthquakes, the exact landfall and path of a hurricane is difficult to accurately predict and even record following a storm. The National Oceanic and Atmospheric Administration (NOAA) produces "best track" hurricane data, which records wind speed

[13] Hurricane Sandy in 2012 is a good example of this latter case. This storm, while was a Category 1 when off the coast of New Jersey, was no longer classified as a tropical cyclone when it made landfall, yet had very large impact due to its tremendous size (Blake et al., 2013).

and minimum pressure in the hurricane eye, along with the eye's location. While these data include some measurements for storm size, these measurements are imprecise and are only available after 2003.[14] Therefore, plotting the exact path of a hurricane and matching its incidence to a particular area is difficult, as measurements are scarce and alternative approaches, such as using satellite images, are rough estimates and available only in later years.

Tables 3 and 4 list the hurricane strikes included in this thesis, both as individual storms and overall by year. It is important to note that this list differs from all hurricanes during this time frame, or even those that made landfall in the North Atlantic United States from 1970-2012. Rather, these tables list the states and number of counties matched to the named storm whose eye location was within 200 km. There may be more counties impacted by a particular storm, but identifying those counties is imprecise.[15] Therefore, this thesis takes a conservative approach and only includes counties whose geographical centers are within 200 km of the location of the eye of the hurricane.

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[14] These measurements include distance from eye at which 34 knots, 50 knots, and 65 knots wind speeds are recorded.

[15] Hurricane Katrina in 2005 is a good example. Table 3 shows that only nine counties in three states were impacted by this hurricane, which appears to be rather low estimate.

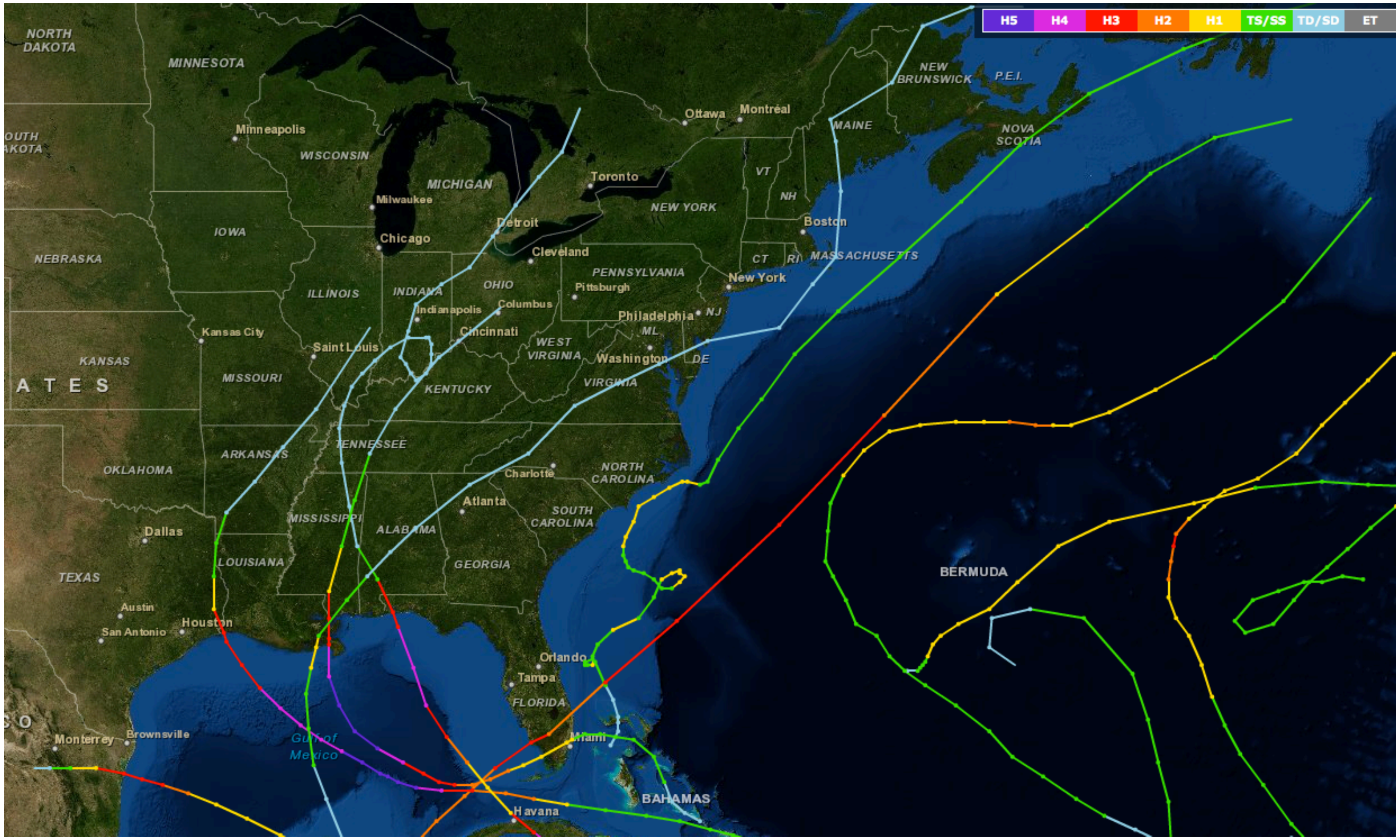

Figure 1. Tracks and Strengths of Hurricanes in the North Atlantic Basin in 2005

Notes: This figure was constructed using the ICAT Damage Estimator (http://www.icatdamageestimator.com/viewdata), which uses Google Maps API to plot storm track data from the NOAA's HURDAT2 dataset. The color of the hurricane track denotes the Saffir-Simpson category of the storm, where yellow is a Category 1 storm and purple is a Category 5 storm. The Gulf of Mexico harbored three Category 5 storms in 2005, although all three dropped to Category 3 storms before making landfall.

Table 1. Anti-Price Gouging Laws by State, 1979-2012

State	Passage Year	Fines	Goods Covered	Triggering Event	Criminal Penalties	Ceiling
AL	1996	$1,000/violation; $25,000 max fine in 24 hours	General goods and services	Gov declared SOE	None	25% above pre-emergency prices
AR	1997	≤$10,000/violation	General goods and services	Pres, Gov, or locally declared SOE	Provided in law	10% above pre-emergency prices
CA	1994	$10,000 or less	General goods and services	Pres, Gov, or locally declared SOE	≤1 year in prison	10% above pre-emergency prices
CT	1986	$1,000 or less	Goods and energy	Gov declared SOE	≤1 year in prison	Pre-emergency prices
FL	1992	Unspecified	General goods and services	Gov declared SOE	None	Pre-emergency prices
GA	1995	≤$10,000/ transaction	General goods and services	Gov declared SOE	None	Pre-emergency prices
HI	1983	Unspecified	General goods and services	Gov declared SOE / severe weather warning	None	Pre-emergency prices
IA	1993	Unspecified	General goods and services	"Disaster"	None	Pre-emergency prices
ID	2002	Unspecified	Food, fuel, pharmaceuticals, water	Gov or Pres declared SOE	None	Pre-emergency prices
IL	2005	Unspecified	Petroleum	"Market emergency"	None	Pre-emergency prices
IN	2002	≤$1,000/ transaction	Fuel	Gov declared SOE	None	Pre-emergency prices
KS	2002	Unspecified	General goods and services	Gov or Pres declared SOE	None	25% above pre-emergency prices
KY	2004	≤$5,000 for first violation, ≤$10,000 afterwards	General goods and services	Gov or Pres declared SOE	None	Pre-emergency prices

Table 1 (continued). Anti-price Gouging Laws by State, 1979-2012

State	Passage Year	Fines	Goods Covered	Triggering Event	Criminal Penalties	Ceiling
LA	1993	Provided in law	General goods and services	Gov/parish pres declared SOE or hurricane threatening in Gulf	Provided in law	Pre-emergency prices
MA	1990	Unspecified	Petroleum	"Market emergency"	None	Pre-emergency prices
ME	2006	Provided in law	General goods and services	Gov declared "abnormal market disruption"	None	15% above pre-emergency prices
MO	1994	Unspecified	"Necessities"	Not clearly specified	None	"Excessive" prices
MS	1986	≤$5,000	General goods and services	SOE (no declaration required)	0-5 years in prison	Pre-emergency prices
NC	2003	Unspecified	General goods and services	Gov declared SOE	None	"Unreasonably excessive" prices
NJ	2001	Unspecified	General goods and services	Pres, Gov, or locally declared SOE	None	10% above pre-emergency prices
NY	1979	≤$10,000 and restitution	General goods and services	Gov declared SOE	None	Pre-emergency prices
OK	1999	Unspecified	General goods and services	Gov or Pres declared SOE	None	10% above pre-emergency prices
OR	2007	Unspecified	General goods and services	Gov declared SOE	None	15% above pre-emergency prices
PA	2006	≤$10,000/violation plus restitution	General goods and services	Gov declared "abnormal market disruption" or SOE	None	Pre-emergency prices

Table 1 (continued). Anti-price Gouging Laws by State, 1979-2012

State	Passage Year	Fines	Goods Covered	Triggering Event	Criminal Penalties	Ceiling
RI	2012	≤$500	General goods and services	Gov declared SOE	≤90 days in prison	Pre-emergency prices
SC	2002	≤$1,000	General goods and services	Gov or Pres declared SOE	≤30 days in prison	Pre-emergency prices
TN	2002	Unspecified	General goods and services	Gov or Pres declared SOE	None	Pre-emergency prices
TX	1995	Unspecified	General goods and services	Gov declared SOE	None	"Exorbitant or excessive price"
UT	2005	≤$1,000/violation or $10,000 total	General goods and services	Gov or Pres declared SOE	None	Pre-emergency prices
VA	2004	Unspecified	General goods and services	Gov or Pres declared SOE	None	Pre-emergency prices
VT	2006	Unspecified	"Petroleum or heating fuel product"	"Abnormal disruption of any market for petroleum products or heating fuel products"	None	Pre-emergency prices
WI	2006	≤$10,000	General goods and services	Gov declared "abnormal economic disruption"	None	"Excessive prices"
WV	2002	≤$1,000	General goods and services	Gov or Pres declared SOE	≤1 year in prison	10% above pre-emergency prices

Gov = Governor, Pres = President, SOE = state of emergency, NA = information not available.

Note: This table was originally compiled by Davis (2008) using legislative records, and has been updated using lists compiled by Benavides (2006) and Giberson (2012).

Table 2. Anti-Price Gouging Law Passages, 1979-2012

State	Passage Year
New York	1979
Hawaii	1983
Connecticut	1986
Mississippi	1986
Massachusetts	1990
Florida*	1992
Iowa	1993
Louisiana	1993
California	1994
District of Columbia	1994
Missouri	1994
Georgia	1995
Texas	1995
Alabama*	1996
Arkansas	1997
Oklahoma	1999
New Jersey***	2001
Idaho***	2002
Indiana***	2002
Kansas***	2002
South Carolina***	2002
Tennessee***	2002
West Virginia***	2002
North Carolina	2003
Kentucky	2004
Virginia*	2004
Illinois	2005
Utah	2005
Maine	2006
Pennsylvania**	2006
Vermont**	2006
Wisconsin**	2006
Oregon	2007
Rhode Island	2012

* = APG law adopted in response to previous direct hurricane
** = APG law adopted in response to Hurricane Katrina
*** = APG law adopted in response to 9/11

Notes: This table is based on information compiled by Davis (2008) and Giberson (2012). The adoption of an APG law due to previous direct hurricane or Hurricane Katrina was determined through case studies provided in Davis (2008).

Table 3. Individual Hurricane Strikes in Dataset, 1970-2012

Year	Category Storm	Storm Name	State(s) Impacted	Counties Impacted
1970	3	CELIA	TX	4
1971	1	FERN	TX	3
1971	1	EDITH	LA, TX	5
1971	1	GINGER	NC	2
1972	1	AGNES	FL	3
1974	4	CARMEN	LA	5
1975	3	ELOISE	FL	2
1976	2	BELLE	NC, NJ	6
1977	1	BABE	LA	2
1979	1	BOB	LA	2
1979	1	DAVID	FL, GA, SC	15
1979	4	FREDERIC	AL, LA, MS	7
1980	3	ALLEN	TX	6
1983	1	ALICIA	TX	4
1983	1	BARRY	TX	2
1984	1	DIANA	FL, GA, NC, SC	11
1985	1	BOB	FL, GA, SC	6
1985	1	DANNY	LA	5
1985	2	ELENA	FL, MS	9
1985	2	GLORIA	CT, DE, MA, MD, NC, NY	9
1985	1	JUAN	LA	3
1985	2	KATE	FL, GA	5
1986	1	BONNIE	LA, TX	5
1986	1	CHARLEY	NC, VA	8
1987	1	FLOYD	FL	2
1988	1	FLORENCE	LA	2
1989	1	CHANTAL	LA, TX	3
1989	4	HUGO	SC	4
1989	1	JERRY	TX	2
1991	2	BOB	NC, NY, RI	8
1992	4	ANDREW	FL, LA	14
1993	3	EMILY	NC	5
1994	1	GORDON	NC	2
1995	1	ERIN	AL, FL	11
1995	3	OPAL	AL, LA	2

Table 3 (continued). Individual Hurricane Strikes in Dataset, 1970-2012

Year	Category Storm	Storm Name	State(s) Impacted	Counties Impacted
1996	2	BERTHA	NC, SC	7
1996	1	EDOUARD	MA	1
1996	1	FRAN	NC	2
1997	1	DANNY	AL, LA, MS	7
1998	3	BONNIE	NC, SC	11
1998	1	EARL	FL, LA	7
1998	2	GEORGES	FL, MS	6
1999	4	BRET	TX	4
1999	2	DENNIS	NC	2
1999	1	FLOYD	NC	2
1999	1	IRENE	FL, GA, NC, SC	18
2000	1	GORDON	FL	3
2002	3	LILI	LA	4
2003	1	CLAUDETTE	TX	5
2003	1	ERIKA	TX	2
2003	2	ISABEL	NC	2
2004	1	ALEX	NC	6
2004	4	CHARLEY	FL, SC	11
2004	1	GASTON	SC	1
2004	2	FRANCES	FL	4
2004	3	IVAN	AL, LA	6
2004	1	JEANNE	FL	1
2005	1	CINDY	LA	3
2005	4	DENNIS	FL	3
2005	3	EMILY	TX	3
2005	1	KATRINA	FL, LA, MS	9
2005	1	OPHELIA	FL, NC, SC	9
2005	3	RITA	LA, TX	6
2005	2	WILMA	FL	2
2007	1	HUMBERTO	LA, TX	4
2007	1	NOEL	MA, ME	3
2008	1	DOLLY	TX	3
2008	2	GUSTAV	LA	5
2008	2	IKE	TX	4
2008	1	KYLE	ME	2

Table 3 (continued). Individual Hurricane Strikes in Dataset, 1970-2012

Year	Category Storm	Storm Name	State(s) Impacted	Counties Impacted
2009	1	IDA	LA	2
2010	2	EARL	NC	1
2011	1	IRENE	MD, NC	10
2012	1	ISAAC	LA	5
2012	1	SANDY	NJ	3

Notes: The above list was constructed using 200 km radius to match hurricane eye measurements to counties using the *geonear* package in STATA. The number of counties matched to a particular storm was then summed to calculate total number of counties impacted. NOAA's HURDAT2 provides a storm's eye location (in latitude and longitude measurements) every six hours, whether the storm is far from the coast or has already made landfall. These locations were compared to county geographic centers (also in latitude and longitude) provided by the U.S. Census 2013 Gazetteer Files. Storm eye locations with corresponding storm characteristics (maximum wind speed, minimum air pressure, Saffir-Simpson categorization) were matched to counties with latitude and longitude measurements within 200 km. This process allowed for multiple counties to be matched to one particular eye observation, although a county where only 10% is impacted by the storm is assigned the same value as another county where 100% is impacted as long as both have geographic centers with 200 km of the storm's eye. Furthermore, this process does not allow for differences in storm radius. Therefore, storms with radii smaller than 200 km are matched to counties not actually impacted, while storms with radii greater than 200 km were not matched to counties that were in fact impacted by the storm.

Table 4. Hurricane Strikes in Dataset by Year, 1970-2012

Year	Storm Name(s)	State(s) Impacted	Counties Impacted
1970	CELIA	TX	4
1971	FERN, EDITH, GINGER	LA, NC, TX	10
1972	AGNES	FL	3
1973			0
1974	CARMEN	LA	5
1975	ELOISE	FL	2
1976	BELLE	NC, NJ	6
1977	BABE	LA	2
1978			0
1979	BOB, DAVID, FREDERIC	AL, FL, LA, GA, MS, SC	24
1980	ALLEN	TX	6
1981			0
1982			0
1983	ALICIA, BARRY	TX	6
1984	DIANA	FL, GA, NC, SC	11
1985	BOB, DANNY, ELENA, GLORIA, JUAN, KATE	CT, DE, FL, GA, LA, MA, MD, MS, NC, NY SC	37
1986	BONNIE	LA, NC, TX, VA	13
1987	FLOYD	FL	2
1988	FLORENCE	LA	1
1989	CHANTAL, HUGO, JERRY	LA, SC, TX	9
1990			0
1991	BOB	NC, NY, RI	8
1992	ANDREW	FL, LA	14
1993	EMILY	NC	5
1994	GORDON	NC	2
1995	ERIN, OPAL	AL, FL, LA	13
1996	BERTHA, EDOUARD, FRAN	MA, NC, SC	10
1997	DANNY	AL, LA, MS	7
1998	BONNIE, EARL, GEORGES	FL, LA, MS, NC, SC	24
1999	BRET, DENNIS, FLOYD, IRENE	FL, GA, NC, SC, TX	26
2000	GORDON	FL	3
2001			0
2002	LILI	LA	4
2003	CLAUDETTE, ERIKA, ISABEL	NC, TX	9

Table 4 (continued). Hurricane Strikes in Dataset by Year, 1970-2012

Year	Storm Name(s)	State(s) Impacted	Counties Impacted
2004	ALEX, CHARLEY, GASTON, FRANCES, IVAN, JEANNE	AL, FL, LA, NC, SC	29
2005	CINDY, DENNIS, EMILY, KATRINA, OPHELIA, RITA, WILMA	LA, LA, MS, NC, SC, TX	35
2006			0
2007	HUMBERTO, NOEL	LA, MA, ME, TX	7
2008	DOLLY, GUSTAV, IKE, KYLE	LA, ME, TX	14
2009	IDA	LA	2
2010	EARL	NC	1
2011	IRENE	MD, NC	10
2012	ISAAC, SANDY	LA, NJ	8

Notes: The above list was constructed using a 200 km radius to match eye measurements to counties using the *geonear* package in STATA. The number of counties matched to a particular storm was then summed to calculate total number of counties impacted. NOAA's HURDAT2 provides a storm's eye location (in latitude and longitude measurements) every six hours, whether the storm is far from the coast or has already made landfall. These locations were compared to county geographic centers (also in latitude and longitude) provided by the U.S. Census 2013 Gazetteer Files. Storm eye locations with corresponding storm characteristics (maximum wind speed, minimum air pressure, Saffir-Simpson categorization) were matched to counties with latitude and longitude measurements within 200 km. This process allowed for multiple counties to be matched to one particular eye observation, although a county where only 10% is impacted by the storm is assigned the same value as another county where 100% is impacted as long as both have geographic centers with 200 km of the storm's eye. Furthermore, this process does not allow for differences in storm radius. Therefore, storms with radii smaller than 200 km are matched to counties not actually impacted, while storms with radii greater than 200 km were not matched to counties that were in fact impacted by the storm.

LITERATURE

Anti-price gouging (APG) laws are predominantly in place in states that frequently experience natural disasters (Davis 2008). Politicians usually propose APG laws in support of constituent consumers, arguing economic welfare is greater under these laws than otherwise (Culpepper and Block 2008). Natural disasters not only create demand and supply shocks for goods and services, but also impact labor markets and growth (Strobl 2012). Therefore, while APG laws are inherently linked to natural disasters, the previous literature has generally focused on only one of these areas: price controls or natural disasters.

Anti-Price Gouging Laws

APG laws are a form of price control. Economic literature specific to APG laws is limited, while there is more work on price controls in general. The literature on price controls is primarily theoretical, yet varies in what theoretical results are considered. This section is divided by papers concerned with (1) baseline theory, (2) theoretical reasons for price controls, and (3) theoretical and empirical results of price controls.

APG laws apply price ceilings to markets for goods and services in times of emergency, preventing the price from rising in response to shocks to supply or demand.[16] A price ceiling creates a distortion in the market that can result in different outcomes, including shortages, waiting in line, adjustments in quality, or black markets.

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[16] Examples of supply shocks include the disruption in gasoline markets following Hurricane Katrina due to damaged oil refineries, or the decrease in available hotel rooms after destruction of coastal hotels. Demand shocks are often the result of increased demand from consumers for generators, ice, hotel rooms and cleanup services following a hurricane.

With perfect enforcement of a price ceiling, a shortage will occur and markets must equilibrate through adjustments along non-price margins. Alternatively, Barzel (1974) discusses the concept of rationing by waiting, where the total price paid by consumers is not only the fixed dollar price, but also a waiting cost from standing in line to obtain the desired good or service. Under this scenario, while the market clearing quantity decreases, there is no shortage in the market, as the effective market price includes waiting time.

Barzel (1997) also proposes that suppliers compensate for price controls through adjustments in quality. Gasoline retailers during the price controls of the 1970s provided lower octane gasoline, adjusted service hours, and offered packaged services.[17] Hirshleifer, Glazer, and Hirshleifer (2005) discuss the possibility of black markets or violence to evade price controls. Lott and Roberts (1989) argue that the one-sided enforcement policies most states use with APG laws, where only consumers report suspected price gouging, are effective deterrents to black markets, even when both consumer and supplier may benefit from circumventing the APG law.

Deacon and Sonstelie (1989) examine Barzel's rationing by waiting model and conclude that deadweight losses arise from price ceilings due to waiting. Fleck (2014) argues, however, that in instances where there are positive externalities from consumption of the goods affected, APG laws create the expectation of future shortages,

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[17] Some gasoline retailers offered a full tank of gas at a different price than gas would be otherwise if the consumer also purchased lubrication services.

which encourages rational consumers towards socially beneficial preparedness in times of acute scarcity.[18]

If APG laws and other price controls decrease welfare in most cases, why are they so common? Agénor and Asilis (1997) argue that price controls are a political device employed to garner votes during election season and are not strictly enforced outside of the election season. Davis (2008) presents the idea that APG laws are primarily enacted in response to previous natural disasters yet without understanding of market behavior. Rather, as Culpepper and Block (2008) discuss, politicians pass APG laws because they believe government can more effectively allocate resources than the price system in the wake of a natural disaster.

Regardless of the motivations for enacting price controls, the theoretical models discussed above predict welfare losses from these market distortions. Bulow and Klemperer (2012), following an approach similar to that of Barzel, argue that price controls reduce consumer surplus and lead to rent-seeking behavior. Carden (2009) discusses a reduction in investment and provision of goods and services following natural disasters that is due to APG policy and general distrust of allocation by the price system.

Empirical studies are few. Deacon and Sonstelie (1985), after surveying California motorists in 1980 that are faced with waiting in line for low-priced gasoline or purchasing more expensive gasoline without waiting, estimate individuals' value of time to be similar to individuals' after-tax wages. Davis and Kilian (2011) estimate the welfare loss from price controls in the natural gas market during the period 1954-1989 to be $3.6

[18] Fleck mentions flu vaccines as an example of when private consumption has external benefits, as well as the use of chainsaws to clear fallen trees from roadways following a natural disaster.

billion annually, partially due to some consumers being locked out of the market altogether. Montgomery et al. (2007) conclude that proposed federal APG laws would have increased economic damages by an estimated $1.5-2.9 billion during the two months following Hurricanes Katrina and Rita in 2005.

Distrust of the price system is related to the concept of a “just price.” Samuels and Puro (1991) examine responses to Hurricane Hugo and the 1989 earthquake in San Francisco, California, and argue that goods are provided without government direction following a natural disaster. Even without price controls, Samuels and Puro argue that prices do not rise because they are either rigid or firms fear negative reactions from consumers to increased prices (1991). Firms that do raise their prices are motivated by short run returns, rather than by a long run outlook that also considers consumers’ perceptions of the firm.

Therefore, “consumer anger fear” is important to a supplier’s behavior. Rotemberg (2011) finds that a firm’s fear of backlash from consumers causes firms to avoid price increases following a natural disaster, regardless of whether an APG law is in effect. Firms consider consumer anger when determining profit-maximizing behavior. Firms that do not raise prices following a natural disaster determine that the payoff of future positive perceptions by consumers outweighs the foregone short-run gains from increased prices. Davis discusses these “reputation costs,” and their importance for local retailers, as well as nationally recognized chains (2008).

Profit maximizing behavior that accounts for possible consumer anger is evidenced by an empirical study by Neilson (2009). Following Hurricane Rita, Neilson hand-collected retail gasoline price data in Texas, searching for evidence of price gouging in response to the hurricane, evidenced by a widening difference between wholesale and retail prices. Neilson argues that a profit-maximizing firm may price gouge if the perceived benefit outweighs the loss due to negative reactions from angry consumers, but an altruistic firm will be indistinguishable from one that determines the losses from consumer anger are greater than the short run benefits from price gouging. Neilson finds no evidence of price gouging following the hurricane, but rather instances of prices decreasing and gasoline retailers running out of gas. This is not sufficient evidence to show that firms were responding solely to possible repercussions of consumer anger. APG laws in Texas were adopted in 1995 and were in effect following Hurricane Rita. Therefore, firms may have also been responding to the expected penalties for price gouging under Texas' APG law.

Natural Disasters

Economic literature on natural disasters is predominantly focused on growth and labor market outcomes. Before Hurricane Katrina, the natural disaster literature primarily examined the effects of disasters on economic development and differences in outcomes among developed and developing countries. Since Hurricane Katrina, interest in the effects of natural disasters expanded to labor market and political realms as well. Therefore, this section is divided by papers concerned with (1) development, (2) growth, (3) labor market outcomes, and (4) behavior, regarding those who experience natural disasters and the political actors involved.

Natural disasters shock an economy, yet these shocks may affect areas differently depending on the development within that area. Toya and Skidmore (2007) propose that developed countries devote more resources to safety, partially insulating them from shocks such as natural disasters. Their paper shows that countries with indicators that are considered positive in most economic contexts, such as better institutions and higher income and education levels, are not as negatively affected by natural disasters as other less developed countries. Kahn (2005) lends support to the role of institutions in buffering natural disaster shocks.

Income inequality also affects the impact of a natural disaster. Anbarci, Escaleras, and Register (2005) show that increased death tolls from natural disasters are related to greater income inequality and lower per capita income, as well as institutional failures such as lack of building codes and zoning enforcement.

Natural disaster shocks also affect growth, both in directly-hit and surrounding areas. Strobl (2011), through the use of a custom hurricane destruction index, finds that hurricane strikes negatively affect growth in southeastern U.S. counties directly hit by the hurricane, but long run effects at the state level are negligible.[19] Strobl (2012) also finds that hurricane strikes decrease output in Central American and Caribbean countries, although the effects of natural disasters vary with the type of disaster experienced. Fomby, Ikeda, and Loayza (2013) show that, while the effects of natural disasters on growth are larger in developing countries, some disasters have no effect or even a

[19] The custom hurricane destruction index used by Strobl (2011), different from the more common use of an incidence dummy, is constructed using population weights, total damages from the storm, and maximum wind speeds by census tract, calculated using the HAZUS software produced by Federal Emergency Management Agency (FEMA). Updating the HAZUS database to include Category 1 and 2 hurricanes as well as storms since 2010 is prohibitively costly and documentation uploaded by Strobl (2011) to *The Review of Economics and Statistics* website for purposes of replication is incomplete. Requests to Strobl for clarification were unanswered, so attempts to reconstruct the custom index for the purposes of this thesis were unsuccessful.

positive effect on growth.[20] Hsiang and Jina (2014) find that the effect of a hurricane is felt over the long run, as both rich and poor countries experience a decline in national incomes that does not recover for 20 years following the natural disaster.

Some areas commonly affected by natural disasters undertake preventative measures beyond enacting APG laws. Skidmore and Toya (2002) find that natural disasters are correlated with higher human capital accumulation, total factor productivity, and economic growth, and countries that frequently experience natural disasters invest heavily in physical capital stock and the adoption of new technologies. This investment is countered by damages to human capital from natural disasters, as shown by Baez, de la Fuente, and Santos (2010). Socioeconomic groups are unequally affected by damages to human capital. They argue the destruction of goods, services, and infrastructure increase the marginal costs of human capital accumulation, which adversely affects poorer groups.

Natural disasters shock the labor market as well, changing conditions for workers in both the disaster-stricken and neighboring areas. Belasen and Polachek (2009) show that, due to worker migration from hurricane-stricken to neighboring counties, per-worker wages increase and employment decreases in Florida counties directly hit by a hurricane, while neighboring counties experience a decrease in earnings but no change in employment levels. Belasen and Polachek (2008) also demonstrate that this effect on earnings and employment is greater after high intensity hurricanes.

Brown, Mason, and Tiller (2006) include states beyond Florida, examining the effect of Hurricane Katrina on employment in the southeastern United States. These

[20] Fomby, Ikeda, and Loayza (2013) find that while droughts and storms have a negative effect on growth, earthquakes have no statistically significant effect and floods have a positive effect due to improved soil quality leading to better agricultural output in the future.

authors find that the decrease in employment was strongest in Louisiana and Mississippi. Although the negative effect was temporary, employment remained depressed. A study by Coughlin (2007) supports the conclusion that the unemployment rate increased more in Louisiana and Mississippi than other areas hit by Hurricane Katrina. Cahoon et al. (2006) find that employment dropped more sharply among Hurricane Katrina evacuees who returned home than among those that did not. Yet, according to Vigdor (2007), the underemployed poor in New Orleans, Louisiana, were not worse off than more wealthy groups because of their initial residence in a depressed region, but rather their own personal characteristics.

Labor market effects vary with type of natural disaster and location of the labor market. Ewing, Kruse, and Thompson (2009) examine the labor market in Oklahoma City, Oklahoma, following a tornado in 1999, and find the negative shock to the labor market was short-lived. Strobl and Walsh (2009), using the same custom hurricane disaster index in other Strobl papers, find that a hurricane strike significantly increases employment yet decreases average monthly wages in the construction industry with efforts to rebuild lost physical capital, with this effect lasting for multiple quarters.

A natural disaster shock affects economic development, growth, and the labor market, as well as the behavior of those directly involved in the disaster. Political actors, frequently discussed in popular news, play an important role in natural disasters due to their effect on legislation and disaster relief. Healy and Malhotra (2009) find that disaster impact and aid efforts are large partially because voters reward the incumbent party for delivering relief spending, but not for investing in disaster preparedness. Chamlee-Wright and Storr (2010) conducted interviews with those involved in rebuilding efforts in New

Orleans, Louisiana, after Hurricane Katrina and found that while these agents were not unrealistically positive in their expectations of government action, they still expected government action in the wake of a natural disaster.

Government action comes at a cost though. Shughart (2006) examines actions of politicians and governmental relief agencies such as the Federal Emergency Management Agency (FEMA) following Hurricane Katrina and argues the expectation of adept behavior by the government following a disaster is unrealistic. This observation is bolstered by Lesson and Sobel (2008), who point out that notoriously corrupt regions, such as the Gulf Coast, are in part corrupt because of greater flows of disaster relief, creating more opportunities for criminal activity by those in power. An earlier paper by Sobel and Leeson (2006) argues that the structure of government and governmental agencies after a natural disaster creates the opportunity for manipulation of resources.

A natural disaster also affects the general population in the stricken area, especially with regard to their perceptions of risk. Cameron and Shah (2013), by surveying those who experienced floods or earthquakes in Indonesia, argue that the experience of natural disaster causes individuals to take fewer risks, due to an increased expectation of future risk. Eckel, El-Gamal, and Wilson (2009) use surveys of women who were evacuated following Hurricane Katrina, and find that women who experienced the disaster were more risk loving than comparison groups. This discrepancy could be due to the differences in individuals surveyed or the type of natural disaster they experienced.

Natural disasters also affect fertility decisions and the health of the resulting children. Using storm advisories for Atlantic and Gulf coast counties, Evans et al. (2010)

find that as the severity of a storm advisory increases from least severe to most severe, fertility decreases monotonically. Currie and Rossin-Slater (2013) argue that exposure to a hurricane during pregnancy increases the probability of abnormal conditions in the newborn, although these authors only examine eight storms in Texas between 1996 and 2008 that caused more than $10 million in damages. Fuller (2014) finds lower math and reading scores among children who experienced prenatal exposure to a disaster in North Carolina than children who did not. Fuller notes this effect is more pronounced for math scores and among black mothers.

Price Controls in Natural Disasters

Natural disasters and APG laws are directly related due to the nature of APG laws, which are enforced during declared a state of emergency following a disaster, yet what qualifies as an emergency in order to invoke an APG law is often vague and varies from state to state (Davis 2008). APG laws also appear to be adopted in reaction to a natural disaster, as proposed protection for consumers from exorbitant prices in the wake of future natural disasters (Davis 2008).

However effective APG laws are as a political tool, they may not be necessary to prevent prices from rising following a natural disaster. Cavallo, Cavallo, and Rigobon (2013) find that in Chile and Japan, two countries without APG laws, prices remained steady following earthquakes due to firms' fear of consumer anger. Rather, product availability fell immediately and then recovered slowly, due to the supply shock sustained. This result supports papers discussed earlier by Samuels and Puro (1991) and

Rotemberg (2011) that suggest firms refrain from increasing prices following a natural disaster due to potential backlash from angered consumers.

APG laws and other price controls affect goods and services markets, as do natural disasters, although the length and magnitude of their effects may differ. Natural disasters create a temporary shock in the market, lasting as long as the disruption in supply or increase in demand sustains, and in magnitude corresponding to the market shock (Davis 2008). The effects of natural disasters extend beyond markets for goods and services, as shocks from natural disasters are also felt in labor markets and by growth in the economy as whole. APG laws, while only in effect immediately following a natural disaster or some other declared state of emergency, vary in length of enforcement, which can extend beyond the temporary market shock due to the disaster (Davis 2008).

THEORY

Anti-Price Gouging Laws

Standard economic theory suggests that price ceilings result in shortages. Anti-price gouging (APG) laws are a form of price ceiling, specifically designed to limit price increases during a declared state of emergency. When a shift occurs in the market, whether through a contraction of supply, an increase in demand, or both, a price ceiling prevents the pecuniary price of the good in question from adjusting to this shift. The difference in quantity demanded and quantity supplied at the ceiling price is the shortage.

Figure 2 presents a contraction of supply. The market originally clears at P^* and Q^*. Supply contracts following a hurricane strike, from S_0 to S_1. In the absence of a price ceiling, price would increase from P^* to P_1, and firms would supply Q_1. Yet, if an APG law imposes a price ceiling at pre-emergency prices, the pecuniary price is held constant at P_c. Due to the contraction in supply, firms are only willing to supply Q_2. The shortage is represented by the difference between Q^* and Q_2.

There are at least three possible outcomes from APG laws besides a shortage. First, Barzel (1974) suggests rather than a shortage in the market, the total price paid will increase, from P_c to P_2. The APG law prevents the pecuniary price from rising, but the total price paid increases due to consumers waiting in line to obtain the good or service (Barzel 1974). In this case, there is no shortage in the market, but rather the market clears at P_2 and Q_2. Consumer surplus is represented by triangle ABC and producer surplus is represented by triangle FGI, while rectangle BCFG is lost to waiting in line. Therefore, the deadweight loss is rectangle BCFG and triangle CGE, and both consumers and producers are worse off under the price control.[21]

Second, goods and services provided may be altered through adjustments in margins other than price, such as quality, bundling of other goods or services, or hours of operation (Barzel 1997). Barzel (1997) discusses adjustments made by gasoline stations under price controls in the 1970s, such as lower octane gasoline, exclusion of anti-knock additives, decreased hours of service and so forth. Third, black markets or violence may develop to avoid price controls (Hirshleifer et al. 2005).[22]

The latter two outcomes are difficult to capture with common economic data, yet an increase in total price paid can potentially be captured in income or wage data. While a hurricane strike destroys capital and consumer goods, decreasing firm owners' revenue, in the absence of an APG law the owner can cushion losses by charging more for available goods and services. When an APG law is in effect and prices are held constant, a firm owner cannot mitigate the losses from the hurricane so easily, leading to a larger decrease in firm revenue. As revenue is used to pay employees, employees in counties with APG laws could see a decrease in their wages. Therefore, hurricane-stricken counties with APG laws are predicted to experience lower growth of income than counties without APG laws. APG laws that define jail time as a possible penalty, do not

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[21] Some consumers may benefit from price controls, as determined by relative magnitudes of income and price elasticities for the goods in question. For example, poor consumers benefit from price controls covering goods with low income elasticies and high price elasticies. See Davis (2008) and Barzel (1974) for a discussion of the possibilities.

[22] Adjustments through margins other than price likely differ depending on the length of the time period in question. In a short time period, such as when an APG law is in effect following a hurricane strike, it is less likely that firms begin to adjust through non-price margins like decreases in quality, as compared to a longer time period, such as gasoline price controls in the 1970s. A similar argument can be made for the development of black markets. Therefore, waiting in line appears to be the most likely outcome when APG laws are in effect.

allow price increases within a specified range, or are in states known for strongly enforcing the APG law are predicted to have a greater negative effect on growth.

Samuels and Puro (1991) and Rotemberg (2011) argue that some firms keep prices constant following a natural disaster due to what Rotemberg refers to as "consumer anger fear," rendering APG laws nonbinding. If all firms behave this way, there would be no difference between hurricane-stricken counties with and without APG laws. The law would have no effect, and employee wages would be similarly impacted regardless of APG laws. If this competing theory holds across all firms, there is no predicted difference between hurricane-stricken counties with and without APG laws.

The effects of APG laws, however, are not predicted to be consistent across all industries, primarily due to states' increased cost provision and fear of consumer anger.[23] Gas station owners, for example, can argue more easily than hotel owners that their costs have increased, and correspondingly increase their prices.[24] Contractors could also cite increased costs for corresponding increased prices following a hurricane, due to transportation costs, hazards, or labor hours.

Firms that heavily rely on repeat business such as building material and garden supply stores or grocery stores would suffer more from consumer anger in response to increased prices than hotels, gas stations, or contractors.[25] Therefore, negative impacts of

[23] "Consumer anger fear" is also referred to as reputation costs.
[24] A gas station owner's main input, gasoline from wholesalers, will likely experience a contraction in supply after a hurricane. A hotel owner does not have a parallel story.
[25] Because prices for gas fluctuate frequently and are often a source of consumer anger, regardless of effects of a recent natural disaster, gas station owners may be less sensitive to potential "consumer anger fear" than grocery store owners, whose prices remain relatively constant over short time periods. Hotels and contractors do not have repeat business in the short run, and contractors who migrate to the area would care less about impacts on their reputation if consumer anger to high prices is among consumers in a different locale.

APG laws following a hurricane strike are predicted to be more pronounced among the accommodations industry than other industries. Rather, the predicted effects among gas stations, specialty trade contractors, building material and supply stores, and food and beverage stores could be zero or negative, due to increased cost provisions in APG laws for the former two and "consumer anger fear" for the latter two industries.

In the absence of a hurricane strike, an APG law is predicted to have no statistically significant effect, because the law is not engaged without a declared state of emergency.[26]

Hurricanes

Hurricanes inflict physical damages through strong winds, rainfall, and temporary increases in coastal sea levels that lead to storm surges. These damages disrupt economic activity in affected areas, most often contracting the supply of goods and services.[27] In the absence of a price ceiling, the market price would increase, from P^* to P_1 in figure 2, yet in the presence of an effective APG law, the pecuniary price is nearly constant while one or more of the four outcomes discussed above occurs: shortage, waiting, adjustments, or black market activity.[28]

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[26] The law could be engaged for a state of emergency declared for some reason other than a hurricane. In this case, the model specified below will not control for the effect of this other natural disaster. Nevertheless, the Atlantic states in the dataset generally experience hurricanes more often than other natural disasters.
[27] The analysis would be similar with a demand expansion as well.
[28] The price may also be allowed to increase slightly, as some states allow a 10-20 percent increase, rather than restricting prices to pre-emergency levels.

A hurricane strike also decreases economic growth, although disaster assistance flows to affected areas following the storm (Strobl 2011).[29] These assistance measures act to buffer the losses sustained and encourage temporary economic growth through the rebuilding of damaged infrastructure, though these assistance measures may not be equal in magnitude to the damages of the hurricane. Damages and assistance measures may also be localized. If the assistance and rebuilding measures are sufficient to outweigh the damages of the hurricane within a particular county, the resulting measured growth effect will be positive.[30] If the assistance measures are insufficient, the effect of a hurricane on growth is negative. Strobl (2011) analyzes 21 Category 3 or greater hurricanes from 1970-2005 and concludes that assistance measures are insufficient to outweigh damages from a hurricane, resulting in negative annual growth in per capita income. Belasen and Polachek (2009) discordantly conclude that hurricane-stricken counties in Florida experience positive quarterly growth in per-worker wages. While a hurricane strike destroys assets and capital stock, its empirical effect on income is therefore unclear. If the measurement of a hurricane strike is precise, for which Strobl (2011) strives, the predicted effect of hurricanes on growth is negative, although the measured effect of hurricanes on growth may instead be positive if the Broken Window Fallacy holds.[31]

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[29] Strobl (2011) mentions insurance payments, clean up, and recovery activity as examples of disaster assistance.
[30] This does not necessarily mean a hurricane is beneficial to an economy, but rather an instance of the Broken Window Fallacy, which is discussed below.
[31] The Broken Window Fallacy, introduced by Frédéric Bastiat in 1850, suggests that the recovery efforts following a disaster such as a hurricane lead to a temporary increase in growth, although this increase does not actually benefit society. Therefore, a county that is hit by a hurricane may experience increased growth in income following the disaster, even though the hurricane decreases social welfare.

Strobl (2011) does not account for the passage and impact of APG laws within the 19 states included in his data.[32] From 1970-2005, 13 of those 19 states passed APG laws. The remaining six states either do not have an APG law or passed one after 2005.[33] Therefore, Strobl (2011) captures the overall growth effect following a hurricane, which consists of the effect of an APG law in effect following the storm, as well as the effect due solely to a hurricane strike. This thesis attempts to separate out these effects.

[32] This thesis analyzes the same 19 states as Strobl (2011), but also includes Arkansas and Vermont.
[33] These states are Delaware (no law), Maine (passage in 2006), Maryland (no law), New Hampshire (no law), Pennsylvania (passage in 2006), and Rhode Island (passage in 2012).

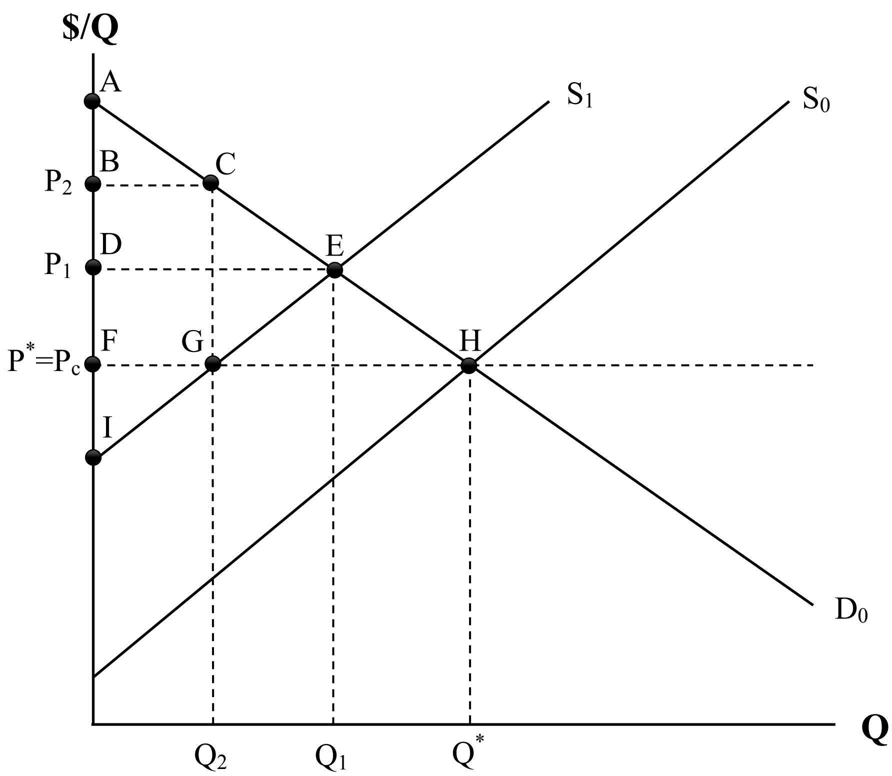

Figure 2. Supply and Demand Diagram with Price Ceiling

Notes: The market originally clears at P^* and Q^*. Supply contracts following a hurricane strike, from S_0 to S_1. In the absence of a price ceiling, price would increase from P^* to P_1, and firms would supply Q_1. Yet if an APG law imposes a price ceiling at pre-emergency prices, the pecuniary price is held constant at P_c. Due to the contraction in supply, firms are only willing to supply Q_2. The shortage is represented by the difference between Q^* and Q_2. Barzel (1974) suggests, however, that rather than a shortage in the market, the total price paid will increase. APG law prevents the pecuniary price from rising, but the total price paid increases due to consumers waiting in line to obtain the good or service (Barzel 1974). In this case, there is no shortage in the market, but rather the market clears at P_2 and Q_2. Consumer surplus is represented by triangle ABC and producer surplus is represented by triangle FGI, while rectangle BCFG is lost to waiting in line. Therefore, deadweight loss is rectangle BCFG and triangle CGE, and both consumers and producers are worse off under the price control. Some consumers, however, may benefit from price controls, as determined by relative magnitudes of income and price elasticities for the goods in question. For example, poor consumers benefit from price controls covering goods with low income elasticies and high price elasticies. See Davis (2008) and Barzel (1974) for a discussion of the possibilities.

ANNUAL DATA & METHODOLOGY

Data

The ideal dataset to address the question of interest in this thesis would include measures of economic growth for all areas that could possibly be affected by a hurricane, with or without an anti-price gouging (APG) law. Economic growth could be measured by changes in per capita output or income at very granular levels for both time and area, such as daily or weekly data for a county or subset of a county. While per capita income data at the county level are available for counties in the United States, the ideal frequency in measurement is not.[34] This thesis initially uses yearly data from the United States' Bureau of Economic Analysis's (BEA) Local Area Personal per Capita Income county-level estimates for the period 1970-2012.

Information on state APG laws is often buried in legal code and legislative journals. The ideal data on APG laws would include not only the date of passage of the law for each state, but specifics for each law, such as the date the law goes into effect for each state, which goods and services are affected, what price increase ranges are allowed, exclusions to the law, penalties for violations, when the laws are triggered into effect, and enforcement levels of the laws, not only for the overall state, but within each particular county. Legal codes for APG laws, however, are rarely this specific; the codes often only specify the goods and services affected in general terms, and leave acceptable price increases, exclusions, penalties, and enforcement levels up for debate or to the discretion

[34] There are also potential problems with using per capita income data. These problems are discussed in the Annual Results chapter.

of later enforcers. This thesis updates data collected by Davis (2008), using lists compiled by Benavides (2006) and Giberson (2012). These data include the year of passage of APG laws, as well as the legal definitions of goods covered, exclusions, penalties, and when the laws are triggered, for the 33 states with APG laws, of which 18 are included in the analysis in this thesis. Table 1 details these APG laws.

To control for the effects of a hurricane strike, the ideal data would consist of county-level damages resulting from a hurricane. Hurricanes are by nature short events, so daily or even hourly measurements of damage would be ideal. Damages of a particular hurricane, however, are hard to assess during clean up and recovery activity that occurs following the disaster. These data are not available, but rather only a measurement of the timing and incidence of a hurricane sustained in a particular county. This thesis uses data from the National Oceanic and Atmospheric Administration's (NOAA) HURDAT2 database for 1970-2012, which tracks six-hourly locations of the hurricane eye, maximum wind speeds, and central pressure of hurricanes in the North Atlantic Basin. Table 3 lists all storms included in the dataset, while table 4 chronologically displays states and counties impacted by hurricanes from 1970-2012.

Therefore, this thesis initially uses county-level annual data from the North Atlantic coastal United States from 1970 to 2012. The data consist of per capita income levels and growth rates, the presence of an APG law within a particular state during each year, and hurricane incidence within a particular county during each year.[35] The per capita income data were obtained from the BEA and include county-level annual per

[35] Note that multiple hurricane strikes within a particular county over the course of a year are not considered due to the nature of yearly hurricane incidence dummy variables. Rather, only the largest hurricane strike during that year is considered.

capita income from 21 Atlantic states.[36] The hurricane data are from the NOAA's HURDAT2 database and consist of all hurricanes in the North Atlantic Basin between 1970 and 2012. Figure 3 displays U.S. Atlantic coastal counties that commonly experience hurricane strikes. This figure shows the number of hurricane strikes within a particular county since 1900, where a darker shade corresponds to a greater number of hurricane strikes.

Table 5 summarizes all the key variables in this county-level annual dataset.[37] Figure 4 plots the growth rate within counties that did not experience a hurricane against those counties that did. Figure 5 presents this relationship using the mean growth rate within these counties.

The HURDAT2 database identifies hurricane location and wind speeds with latitude and longitude measurements but does not include Federal Information Processing Standards (FIPS) county codes for affected areas. The BEA data, however, identifies county-level per capita income by FIPS county codes. Latitude and longitude measurements in the HURDAT2 dataset are matched to corresponding location measurements for a particular FIPS county code in the Gazetteer files. Only those hurricane observations that matched location measurements for a FIPS county code less than 200 kilometers (km) away are kept.[38] According the U.S. Census Bureau, the

[36] These states include Alabama, Arkansas, Connecticut, Delaware, Florida, Georgia, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Texas, Vermont, and Virginia.

[37] As the income data from the BEA are in nominal terms, these data are converted to real terms using the Consumer Price Index, published by United States' Bureau of Labor Statistics, with 2005 as the base year.

[38] In order to merge the two datasets, this thesis employs the STATA *geonear* package and a third dataset of FIPS county codes with corresponding latitude and longitude measurements of counties' geographic centers. This dataset was obtained from the U.S. Census Bureau's 2013 Gazetteer files (https://www.census.gov/geo/maps-data/data/gazetteer2013.html). The Census Bureau defines the latitude

average United States county is approximately 2,500 square km in size, while the average diameter of a hurricane is 500 km, although they can vary considerably (Strobl 2011).[39] By limiting location matches to those less than 200 km away from the corresponding FIPS county code location rather than the average hurricane diameter of 500 km, it is less likely that the FIPS county code assigned to a hurricane observation is that of a unaffected neighboring county.[40] This process also allows for assignment of hurricane incidence to multiple FIPS county codes within the size of an average hurricane.

The county-level dataset includes observations for 43 years from 1970-2012 for 1,264 counties in the 21 Atlantic states listed previously. The growth rate variable in each dataset was constructed by finding the difference in the natural log of per capita income for a particular county between two consecutive years. Within the 1,264 counties included, 143 were hit by hurricanes, where 141 of those counties experienced a Category 1-3 hurricane and 17 counties experienced a Category 4 or 5 hurricane. These hurricanes occurred in 17 states where all 17 of those states experienced a Category 1-3 hurricane and only six states experienced a Category 4 or 5 hurricane.[41]

The first APG law was enacted by New York in 1979. By 2012, all but three states in the dataset had passed an APG law, yet these passages occurred at different

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and longitude measurement of the county "at or near the geographic center of the entity" (for more information, see https://www.census.gov/geo/reference/gtc/gtc_area_attr.html).

[39] Some hurricanes can be much larger. For example, Hurricane Sandy was over 1,600 km in diameter.

[40] This process was replicated using radii of 100 km and 500 km as well. While the 500 km radius allowed for more hurricane strike observations, the standard errors of the coefficient estimates increased substantially, suggesting a radius larger than 200 km introduces measurement error in the model. While the 100 km radius allows more confidence in the matching approach, the number of hurricane observations in the dataset was substantially reduced, decreasing the variation in hurricane strikes with and without APG laws in effect.

[41] The 17 states that experienced hurricanes were Alabama, Connecticut, Delaware, Florida, Georgia, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Jersey, New York, North Carolina, Rhode Island, South Carolina, Texas, and Virginia. The six states that experienced Category 4 or 5 hurricanes were Alabama, Florida, Louisiana, Mississippi, South Carolina, and Texas.

times during 1979-2012.[42] Therefore, a particular state may have experienced a hurricane strike without an APG law and again later when an APG law was in effect.[43] Table 6 shows growth rates for the 176 instances of hurricane strikes experienced by counties in which states have an APG law and the 197 instances of hurricane strikes in counties without an APG law. On average, counties without APG laws that were struck by hurricanes experienced 1.64 percent annual growth in per capita income, compared to 2.64 percent annual growth in per capita income in counties with an APG law in place following a hurricane strike. Figure 6 plots the annual growth in per capita income for the counties without and with an APG law following a hurricane strike, and figure 7 displays the mean annual growth rate within these counties.

Empirical Methodology

To estimate the effect of an APG law on growth in per capita income, the basic econometric specification builds on the neoclassical growth model used by Strobl (2011). Specifically, the following model is used:

$$(1)\ Growth_{ct-1 \rightarrow t} = \beta_0 + \beta_1 \ln(PCI_{ct-1}) + \beta_2 APG_{ct} + \beta_3 HURR_{ct} + \beta_4 (APG*HURR)_{ct} + \pi_t + \mu_c + \varepsilon_{ct}$$

where the dependent variable, $Growth_{ct-1 \rightarrow t}$ is equal to the per capita income growth rate in county *i* and from year *t-1* to year *t*. Ln(PCI_{ct-1}) is the natural log of per capita income in county *i* and year *t-1*. APG_{ct} is equal to one if the corresponding state for county *c* has

[42] The states that had not passed APG laws are Delaware, Maryland, and New Hampshire.

[43] For example, South Carolina did not have an APG law in 1989 during Hurricane Hugo. However, when Hurricane Charley hit South Carolina in 2004, South Carolina had an APG law that went into effect with the governor's declaration of a state of emergency.

an APG law in effect in year *t,* and is equal to zero otherwise. $HURR_{ct}$ is equal to one if county *c* sustained a hurricane strike in year *t*. County and year fixed effects are represented by μ_c and π_t, respectively. Some regressions also control for county-specific linear and quadratic time trends.

The BEA discusses how natural disasters affect personal income estimates.[44] As Strobl points out, natural disasters damage property and consumer goods, which leads to a reduction in enterprise owners' income and rental income through uninsured losses (2011). Natural disasters also disrupt normal economic activity and the flow of income in the economy. This could be due to interruptions in production within some industries, resulting in either an increase or decrease for different industries and at different points in time.[45] The natural logarithm of per capita income data is used as is common to normalize income data (Belasen and Polachek 2009).

The effect of an APG law is inherently linked to the above effects of a hurricane; the APG law will only go into effect with the declared state of emergency corresponding to a hurricane strike. Therefore, the hurricane incidence variable is included to control for the effects of the hurricane strike, where $HURR_{ct}$ equals one if county *c* sustained a hurricane strike in year *t.* The estimated coefficient on $HURR_{ct}$ measures the average difference in annual growth of per capita income between counties that experience hurricane strikes and those that do not. The APG law dummy variable controls for time-invariant effects of the law, where APG_{ct} is equal to one if the corresponding state for

[44] Strobl (2011) uses this discussion as justification for the use of growth and levels of per capita income in the model.
[45] For example, income flows may be temporarily reduced due to disruption in normal economic activity from the hurricane, but increase later during rebuilding efforts.

county c has an APG law in effect in year t. The estimated coefficient on APG_{ct} measures the average difference in annual growth of per capita income between counties that have passed APG laws and those that have not.[46] This leaves the interaction term between the hurricane incidence variable and the APG law dummy variable, which measures the average difference in annual growth of per capita income in hurricane-stricken counties that have APG laws and those that do not.[47]

The datasets in this thesis include a larger number of groups than time periods, so a fixed effect model is used to control for observable and unobservable differences between counties in the dataset.[48] It is unlikely that two counties are identical in every way; the county fixed effects control for any time-invariant differences, both observable and unobservable. Year fixed effects are also included to control for differences between the years included in the data. These year fixed effects control for year-to-year variation in factors that affect economic growth that are common among all counties in the dataset, such as a general increase in disaster assistance measures, macroeconomic conditions, or differences in hurricane season intensity.[49] While concerns of underlying year and county effects could have been controlled by first differencing the model, the dataset consists of substantially more groups than time periods, so a first differenced model will be less efficient than a fixed effect model (Wooldridge 2009).

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[46] Because the APG law is only engaged during a declared state of emergency, there should be no difference between counties within states with APG laws and counties within states without APG laws in the absence of a hurricane strike.
[47] The model is a difference-in-difference model, and therefore estimates measure average effects rather than marginal effects.
[48] According to Wooldridge (2009), if the opposite was true, many time periods and few groups, a fixed effect model may not be appropriate. Rather, a first-differenced model should be used to control for spurious correlation.
[49] For example, the 2005 Atlantic hurricane season was the most active in recorded history while the 2006 season was relatively quiet.

The hurricane incidence dummy was created using the *geonear* package and through a less than ideal method of matching location coordinates to FIPS county codes, so measurement error is a concern in the model.[50] Because the hurricane incidence measurement is a dummy variable, the variance of this variable is not likely to be large relative to the variance in the measurement error. Therefore, if measurement error is present in the model, the estimated coefficient on the hurricane incidence dummy will be attenuated towards zero, leading to an understatement of the effects of a hurricane and the interaction of an APG law and a hurricane strike.

Serial correlation is also a concern. In the presence of serial correlation, a first differenced model will be more efficient than the fixed effects model (Wooldridge, 2009). Serial correlation may be present if the effects of $(APG*HURR)_{ct}$ on growth are lagged, affecting growth in more than the current year. While a hurricane may destroy capital stock that is not rebuilt in the short run, a hurricane's effect on growth is dependent on the difference in damages inflicted by the hurricane and the assistance measures following the disaster. Hurricanes are short events, so their destruction occurs over the course of a few days, although assistance measures occur both immediately following the disaster and some times continuing for several years. While APG laws are only in effect while there is a declared state of emergency, the threat of investigation regarding price-gouging complaints lingers after the state of emergency is lifted (Davis, 2008).[51] Therefore, because the effects of an APG law on growth following a hurricane

[50] Strobl (2011) attempts to reduce measurement error in the hurricane measurement by using a custom hurricane index, rather than dummy variables, as are used by Belasen and Polachek (2009).
[51] Davis (2008) presents case studies where charges are leveled long after the hurricane has subsided at firms for suspected price gouging immediately following the storm.

could last beyond the initial year of the hurricane strike, it is likely that serial correlation is present in the model. A Breusch-Godfrey test provides significant evidence of serial correlation.[52] If serial correlation in the model is ignored, the standard errors may be understated, leading to incorrect inferences.

There is likely heteroskedasticity across the different counties in the sample as the panel data used in this thesis are measured at a group level. Breusch-Pagan and White tests show significant evidence of heteroskedasticity within the county-level dataset.[53] Clustering standard errors, as is common practice with averaged data measured at a group level, will deal with issues of both serial correlation and heteroskedasticity (Wooldridge 2009). The datasets used in this thesis consist of a substantially larger number of groups and observations than time periods so clustered standard errors are appropriate (Wooldridge 2009). Therefore, all regressions in this thesis will use standard errors clustered at the county level.

[52] The Breusch-Godfrey test yields a p-value of < 0.001.
[53] The Breusch-Pagan test yields a p-value of 0.0292, while the Special case of White's test yields a p-value < 0.001.

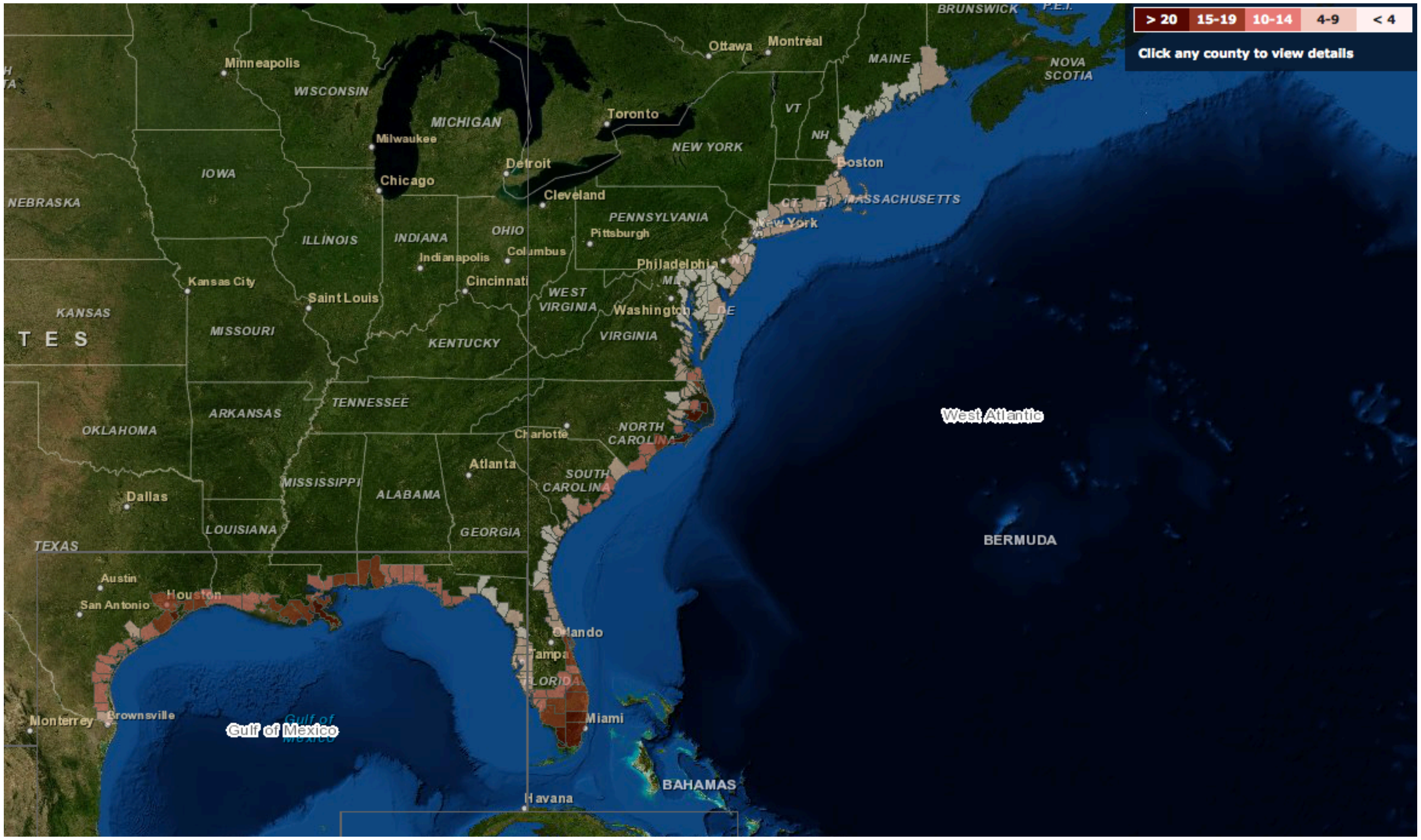

Figure 3. Frequency of Hurricane Strikes on Atlantic Coastal Counties, 1900-2012

Notes: This figure was obtained from the ICAT Damage Estimator (http://www.icatdamageestimator.com/viewdata). The number of hurricane strikes experienced since 1900 determines the shading of the coastal counties shown. A darker shade of brown corresponds to more hurricane strikes, where the darkest-shaded counties are notably within the bayou of Louisiana, the tip of Florida, and the outer banks of North Carolina.

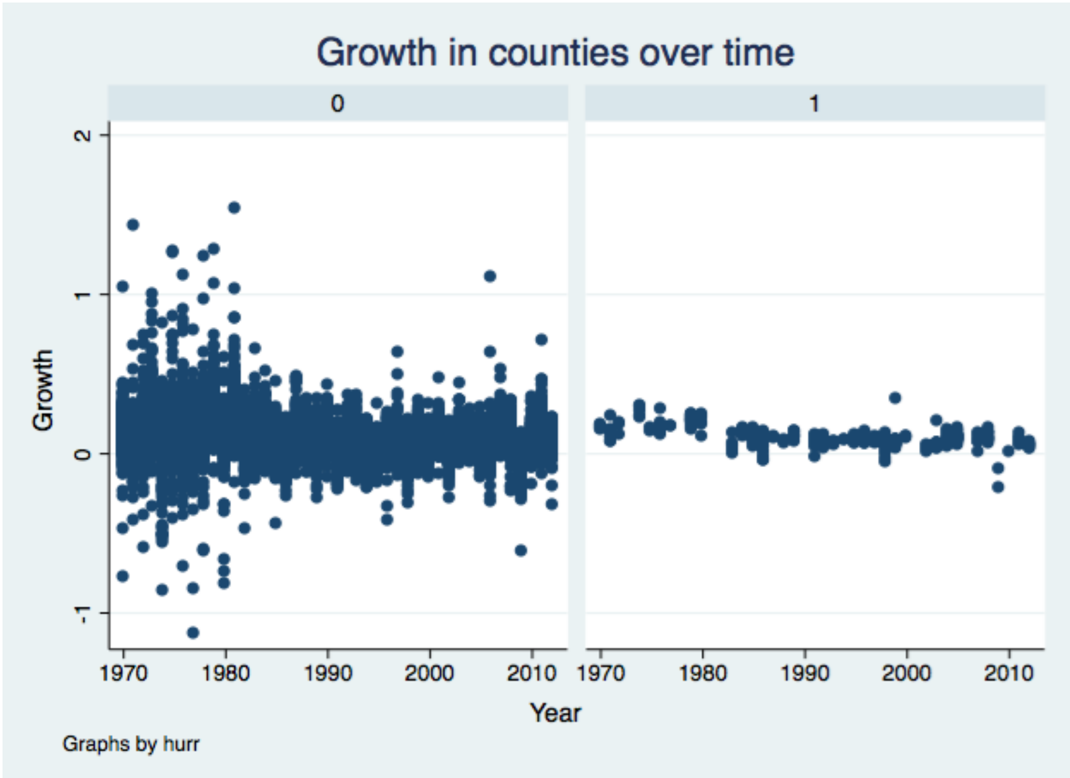

Figure 4. Annual Growth Rates by Hurricane Strike, 1970-2012

Notes: The left-hand side shows annual growth of per capita income over time in any county that was not hit by a hurricane that particular year. The mean of this group is 0.0163. The right-hand side shows annual growth of per capita income over time in any county that experienced a hurricane strike that year. The mean of this group is 0.0211.

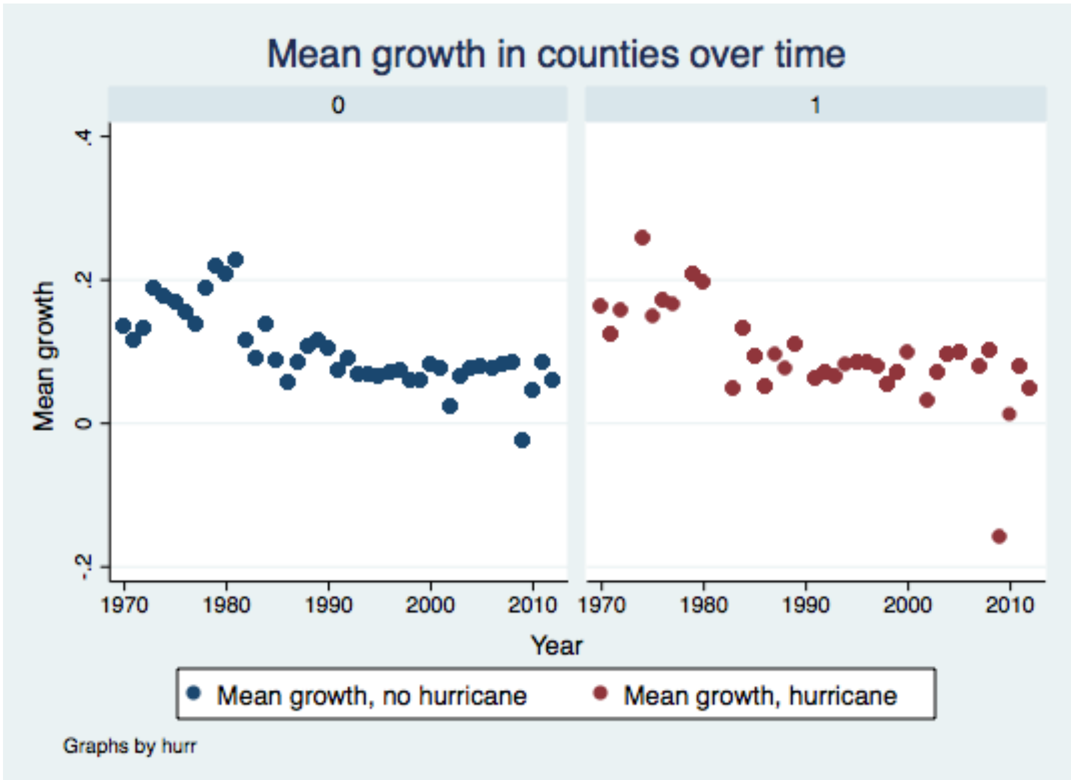

Figure 5. Mean Annual Growth Rates by Hurricane Strike, 1970-2012

Notes: The left-hand side shows mean annual growth of per capita income for all counties that were not hit by a hurricane that particular year. The mean of this group is 0.0163. The right-hand side shows mean annual growth of per capita income for all counties that experienced a hurricane strike that year. The mean of this group is 0.0211.

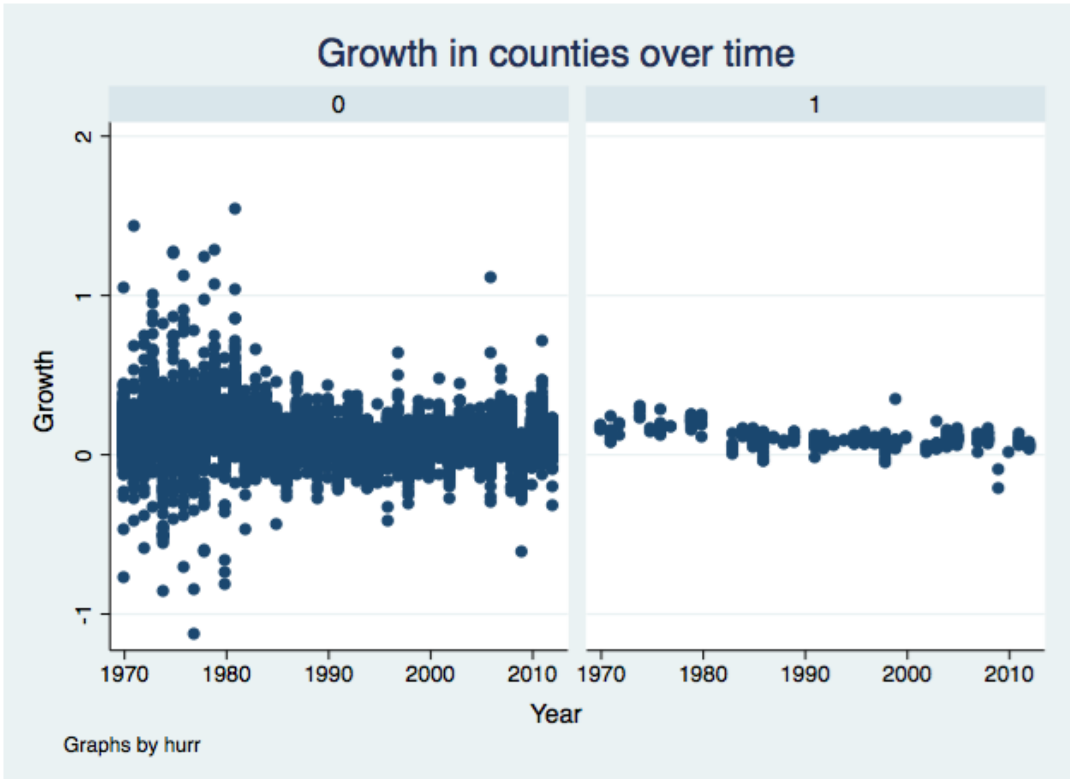

Figure 6. Annual Growth Rates by APG Law and Hurricane Strike, 1970-2012

Notes: The left-hand side shows annual growth of per capita income over time in any county that was hit by a hurricane and did not have an APG law in that particular year. The mean of this group is 0.0164. The right-hand side shows annual growth of per capita income over time in any county that was hit by a hurricane and did have an APG law in that year. The mean of this group is 0.0264.

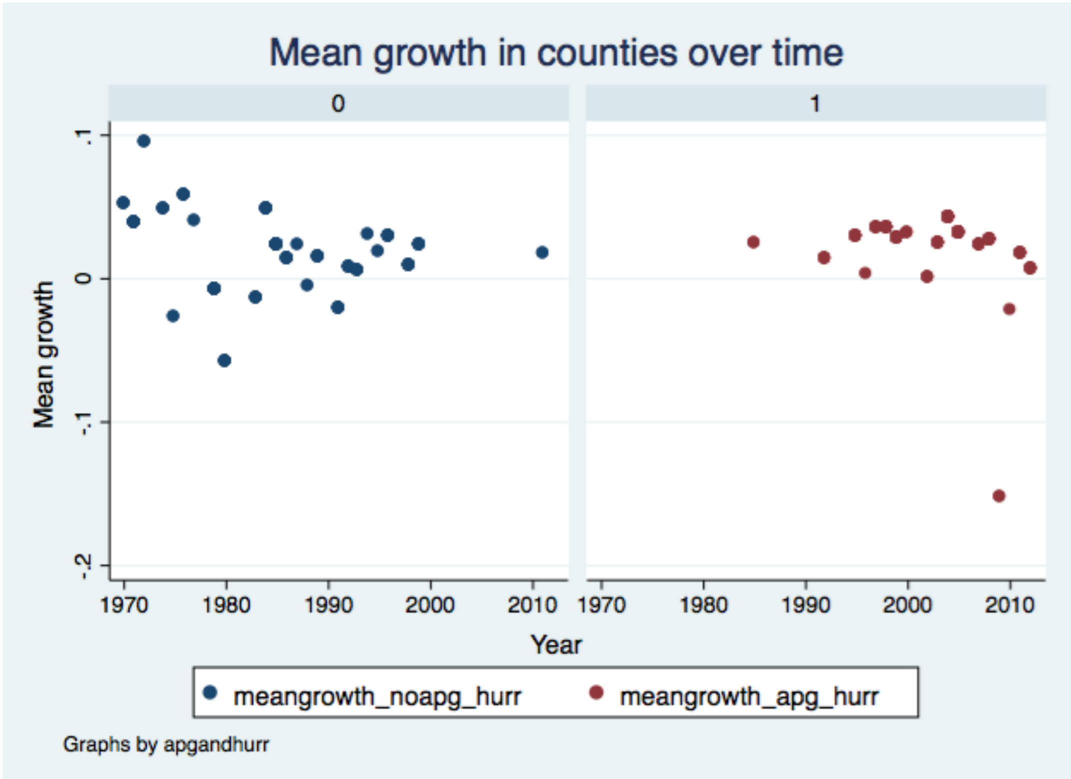

Figure 7. Mean Annual Growth Rates by APG Law and Hurricane Strike, 1970-2012

Notes: The left-hand side shows mean annual growth of per capita income for all counties that were hit by a hurricane and did not have an APG law in that particular year. The mean of this group is 0.0164. The right-hand side shows mean annual growth of per capita income for all counties that were hit by a hurricane and did have an APG law in that year. The mean of this group is 0.0264.

Table 5. Annual County-level Summary Statistics, 1970-2012

Variable	Mean	SD	Min	Max	N	Description
$Growth_{ct-1 \rightarrow t}$	0.0164	0.0586	-1.2620	1.3423	54352	Growth of ln(per capita income) from *t-1* to *t*
$\ln(PCI_{ct-1})$	10.0054	0.3008	8.7158	11.5945	54352	Ln(per capita income) at time *t-1*
APG_{ct}	0.3725	0.4835	0	1	54352	= 1 if the corresponding state for county *c* has an APG law in effect in year *t*, = 0 otherwise
$HURR_{ct}$	0.0069	0.0826	0	1	54352	= 1 if county *c* sustained a hurricane strike in year *t*, = 0 otherwise
$CAT123_{ct}$	0.0065	0.0802	0	1	54352	= 1 if county *c* sustained a Category 1-3 hurricane strike in year *t*, = 0 otherwise
$CAT45_{ct}$	0.0004	0.0197	0	1	54352	= 1 if county *c* sustained a Category 4-5 hurricane strike in year *t*, = 0 otherwise
$CAT1_{ct}$	0.0043	0.0658	0	1	54352	= 1 if county *c* sustained a Category 1 hurricane strike in year *t*, = 0 otherwise
$CAT2_{ct}$	0.0014	0.0369	0	1	54352	= 1 if county *c* sustained a Category 2 hurricane strike in year *t*, = 0 otherwise
$CAT3_{ct}$	0.0008	0.0278	0	1	54352	= 1 if county *c* sustained a Category 3 hurricane strike in year *t*, = 0 otherwise
$CAT4_{ct}$	0.0004	0.0197	0	1	54352	= 1 if county *c* sustained a Category 4 hurricane strike in year *t*, = 0 otherwise

Notes: Growth of per capita income was constructed by taking the difference between the natural log of per capita income in year *t* and the natural log of per capita income in year *t-1*. Income data come from the Bureau of Economic Analysis's Local Area Personal per Capita Income county-level estimates (http://www.bea.gov/regional/). Anti-price gouging law data come from Davis (2008), Benavides (2006), and Giberson (2012). Hurricane data come from the National Oceanic and Atmospheric Administration's Best Track Data (HURDAT2), which give six-hourly information on location, maximum winds, central pressure, and since 2004, estimates of the size of hurricanes as shown by wind speeds measured and different distances from the eye of the hurricane. These data can be found at http://www.nhc.noaa.gov/data/#hurdat.

Table 6. Annual County-level Growth of Per Capita Wages, 1970-2012

Category	Mean	SD	N
When $APG_{ct} = 0$	0.0176	0.0664	34108
When $APG_{ct} = 1$	0.0143	0.0422	20244
When $HURR_{ct\ t} = 0$	0.0163	0.0587	53979
When $HURR_{ct} = 1$	0.0211	0.0403	373
When $APG_{ct} = 1$ and $HURR_{ct} = 0$	0.0142	0.0422	20068
When $APG_{ct} = 0$ and $HURR_{ct} = 1$	0.0164	0.0409	197
When $APG_{ct} = 1$ and $HURR_{ct} = 1$	0.0264	0.0391	176

Notes: The above distributions are for the annual growth rate of per capita income within a county, which is equal to the difference between the natural log of per capita income in year *t* and the natural log of per capita income in year *t-1*. The first two lines show the distribution of growth rates in counties within states with and without an anti-price gouging law in place. The next two lines show the distribution of growth rates in counties that do and do not experience a hurricane strike during a particular year. The final three lines show the distribution of growth rates in counties that have an anti-price gouging law in place but do not experience a hurricane that year, do not have an anti-price gouging law in place and do experience a hurricane that year, and have an anti-price gouging law in place and do experience a hurricane that year.

ANNUAL RESULTS

Baseline Specifications

Table 7 reports fixed effect estimates of the relationship between anti-price gouging (APG) laws and growth in county-level per capita income. The estimates in the first column include county and year fixed effects, those in the second column control for county-specific linear time trends, and the third column estimates control for county-specific linear and quadratic time trends, to control for trends not common among all counties during the time period.

The estimated effect of an APG law in the absence of a hurricane strike is not zero as predicted, but rather negative and statistically significant. This coefficient, however, is likely picking up the effect of previous hurricane strikes. Davis (2008) concludes that on average, states pass APG laws due to experiencing previous natural disasters. The estimated coefficient on the APG dummy may be negative due to lagged effects of previous hurricanes, rather than because of an effect of the APG law in the absence of a hurricane strike.[54]

The estimates presented suggest that APG laws are beneficial to hurricane-stricken counties, yet results are inconsistent with theoretical predictions outlined above.

[54] If the passage of APG laws is not related to previous hurricanes, there should be no difference between counties within states that have passed APG laws and counties in states without APG laws. If states pass APG laws in response to previous hurricanes, suggested by Davis (2008), and long run growth effects of hurricanes are negative, suggested by Hsiang and Jina (2014), APG_{ct} will control for the negative effect of previous hurricanes, although it will appear to suggest that counties within states with APG laws are worse off than those without APG laws, even when the laws are not engaged outside of a declared state of emergency. To test this hypothesis, APG_{ct} was regressed on ten-period lags of $HURR_{ct}$ for state-level annual data from 1970-2012 while including state and year fixed effects. Results suggest that previous hurricane strikes did not influence the adoption of an APG law, although this preliminary exploration was not as thorough as Davis (2008).

If APG laws are binding, economic theory predicts the sign of $APG*HURR_{ct}$ to be negative, as an effective price ceiling results in increased scarcity or total price paid for goods and services affected. If APG laws are not binding, as would be the case if firms suffer from "consumer anger fear" or the laws are sufficiently weak, $APG*HURR_{ct}$ would not be statistically significant from zero. Firms choose to keep prices constant after a hurricane due to fear of backlash from consumers, rather than penalties from infringement of the APG law. Yet, as is shown in table 7, even when controlling for county-specific linear and quadratic time trends, a hurricane-stricken county within a state with an APG law experiences a 0.89 percent increase in growth in per capita wages.[55]

The response variable, $Growth_{ct-1 \rightarrow t}$, measures growth in per capita income within a county across all industries over the course of a full year. Therefore, there are four possible explanations for these results. APG laws, while often vague in definition, usually apply to "goods and services," and not necessarily to all industries. Most complaints of price gouging concern prices for gas and hotel rooms, as well as contractor services such as clearing debris (Davis, 2008). When combining all industries to create the response variable, the effects among goods and services such as contracting, gas, and hotels are potentially washed out by other industries within the county.

The second possible explanation is time frame. These data are yearly, yet an APG law is only in effect while there is a declared state of emergency. While the length of a

[55] This result continues to hold when the hurricane incidence variable was broken down by individual Saffir-Simpson categories, when including one- and two-period lagged hurricane incidence variables, and when controlling for heterogeneity in APG laws. Furthermore, results hold when separately dropping observations for one state at a time, suggesting the results are not driven by any particular state. These estimates are available upon request.

declared state of emergency will differ by storm, it is a strong assumption that the APG law will be in effect long enough for its effect to be measured using yearly data.[56] Therefore, the effect of the APG law in the presence of a hurricane strike may be washed out by other months within that year when the law was not in effect, yet $Growth_{ct\text{-}1 \rightarrow t}$ was measured. Furthermore, counties may experience a lagged rebound as soon as the APG law is lifted, outweighing the predicted initial negative effect.

Thirdly, the BEA county personal income estimates are constructed from income tax returns, which report the income of a resident within a particular county but do not account for where that income was generated. Therefore, a resident in a neighboring county that is not hit by the hurricane may report a decrease in income if that income is generated in the nearby affected county.

Fourth, firms may adjust wages in response to APG laws as discussed above, but they may also adjust employment levels. This latter adjustment may be easier to make in the short run than the former. $Growth_{ct\text{-}1 \rightarrow t}$ measures the growth in total income divided by total population, but does not account for changes in employment within a particular county and will not account for adjustment along this margin.

The estimated effect of APG laws on growth of annual per capita income in a hurricane-stricken county is inconsistent with theoretical predictions above, yet as the data to support these results have many potential problems, the results may not be valid. To address these potential problems, a second dataset was constructed that allows

[56] Lengths of states of emergency vary by state. Some states define the period to be 30 days with the option of renewing the declaration for another 30 days; for example, see Arkansas' Consumer Protection Division's webpage on price gouging (http://www.gotyourbackarkansas.org/my-money/price-gouging/) and the legal code for Virginia (https://leg1.state.va.us/cgi-bin/legp504.exe?000+cod+59.1-526). Other states leave the defined length vague; for example, see a price gouging "spotlight" from South Carolina (http://www.consumer.sc.gov/Documents/SpotLight/SCDCA%20Spotlight-%20PriceGouging.pdf).

examination at a shorter time frame and by industry, addressing the first two problems mentioned above. The second dataset is also constructed with employer reports, rather than employee tax forms, so income is reported in the county in which it was generated, rather than the county in which the employee lives.[57] This will address the third problem with the initial BEA dataset. Finally, the response variable in the second dataset is growth of per-worker wages, which is constructed by dividing the total wage bill by total employed for a particular county. Including employment levels in the response variable will capture adjustments to APG laws not only along wage margins but also employment margins.

The initial annual dataset includes more variation in APG laws and hurricane strikes over time, covering the period 1970-2012, but at the expense of granularity. The second dataset offers a more granular time frame for examination, but at the expense of APG law variation over time, as the second dataset only covers the period 1990-2012. The validity of sacrificing variation over time for granularity is explored below.

[57] For more information, see http://www.bls.gov/cew/cewbultncur.htm#comparison.

Table 7. Growth of Annual Per Capita Income with APG Laws, 1970-2012

	Reg (1) Growth	Reg (2) Growth	Reg (3) Growth
Intercept	2.1147***	3.2209***	4.2166***
	(0.1627)	(0.2064)	(0.2266)
ln$(PCI)_{ct-1}$	-0.2174***	-0.3330***	-0.4364***
	(0.0169)	(0.0215)	(0.0236)
APG_{ct}	-0.0036***	-0.0069***	-0.0055***
	(0.0009)	(0.0012)	(0.0013)
$HURR_{ct}$	-0.0012	-0.0025	-0.0035
	(0.0028)	(0.0030)	(0.0029)
$(APG*HURR)_{ct}$	0.0125***	0.0119***	0.0089**
	(0.0041)	(0.0042)	(0.0043)
Year FE's	Yes	Yes	Yes
County FE's	Yes	Yes	Yes
County-specific linear time trends	No	Yes	Yes
County-specific quadratic time trends	No	No	Yes
Number of counties	1264	1264	1264
Observations	54352	54352	54352
Adjusted R^2	0.2286	0.2680	0.3173

* Statistically significant at 10% level, ** at 5% level, *** at 1% level.

Notes: Each column represents the results from a separate OLS regression. The dependent variable is equal to the difference between the natural log of per capita income in year *t* and the natural log of per capita income in year *t-1*, or the annual growth rate of per capita income within a county. All standard errors are corrected for clustering at the county level.

QUARTERLY DATA & METHODOLOGY

Data

Quarterly income data for United States counties along the North Atlantic Basin were obtained from the Quarterly Census of Employment and Wages (QCEW), conducted by the Bureau of Labor Statistics (BLS), for the period 1990-2012. The Standard Industrial Classification (SIC) system was used to classify industry data from 1975-1990, while the North American Industry Classification System (NAICS) was used from 1990 forward. Hence, this thesis only uses consistent NAICS-classified data from 1990-2012.[58]

The QCEW includes county-level income and employment for all industries as well as by specific industry sector, using the NAICS standard mentioned above. These industry classifications provide data by domain, super-sector, and NAICS-sector.[59] The NAICS system offers highly detailed data, including specific classifications of businesses within NAICS-sector.[60] These data allow examination within specific industries often cited in anti-price gouging (APG) law disputes: hotels, gas stations, and contractors.

The QCEW provides the county-level total wage bill and employment rather than per capita figures, so the total wage bill is divided by total employment to construct per-

[58] While there is a crosswalk between SIC- and NAICS-coded data, or a method to convert SIC-coded data to NAICS-coded data, it is not comprehensive and could not be used to accurately combine SIC-coded pre-1990 data and NAICS-coded post-1990 data.

[59] A domain can be goods producing or service providing. A super-sector is a general category within a domain, such as construction or financial activities. A NAICS-sector is a specific group of industries within a super-sector, such as retail trade or education services (for more information, see http://www.bls.gov/cew/doc/titles/industry/high_level_industries.htm).

[60] For example, within the NAICS-sector 72 for accommodations and food services, businesses are classified as hotels and motels (except casino hotels), casino hotels, bed-and-breakfast inns, full-service restaurants, cafeterias, grill buffets, and buffets, and caterers (for more information, see http://www.bls.gov/cew/doc/titles/industry/industry_titles.htm).

worker wages. Therefore, the model will capture adjustments to APG laws on both wages and employment margins. Nominal income data are converted to 2005 dollars using the Consumer Price Index published by the BLS.[61]

Data on APG laws come from previous lists by Davis (2008), Benavides (2006), and Giberson (2012). These data include the year of passage of APG laws, legal definitions of goods covered, exclusions, penalties, and when the laws are triggered, for the 33 states with APG laws, of which 18 are included in this thesis. Hurricane data were obtained from the National Oceanic and Atmospheric Administration's (NOAA) HURDAT2 database for 1990-2012, which tracks six-hourly locations of the hurricane eye, maximum wind speeds, and central pressure of hurricanes in the North Atlantic Basin.

Population characteristics and state legislature party control were also collected. Population data come from the Surveillance, Epidemiology, and End Results (SEER) Program of the National Cancer Institute, which include yearly, county-level populations sorted by race, gender, and age group.[62] These data were then collapsed to create demographic controls for the percentage of the county population that is nonwhite, adult male, and 19 years or older. Using the U.S. Census Bureau's 2013 Gazetteer files, the total county population was divided by the county land area to create a population density

[61] Belasen and Polachek (2009) and Strobl (2011) use 2005 as the base year for real income and wage data. This thesis uses 2005 dollars as well to allow for easy comparisons.
[62] Population estimates for 2005 are adjusted for migration due to Hurricanes Katrina and Rita. These adjustments specifically affect populations within Alabama, Mississippi, Louisiana, and Texas (for more information, see http://seer.cancer.gov/popdata/hurricane_adj.html).

measure.[63] As these data are yearly, values are constant across observations within one year. These measures of demographics, however, are unlikely to vary much within a year.

Data on state legislature party control come from the National Conference of State Legislatures. These data reflect whether the Democratic Party or GOP held a majority in both legislative chambers, or if the chambers were split between the two parties.[64] From these data, a dummy variable was created to indicate whether the Democratic Party held majority in both state legislative chambers, as Democratic Party control may signify a political environment more favorable to enforcement of an APG law.[65] Elections in state legislatures are bi-yearly so these data are for every even year, and values for a particular even year were carried over to the following year as well. Table 8 summarizes all the key variables in the quarterly wage dataset. On average, counties in the dataset experienced 0.26 percent growth in quarterly per-worker wages, and approximately two-thirds of all county-level observations in the dataset occur with APG laws in place.

As previously with annual Bureau of Economic Analysis (BEA) data, HURDAT2 hurricane observations are matched to Federal Information Processing Standards (FIPS) county codes within the quarterly BLS data.[66] Within the 1,292 counties included, 144 were hit by hurricanes, where 141 of those counties experienced a Category 1-3 hurricane

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[63] The U.S. Census Bureau's 2013 Gazetteer files can be found here: https://www.census.gov/geo/maps-data/data/gazetteer2013.html.

[64] For more information, see http://www.ncsl.org/research/about-state-legislatures/partisan-composition.aspx.

[65] Davis (2008) hypothesizes that passage of an APG law may be more likely when the Democratic Party has state legislative control. The hypothesis is similar for enforcement of the law once it has been enacted.

[66] This process again employed the *geonear* package in STATA, matching latitude and longitude measurements for hurricanes in the HURDAT2 dataset to latitude and longitude measurements of the geographic centers of counties with 200 km from the eye of the hurricane, and allowing for assignment of hurricane incidence to multiple FIPS county codes within 200 km from the hurricane eye. This process did not account for multiple hurricane strikes on a particular county within one quarter. Instead, the highest category storm experienced during that quarter was kept.

and seven counties experienced a Category 4 hurricane.[67] These hurricanes occurred in 15 states where all 15 of those states experienced a Category 1-3 hurricane and only one state experienced a Category 4 hurricane.[68]

The first APG law enacted during this time period was by Maine in 1990. New York (1979), Hawaii (1983), Connecticut (1986), and Mississippi (1986) passed APG laws before 1990. By 2012, all states in the dataset but Delaware, Maryland, and New Hampshire passed an APG law, yet these passages occurred at different times during 1990-2012. Therefore, a particular state may have experienced a hurricane strike without an APG law and again later when an APG law was in effect. Table 9 shows growth rates of per-worker wages for the 179 instances of hurricane strikes experienced by counties within states with an APG law and the 63 instances of hurricane strikes in counties without an APG law. On average, hurricane-stricken counties without APG laws experienced 7.59 percent growth in per-worker wages during the initial quarter following the hurricane strike, while hurricane-stricken counties with APG laws experienced 4.65 percent growth in comparable per-worker wages. Figure 8 plots the quarterly growth in per capita income for the counties without and with an APG law following a hurricane strike, and figure 9 displays the mean quarterly growth rate within these counties.

[67] No Category 5 hurricanes made landfall in the North Atlantic Basin during 1990-2012. Hurricane Katrina, which made landfall in 2005, was a Category 5 while in the Gulf of Mexico but dropped to a Category 3 before making landfall.

[68] The 15 states that experienced hurricanes were Alabama, Connecticut, Delaware, Florida, Georgia, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Jersey, North Carolina, South Carolina, Texas, and Virginia. The one state that experienced a Category 4 hurricane was Florida. Note that Hurricane Sandy was classified as a tropical storm when it made landfall in 2012, so that the only state with a hurricane observation for this storm is New Jersey, when the storm was still offshore yet had sufficiently high wind speeds to be classified as a Category 1 storm.

Empirical Methodology

As with the annual data, the initial econometric specification builds on the neoclassical growth model used by Strobl (2011), although per-worker wages are substituted for per capita income. Specifically, the following model is used:

$$(2)\ Growth_{ct\text{-}1 \rightarrow t} = \beta_0 + \beta_1 \ln(PWW_{ct\text{-}1}) + \beta_2 APG_{ct} + \beta_3 HURR_{ct} + \beta_4 (APG{*}HURR)_{ct} + \boldsymbol{\beta}_5 \boldsymbol{X}_{ct} + \pi_t + \mu_c + \varepsilon_{ct}$$

where the dependent variable, $Growth_{ct\text{-}1 \rightarrow t}$ is equal to the growth rate in per-worker wages in county *i* and from quarter *t-1* to quarter *t*. Ln$(PWW_{ct\text{-}1})$ is the natural log of per-worker wages in county *i* and quarter *t-1*. APG_{ct} is equal to one if the corresponding state for county *c* has an APG law in effect in quarter *t* (and is equal to zero otherwise). $HURR_{ct}$ is equal to one if county *c* sustained a hurricane strike in quarter *t*.[69] The vector $\boldsymbol{X}_{ct}$ includes controls for county-level population density, demographics (percent of the county population that was nonwhite, male, and 19 years of age or older), and whether the Democratic Party controlled both chambers of legislature within that state.[70] County fixed effects are represented by μ_c, and year and quarter fixed effects are represented by π_t.

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[69] Note that this dummy variable is equal to one only in the quarter of the hurricane strike, rather than all quarters within the year of the strike. The latter would be consistent with hurricane observations in the initial annual dataset, but would be incorrectly specified with these quarterly data.

[70] The Democratic Party is more often cited in support of APG laws. Although Davis (2008) finds no evidence of legislative control by the Democratic Party to significantly affect the passage of an APG law within a particular state, this may not be the case with enforcement of the law. Davis (2008) presents instances of Democratic Party politicians lamenting the absence of an APG law, perhaps suggesting that when the Democratic Party is in power within a particular state, the political atmosphere is more favorable towards enforcement of an APG law.

A second econometric specification is also used. This model builds on the generalized difference in difference labor market model employed by Belasen and Polachek (2009), which measures the degree to which growth of per-worker wages in a hurricane-stricken county deviates from the average county within the state. The model is as follows:

$$(3)\ (\Delta\ln PWW_{ct} - \Delta\ln PWW_{st}) = \beta_0 + \beta_1 APG_{ct} + \beta_2 HURR_{ct} + \beta_3 (APG*HURR)_{ct} + \boldsymbol{\beta_4 X_{ct}} + \pi_t + \mu_c + \varepsilon_{ct}$$

These models attempt to address four potential problems with the previous analysis of annual data: industry effects, time frame, income reporting location, and employment adjustments. The BLS data are quarterly, rather an annual, offering a better snapshot to capture the effect of an APG law. The BLS data are also reported by employers in order to meet unemployment insurance regulation.[71] Therefore, wages are reported in the county in which the worker in employed, rather than the county in which the worker resides, as was the case with the previous BEA data. The response variable is now constructed using total wages and total employment, rather than total income and total population as with the previous annual BEA data, so the model will capture adjustments on either margin. The BLS data are categorized by NAICS code, so industry effects will be explored below.

There is still likely measurement error present in the model due to the creation of the hurricane incidence dummy using the *geonear* package, which will attenuate the

[71] The BLS offers further explanation here: http://www.bls.gov/cew/cewbultncur.htm#Introduction.

estimates towards zero, and result in an understatement of the relationship between APG laws and growth in hurricane-stricken counties.

Serial correlation also remains a concern, along with heteroskedasticity across the different counties in the sample. If these issues are ignored, the standard errors may be understated, leading to incorrect inferences. Therefore, all regressions will use standard errors clustered at the county level.

The above models are further applied across specific industries to explore the effect of an APG law on growth of per-worker wages in hotels, gas and other retail, and contracting. These by-industry models will use the labor market model, focusing on differences within the specified industry, *i*, and across all industries in the average county. Specifically, the following models are estimated:

$$(4)\ (\Delta\ln PWW_{ict} - \Delta\ln PWW_{st}) = \beta_0 + \beta_1 APG_{ct} + \beta_2 HURR_{ct} + \beta_3 (APG*HURR)_{ct} + \boldsymbol{\beta_4 X_{ct}} + \pi_t + \mu_c + \varepsilon_{ct}$$

where $\ln(PWW_{ict})$ is the natural log of per-worker wages in affected industry *i* within county *c* in quarter *t* and $\ln(PWW_{st})$ is the natural log of per-worker wages across all industries for the average county within state *s* in quarter *t*.

Hotels prices are often cited in price gouging complaints. Therefore, this thesis first examines growth of per-worker wages within the NAICS classification for accommodations. As shown in the models above, these wages are compared to wages across all industries within the average county in that state. Discussion above predicts APG laws following a hurricane will adversely affect the accommodations industry.

Secondly, wages within the NAICS classification for gas stations are examined. Building material and garden supply stores and food and beverage stores are also examined.[72] Although these retail businesses are discussed in price gouging debates, the predicted effect of an APG law is ambiguous; the effect could be zero or negative due to increased cost provisions and "consumer anger fear."

Finally, wages are examined within the NAICS classification for specialty trade contractors.[73] There is no clear category for the contractors that arrive in a disaster area to clean up debris, but sub-categories within specialty trade contractors include building equipment contractors, building exterior contractors, flooring contractors, glass contractors, roofing contractors, and siding contactors. Therefore, this classification appears to be the closest fit. Also discussed above, the predicted effect of APG laws in hurricane-stricken counties on specialty trade contractors is also ambiguous.

[72] Building material and garden supply stores are those such as Home Depot or Lowes. Food and beverage stores generally encompass grocery stores.
[73] Construction is broken down by three main categories: construction of buildings, heavy and civil engineering construction, and specialty trade contractors. The first two appear to be less appropriate classifications for the contractors that offer cleanup services following a disaster, so the last category is examined.

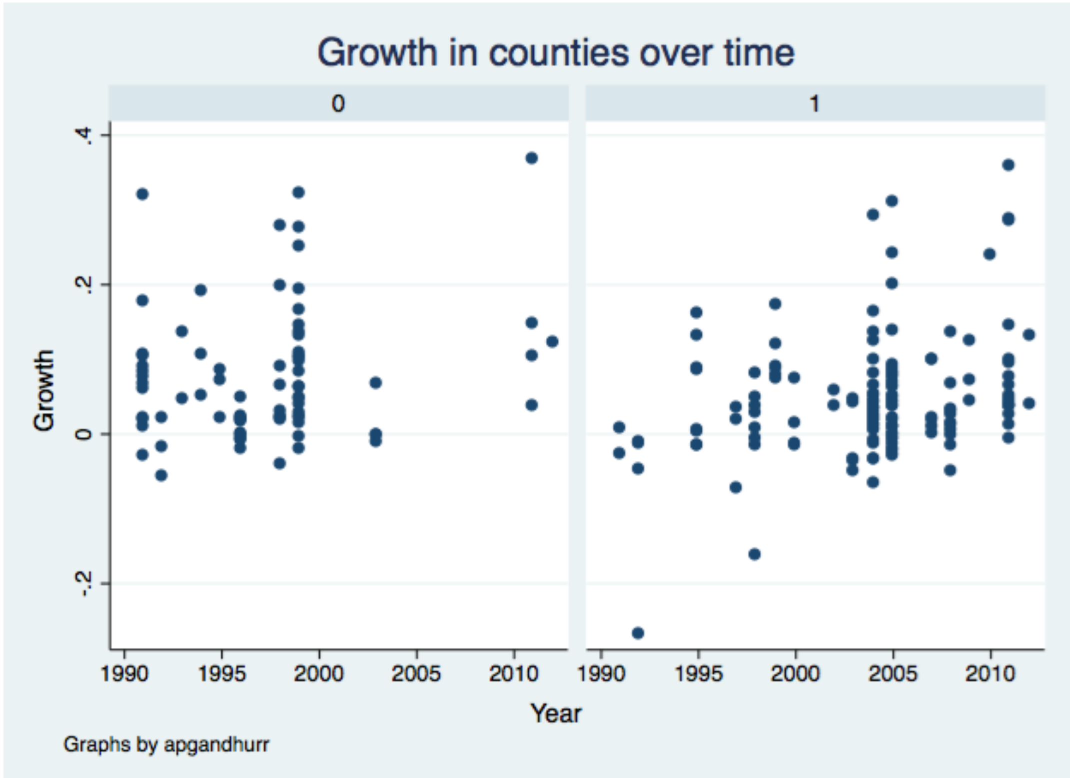

Figure 8. Quarterly Growth Rates by APG Law and Hurricane Strike, 1990-2012

Notes: The left-hand side shows quarterly growth of per-worker wages over time in any county that was hit by a hurricane and did not have an APG law in that particular quarter. The mean for this group is 0.0759. The right-hand side shows quarterly growth of per-worker wages over time in any county that was hit by a hurricane and did have an APG law in that quarter. The mean for this group is 0.0465.

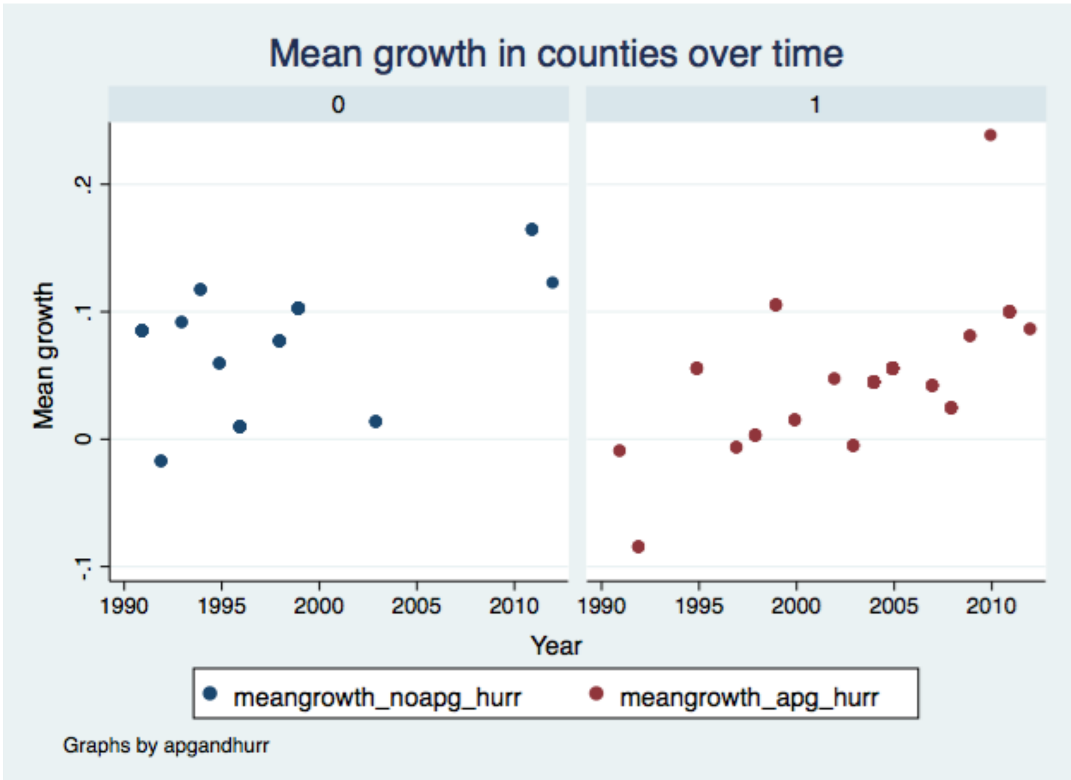

Figure 9. Mean Quarterly Growth Rates by APG Law and Hurricane Strike, 1990-2012

Notes: The left-hand side shows mean quarterly growth of per-worker wages over time for all counties that were hit by a hurricane and did not have an APG law in that particular quarter. The mean for this group is 0.0759. The right-hand side shows mean quarterly growth of per-worker wages over time for all counties that were hit by a hurricane and did have an APG law in that quarter. The mean for this group is 0.0465.

Table 8. Quarterly County-level Summary Statistics, All Industries, 1990-2012

Variable	Mean	SD	Min	Max	N	Description
$Growth_{ct-1àt}$	0.0026	0.0981	-1.8074	1.6477	117798	Growth of ln(per-worker wages) across all industries in county *c* from quarter *t-1* to *t*
$Growth_{st-1àt}$	0.0029	0.0744	-1.1017	0.9906	118565	Average county growth of ln(per-worker wages) in state *s* from quarter *t-1* to *t*
$\ln(PWW_{ct-1})$	8.8430	0.2440	7.6579	10.9426	117886	Ln(per-worker wages) in county *c* in quarter *t-1*
APG_{ct}	0.6708	0.4699	0	1	119880	= 1 if the corresponding state for county *c* has an APG law in effect in quarter *t*, = 0 otherwise
$HURR_{ct}$	0.0018	0.0428	0	1	119880	= 1 if county *c* sustained a hurricane strike in quarter *t*, = 0 otherwise
$CAT123_{ct}$	0.0018	0.0421	0	1	119880	= 1 if county *c* sustained a Category 1-3 hurricane strike in quarter *t*, = 0 otherwise
$CAT1_{ct}$	0.0012	0.0344	0	1	119880	= 1 if county *c* sustained a Category 1 hurricane strike in quarter *t*, = 0 otherwise
$CAT2_{ct}$	0.0004	0.0189	0	1	119880	= 1 if county *c* sustained a Category 2 hurricane strike in quarter *t*, = 0 otherwise
$CAT3_{ct}$	0.0002	0.0153	0	1	119880	= 1 if county *c* sustained a Category 3 hurricane strike in quarter *t*, = 0 otherwise
$CAT4_{ct}$	0.0001	0.0076	0	1	119880	= 1 if county *c* sustained a Category 4 hurricane strike in quarter *t*, = 0 otherwise
DEM_{st}	0.5105	0.4999	0	1	119880	= 1 if both chambers of legislature in state *s* are controlled by the Democratic Party in year *t*, = 0 otherwise
POP_DENS_{ct}	415	2519	0.0822	71534	118776	Total population in county *c* in year *t* divided by total land area for county *c*, in square miles
$\%NONWHITE_{ct}$	0.2006	0.1828	0	0.8690	118776	Percent of the population in county *c* that was nonwhite
$\%ADULTMALE_{ct}$	0.4927	0.0226	0.4263	0.6881	118776	Percent of the population in county *c* that was male
$\%19OLDER_{ct}$	0.7216	0.0353	0.5539	0.9101	118776	Percent of the population in county *c* that was 19+ years of age

Table 8 (continued). Quarterly County-level Summary Statistics, All Industries, 1990-2012

Notes: Growth of per-worker wages were constructed by taking the difference between the natural log of per-worker wages in quarter *t* and the natural log of per-worker wages in quarter *t-1*. Wage data come from the Bureau of Labor Statistics Quarterly Census of Employment and Wages (http://www.bls.gov/cew/datatoc.htm). Anti-price gouging law data come from Davis (2008), Benavides (2006), and Giberson (2012). Hurricane data come from the National Oceanic and Atmospheric Administration's Best Track Data (HURDAT2) (http://www.nhc.noaa.gov/data/#hurdat). There are no Category 5 storms in the dataset. State legislature data come from the National Conference of State Legislatures (http://www.ncsl.org/research/about-state-legislatures/partisan-composition.aspx). Population characteristics come from the Surveillance, Epidemiology, and End Results Program of the National Cancer Institute (http://seer.cancer.gov/popdata/), and the U.S. Census Bureau's 2013 Gazetteer files (https://www.census.gov/geo/maps-data/data/gazetteer2013.html).

Table 9. Quarterly County-level Growth of Per-Worker Wages, All Industries, 1990-2012

Category	Mean	SD	N
When APG_{ct} = 0	0.0038	0.0948	38083
When APG_{ct} = 1	0.0020	0.0996	79715
When $HURR_{ct\ t}$ = 0	0.0025	0.0981	117579
When $HURR_{ct}$ = 1	0.0567	0.0846	219
When APG_{ct} = 1 and $HURR_{ct}$ = 0	0.0019	0.0996	79572
When APG_{ct} = 0 and $HURR_{ct}$ = 1	0.0759	0.0884	76
When APG_{ct} = 1 and $HURR_{ct}$ = 1	0.0465	0.0810	143

Notes: The above distributions are for the quarterly growth rate of per-worker wages within a county, which is equal to the difference between natural log of per-worker wages in quarter *t* and the natural log of per-worker wages in quarter *t-1*. The first two lines show the distribution of growth rates in counties within states with and without an anti-price gouging law in place. The next two lines show the distribution of growth rates in counties that do and do not experience a hurricane strike during a particular quarter. The final three lines show the distribution of growth rates in counties that have an anti-price gouging law in place but do not experience a hurricane that quarter, do not have an anti-price gouging law in place and do experience a hurricane that quarter, and have an anti-price gouging law in place and do experience a hurricane that quarter.

QUARTERLY RESULTS

All Industries

Neoclassical Growth Model

Table 10 presents fixed effect estimates of growth of county-level per-worker wages. The estimates in the first column do not control for county-specific time trends, while the second and third column regressions add controls for county-specific linear and quadratic time trends, respectively. These regressions use the same model specification as with previous annual data but different data. Whereas previous data measured annual growth of per capita income, as reported by employees on their tax forms, these regressions now measure quarterly growth of per-worker wages, as reported by employers for unemployment insurance purposes, and constructed with county-level total employment rather than total population. The more granular time frame better captures the duration of an active anti-price gouging (APG) law following a hurricane, while reporting by the employer ensures wages are generated in the county in which they are reported and the construction of the response variable captures adjustments in wages as well as employment.

By changing the above measurements, the estimated effects counter those found previously. When controlling for county-specific linear and quadratic time trends, table 10 indicates that counties with an APG law in effect following a hurricane experience a 1.67 percent lower growth of quarterly per-worker wages than hurricane-stricken counties without APG laws.[74] Measurement error present in the model will attenuate estimates toward zero, so this negative effect is likely understated.[75]

Table 11 reports estimates when including one- and two-period lags in the hurricane variable and the interaction term. These results suggest that while counties with APG laws in effect following a hurricane suffer immediately during a declared state of emergency, counties experience a later rebound as the twice-lagged interaction term is statistically significant and positive both with and without controlling for county-specific time trends. In the third column, the rebound effect is almost equal in size to the estimated negative impact of the APG law immediately following a storm.[76] This lagged rebound, which appears when the APG law has likely been lifted, appears to be a form of conditional convergence, or that the economic gap between two comparable counties narrows over time.[77] These results are robust to controlling for heterogeneity among APG

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[74] The results are sensitive to weighting by population, suggesting that effects of APG laws may be larger in less populated hurricane-stricken counties. The estimated effect is less clear when the hurricane dummy is separated by Saffir-Simpson category; the estimated negative effects of an APG law appear to be pronounced in the presence of Category 2 storms, yet the law seems to have no significant effect when any other category storm strikes. These results, however, are likely partially due to the lack of observations for larger category storms; for instance, there are only seven Category 4 storms in this dataset and all seven hit counties in Florida. Estimates are similar when also including one- and two-period lags for separate Saffir-Simpson categories. These estimates are available upon request.

[75] Appendix B further explores measurement error in the model.

[76] To test whether previously estimated positive annual growth in per capita income is due to this lagged rebound effect, the annual dataset was restricted to the same period as the quarterly data, 1990-2012, and coefficients for the neoclassical model were estimated while controlling for linear and quadratic time trends. The model was then estimated using quarterly data but including a third lagged interaction term so that model controlled for effects of APG laws in hurricane-stricken counties over a full year. Using the quarterly results, an F-test for whether $(APG*HURR)_{ct} + (APG*HURR)_{ct-1} + (APG*HURR)_{ct-2} + (APG*HURR)_{ct-3} = 0$ yielded a p-value of 0.4785, suggesting that over the course of a full year the lagged rebound effect is equal in size to the initial negative effect of the APG law following a hurricane. Estimates are reported in Appendix A.

[77] Therefore, counties with worse economic conditions, due to the initial negative effect of the APG law following a hurricane, experience higher rates of growth than comparable counties with better economic conditions, in this case, hurricane-stricken counties that do not have APG laws in place. This could be due to consumers making up for rationing or living without goods and services when APG laws were in effect and there were shortages or waiting lines. Conditional convergence is also the explanation for the estimated negative coefficient on ln(PWW_{ct-1}) (Strobl 2011).

laws, where controls are included for APG laws that define jail time as possible penalty, those that do not allow price increases within a specified range, and states with a history of strong enforcement of the law, both with and without one- and two-period lags.[78]

Labor Market Model

To observe the effects of a hurricane strike on wages and employment in Florida, Belasen and Polachek (2009) examine BLS QCEW data, although their model specification differs from that of Strobl (2011). Rather than including once-lagged county-specific per-worker wages to control for the initial economic conditions of a particular county, Belasen and Polachek (2009) include growth of per-worker wages measured at the state level as a control for economic conditions of the "average county" within that state. This control is then moved to the left-hand side, where it is differenced from growth of per-worker wages within a particular county. This leads to a nice interpretation of the response variable: the change in growth of per-worker wages in a hurricane-stricken county as compared to the average county within that state. APG laws are statewide but hurricane impacts are localized, so this approach yields the average county as a fitting comparison for counties within states with APG laws but that also experience a hurricane strike.[79]

Table 12 presents estimates using the labor market model. As shown in the third column, when controlling for county-specific linear and quadratic time trends, the estimated effect of an APG law on change in growth of per-worker wages in a hurricane-

[78] These estimates are available upon request.
[79] Note that because per-worker wages in the average county are constructed using state-level per-worker wages, the average county includes per-worker wages within hurricane-stricken counties as well.

stricken county is negative and statistically significant. This implies that counties within states with APG laws that are struck by hurricanes experience a decrease in growth of per-worker wages of 2.30 percent as compared to the average county within that state.[80] This estimated effect is larger than in the previous neoclassical growth model specification, due to comparison with the average county in the state, rather than that particular county's previous income level.[81] Table 13 reports estimates when including one- and two-period lags. These results are similar to those from before when using the quarterly data and neoclassical growth model specification of Strobl (2011).

Hotels

Complaints of price gouging are most commonly for prices of gas and hotel rooms (Davis 2008). Therefore, firms within these industries are likely more greatly affected by the law. To examine this hypothesis, quarterly data from 1990-2012 were separated out by NAICS industry codes for accommodations, contractors, and retail stores, which include building material and garden supply stores, food and beverage stores, and gas stations.

The model used to evaluate industry effects is the same as above, following previous research on the effect of hurricanes by Belasen and Polachek (2009). The response variable is the difference in growth of per-worker wages between the specific industry in a hurricane-stricken county and the average county across all industries.

[80] The results change little when weighting the regressions by county populations.
[81] Estimates are qualitatively the same when controlling for Saffir-Simpson category-specific effects and heterogeneous effects of APG laws, with and without the inclusion of one- and two-period lags. Allowing for heterogeneous effects of APG laws, however, yields some peculiar results. These estimates are available upon request.

Saffir-Simpson category effects and the validity of controlling for county-specific time trends have been explored earlier, so to allow for easier comparison with previous regressions, all industry-specific regressions use a hurricane incidence variable and control for county-specific linear and quadratic time trends.[82]

Table 14 presents summary statistics for the accommodations industry. Table 15 reports growth rates of per-worker wages in the accommodations industry in the presence of APG laws, hurricanes, and combinations of both. On average, the accommodation industry appears to suffer from APG laws following a hurricane strike, as quarterly growth of per-worker wages within the industry is 15.96 percent without an APG law in place, yet only 8.02 percent in the presence of an APG law.

Table 20 presents estimates for specific industries, where column (1) reports estimates for the accommodations industry. An APG law in a hurricane-stricken county has a larger estimated negative effect within the accommodation industry than when previously examining wages across all industries; growth of per-worker wages among the accommodations industry decreases by an estimated 6.02 percent in hurricane-stricken counties with APG laws. This result supports the hypothesis that industries more commonly cited in APG law complaints are more adversely affected by APG laws following a hurricane strike.[83]

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[82] Additional regressions including dummy variables for heterogeneity in APG laws and one- and two-period lags were also estimated. These estimates are available upon request.

[83] Regressions were also estimated with controls for heterogeneity among APG laws. Results appear to suggest a more negative effect from threat of jail time as a possible penalty for infringement and a higher likelihood of leveled penalties for suspected price gouging. The results hold when including one- and two-period lags.

Gas & Other Retail

Gas Stations

Along with prices for hotel rooms, gas prices are also commonly cited in price gouging complaints. Nevertheless, APG laws in most states include an "increased cost" provision that allows firms to increase their prices if they face higher input costs.[84] Therefore, it may be easier for firms such as gas stations to escape charges of price gouging; hurricanes in the Gulf of Mexico can damage oil refineries and other infrastructure, leading to higher input costs. APG laws in hurricane-stricken counties may then have little impact on gas stations. Table 16 presents summary statistics for the retail industry, and table 17 reports growth rates of per-worker wages among gas stations in the presence of APG laws, hurricanes, and combinations of both. On average, gas stations do not appear to be affected by APG laws following a hurricane strike, as quarterly growth of per-worker wages within these firms is 5.99 percent without an APG law in place and 5.53 percent in the presence of an APG law. Table 20 presents estimates when examining only firms classified by the NAICS code 447 for gas stations in column (2). These results suggest that APG laws following a hurricane indeed have little effect on per-worker wages at gas stations.[85]

[84] Missouri, Texas, and Wisconsin are the only states with APG laws that do not have increased cost provisions (Davis 2008).

[85] Waiting lines at gas stations, mentioned above, suggest there may indeed be an effect of APG laws on gas stations, but the model does not capture this effect; the adjustment to the price control may occur on some margin other than wages or employment. Non-price adjustments may be more or less observable depending on the industry. Gas stations may develop waiting lines as an adjustment to APG laws, which is easily observed, while hotels do not develop lines but do appear to experience a decrease in growth of per-worker wages. See Barzel (1997) for a discussion of non-price margins for adjustments to price controls.

Building Material & Garden Supply Stores

Building material and garden supply stores such as Home Depot and Lowes frequently capture public attention following a hurricane strike, although the attention is usually for a commitment to keep prices constant following the strike, rather than for suspected price gouging.[86] This behavior would render the APG law ineffective, as there would be no difference in outcomes in states with and without APG laws if large corporate stores were following the same pricing policy in both states. Table 20 presents regressions for only those firms classified by the NAICS code for building material and garden supply stores in column (3). These results suggest that APG laws are mostly nonbinding in this industry, as the interaction term is not statistically different from zero.

Food & Beverage Stores

Firms classified as food and beverage stores may also be affected by APG laws. Grocery stores make up the dominant portion of these firms; an APG law in effect following a hurricane could result in shortages or waiting in line for necessities such as dry goods and water. Yet, Davis presents few instances of price gouging complaints regarding grocery stores or other food and beverage stores (2008). Table 20 reports estimates for changes in growth of per-worker wages for food and beverage stores in column (4). These results indicate that APG laws do not have much impact on these stores in hurricane-stricken counties.

[86] For example, following Hurricane Andrew in 1992, see http://www.nytimes.com/1992/09/22/business/lessons-from-a-hurricane-it-pays-not-to-gouge.html.

Construction

Finally, per-worker wages among specialty trade contractors are examined. While there is no clear NAICS classification for contractors who remove debris following a hurricane strike, the NAICS code 238 for specialty trade contractors includes exterior building contractors such as roofing and siding contractors. Therefore, this classification appears more appropriate than alternatives within the NAICS system. Table 18 presents summary statistics for the construction industry. Table 19 reports growth rates of per-worker wages among specialty trade contractors in the presence of APG laws, hurricanes, and combinations of both. On average, APG laws do not appear to affect specialty trade contractors following a hurricane strike, as quarterly growth of per-worker wages for these workers is 3.82 percent without an APG law in place and 3.76 percent in the presence of an APG law. Table 20 presents estimates for specialty trade contractors in column (5); the estimated effect of APG laws on per-worker wages in specialty contracting is not statistically different from zero.

Table 21 reports estimates for the above industries while allowing for lagged effects. These results support the above discussion that the accommodation industry suffers from an APG law immediately following a hurricane. Specialty trade contractors also appear to be negatively affected by an APG law in effect, although the impact on this industry occurs one quarter after the hurricane strike, perhaps due to the timing of billing in this industry.[87] The retail industries examined experience no initial or lagged negative

[87] While contractors generally give an initial estimate, the actual price of services rendered is not known until after the service has been completed, which may well be a few months after the hurricane strike. This

statistically significant effects statistically, perhaps due to increased cost provisions or fear of backlash from angered consumers. In fact, building material and garden supply stores experience an estimated positive effect two quarters after the strike, likely due to rebuilding efforts.

contrasts with the prices of hotel rooms, which are known immediately when the hotel rooms are purchased.

Table 10. Growth of Quarterly Per-Worker Wages with APG Laws, 1990-2012

	Reg (1)	Reg (2)	Reg (3)
	Growth	Growth	Growth
Intercept	3.8311***	5.7167***	6.8320***
	(0.1531)	(0.2105)	(0.2298)
ln(PWW_{ct-1})	-0.4384***	-0.6345***	-0.7740***
	(0.0162)	(0.0176)	(0.0179)
APG_{ct}	-0.0069***	-0.0099***	-0.0012
	(0.0013)	(0.0016)	(0.0015)
$HURR_{ct}$	0.0285***	0.0292***	0.0262***
	(0.0098)	(0.0091)	(0.0083)
$(APG*HURR)_{ct}$	-0.0135	-0.0187**	-0.0167**
	(0.0090)	(0.0086)	(0.0083)
Year & Quarter FE's	Yes	Yes	Yes
County FE's	Yes	Yes	Yes
Covariates	Yes	Yes	Yes
County-specific linear time trends	No	Yes	Yes
County-specific quadratic time trends	No	No	Yes
Number of counties	1292	1292	1292
Observations	117082	117082	117082
Adjusted R^2	0.5524	0.6048	0.6419

* Statistically significant at 10% level, ** at 5% level, *** at 1% level.

Notes: Each column represents the results from a separate OLS regression. The dependent variable is equal to the difference between the natural log of per-worker wages in quarter *t* and the natural log of per-worker wages in quarter *t-1*, or the quarterly growth rate of per-worker wages within a county. Covariates included are county population density (population per square mile), percent of the county population that is nonwhite, percent of the county population that is male, percent of the county population that is 19 years of age or older, and a dummy variable for whether the Democratic Party controlled both chambers of state legislature. All standard errors are corrected for clustering at the county level.

Table 11. Lagged Growth of Quarterly Per-Worker Wages with APG Laws, 1990-2012

	Reg (1) Growth	Reg (2) Growth	Reg (3) Growth
Intercept	3.8343***	5.7356***	6.8321***
	(0.1581)	(0.2130)	(0.2288)
$\ln(PWW_{ct-1})$	-0.4412***	-0.6372***	-0.7782***
	(0.0163)	(0.0177)	(0.0178)
APG_{ct}	-0.0069***	-0.0097***	-0.0009
	(0.0013)	(0.0016)	(0.0016)
$HURR_{ct}$	0.0284***	0.0289***	0.0257***
	(0.0097)	(0.0089)	(0.0081)
$HURR_{ct-1}$	0.0095	0.0179**	0.0210***
	(0.0061)	(0.0072)	(0.0079)
$HURR_{ct-2}$	-0.0087	-0.0073	-0.0081
	(0.0072)	(0.0071)	(0.0070)
$(APG*HURR)_{ct}$	-0.0127	-0.0174**	-0.0151*
	(0.0089)	(0.0086)	(0.0082)
$(APG*HURR)_{ct-1}$	0.0030	-0.0071	-0.0097
	(0.0072)	(0.0077)	(0.0081)
$(APG*HURR)_{ct-2}$	0.0133*	0.0124*	0.0138*
	(0.0071)	(0.0071)	(0.0071)
Year & Quarter FE's	Yes	Yes	Yes
County FE's	Yes	Yes	Yes
Covariates	Yes	Yes	Yes
County-specific linear time trends	No	Yes	Yes
County-specific quadratic time trends	No	No	Yes
Number of counties	1292	1292	1292
Observations	115790	115790	115790
Adjusted R^2	0.5548	0.6070	0.6448

* Statistically significant at 10% level, ** at 5% level, *** at 1% level.

Notes: Each column represents the results from a separate OLS regression. The dependent variable is equal to the difference between the natural log of per-worker wages in quarter *t* and the natural log of per-worker wages in quarter *t-1*, or the quarterly growth rate of per-worker wages within a county. Covariates included are county population density (population per square mile), percent of the county population that is nonwhite, percent of the county population that is male, percent of the county population that is 19 years of age or older, and a dummy variable for whether the Democratic Party controlled both chambers of state legislature. All standard errors are corrected for clustering at the county level.

Table 12. Change in Growth of Quarterly Per-Worker Wages with APG Laws, 1990-2012

	Reg (1) Δ Growth	Reg (2) Δ Growth	Reg (3) Δ Growth
Intercept	-0.5249***	-0.1012	-0.3232*
	(0.1234)	(0.1796)	(0.1694)
APG_{ct}	-0.0124***	-0.0122***	-0.0000
	(0.0029)	(0.0024)	(0.0020)
$HURR_{ct}$	0.0043	0.0190**	0.0215***
	(0.0083)	(0.0080)	(0.0077)
$(APG*HURR)_{ct}$	0.0060	-0.0169**	-0.0230***
	(0.0097)	(0.0085)	(0.0084)
Year & Quarter FE's	Yes	Yes	Yes
County FE's	Yes	Yes	Yes
Covariates	Yes	Yes	Yes
County-specific linear time trends	No	Yes	Yes
County-specific quadratic time trends	No	No	Yes
Number of counties	1292	1292	1292
Observations	118425	118425	118425
Adjusted R^2	0.1086	0.3620	0.4574

* Statistically significant at 10% level, ** at 5% level, *** at 1% level.

Notes: Each column represents the results from a separate OLS regression. The dependent variable is equal to the difference between the natural log of per-worker wages in county *i* and the natural log of per-worker wages in the “average county” in quarter *t*, or the change in growth of per-worker wages within a hurricane-stricken county as compared to an average county within that state. Covariates included are county population density (population per square mile), percent of the county population that is nonwhite, percent of the county population that is male, percent of the county population that is 19 years of age or older, and a dummy variable for whether the Democratic Party controlled both chambers of state legislature. All standard errors are corrected for clustering at the county level.

Table 13. Lagged Change in Growth of Quarterly Per-Worker with APG Laws, 1990-2012

	Reg (1) Δ Growth	Reg (2) Δ Growth	Reg (3) Δ Growth
Intercept	-0.6098***	-0.0690	-0.3271*
	(0.1315)	(0.1835)	(0.1701)
APG_{ct}	-0.0132***	-0.0117***	0.0003
	(0.0029)	(0.0024)	(0.0020)
$HURR_{ct}$	0.0029	0.0183**	0.0215***
	(0.0083)	(0.0081)	(0.0077)
$HURR_{ct-1}$	0.0125	0.0262***	0.0296***
	(0.0080)	(0.0084)	(0.0086)
$HURR_{ct-2}$	0.0063	0.0032	-0.0028
	(0.0086)	(0.0079)	(0.0075)
$(APG*HURR)_{ct}$	0.0073	-0.0158*	-0.0220***
	(0.0096)	(0.0086)	(0.0084)
$(APG*HURR)_{ct-1}$	0.0081	-0.0136	-0.0205**
	(0.0090)	(0.0083)	(0.0085)
$(APG*HURR)_{ct-2}$	0.0336***	0.0251***	0.0213***
	(0.0079)	(0.0076)	(0.0075)
Year & Quarter FE's	Yes	Yes	Yes
County FE's	Yes	Yes	Yes
Covariates	Yes	Yes	Yes
County-specific linear time trends	No	Yes	Yes
County-specific quadratic time trends	No	No	Yes
Number of counties	1292	1292	1292
Observations	115841	115841	115841
Adjusted R^2	0.1086	0.3576	0.4546

* Statistically significant at 10% level, ** at 5% level, *** at 1% level.

Notes: Each column represents the results from a separate OLS regression. The dependent variable is equal to the difference between the natural log of per-worker wages in county *i* and the natural log of per-worker wages in the “average county” in quarter *t*, or the change in growth of per-worker wages within a hurricane-stricken county as compared to an average county within that state. Covariates included are county population density (population per square mile), percent of the county population that is nonwhite, percent of the county population that is male, percent of the county population that is 19 years of age or older, and a dummy variable for whether the Democratic Party controlled both chambers of state legislature. All standard errors are corrected for clustering at the county level.

Table 14. Quarterly County-level Summary Statistics, Accommodations, 1990-2012

Variable	Mean	SD	Min	Max	N	Description
$Growth_{721ct-1\text{à}t}$	0.0044	0.2159	-2.3250	2.1058	64644	Growth of ln(per-worker wages) in accommodations in county *c* from quarter *t-1* to *t*
$Growth_{st-1\text{à}t}$	0.0026	0.0780	-1.1017	0.9906	85474	Average county growth of ln(per-worker wages) in state *s* from quarter *t-1* to *t*
APG_{ct}	0.7269	0.4455	0	1	86800	= 1 if the corresponding state for county *c* has an APG law in effect in quarter *t*, = 0 otherwise
$HURR_{ct}$	0.0021	0.0456	0	1	86800	= 1 if county *c* sustained a hurricane strike in quarter *t*, = 0 otherwise
$CAT123_{ct}$	0.0020	0.0449	0	1	86800	= 1 if county *c* sustained a Category 1-3 hurricane strike in quarter *t*, = 0 otherwise
$CAT1_{ct}$	0.0014	0.0368	0	1	86800	= 1 if county *c* sustained a Category 1 hurricane strike in quarter *t*, = 0 otherwise
$CAT2_{ct}$	0.0004	0.0198	0	1	86800	= 1 if county *c* sustained a Category 2 hurricane strike in quarter *t*, = 0 otherwise
$CAT3_{ct}$	0.0003	0.0163	0	1	86800	= 1 if county *c* sustained a Category 3 hurricane strike in quarter *t*, = 0 otherwise
$CAT4_{ct}$	0.0001	0.0083	0	1	86800	= 1 if county *c* sustained a Category 4 hurricane strike in quarter *t*, = 0 otherwise
DEM_{st}	0.4392	0.4963	0	1	86800	= 1 if both chambers of legislature in state *s* are controlled by the Democratic Party in year *t*, = 0 otherwise
POP_DENS_{ct}	539	2946	0.2866	71534	85756	Total population in county *c* in year *t* divided by total land area for county *c*, in square miles
$\%NONWHITE_{ct}$	0.1903	0.1719	0.0024	0.8670	85756	Percent of the population in county *c* that was nonwhite
$\%ADULTMALE_{ct}$	0.4926	0.0208	0.4263	0.6881	85756	Percent of the population in county *c* that was male
$\%19OLDER_{ct}$	0.7270	0.0333	0.5801	0.9101	85756	Percent of the population in county *c* that was 19+ years of age

Table 14 (continued). Quarterly County-level Summary Statistics, Accommodations, 1990-2012

Notes: Growth of per-worker wages in the accommodations industry were constructed by taking the difference between natural log of per-worker wages in quarter *t* and the natural log of per-worker wages in quarter *t-1* for all business categorized by NAICS code 721 for accommodations. Wage data come from the Bureau of Labor Statistics Quarterly Census of Employment and Wages (http://www.bls.gov/cew/datatoc.htm). Anti-price gouging law data come from Davis (2008), Benavides (2006), and Giberson (2012). Hurricane data come from the National Oceanic and Atmospheric Administration's Best Track Data (HURDAT2) (http://www.nhc.noaa.gov/data/#hurdat). There are no Category 5 storms in the dataset. State legislature data come from the National Conference of State Legislatures (http://www.ncsl.org/research/about-state-legislatures/partisan-composition.aspx). Population characteristics come from the Surveillance, Epidemiology, and End Results Program of the National Cancer Institute (http://seer.cancer.gov/popdata/), and the U.S. Census Bureau's 2013 Gazetteer files (https://www.census.gov/geo/maps-data/data/gazetteer2013.html).

Table 15. Quarterly County-level Growth of Per-Worker Wages, Accommodations, 1990-2012

Category	Mean	SD	N
When APG_{ct} = 0	0.0060	0.2187	20587
When APG_{ct} = 1	0.0036	0.2146	44057
When $HURR_{ct\,t}$ = 0	0.0042	0.2160	64501
When $HURR_{ct}$ = 1	0.1052	0.1742	143
When APG_{ct} = 1 and $HURR_{ct}$ = 0	0.0035	0.2147	43959
When APG_{ct} = 0 and $HURR_{ct}$ = 1	0.1596	0.2034	45
When APG_{ct} = 1 and $HURR_{ct}$ = 1	0.0802	0.1539	98

Notes: The above distributions are for the quarterly growth rate of per-worker wages within a county, which is equal to the difference between the natural log of per-worker wages in quarter *t* and the natural log of per-worker wages in quarter *t-1* for all business categorized by NAICS code 721 for accommodations. The first two lines show the distribution of growth rates in counties within states with and without an anti-price gouging law in place. The next two lines show the distribution of growth rates in counties that do and do not experience a hurricane strike during a particular year. The final three lines show the distribution of growth rates in counties that have an anti-price gouging law in place but do not experience a hurricane that year, do not have an anti-price gouging law in place and do experience a hurricane that year, and have an anti-price gouging law in place and do experience a hurricane that year.

Table 16. Quarterly County-level Summary Statistics, Retail, 1990-2012

Variable	Mean	SD	Min	Max	N	Description
$Growth_{447ct-1 \rightarrow t}$	0.0008	0.1116	-2.4840	2.5396	55739	Growth of ln(per-worker wages) in gas stations in county *c* from quarter *t-1* to *t*
$Growth_{444ct-1 \rightarrow t}$	0.0011	0.1561	-1.6772	1.9405	52822	Growth of ln(per-worker wages) in building materials & garden supply stores in county *c* from quarter *t-1* to *t*
$Growth_{445ct-1 \rightarrow t}$	0.0008	0.1054	-2.6687	2.4425	53804	Growth of ln(per-worker wages) in food & beverage stores in county *c* from quarter *t-1* to *t*
$Growth_{st-1 \rightarrow t}$	0.0022	0.0790	-1.1017	0.9906	57740	Average county growth of ln(per-worker wages) in state *s* from quarter *t-1* to *t*
APG_{ct}	0.8109	0.3916	0	1	58964	= 1 if the corresponding state for county *c* has an APG law in effect in quarter *t*, = 0 otherwise
$HURR_{ct}$	0.0019	0.0439	0	1	58964	= 1 if county *c* sustained a hurricane strike in quarter *t*, = 0 otherwise
$CAT123_{ct}$	0.0019	0.0433	0	1	58964	= 1 if county *c* sustained a Category 1-3 hurricane strike in quarter *t*, = 0 otherwise
$CAT1_{ct}$	0.0013	0.0361	0	1	58964	= 1 if county *c* sustained a Category 1 hurricane strike in quarter *t*, = 0 otherwise
$CAT2_{ct}$	0.0003	0.0175	0	1	58964	= 1 if county *c* sustained a Category 2 hurricane strike in quarter *t*, = 0 otherwise
$CAT3_{ct}$	0.0003	0.0165	0	1	58964	= 1 if county *c* sustained a Category 3 hurricane strike in quarter *t*, = 0 otherwise
$CAT4_{ct}$	0.0001	0.0071	0	1	58964	= 1 if county *c* sustained a Category 4 hurricane strike in quarter *t*, = 0 otherwise
DEM_{st}	0.4083	0.4915	0	1	58964	= 1 if both chambers of legislature in state *s* are controlled by the Democratic Party in year *t*, = 0 otherwise
POP_DENS_{ct}	647	3527	0.4220	71534	58020	Total population in county *c* in year *t* divided by total land area for county *c*, in square miles

Table 16 (continued). Quarterly County-level Summary Statistics, Retail, 1990-2012

Variable	Mean	SD	Min	Max	N	Description
$\%NONWHITE_{ct}$	0.1982	0.1751	0.0045	0.8620	58020	Percent of the population in county *c* that was nonwhite
$\%ADULTMALE_{ct}$	0.4928	0.0201	0.4263	0.6587	58020	Percent of the population in county *c* that was male
$\%19OLDER_{ct}$	0.7312	0.0311	0.5926	0.9101	58020	Percent of the population in county *c* that was 19+ years of age

Notes: Growth of per-worker wages in the retail industry were constructed by taking the difference between the natural log of per-worker wages in quarter *t* and the natural log of per-worker wages in quarter *t-1* for all business categorized by each respective NAICS code. Wage data come from the Bureau of Labor Statistics Quarterly Census of Employment and Wages (http://www.bls.gov/cew/datatoc.htm). Anti-price gouging law data come from Davis (2008), Benavides (2006), and Giberson (2012). Hurricane data come from the National Oceanic and Atmospheric Administration's Best Track Data (HURDAT2) (http://www.nhc.noaa.gov/data/#hurdat). There are no Category 5 storms in the dataset. State legislature data come from the National Conference of State Legislatures (http://www.ncsl.org/research/about-state-legislatures/partisan-composition.aspx). Population characteristics come from the Surveillance, Epidemiology, and End Results Program of the National Cancer Institute (http://seer.cancer.gov/popdata/), and the U.S. Census Bureau's 2013 Gazetteer files (https://www.census.gov/geo/maps-data/data/gazetteer2013.html).

Table 17. Quarterly County-level Growth of Per-Worker Wages, Gas Stations, 1990-2012

Category	Mean	SD	N
When $APG_{ct} = 0$	0.0016	0.1040	10328
When $APG_{ct} = 1$	0.0007	0.1132	45411
When $HURR_{ct\,t} = 0$	0.0007	0.1115	55626
When $HURR_{ct} = 1$	0.0561	0.1098	113
When $APG_{ct} = 1$ and $HURR_{ct} = 0$	0.0006	0.1132	45317
When $APG_{ct} = 0$ and $HURR_{ct} = 1$	0.0599	0.0793	19
When $APG_{ct} = 1$ and $HURR_{ct} = 1$	0.0553	0.1153	94

Notes: The above distributions are for the quarterly growth rate of per-worker wages within a county, which is equal to the difference between the natural log of per-worker wages in quarter *t* and the natural log of per-worker wages in quarter *t-1* for all business categorized by NAICS code 447 for gas stations. The first two lines show the distribution of growth rates in counties within states with and without an anti-price gouging law in place. The next two lines show the distribution of growth rates in counties that do and do not experience a hurricane strike during a particular year. The final three lines show the distribution of growth rates in counties that have an anti-price gouging law in place but do not experience a hurricane that year, do not have an anti-price gouging law in place and do experience a hurricane that year, and have an anti-price gouging law in place and do experience a hurricane that year.

Table 18. Quarterly County-level Summary Statistics, Construction, 1990-2012

Variable	Mean	SD	Min	Max	N	Description
$Growth_{238ct-1 \rightarrow t}$	0.0046	0.1717	-2.3365	2.5413	98104	Growth of ln(per-worker wages) in specialty contractors in county *c* from quarter *t-1* to *t*
$Growth_{st-1 \rightarrow t}$	0.0028	0.0748	-1.1017	0.9906	105900	Average county growth of ln(per-worker wages) in state *s* from quarter *t-1* to *t*
APG_{ct}	0.6938	0.4609	0	1	107240	= 1 if the corresponding state for county *c* has an APG law in effect in quarter *t*, = 0 otherwise
$HURR_{ct}$	0.0020	0.0442	0	1	107240	= 1 if county *c* sustained a hurricane strike in quarter *t*, = 0 otherwise
$CAT123_{ct}$	0.0019	0.0435	0	1	107240	= 1 if county *c* sustained a category 1-3 hurricane strike in quarter *t*, = 0 otherwise
$CAT1_{ct}$	0.0013	0.0355	0	1	107240	= 1 if county *c* sustained a category 1 hurricane strike in quarter *t*, = 0 otherwise
$CAT2_{ct}$	0.0004	0.0198	0	1	107240	= 1 if county *c* sustained a category 2 hurricane strike in quarter *t*, = 0 otherwise
$CAT3_{ct}$	0.0002	0.0156	0	1	107240	= 1 if county *c* sustained a category 3 hurricane strike in quarter *t*, = 0 otherwise
$CAT4_{ct}$	0.0001	0.0081	0	1	107240	= 1 if county *c* sustained a category 4 hurricane strike in quarter *t*, = 0 otherwise
DEM_{st}	0.4899	0.4999	0	1	107240	= 1 if both chambers of legislature in state *s* are controlled by the Democratic Party in year *t*, = 0 otherwise
POP_DENS_{ct}	430	2637	0.1166	71534	106140	Total population county *c* in year *t* divided by total land area for county *c*, in square miles
$\%NONWHITE_{ct}$	0.1984	0.1759	0.0014	0.8670	106140	Percent of the population in county *c* that was nonwhite
$\%ADULTMALE_{ct}$	0.4927	0.0215	0.4263	0.6881	106140	Percent of the population in county *c* that was male
$\%19OLDER_{ct}$	0.7234	0.0342	0.5652	0.9101	106140	Percent of the population in county *c* that was 19+ years of age

Table 18 (continued). Quarterly County-level Summary Statistics, Construction, 1990-2012

Notes: Growth of per-worker wages in the construction industry were constructed by taking the difference between the natural log of per-worker wages in quarter *t* and the natural log of per-worker wages in quarter *t-1* for all business categorized by NAICS code 238 for specialty contractors. Wage data come from the Bureau of Labor Statistics Quarterly Census of Employment and Wages (http://www.bls.gov/cew/datatoc.htm). Anti-price gouging law data come from Davis (2008), Benavides (2006), and Giberson (2012). Hurricane data come from the National Oceanic and Atmospheric Administration's Best Track Data (HURDAT2) (http://www.nhc.noaa.gov/data/#hurdat). There are no Category 5 storms in the dataset. State legislature data come from the National Conference of State Legislatures (http://www.ncsl.org/research/about-state-legislatures/partisan-composition.aspx). Population characteristics come from the Surveillance, Epidemiology, and End Results Program of the National Cancer Institute (http://seer.cancer.gov/popdata/), and the U.S. Census Bureau's 2013 Gazetteer files (https://www.census.gov/geo/maps-data/data/gazetteer2013.html).

Table 19. Quarterly County-level Growth of Per-Worker Wages, Specialty Trade Contractors, 1990-2012

Category	Mean	SD	N
When $APG_{ct} = 0$	0.0055	0.1686	30912
When $APG_{ct} = 1$	0.0041	0.1732	67192
When $HURR_{ct\,t} = 0$	0.0045	0.1718	97902
When $HURR_{ct} = 1$	0.0378	0.1500	202
When $APG_{ct} = 1$ and $HURR_{ct} = 0$	0.0041	0.1732	67057
When $APG_{ct} = 0$ and $HURR_{ct} = 1$	0.0382	0.1934	67
When $APG_{ct} = 1$ and $HURR_{ct} = 1$	0.0376	0.1238	135

Notes: The above distributions are for the quarterly growth rate of per-worker wages within a county, which is equal to the difference between the natural log of per-worker wages in quarter *t* and the natural log of per-worker wages in quarter *t-1* for all business categorized by NAICS code 238 for specialty trade contractors. The first two lines show the distribution of growth rates in counties within states with and without an anti-price gouging law in place. The next two lines show the distribution of growth rates in counties that do and do not experience a hurricane strike during a particular year. The final three lines show the distribution of growth rates in counties that have an anti-price gouging law in place but do not experience a hurricane that year, do not have an anti-price gouging law in place and do experience a hurricane that year, and have an anti-price gouging law in place and do experience a hurricane that year.

Table 20. Change in Growth of Quarterly Per-Worker Wages with APG Laws, Specific Industries, 1990-2012

	Reg (1) Δ Growth Hotels	Reg (2) Δ Growth Gas	Reg (3) Δ Growth Building	Reg (4) Δ Growth Food & Bev	Reg (5) Δ Growth Contracting
Intercept	-0.4803	-0.5498	0.4631	-0.4288	-0.1128
	(0.4429)	(0.4061)	(0.5033)	(0.5241)	(0.3636)
APG_{ct}	0.0008	0.0037	-0.0100*	0.0032	-0.0010
	(0.0052)	(0.0051)	(0.0056)	(0.0049)	(0.0042)
$HURR_{ct}$	0.0439*	0.0111	-0.0060	0.0293	-0.0116
	(0.0244)	(0.0125)	(0.0108)	(0.0211)	(0.0135)
$(APG*HURR)_{ct}$	-0.0602**	-0.0116	-0.0073	-0.0341	0.0028
	(0.0282)	(0.0165)	(0.0138)	(0.0251)	(0.0189)
Year & Quarter FE's	Yes	Yes	Yes	Yes	Yes
County FE's	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
County-specific linear time trends	Yes	Yes	Yes	Yes	Yes
County-specific quadratic time trends	Yes	Yes	Yes	Yes	Yes
Number of counties	1008	1131	1083	1113	1224
Observations	66383	56791	53562	54672	99677
Adjusted R^2	0.3104	0.4545	0.3971	0.5076	0.3689

* Statistically significant at 10% level, ** at 5% level, *** at 1% level.

Notes: Each column represents the results from a separate OLS regression. The dependent variable is equal to the difference between the natural logs of per-worker wages in county *i* for all business categorized by each specific NAICS code and the natural log of per-worker wages across all industries in the "average" county in quarter *t*, or the quarterly growth rate of per-worker wages in a specific industry within a hurricane-stricken county as compared to average wages in an average county within that state. The regression in column (1) covers the accommodations industry, column (2) covers gas stations, column (3) covers building material and garden supply stores, column (4) covers food and beverage stores, and column (5) covers specialty trade contractors. Not all counties have observations every year and quarter so some industries include more counties but fewer observations. Covariates included are county population density (population per square mile), percent of the county population that is nonwhite, percent of the county population that is male, percent of the county population that is 19 years of age or older, and a dummy variable for whether the Democratic Party controlled both chambers of state legislature. All standard errors are corrected for clustering at the county level.

Table 21. Lagged Change in Growth of Quarterly Per-Worker Wages with APG Laws, Specific Industries, 1990-2012

	Reg (1) Δ Growth Hotels	Reg (2) Δ Growth Gas	Reg (3) Δ Growth Building	Reg (4) Δ Growth Food & Bev	Reg (5) Δ Growth Contracting
Intercept	-0.5164	-0.6692*	0.6296	-0.6769	-0.0504
	(0.4521)	(0.3903)	(0.5122)	(0.5140)	(0.3598)
APG_{ct}	0.0031	0.0051	-0.0077	0.0045	0.0003
	(0.0052)	(0.0052)	(0.0056)	(0.0049)	(0.0042)
$HURR_{ct}$	0.0420*	0.0118	-0.0040	0.0320	-0.0100
	(0.0246)	(0.0133)	(0.0110)	(0.0213)	(0.0140)
$HURR_{ct-1}$	0.0511**	0.0027	-0.0199	0.0208	0.0460*
	(0.0235)	(0.0140)	(0.0256)	(0.0178)	(0.0241)
$HURR_{ct-2}$	0.0010	-0.0090	-0.0266*	-0.0222*	-0.0128
	(0.0157)	(0.0104)	(0.0157)	(0.0117)	(0.0122)
$(APG*HURR)_{ct}$	-0.0571**	-0.0112	-0.0061	-0.0345	0.0020
	(0.0284)	(0.0170)	(0.0140)	(0.0252)	(0.0191)
$(APG*HURR)_{ct-1}$	-0.0319	-0.0071	0.0293	-0.0277	-0.0462*
	(0.0288)	(0.0163)	(0.0295)	(0.0201)	(0.0270)
$(APG*HURR)_{ct-2}$	0.0154	0.0100	0.0261**	0.0070	0.0124
	(0.0259)	(0.0088)	(0.0109)	(0.0093)	(0.0099)
Year & Quarter FE's	Yes	Yes	Yes	Yes	Yes
County FE's	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
County-specific linear time trends	Yes	Yes	Yes	Yes	Yes
County-specific quadratic time trends	Yes	Yes	Yes	Yes	Yes
Number of counties	1008	1131	1083	1113	1224
Observations	64913	54464	51407	52426	97367
Adjusted R^2	0.3145	0.4540	0.3959	0.5071	0.3693

* Statistically significant at 10% level, ** at 5% level, *** at 1% level.

Table 21 (continued). Lagged Change in Growth of Quarterly Per-Worker Wages with APG Laws, Specific Industries, 1990-2012

Notes: Each column represents the results from a separate OLS regression. The dependent variable is equal to the difference between the natural logs of per-worker wages in county *i* for all business categorized by each specific NAICS code and the natural log of per-worker wages across all industries in the "average" county in quarter *t*, or the quarterly growth rate of per-worker wages in a specific industry within a hurricane-stricken county as compared to average wages in an average county within that state. The regression in column (1) covers the accommodations industry, column (2) covers gas stations, column (3) covers building material and garden supply stores, column (4) covers food and beverage stores, and column (5) covers specialty trade contractors. Not all counties have observations every year and quarter so some industries include more counties but fewer observations. Covariates included are county population density (population per square mile), percent of the county population that is nonwhite, percent of the county population that is male, percent of the county population that is 19 years of age or older, and a dummy variable for whether the Democratic Party controlled both chambers of state legislature. All standard errors are corrected for clustering at the county level.

CONCLUSION

This thesis examines the economic effects of anti-price gouging (APG) laws, which prohibit firms from significantly increasing prices during a declared state of emergency, such as following a hurricane strike. While the economic effects of a hurricane strike have been examined, this thesis is the first to exploit the spatial and temporal variation of hurricane strikes and passages of APG laws to estimate the relationship between APG laws and economic growth.

In the initial econometric specification, using a fixed effect model and annual per capita income data for the period 1970-2012, results appear to suggest that APG laws are beneficial to hurricane-stricken counties within states that pass them. These results are spurious, however, due to industry-specific effects, the annual time frame for analysis, and the income data used for analysis.

Using a second econometric specification that employs quarterly firm-reported per-worker wages for the period 1990-2012 and a fixed effect model that captures adjustments by firms on both wage and employment margins and allows for observation of effects on specific industries, results indicate that hurricane-stricken counties are worse off in the presence of APG laws. Negative effects are pronounced within the accommodations industry, although there is no statistically significant immediate effect on growth of per-worker wages among other industries commonly cited for supposed price gouging. The estimated effect on gas stations is not statistically different from zero, perhaps due to adjustment on non-price margins, such as the development of waiting lines or rationing by violence, as well as increased cost provisions in most states' APG laws. Building material and garden supply stores do not experience a statistically significant immediate effect either, likely due to firms' fear of backlash from consumers in response to raised prices. The estimated immediate effects among food and beverage stores and specialty trade contractors do not statistically differ from zero.

The negative effects of APG laws appear to be short-lived, however, as affected counties experience a rebound once the declared state of emergency is lifted and the laws are no longer in effect. Hurricane-stricken counties with APG laws catch up to hurricane-stricken counties that did not suffer from the effects of APG laws, likely because of the dissipation of waiting lines or shortages when the APG law is lifted. Not all industries experience this rebound, however. Building material and garden supply stores experience the only estimated lagged rebound when examining specific industries, perhaps because shortages for lumber and other rebuilding materials disappear after the APG law is no longer in effect and residents begin rebuilding. A similar story, however, cannot be made for hotels, gas stations, or even food and beverage stores.[88]

Results are stronger when considering the prediction given by Barzel (1974) and measurement error present in the model. All reported estimates are tested for statistical significance using two-tailed tests rather than one-tailed tests suggested by the negative prediction given by Barzel (1974). Furthermore, measurement error in the model attenuates the estimates towards zero, so the economic effect of APG laws following a hurricane is likely understated.

[88] It is unlikely that vacationers put off venturing to coastal areas from when a hurricane is threatening until a few quarters after a hurricane strike. Gas stations and food and beverage stores provide goods for which demand is rather inelastic, and delaying consumption by six months, especially in the latter category, could result in dire outcomes.

Few previous studies have examined the empirical effects of price controls. To my knowledge, this is the first empirical study of the economic effects of APG laws. These results support standard economic theory regarding price ceilings and counter political rhetoric in support of APG laws. When APG laws bind, counties may also experience shortages, increases in the total price paid for goods and services due to waiting time, and adjustments on non-price margins such as quality adjustments, the development of black markets, and rationing by violence. Further research should explore these non-price margins to determine the full economic effect of APG laws on hurricane-stricken counties.

REFERENCES CITED

Agénor, P., & Asilis, C. M. (1997). Price Controls and Electoral Cycles. *European Journal of Political Economy*, *13*(1), 131-142.

Anbarci, N., Escaleras, M., & Register, C. A. (2005). Earthquake Fatalities: The Interaction Of Nature And Political Economy. *Journal of Public Economics*, *89*(9-10), 1907-1933.

Baez J., de la Fuente A., & Santos I. (2010). *Do Natural Disasters Affect Human Capital? An Assessment Based on Existing Empirical Evidence.* IZA Discussion Papers, IZA Discussion Paper: 5164.

Barzel, Y. (1974). A Theory of Rationing by Waiting. *Journal of Law and Economics, 17*, 73-95.

Barzel, Y. (1997). *Economic Analysis of Property Rights*. Cambridge: Cambridge University Press.

Belasen A. & Dai C. (2013). When Oceans Attack: Using a Generalized Difference-in-Difference Technique to Asses the Impact of Hurricanes on Localized Taxable Sales. *Annals of Regional Science,* 1-18.

Belasen, A. R., & Polachek, S. W. (2008). How Hurricanes Affect Wages and Employment in Local Labor Markets. *American Economic Review*, *98*(2), 49-53.

Belasen, A. R., & Polachek, S. W. (2009). How Disasters Affect Local Labor Markets: The Effects of Hurricanes in Florida. *Journal of Human Resources*, *44*(1), 251-276.

Benavides, R. H. (2006). *Summary of State "Price Gouging Statutes and Regulations."* Retrieved April 21, 2014, from http://apps.americanbar.org/antitrust/at-committees/at-fe/pdf/programs/spring-06/price-gouging-statutes.pdf.

Blake, E. et al. (2013). Tropical Cyclone Report: Hurricane Sandy. *National Hurricane Center.*

Brown, S. P., Mason, S. L., & Tiller, R. B. (2006). The Effect of Hurricane Katrina on Employment and Unemployment. *Monthly Labor Review, 129*(8), 52-69.

Bulow, J., & Klemperer P. (2012). Regulated Prices, Rent Seeking, and Consumer Surplus. *Journal of Political Economy, 120*(1), 160-186.

Cahoon, L. S. (2006). The Current Population Survey Response to Hurricane Katrina. *Monthly Labor Review, 129*(8), 40-51.

Cameron, L., & Shah, M. (2013). *Risk-taking Behavior in the Wake of Natural Disasters.* National Bureau of Economic Research, Inc, NBER Working Papers: 19534.

Carden, A. (2008). Beliefs, Bias, and Regime Uncertainty after Hurricane Katrina. *International Journal of Social Economics*, *35*(7), 531-545.

Cavallo, A., Cavallo, E., & Rigobon, R. (2013). *Prices and Supply Disruptions During Natural Disasters.* National Bureau of Economic Research, Inc, NBER Working Papers: 19474.

Chamlee-Wright E. & Storr V. (2010). Expectations of government's response to disaster. *Public Choice, 144*(1), 253-274.

Coughlan, J. A. (2012). Gulf Coast Unemployment Trends, 2000 to 2010: Hurricanes, Recessions, Oil Spills. *Monthly Labor Review, 135*(8), 11-18.

Culpepper D. & Block W. (2008). Price Gouging in the Katrina Aftermath: Free Markets at Work. *International Journal of Social Economics, 35*(7), 512-520.

Currie, J., & Rossin-Slater, M. (2013). Weathering the Storm: Hurricanes and Birth Outcomes. *Journal of Health Economics, 32*(3), 487-503.

Davis, C. W. (2008). An Analysis of the Enactment of Anti-price Gouging Laws. Montana State University (Masters thesis).

Davis, L. W., & Kilian, L. (2011). The Allocative Cost of Price Ceilings in the U.S. Residential Market for Natural Gas. *Journal of Political Economy, 119*(2), 212-241.

Deacon, R. T., & Sonstelie J. (1985). Rationing by Waiting and the Value of Time: Results from a Natural Experiment. *Journal of Political Economy, 93*(4), 627-647.

Deacon, R. T., & Sonstelie, J. (1989). Price Controls and Rent-seeking Behavior in Developing Countries. *World Development*, *17*(12), 1945-1954.

Eckel, C. C., El-Gamal, M. A., & Wilson, R. K. (2009). Risk Loving After the Storm: A Bayesian-Network Study of Hurricane Katrina Evacuees. *Journal of Economic Behavior & Organization*, *69*(2), 110-124.

Evans, R. W., Hu, Y., & Zhao, Z. (2010). The Fertility Effect of Catastrophe: U.S. Hurricane Births. *Journal of Population Economics 23*(1), 1-36.

Ewing, B. T., Kruse, J. B., & Thompson, M. A. (2009). Twister! Employment responses to the 3 May 1999 Oklahoma City tornado. *Applied Economics*, *41*(6), 691-702.

Fleck R. (2014). Can Prohibitions on "Price-Gouging" Reduce Deadweight Losses? *International Review of Law and Economics, 37*, 100-107.

Fomby, T., Ikeda, Y., & Loayza, N. V. (2013). The Growth Aftermath of Natural Disasters. *Journal of Applied Econometrics, 28*(3), 412-434.

Fuller S. (2014). The Effect of Prenatal Natural Disaster Exposure on School Outcomes. *Demography 51*(4). 1501-1525.
Giberson, M. (2012). *List of State Anti-Price Gouging Laws.* Retrieved April 21, 2014, from http://knowledgeproblem.com/2012/11/03/list-of-price-gouging-laws/.

Healy, A., & Malhotra, N. (2009). Myopic Voters and Natural Disaster Policy. *American Political Science Review, 103*(3), 387-406.

Hirshleifer, J., Glazer, A., Hirshleifer D. (2005). *Price Theory and Applications* (7th ed.). Cambridge, UK. New York: Cambridge University Press.

Hsiang, S. M., & Jina, A. S. (2014). *The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence from 6,700 Cyclones.* National Bureau of Economic Research, Inc, NBER Working Papers: 20352.

Kahn, M. E. (2005). The Death Toll From Natural Disasters: The Role Of Income, Geography, And Institutions. *Review of Economics and Statistics*, *87*(2), 271-284.

Leeson, P., & Sobel, R. (2008). Weathering Corruption. *The Journal of Law and Economics*, *51*(4), 667-681.

Lott, John R., Jr, & Roberts, R. D. (1989). Why comply: One-sided enforcement of price controls and victimless crime laws. *Journal of Legal Studies, 18*(2), 403-414.

Montgomery, W. D., Baron, R., & Weisskopf, M. (2007). Potential Effects of Proposed Price Gouging Legislation on the Cost and Severity of Gasoline Supply Interruptions. *The Journal of Competition Law and Economics, 3*(3), 357-397.

National Oceanic and Atmospheric Association. (n.d.). *Tropical Cyclone Climatology*. Retrieved April 21, 2014, from http://www.nhc.noaa.gov/climo/.

Neilson, H. (2009). Price Gouging Versus Price Reduction in Retail Gasoline Markets During Hurricane Rita. *Economics Letters*, *105*(1), 11-13.

Nordhaus, W. D. (2006). *The Economics of Hurricanes in the United States.* National Bureau of Economic Research, Inc, NBER Working Papers: 12813.

Nordhaus, W. D. (2010). The Economics of Hurricanes and Implications of Global Warming. *Climate Change Economics 1*(1), 1-20.

Rotemberg, J. J. (2011). Fair Pricing. *Journal of the European Economic Association*, *9*(5), 952-981.

Samuels, W. J., & Puro, E. (1991). The Problem of Price Controls at the Time of Natural Disasters. *Review of Social Economy*, *49*(1), 62-75.

Shughart, W. F. (2006). Katrinanomics: The politics and economics of disaster relief. *Public Choice*, *127*(1-2), 31-53.

Skidmore, M., & Toya, H. (2002). Do Natural Disasters Promote Long-Run Growth? *Economic Inquiry*, *40*(4), 664-687.

Smothers, R. (2005). Gas Stations Violated Pricing Law, New Jersey Says. *The New York Times*.

Sobel, R. S., & Leeson, P. T. (2006). Government's Response To Hurricane Katrina: A Public Choice Analysis. *Public Choice*, *127*(1-2), 55-73.

Strobl, E. (2011). The Economic Growth Impact of Hurricanes: Evidence from U.S. Coastal Counties. *Review of Economics and Statistics*, *93*(2), 575-589.

Strobl, E. (2012). The Economic Growth Impact of Natural Disasters in Developing Countries: Evidence from Hurricane Strikes in the Central American and Caribbean Regions. *Journal of Development Economics, 97*(1), 130-141.

Strobl, E. & Walsh, F. (2009). The Re-building Effect of Hurricanes: Evidences from Employment in the US Construction Industry. *Economics Bulletin 29*(4), 3059-3066.

Toya, H., & Skidmore, M. (2007). Economic Development and the Impacts of Natural Disasters. *Economics Letters*, *94*(1), 20-25.

Vigdor J. (2007). *The Katrina Effect: Was There a Bright Side to the Evacuation of Greater New Orleans?* National Bureau of Economic Research, Inc, NBER Working Papers: 13022.

Vu, L., Vanlandingham, M. J., Do, M., & Bankston, C. L. (2009). Evacuation and Return of Vietnamese New Orleanians Affected by Hurricane Katrina. *Organization & Environment*, *22*(4), 422-436.

Wooldridge, J. M. (2009). Introductory Econometrics: A Modern Approach (4th ed.). Mason, OH: South Western, Cengage Learning.

APPENDICES

APPENDIX A

REBOUND EFFECT

Table 22. Lagged Growth of Per Capita Income and Per-Worker Wages with APG Laws, 1990-2012

	Reg (1) Annual Growth	Reg (2) Quarterly Growth
Intercept	3.5294***	5.8479***
	(0.1763)	(0.2146)
$\ln(PCI_{ct-1})$	-0.5786***	
	(0.0205)	
$\ln(PWW_{ct-1})$		-0.6401***
		(0.0178)
APG_{ct}	-0.0031**	-0.0093***
	(0.0013)	(0.0016)
$HURR_{ct}$	-0.0086**	0.0294***
	(0.0033)	(0.0091)
$HURR_{ct-1}$		0.0181**
		(0.0075)
$HURR_{ct-2}$		-0.0071
		(0.0070)
$HURR_{ct-3}$		0.0081
		(0.0086)
$(APG*HURR)_{ct-1}$		-0.0079
		(0.0079)
$(APG*HURR)_{ct}$	0.0091*	-0.0181**
	(0.0049)	(0.0088)
$(APG*HURR)_{ct-2}$		0.0121*
		(0.0072)
$(APG*HURR)_{ct-3}$		0.0005
		(0.0067)
Year FE's	Yes	Yes
Quarter FE's	No	Yes
County FE's	Yes	Yes
Covariates	No	Yes
County-specific linear time trends	Yes	Yes
County-specific quadratic time trends	Yes	Yes
Number of counties	1264	1292
Observations	29072	114498
Adjusted R^2	0.3528	0.6098

* Statistically significant at 10% level, ** at 5% level, *** at 1% level.

Notes: Each column represents the results from a separate OLS regression. The dependent variable in the first column is the annual growth rate of per capita income within a county. The dependent variable in the second column is the quarterly growth rate of per-worker wages within a county. An F-test for whether $(APG*HURR)_{ct} + (APG*HURR)_{ct-1} + (APG*HURR)_{ct-2} + (APG*HURR)_{ct-3} = 0$ yielded a p-value of 0.4785, suggesting that over the course of a full year the lagged rebound effect is equal in size to the initial negative effect of the APG law following a hurricane. Covariates included in the quarter-level regression are county population density (population per square mile), percent of the county population that is nonwhite, percent of the county population that is male, percent of the county population that is 19 years of age or older, and a dummy variable for whether the Democratic Party controlled both chambers of state legislature. All standard errors are corrected for clustering at the county level.

APPENDIX B

OFFICIAL STORM IMPACTS

Table 23 presents the hurricanes that impacted the North Atlantic United States between 1990 and 2012, according the National Oceanic and Atmospheric Administration (NOAA), with Saffir-Simpson categories for the storm within each state affected in parenthesis. To explore the measurement error in recording hurricane incidence discussed above, hurricane observations under the *geonear* package matching approach were compared to the NOAA list. Hurricane observations under the *geonear* package were either corrected or dropped, where Saffir-Simspon categories were corrected when states affected were consistent with the NOAA's list but the category differed, and the hurricane observation was removed when the NOAA's list did not include that particular state among those impacted by the storm. In the case of the NOAA's list including a state that was not accounted for under the *geonear* package, nothing was done, as there is no clear way to match the hurricane to counties in the missing state without introducing more measurement error in the model.[89]

After correcting hurricane observations to match the NOAA's list, coefficients were estimated under the neoclassical growth and labor market models. Table 24 presents estimates under the neoclassical growth model, while table 25 reports estimates under the labor market model. The regressions reported in these tables parallel those in tables 10 and 12 but are even larger in magnitude. This suggests that measurement error in the model does indeed attenuate estimates toward zero, understating the true effect of an APG law in place following a hurricane strike.

[89] This is because the NOAA's list does not include information on the counties impacted by the storm, only the states, and any assignment of those counties would not be better than the *geonear* approach.

Table 23. States Impacted by Hurricane Strikes According to NOAA, 1990-2012

Year	Storm Name	State(s) Impacted Per NOAA (Category Storm)
1991	BOB	CT (2), MA (2), NY (2), RI (2)
1992	ANDREW	FL (4), LA (3)
1993	EMILY	NC (3)
1995	ERIN	FL (2)
1995	OPAL	FL (3)
1996	BERTHA	NC (2)
1996	FRAN	NC (3)
1997	DANNY	AL (1), LA (1)
1998	BONNIE	NC (2)
1998	EARL	FL (1)
1998	GEORGES	FL (2), MS (2)
1999	BRET	TX (3)
1999	FLOYD	NC (2)
1999	IRENE	FL (1)
2002	LILI	LA (1)
2003	CLAUDETTE	TX (1)
2003	ISABEL	NC (2), VA (1)
2004	ALEX	NC (1)
2004	CHARLEY	FL (4), NC (1), SC (1)
2004	GASTON	SC (1)
2004	FRANCES	FL (2)
2004	IVAN	AL (3), FL (3)
2004	JEANNE	FL (3)
2005	CINDY	LA (1)
2005	DENNIS	AL (2), FL (3)
2005	KATRINA	AL (2), FL (1), LA (3), MS (3)
2005	RITA	LA (2), TX (3)
2005	WILMA	FL (3)
2007	HUMBERTO	LA (1), TX (1)
2008	DOLLY	TX (1)
2008	GUSTAV	LA (2)
2008	IKE	TX (2)

Table 23 (continued). States Impacted by Hurricane Strikes According to NOAA, 1990-2012

Year	Storm Name	State(s) Impacted Per NOAA (Category Storm)
2011	IRENE	NC (1)
2012	ISAAC	LA (1)
2012	SANDY	NY (1)

Notes: The above list comes from NOAA's Chronological List of All Hurricanes which Affected the Continental United States, and was compiled by the NOAA using HURDAT2 data (http://www.aoml.noaa.gov/hrd/tcfaq/E23.html).

Table 24. Growth of Quarterly Per-Worker Wages with APG Laws, Corrected for NOAA Records, 1990-2012

	Reg (1) Growth	Reg (2) Growth	Reg (3) Growth
Intercept	3.8256***	5.7235***	6.8326***
	(0.1530)	(0.2106)	(0.2299)
ln(PWW_{ct-1})	-0.4380***	-0.6349***	-0.7740***
	(0.0162)	(0.0176)	(0.0179)
APG_{ct}	-0.0056***	-0.0115***	-0.0011
	(0.0013)	(0.0017)	(0.0016)
$HURR_{ct}$	0.0281***	0.0303***	0.0285***
	(0.0088)	(0.0089)	(0.0087)
$(APG*HURR)_{ct}$	-0.0130	-0.0203**	-0.0193**
	(0.0091)	(0.0093)	(0.0093)
Year & Quarter FE's	Yes	Yes	Yes
County FE's	Yes	Yes	Yes
Covariates	Yes	Yes	Yes
County-specific linear time trends	No	Yes	Yes
County-specific quadratic time trends	No	No	Yes
Number of counties	1292	1292	1292
Observations	117082	117082	117082
Adjusted R^2	0.5522	0.6049	0.6419

* Statistically significant at 10% level, ** at 5% level, *** at 1% level.

Notes: Each column represents the results from a separate OLS regression. The dependent variable is equal to the difference between the natural log of per-worker wages in quarter *t* and the natural log of per-worker wages in quarter *t-1*, or the quarterly growth rate of per-worker wages within a county. Covariates included are county population density (population per square mile), percent of the county population that is nonwhite, percent of the county population that is male, percent of the county population that is 19 years of age or older, and a dummy variable for whether the Democratic Party controlled both chambers of state legislature. Hurricane observations under the *geonear* package were compared to a list from the National Oceanic and Atmospheric Administration (NOAA) of hurricanes that impacted the North Atlantic United States from 1990-2012. Hurricane observations were corrected when states affected were consistent with the NOAA's list but the category differed under the *geonear* assignment, and removed when the NOAA's list did not include that particular state among those impacted by the storm. When the NOAA's list included a state that was not accounted for under the *geonear* package, hurricane observations within that state were not added, as the NOAA's list only shows impacts by state, so there is no clear way of assigning county-level observations. All standard errors are corrected for clustering at the county level.

Table 25. Change in Growth of Quarterly Per-Worker Wages with APG Laws, Corrected for NOAA Records, 1990-2012

	Reg (1) Δ Growth	Reg (2) Δ Growth	Reg (3) Δ Growth
Intercept	-0.5262***	-0.0959	-0.3238*
	(0.1236)	(0.1794)	(0.1695)
APG_{ct}	-0.0110***	-0.0131***	0.0003
	(0.0030)	(0.0026)	(0.0021)
$HURR_{ct}$	0.0081	0.0221**	0.0253***
	(0.0091)	(0.0093)	(0.0086)
$(APG*HURR)_{ct}$	0.0027	-0.0197**	-0.0265***
	(0.0110)	(0.0099)	(0.0094)
Year & Quarter FE's	Yes	Yes	Yes
County FE's	Yes	Yes	Yes
Covariates	Yes	Yes	Yes
County-specific linear time trends	No	Yes	Yes
County-specific quadratic time trends	No	No	Yes
Number of counties	1292	1292	1292
Observations	118425	118425	118425
Adjusted R^2	0.1083	0.3620	0.4574

* Statistically significant at 10% level, ** at 5% level, *** at 1% level.

Notes: Each column represents the results from a separate OLS regression. The dependent variable is equal to the difference between the natural log of per-worker wages in county *i* and the natural log of per-worker wages in the "average county" in quarter *t*, or the change in growth of per-worker wages within a hurricane-stricken county as compared to an average county within that state. Covariates included are county population density (population per square mile), percent of the county population that is nonwhite, percent of the county population that is male, percent of the county population that is 19 years of age or older, and a dummy variable for whether the Democratic Party controlled both chambers of state legislature. Hurricane observations under the *geonear* package were compared to a list from the National Oceanic and Atmospheric Administration (NOAA) of hurricanes that impacted the North Atlantic United States from 1990-2012. Hurricane observations were corrected when states affected were consistent with the NOAA's list but the category differed under the *geonear* assignment, and removed when the NOAA's list did not include that particular state among those impacted by the storm. When the NOAA's list included a state that was not accounted for under the *geonear* package, hurricane observations within that state were not added, as the NOAA's list only shows impacts by state, so there is no clear way of assigning county-level observations. All standard errors are corrected for clustering at the county level.