INFORMATION, ENVIRONMENTAL POLICY, AND AQUACULTURAL EXPANSION: THREE ESSAYS IN NON-MARKET VALUATION

By

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Agricultural, Food and Resource Economics – Doctor of Philosophy
Economics – Dual Major

2022

ABSTRACT

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Private management of non-point sources of pollution is an important concept in economics. Regulators are often unable to trace pollutants to their origins and efforts to limit many disaggregated sources of pollution are costly and invasive. Wells and septic systems, common in the rural and suburban United States, represent privately-owned non-point water pollution sources when they fail to protect households and water resources. "Time of Sale or Transfer" (TOST) policies are gaining popularity across the state of Michigan and in other states across the country to require rigorous well and septic system evaluations at the time a house is sold. In cases where threats to public and environmental health are identified, Health Department administrators impose mandatory repair or replacement orders. Without a letter of Health Department approval, a house with a well or septic system cannot be legally transferred. Despite the growing traction of these policies, however, little is known about the effects of TOST program adoption on the housing market. In lieu of empirical evidence, many homeowners and policymakers in Michigan claim that the policies suppress house prices and argue against the instruments. My first essay addresses this empirical gap in the economic literature by estimating the causal impact of policy adoption on house values. I use an event study approach to compare regulated well and septic system homes to a set of neighboring controls just outside the regulation area. Results suggest that there is not a large, statistically significant price decline following policy adoption, with evidence indicating a price penalty no larger than 4 percent.

The second essay analyzes the effect of TOST inspection resulting in Health Department required corrective actions. I motivate my empirical strategy with a model of negative TOST information shocks during the contract closing period of a house sale. The data for this essay are inspection-sale pairs constructed by combining county-level inspection records, housing transaction records, and property characteristics. I identify a house price penalty of about 7.5 percent to 10.5

percent after TOST adoption by using a hedonic price model with structural controls, spatial controls, and time fixed effects. These results are robust to a repeat sales model specification as well as an approach controlling for building quality with assessor-assigned grades. Further, there is no evidence of significant heterogeneity based on whether a well or septic system triggers mandatory corrective action, whether the problems identified are high- or low-risk, or which Health Department administers the program. In contrast, a quantile regression shows strong evidence of price impacts led by the low end of the house price spectrum. This suggests that the houses that fail at the highest rates also experience the largest price penalties and belong to homeowners least able to shoulder the costs. Regulators must consider the heterogeneity of these pecuniary effects when regulating externality-generating on-site water systems through the housing market.

The third essay studies how to expand aquaculture production int he North Central Region (NCR). U.S. per capita seafood consumption stands at an all-time high due to population and income growth and consumer preference shifts toward healthy proteins. U.S. aquaculture, however, has not kept pace and imports serve most of the U.S. fish market. This study estimates willingness-to-pay (WTP) for several search and credence fish attributes using a hypothetical choice experiment of U.S. fish consumers. Search attributes, like prices, can be readily discerned by consumers before purchase while credence attributes, such as region of production, cannot be easily identified before or after purchase and require labels. Our study varied attributes and levels over three species historically produced in the North Central Region (NCR) but underrepresented in the literature—rainbow trout, yellow perch, and walleye. Using a random utility framework, we identify average price premia of \$1.64/lb., \$1.97/lb., and \$0.84/lb. for an NCR-specific label, wild-caught label, and fresh fillet forms, respectively. We also estimate marginal WTP for trout, yellow perch, and walleye of \$19.99/lb., \$15.89/lb., and \$17.37/lb., respectively. Our findings suggest that NCR aquaculture producers can expand by intensifying trout production while continuing to market yellow perch and walleye in the region. Nationally, an NCR-source label is not valued more than a wild-caught label, implying that overcoming consumers' aversion to farmed fish will require more than marketing fish as products of the NCR.

I dedicate this dissertation to everyone who takes a little while to get up after falling down. What matters is that you keep getting up.

ACKNOWLEDGMENTS

These essays were made possible by my family, advisors, and friends. First, I would not be crossing the finish line without Don and Wally. Your daily love, play, and companionship enabled this work and helped me push through. I also thank my Mom and Dad for always believing in me and cheerleading from Wisconsin. Thank you to Rachel, Deanna, and Steven for providing support and needed breaks.

Thank you to Dr. Cloé Garnache for seeing my potential and bringing me to MSU. To Dr. Scott Swinton, thank you for spending more time on me than I ever believed I deserved. To Dr. Soren Anderson, thank you for all the meetings and discussions. This work is much stronger thanks to your thoughtful consideration and many readings. To Dr. Joe Herriges, thanks for sticking with me even into retirement. To Dr. Bob Myers, you've pushed and guided me in the ways I needed to grow. To Dr. Simone Valle de Souza, thank you so much for all the time and energy you've put into making me a better economist and person.

A special shout out to my Toucan friends. Though we may be far apart, you have left indeliable marks on my approach to friendship, persistance, and work. I miss you all dearly.

Thank you to Alex and Jason for enabling my much-needed perspective change in the Fall of 2021. I made quite a few breakthroughs while you graciously let me stay at your house. Thank you to Matt for much the appreciated company, dinners, and drinks during that week. My work advanced significantly on my first-ever writing retreat.

Thank you to the numerous Health Department employees and directors who took meetings with me, shared data, and made this work possible. Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author(s) and do not reflect the position of Zillow Group.

Last, though I refuse to thank the hell-storm that is this ongoing pandemic, I sure have learned a lot since Spring 2020. These have been the longest years of my life.

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CHAPTER 1

UNDERGROUND LEMONS: THE EFFECT OF TIME OF SALE SEPTIC SYSTEM AND WELL REGULATIONS ON THE HOUSING MARKET

1.1 Introduction

Non-point source pollution and residential drinking water safety are two perennial concerns in the environmental economics literature (Segerson, 1988; Shortle and Horan, 2017). The two concepts intersect in the rural and suburban United States, where households rely on privately owned wells and septic systems to provide potable water and treat wastewater. Low-quality on-site water systems (OWS) endanger the health of not only their owners but also nearby communities through the ground and surface water. The U.S. Geological Survey estimates that 20 percent of U.S. private wells are contaminated to a level of potential health concern (Desimone et al., 2009), while exposed wellheads and cracked casings threaten shared groundwater resources (EPA, 2015). In addition, septic systems fail at rates between 5% and 25% throughout their 20 to 30-year lifespans (EPA, 2001; Halvorsen and Gorman, 2006), causing some 168,000 viral illnesses and 34,000 bacterial illnesses annually (EPA, 2002) and contributing to nutrient pollution (Shortle and Horan, 2017). Private OWS maintenance generates positive externalities by protecting the public and environmental health elsewhere.

Compounding the non-point source pollution problem, significant portions of OWS are unobservable—they operate underground. Further, OWS performance is affected by risk factors including age, ground composition, weather events, and maintenance (LaGro, 1996; Steffy and Kilham, 2004; Thomas, 2000), while improper design or construction flaws exacerbate these risks (EPA, 2015). Homeowners hold better information about the risk factors affecting their OWS quality because they have lived in the house. Even if their tenure is short, homeowners know their OWS maintenance history and day-to-day performance. However, when homeowners wish to sell their houses, two problems emerge. First, many homeowners do not know the underlying quality of their wells or septic systems. Public health officials claim many homeowners feel a false sense of security if their OWS perform as expected, for example, as long as toilet water flushes (Ogutu, 2011). Second, homeowners with knowledge of their low-quality systems are motivated to keep this information private to avoid costly repairs and replacement (Mohamed, 2009). This leads to an Akerlof-style “lemons” problem where sellers withhold information about the lowest-quality OWS at time of resale (Akerlof, 1970). It is compounded by the fact that many of the benefits from OWS maintenance accrue to the surrounding community. Economic theory predicts homeowners will underinvest in OWS maintenance relative to the social optimum because they do not capture all the benefits of investments. Further, given the nature of non-point source pollution, low-quality house prices will not reflect the damages they inflict on society.

To address these OWS-related market failures, regulators in various municipalities across Michigan have designed and adopted “Time of Sale or Transfer" (TOST) policy instruments.[1] These policies, in use at the state, county, and township level across the United States, blend mandatory inspections with minimum quality standards with information disclosure. They allow regulators to identify NSP from OWS and target the time when a house sells for inspection and remediation. If inspections identify OWS problems, buyers and sellers can negotiate how to cover the costs of repairs or replacements. The costs associated with fixing or installing new systems can range from a few hundred dollars for pumping a septic tank to over $20,000 for installing a specialized mound septic system. In response, stakeholder complaints about the costs, administrative hurdles, and delays in property sales due to mandatory inspections (Gallup, 2018; Interlochen Public Ratio, 2020) have spurred some Michigan counties to revoke or seek the repeal of their TOST programs. In particular, real estate professionals strongly oppose TOST programs (McWhirter, 2019) and join claims that the inspection regimes reduce property values (Barry County, 2017).

In this paper, I empirically test claims that TOST policies depress housing values. I compile housing transaction records and house characteristics from fifteen Michigan-based multiple listing services (MLSs) and Zillow data to facilitate my analysis. I use three difference-in-differences style

[1] Such regulations are also known as "Time of Transfer," “Point of Sale," or “Time of Sale" programs.

specifications to test whether or not TOST programs lead to lower house values among OWS homes. The models, which vary in their levels of aggregation and house-specific controls, do not produce evidence of a large, negative price effect from adopting such regulations. In particular, when I compare TOST-regulated OWS houses to similar houses within 5 miles of regulatory boundary and use locally defined time fixed effects, the house price changes are 1 percent or less and statistically insignificant. These results are robust to a repeat sales model approach as well as a pooled cross section approach and lead me to conclude that, on average, house prices fall no more than 4 percent when regulators enact TOST policies.

Mandatory disclosure policies inject private information into markets to increase efficiency. The Securities Exchange Act of 1934, enacted during the Great Depression, is one of the best-known, earliest instances of U.S. mandatory disclosure policy (Benston, 1973). Instead of providing government accreditation or approval, the Act opted to allow investors to make their own investment decisions with an improved information set. Other mandatory disclosure regulations affect food, utility, and tobacco markets, including food safety labels (Shimshack et al., 2006), nutrition labels (Brown and Schraeder, 1990; Cawley et al., 2015; Ellison et al., 2014), drinking water notifications (Bennear and Olmstead, 2008), and tobacco product labels (Fenn et al. 2001; Sloan et al., 2002). In the context of housing markets, mandatory disclosure regulations rose in prominence following the adoption of California's Disclosure Article[2] in 1986, as explained in Washburn (1994). These policies require homeowners to disclose known quality or defects with respect to over a dozen home systems and represent a transition away from *caveat emptor* or "buyer beware" toward what Lefcoe describes as "seller tell all" (Lefcoe, 2004). Through an economic lens, these mandatory disclosures seek to close knowledge gaps between buyers and sellers to produce more efficient outcomes. The theoretical basis for such measures stems from Akerlof's seminal "Lemons" paper, which identifies information asymmetries as sources of quality declines, price decreases, and welfare loss in the resale car market (Akerlof, 1970). The conventional understanding of the "lemons" problem in the economic literature rests on the behavior of low-quality sellers hiding their information from

[2]CAL. CIV. CODE §§ 1102-1102.15

buyers when it is difficult or impossible for those buyers to distinguish high-quality products from low-quality products (Milgrom, 1981). Economists believe introducing information into markets with knowledge gaps will lead to higher quality and improved welfare (Myers et al., 2021).

A significant segment of the mandatory disclosure literature analyzes environmental externalities borne by homeowners, though not necessarily caused by them. Examples include the price impacts induced by proximity to airport noise (Pope, 2008a), flood zones (Pope, 2008b), toxic plants (Currie et al., 2015), brownfields, and Superfund sites (Haninger et al., 2017; Lang and Cavanaugh, 2018; Walsh and Mui, 2017). In addition, some exogenous, publicly disclosed environmental disamenities, like radon, suppress home prices (Pinchbeck et al., 2020; Söderqvist, 1995) though homeowners may mitigate exposure risk through costly remediation. Similarly, the natural disaster mitigation literature finds hurricane defense features become more capitalized following mandatory disclosure regulations (Gatzlaff et al., 2018). Finally, some policies require disclosing endogenous disamenities, including lead paint and residential energy (in)efficiency (Bae, 2012; Billings and Schnepel, 2017; Myers et al., 2021).

Several recent studies focus on mandatory energy audits and information disclosures in the housing market (Cassidy, 2022; Frondel et al., 2020; Myers et al., 2021). These programs seek to raise the energy efficiency of housing stock to decrease the negative climate externalities of energy consumption. The empirical literature shows mandatory disclosures induce greater investment in energy efficiency and energy-efficient attributes become more heavily capitalized into housing values (Cassidy, 2022). Sellers list energy-inefficient houses for less, suggesting that mandatory disclosure policies increase transparency and more closely align house prices with energy performance (Frondel et al., 2020). The authors of these studies hypothesize that home buyers value housing attributes that save them money in the long-run such as increased energy efficiency (Cassidy, 2022; Myers et al., 2021).

From a theoretical perspective, Myers et al. (2021) develop a model showing homeowner uncertainty about residential energy efficiency prevents voluntary disclosure of energy efficiency, even for well-performing houses in situations that would increase welfare. Their findings suggest mandatory disclosures improve market outcomes in the presence of bilateral incomplete information in the housing market. It is reasonable to expect bilateral incomplete information in the housing market because readily observed OWS system performance and underlying quality are not perfectly correlated.[3] This also suggests that voluntary disclosure may be insufficient to address information asymmetry problems despite seminal conclusions to the contrary (Grossman, 1981; Milgrom, 1981).

While TOST regulations involve an information disclosure mandate, they also impose a minimum quality standard. This policy component enables the Health Department to limit the negative externalities borne by the community. Theory predicts the private market will under-provide both OWS inspections and maintenance. In a regulatory environment where the minimum quality standard does not bind, houses sold in the residential housing market would be of sufficient OWS quality that remediation or intervention would be unnecessary. In reality, there is evidence that the private market level of OWS quality does not meet the expectations or requirements of Health Departments. For example, TOST evaluations commonly result in required corrective actions. In Ingham County, for example, the Health Department found roughly 40 percent of inspected OWS were "non-compliant" in the first ten years of its TOST program (Ingham County Health Department, 2018). In neighboring Barry and Eaton Counties, 20 percent of wells and 27 percent of septic systems required corrective actions in the first ten years of their TOST program (Barry Eaton District Health Department, 2017).

To better understand the context of TOST regulations, I provide a brief history of TOST policies in Michigan and introduce the basic provisions of such regulations. Next, I outline a theoretical framework to understand the concepts of information disclosure and capitalization. I then explain and describe the data necessary for estimation. Next, I lay out the empirical specifications used for identification. Penultimately, I present results before concluding with a discussion of the implications and limitations of this analysis.

[3]For example, a homeowner may perceive that her septic system is performing well because the sink consistently drains and the toilet always flushes. Meanwhile, the septic tank may have a crack and leak untreated sewage into the ground.

1.2 Background

1.2.1 History of Time-of-Sale or Transfer Regulations in Michigan

The progression of OWS use in Michigan followed a trend similar to the broader U.S. Historically, farms and other rural areas relied on simple septic systems known as conventional systems. These systems divert wastewater from a house to an underground septic tank where solids settle, and remaining liquids flow out to a drain field (Halvorsen and Gorman, 2006). Following World War II, rapid suburban expansion increased the demand for wastewater disposal in unsewered areas. As a result, many residential developments adopted septic systems without significant regulatory oversight from public health officials (Halvorsen and Gorman, 2006). This development approach assumed that OWS reliance would be temporary and that municipal water systems would eventually serve the water needs of the developments (Alexander, 2013; Gibb, 2016). As in many other parts of the country, piped water expansion decreased and public water systems never replaced many Michigan OWS. Instead, private homeowners managed new and pre-existing OWS. A quarter of newly constructed houses in Michigan rely on OWS and new houses rely on OWS at higher rates than the extant housing stock (EPA, 2003; U.S. Census, 2020). Newer developments benefit from more stringent building permit systems and require Health Department guidance, approval, and permitting before new OWS construction. However, long overdue for maintenance and replacement, neglected systems remain buried across the suburban and rural landscape.

The State of Michigan delegates local jurisdictions the authority to regulate public health through Sections 2435 & 2441 of the Michigan Public Health Code.[4] This provision enables county and local leadership to direct and enforce public and environmental health policy. Starting in the 1980s, regulators across Michigan began adopting TOST policies to regulate the quality and performance of residential septic systems and wells. The gradual adoption of TOST regulations over time by different counties, townships, and villages provides the policy variation necessary for this study.

[4]Michigan Compiled Laws Annotated (MCLA) 333.1101 et seq., as amended and authorized by MCLA 46.11 allows county boards of commissioners to adopt ordinances to protect the public health and safety.

Figure 1.1 shows the locations of the counties in Michigan's lower peninsula, highlighting the jurisdictions with TOST policies. The jurisdictions included in this study are green while excluded jurisdictions are pink. Table 1.1 presents all the dates of TOST implementation. Table 1.1 also explains the exclusion logic for each excluded entity—some areas adopted their policies long before the study period, some have insufficient temporal data coverage, and some areas fall outside the geographic coverage of the data. Three types of jurisdictions appear: counties, townships, and villages. Townships are the county subdivisions that initially defined Michigan's governmental units. There are 1,240 townships across Michigan, they are typically squares with six miles sides, and township governments regulate the whole state except for cities (U.S. Census, 2010). In addition, Michigan has 258 villages, which are considered incorporated places within the U.S. Census geography but still fall within the jurisdiction of larger townships.

The earliest TOST programs in Michigan occurred before a state-wide house system disclosure policy rolled out in 1993. Ottawa County became the first Michigan county to adopt a TOST on June 1, 1984. Benzie County followed suit in 1990, with County Commissioners attributing worsened water quality of Crystal Lake, a popular recreation destination, with septic system discharges. Both Ottawa and Benzie counties sit on the eastern shores of Lake Michigan and benefit from substantial tourism industry activity. In 1993, the state of Michigan adopted the Seller Disclosure Act[5] which requires sellers to disclose the working order of dozens of appliances, systems, and services by indicating *Yes, No, Unknown,* or *Not Available*. In the context of this study, sellers must share the known conditions of their wells, well pumps, septic tanks, and drain fields. Additional property condition and improvement information must also be disclosed, if known. These include well details including the depth, diameter, age, repair history, and water sample history and septic system condition. These disclosures, however, require sellers to reveal only what they know— they are not expected to perform discovery activities.

A later wave of mandatory OWS inspection policies began in Eastern Michigan around 2000. In the 1990s, Washtenaw and Wayne Counties faced water quality problems in the River Rouge

[5]MICH. STAT. ANN. 9 26.1286(51)-(66) (Callaghan Supp. 1993)

Watershed near Detroit. A federal court case drew attention to the role of septic systems in generating water pollution in Metropolitan Detroit (Johnson et al., 2001). Further, several studies estimated septic system failure rates between 20 percent and 50 percent (Johnson et al., 2001). These findings motivated Washtenaw and Wayne counties to adopt mandatory inspection regulations for septic systems.

Mandatory OWS inspection policies spread westward from Detroit over the next decade. Macomb County, Shiawassee County, and West Bloomfield Township adopted TOST policies in 2002, followed by Brooks Township in 2005, Ingham County in 2006, Barry and Eaton Counties in 2007. Then, the policies gained traction to the north: Long Lake Township in Grand Traverse County and Caledonia Township adopted TOST programs in 2008, followed by Alcona Township, Kalkaska County, Manistee County in 2009. Milton Township in Antrim County started a program in 2012. The Village of Empire and Glen Arbor Township, both in Leelanau County, enacted TOST policies in 2013 and 2014, respectively. Following a short gap in adoption, Isabella County and the Village of Elk Rapids in Antrim County began their programs TOST in 2018. At present, ten counties, eight townships, and two villages across Michigan's lower peninsula require TOST evaluations during OWS housing transactions.

The question of the efficacy and desirability of TOST regulations is one of heated debate across Michigan. The most striking examples originate from the now-defunct TOST program of Barry and Eaton Counties. The two counties, which shared a TOST regulation administered through the Barry-Eaton District Health Department, revoked their mandatory inspection regulations in 2018 following ten years of regulation and enforcement. Community members and County Commissioners argued the policy was too expensive and stringent, caused property transaction delays, and conflated property rights with public and environmental health administration.[6]

[6]Barry County Commissioner David Jackson told those gathered at a February 28, 2018 public meeting that "...for as long as the TOST regulation has been enacted, there has been a constant flow of complaints and criticism about the expense, the heavy handedness, the delay in property sales, and the issue of your health department not allowing you to sell your property without their permission, until you pass a well and septic inspection." (Gallup, 2018).

1.2.2 Time-of-Sale Regulation Provisions

Although municipalities write, approve, and enforce their own TOST regulations, there is substantial overlap in the layout and language used across Michigan. A typical TOST regulation includes definitions for failure and non-conformance, an inspection checklist, criteria and provisions for inspectors, and consequences for non-compliance.

In general these policies define system failure as:

- The backup of sewage into a structure
- Discharge of effluent onto the ground surface
- The connection of an onsite sewage disposal system to a storm drain
- Liquid level in the septic tank above the outlet invert
- Structural failure of a septic tank
- Discharge of sewage into any stream or any body of water
- The liquid level in a disposal field above the outlet holes in the pipe of such field
- Unsafe water sample (for properties with wells)
- Substantial non-conformance with water well construction requirements
- Substantial non-conformance with water well isolation from contamination source requirements (Washtenaw County, 2000)

Registered TOST evaluators investigate the quality of any wells and septic systems on a property during an evaluation. The inspector does not determine the compliance status of the wells or septic systems at this time, but rather submits their report to the Health Department. After review, Health Department staff decide whether the OWS perform well enough to pass the evaluation or if repairs or replacement are needed. The Health Department then shares these conclusions by issuing a letter to the homeowner and potential buyer.

Following a formal letter of required corrective action from the Health Department, an owner must contact the Health Department to complete the mandate. In this case, the owner, buyer, or an authorized agent must submit a plan within 30 days of notification. Often, such a plan will establish an escrow if it is not possible to complete the repairs ahead of sale closing.[7] The price of performing corrective actions can vary significantly: replacing a conventional septic system can run between $\$3,000$ and $\$8,000$ while pumping can range from \$250 to \$500. It is not uncommon for repairs to cost more than \$10,000 in total (Blakely, 2021). Typically, homeowners receive 180 days to perform mandated repairs or replacement, though urgent health hazards require immediate attention as advised by the Health Department. A violation notice is issued if the property owner and Health Department cannot reach a voluntary agreement. It is important to note that homeowners are responsible for ensuring that repairs are performed *whether or not their property actually sells*. In other words, the prescribed corrective actions must be taken even if the buyer or the seller withdraw from the transaction based on inspection results. Failing to comply with regulation requirements can result in an affidavit filing with the County Registrar of Deeds under the legal classification of a misdemeanor offense.[8]

TOST evaluations differ from standard home inspections because the standards and results are set out by the Health Department. However, TOST evaluations are distinctly different from other types of inspections in other notable ways. For example, some mortgage lenders require septic system and well inspections to secure a mortgage. One might think this would alleviate the information asymmetry for all mortgaged OWS properties, but TOST evaluations and mortgage inspections differ. First, TOST program evaluations are typically more thorough than mortgage inspections. For example, lenders usually rely on "dye test" results to issue a loan. These procedures introduce a brightly colored indicator dye into the septic system. After a fixed time has passed (e.g., 24 hours), the inspector returns and looks for dye outside the system. While this method provides valuable evidence of surface discharges, it fails to provide information on underground conditions, performance during seasonal flooding, or other risk factors (Tooke et al., 2014). Figure A.1 in the Appendix illustrates the advantages and limitations of dye tests. Second, evaluations performed to

[7] This is particularly common for houses that sell during winter months. The housing market is less active during winter months, but TOST provisions acknowledge evaluations and corrective actions might require extensions for winter weather.

[8] This part of county ordinance ensures that the regulation has the force of law, but conversations with Health Department officials confirm that punitive measures are rarely, if ever, used.

secure a mortgage are not public information—neither the local Health Department officials nor community members receive the findings. Finally, lenders determine their minimum OWS quality levels based on financial risk instead of public health risk.

1.3 Theoretical Framework

In his seminal 1970 paper, George Akerlof showed how information asymmetries between buyers and sellers in the automobile market generate inefficient market outcomes. His model considers two types of cars: high quality "peaches" and low quality "lemons." Due to unobservable quality, buyers cannot differentiate peaches from lemons. This uncertainty causes buyers to pay some average between the value of the high and low-quality levels, regardless of true quality. In turn, sellers pull their valuable peaches off the market, leaving a higher share of lemons behind. As the market becomes more heavily composed of lemons, expected quality decreases and prices fall further. This downward spiral induces sellers to supply fewer and fewer peaches to the market.

Akerlof's incomplete information model applies to both the automobile and housing markets. Houses in suburban or rural areas with low-quality OWS are lemons while houses in the same areas with high-quality OWS are peaches. A potential buyer does not possess the skills to discern the difference between a high-quality septic system and a low-quality septic system. Akerlof's framework predicts that house prices would be lower for OWS properties than municipal properties due to the presence of OWS quality information asymmetries.

Information disclosure regulations seek to resolve information disparities in the marketplace. Their impacts on housing market values are well known. They include proximity to airport noise (Pope, 2008a), flood zones (Pope, 2008b), brownfields, and Superfund sites (Haninger et al., 2017; Lang and Cavanaugh, 2018; Lui and Walsh, 2017), radon (Pinchbeck et al., 2020; Söderqvist, 1995), hurricane defense features (Gatzlaff et al., 2018), lead paint (Bae, 2012; Billings and Schnepel, 2017) and residential energy (in)efficiency (Cassidy, 2022; Frondel et al., 2020; Myers et al., 2021). Tietenberg (1998) developed four conditions of environmental community information disclosure programs. Since all four of Tietenberg's criteria are satisfied, it is valid to view TOST policies as information disclosure regulations[9]. Further, buyers, sellers, and regulators receive TOST well and septic system evaluation reports, alleviating information asymmetries in the housing market and regulatory environment.

In this study, I employ hedonic price models to capture the causal effect of TOST regulation adoption on house values (Rosen, 1974).[10] Several preeminent papers use hedonic price models to measure the value of environmental quality changes and policy impacts. These include studies of air quality (Bajari et al., 2012; Chay and Greenstone, 2005; Davis, 2011) and water quality (Keiser and Shapiro, 2019; Leggett and Bockstael, 2000; Muehlenbachs et al., 2015), among others. Hedonic price models decompose the market values of differentiated products into values for each constituent product characteristic. The housing market context is an appropriate use of a hedonic model because home buyers are the agents in the model, houses are differentiated products, houses vary significantly in their characteristics, and the residential property market is highly structured.

In the housing market, a house is represented by a vector of attribute variables. This vector contains each attribute relevant to market participants, including property-specific features, community characteristics, and environmental quality measures (Greenstone, 2017). Mathematically, the price of a house i is disaggregated into the price of its attributes a such as number of bedrooms, lot size, and local school quality, $P_i = P(a_{i1}, a_{i2}, ..., a_{in})$. The change in the price with respect to a characteristic k, $\partial P_i / \partial a_{ik}$, provides the implicit marginal price of characteristic k.

While Rosen's model provides the mechanics necessary to estimate the price effects of TOST

[9] **Establishing mechanisms for discovering environmental risks.** TOST regulations require physical evaluation and Health Department approval for any wells or septic systems on a property as a precondition of selling a house. These inspections require thorough scrutiny of the entire system and do not rely on readily observable characteristics. **Assuring the reliability of the information.** Only Health Department officials or certified inspectors registered with the Health Department may perform TOST evaluations. Health Departments may revoke certification for inspectors operating outside inspection protocols. Further, Health Departments conduct internal audits to confirm and corroborate evaluation reports (Personal correspondence with Ingham County Environmental Health Director, October 4, 2018). **Publicizing or sharing the information.** Records of inspections must be filed with the Health Department, issued to the homeowner, and disclosed to the potential buyer. In addition, the public may access TOST evaluations through FOIA requests, county clerk's offices, or on jurisdictional websites. **Acting on the information.** Homeowners must perform any necessary maintenance or replacement once they the official TOST evaluation results from the Health Department. Homeowners and potential buyers can change their housing transaction offers, bids, or negotiations based on disclosed information.

[10] For a full explanation of the theoretical underpinning of Rosen's model, please see Greenstone (2017), p1892-1895.

regulations, it does not lay out any expectations regarding the magnitude or sign one should expect to find. Instead, I turn to other aspects of economic theory to develop a clearer understanding of the mechanisms at play.

1.3.1 Externalities

High-quality wells and septic systems provide ecosystem services to households and communities. Absent a properly drilled, adequately encased, correctly sealed well, the quality of water provided to a household would be lower, as would groundwater quality, due to contamination. Similarly, without a properly-sited, well-maintained, and regularly pumped septic system residents can be sickened, surface water and groundwater may be fouled, and downstream nutrient pollution intensifies. Given these private decisions and shared consequences, regular maintenance and management of OWS produce positive externalities. As a result, the private benefits experienced by homeowners from OWS investment are inherently lower than the benefits captured by other members of society. This leads to the familiar under-provision of OWS maintenance and management which in turn produces inefficient levels of environmental quality. Given the characteristics of non-point source pollution, the costs of the negligence are not exclusively borne by the homeowner and are prohibitively costly for regulators to trace to a household.

One might expect the value of OWS properties to fall after TOST program institution because the minimum quality standard set by regulators is above the private market quality standard. This is likely given the fact that TOST programs have been responsible for identifying thousands of OWS threats across the State of Michigan. From a welfare perspective, the public benefit of the minimum quality standard exceeds the private cost to the homeowner of maintaining their OWS. However, since the socially efficient quality level exceeds the privately efficient quality level, the marginal cost has been pushed past the level of quality where the marginal benefits to the homeowner are justifiable. As a result, in order to capture these costs, one might expect homeowners to increase their willingness to accept. In contrast, this also increases the discounted value of future maintenance to potential homebuyers, and would lower their value of the system given the increased cost of ownership.

Some empirical evidence shows that information alone is not enough to help overcome the difference between private costs and benefits and public costs and benefits. Simply put—for the average homeowner knowing that their behavior generates negative spillovers is not enough to induce action. A study of an Ohio septic system information campaign meaninfully increased awareness and information septic system owners had about their systems, but did not change their maintenance and management behaviors (Silverman, 2005). Further, any regulatory environment that does not sufficiently incentivize homeowners to maintain a level of quality above their private preference is bound to fail (Mohamed, 2009).

1.3.2 Salience

A growing literature studies the effects of increased attention to certain housing attributes on house values as well as the impact of increased salience on risk behaviors. These studies focus on risk salience in home construction and maintenance regarding natural disasters like wildfires (Garnache, 2020; McCoy and Walsh, 2018), floods (Atreya et al., 2013; Bin and Landry, 2013; Kousky, 2010), earthquakes, and tornadoes (Chueng et al., 2018).

Another line of the literature looks at how shocks increase or decrease the capitalization of housing attributes. These include energy efficiency features and hurricane protective features. These studies show that energy-efficient windows, insulation, and appliances command larger premiums after energy audits and disclosures are mandated (Cassidy, 2022; Myers et al., 2021). These studies focus on the Energy Conservation Audit and Disclosure (ECAD) program in Austin, Texas and rely on a future stream of payments model to value energy efficiency. In other studies, housing codes that require protective construction features designed to protect against hurricane wind and debris damage sell at a premium compared to less rigorously-constructed homes nearby—and these premiums grow following hurricanes (Dumm et al., 2012).

In the context of OWS houses, TOST programs increase attention and awareness to the various ways OWS can depreciate and generate public health hazard. As a consequence, homebuyers may decrease their willingness-to-pay (WTP) for OWS houses. If we think of the present value of the stream of future costs of OWS maintenance and replacement, not only are the costs potentially higher than before TOST institution, but the probability that a homebuyer considers the present value of these costs is also higher. One would expect WTP to fall in this case as OWS houses become costlier to own under TOST programs than before due to a binding quality level required to sell an OWS-reliant house.

1.3.3 Environmental Quality

Regulating authorities point to the protection of water quality and public health interests as the major reasons for adopting TOST policies. A large literature shows the economic benefits associated with increased water quality at multiple levels of a watershed (Leggett and Bockstael, 2000; Moore et al., 2020 ; Walsh et al., 2011). These include large and significant gains to house values when water clarity increases and nutrient loading decreases. If TOST programs are successful, then there should be a reduction not only in the flow of pathogens through the watershed, but also decreased nutrient loading. As such, one would expect housing prices to increase in response to the higher levels of water quality induced by the program. This idea, however enticing, is unlikely given estimates of how long it would take to identify and remediate most problem OWS through a TOST program. Assuming a 10 percent failure rate, some areas with long house tenure would take 50 or more years to correct 90 percent of failures.

The hypotheses generated by this theoretical framework are informed by the findings of the energy efficiency literature, which finds housing characteristics associated with the disclosed information are more intensely capitalized into house values. After TOST implementation, houses experiencing larger information, compliance and quality shocks should experience larger capitalization effects, all else equal.

1.4 Data

I constructed a dataset of residential property sales across the State of Michigan to estimate the causal effect of TOST regulations on housing values. I obtained confidential home transaction data from fifteen Michigan-based Multiple Listing Services (MLSs) as well as Zillow. Private organizations of professional real estate agents (REALTORS) run and govern MLSs. These groups collect and share information about property sale listings and include detailed profiles of house characteristics. When a house sells, the MLS records the sale price, closing date, and other sale features. The MLS data I received provide significantly richer attribute information than the Zillow data but lack regional and temporal uniformity.[11] The Zillow data helps fill in the gaps in the MLS data. While, the Zillow data cover more time, fewer housing characteristics are available and rural data coverage is patchy at best.

Several factors support using MLS data in tandem with Zillow's data. First, there are well-known problems associated with Zillow ZTrax data. These are documented in Nolte et al. (2021) and include missing or mismeasured data for standard housing attributes.[12] A relevant, consistent attribute bundle must be available to serve as hedonic analysis controls. Yet, ZTrax coverage is especially poor for lot size, building valuation, total living area, number of bathrooms, number of bedrooms, and total number of rooms across Michigan.[13]

Of particular interest in this paper, Zillow has unusable information about OWS. The variables WaterStndCode and SewerStndCode purportedly capture each house's water provision and disposal systems. Unfortunately, in Michigan, this information is typically unavailable or only reported as "YY" meaning "*Yes, but not specified*". Since I expect the impacts of TOST policies to accrue primarily to properties with OWS, my identification rests on available, accurate wells and septic systems variables. Luckily, the MLS data contain water system and sewer system indicators. As

[11] One large MLS did not wish to participate and some MLSs did not have digitized records for most of the period considered.

[12] Nolte et al. (2021) provide compelling images of county-level coverage of these variables.

[13] "Missing data means that researchers face sample-section bias issues, while unreliable data is a measurement error issue. Both are likely to involve trade-offs between empirical specification and geographic coverage." Nolte et al., (2021, p6)

such, using the MLS and Zillow data together helps generate complete profiles of the houses in the sample.

I restrict my empirical analysis to single-family houses sold through arms-length transactions in the resale residential housing market. Arms-length transactions represent traditional home sales which result from buyers and sellers acting in their own self-interest. As previously discussed, property owners seek to maximize their welfare and profits they by posting asking prices. Similarly, buyers try to maximize their welfare by minimizing the amount of money they must pay by issuing counteroffers. The result is a market price generated when the buyer and seller agree on a price: this reflects the equalization of the house's value between the buyer and seller, a critical assumption to achieve equlibrium in the housing market. Intra-family transfers and sales between business entities are classic examples of non-arms-length transactions that violate these equilibrium assumptions (Taylor, 2017).

I constructed the dataset in two stages. First, I removed any single-family, attached, non-residential, mixed residential, or vacant properties. Specifically, I omitted homes zoned agricultural, regardless of their residential zoning status, to eliminate confounding from unobserved land productivity. I dropped condominuims from the sample because TOST regulations target privately-owned and managed OWS. The shared ownership and communal management of condominuim properties and OWS falls outside the scope of this study. I also discarded records for houses did not meet basic housing code standards (e.g., at least one bedroom and at least one bathroom) or carried measurement error. Further, I pruned properties with abnormally small lot sizes or living areas (lots smaller than 0.02 acres and living areas smaller than 600 square feet).

At this point, I faced a decision regarding the completeness and quality of the house-specific data. To retain as much information as possible, I kept all properties with missing or incomplete information in one sample that would be used only at an aggregate level. From this sample I then discarded any properties with reported zeros for important attributes like the number of bedrooms or bathrooms to form another or had incomplete coverage of important housing characteristics. This left me with two samples in need of further filtering based on transaction quality.

Next, I dropped any transactions of the same property within a one-year period to remove "flipped" houses with drastic, quick unobserved quality improvements. Then, I removed any transactions indicating non-competitive, non-arms length transactions like intra-family sales. Table 1.2 presents the complete list of property-specific controls and descriptions. These include structural controls like number of bedrooms, living area, and lot size and spatial controls like an inland lakefront dummy and Great Lake dummy to control for large premiums associated with lake proximity. Such environmental indicators are critical because jurisdictions rich in water resources frequently adopt TOST policies and failing to control for these differences could bias estimates.

All observations fall either inside a regulated area or within ten miles of a TOST regulated area. For clarity and consistency, I define the following several geographic terms in the context of this paper. A **market** is a geographic region defined by a TOST-regulated jurisdiction and a buffer around that jurisdiction. Therefore, a market is a pairing: a regulated "inside" area and an adjacent unregulated "outside" area. TOST-regulated jurisdictions in this study include counties, townships, and villages, thus markets can vary in size. I generated several samples of different buffer lengths to facilitate sensitivity analysis based on buffer distance. These samples include 5-, 7.5-, and 10-mile buffers.

Figure 1.2 presents a visual example of a market. West Bloomfield Township, which adopted a TOST program in 2002, is shown in light green. This "inside" area contrasts with the lighter speckled "outside" area. The combination of these two areas composes a single market. The remainder of this paper focuses on the 13 in-study markets presented in Table 1.1. Real estate markets often get grouped based on metropolitan area or region in the hedonic price model literature. I break Michigan's Lower Peninsula into four **regions** using the same logic: Southeastern Michigan, Central Michigan, Western Michigan, and Northwestern Lower Peninsula. These regions and their corresponding markets can also be found in Table 1.1.

1.5 Empirical Methodology

Do TOST regulations depress housing values? Answering this question requires an identification strategy that addresses the endogeneity arising from which jurisdictions adopt TOST programs. For example, houses subject to TOST regulations are almost certainly located in counties, townships, or villages where residents and leaders value water quality differently from people in other jurisdictions. Depending on the motivation for TOST adoption, these differences could bias naive comparisons of houses in locations with TOST policies compared to houses in unregulated areas.

This section develops empirical strategies for estimating the policy effects of Time-of-Sale regulations on house values. I consider three lines of econometric analysis to exploit different aspects of my dataset. First, following Currie et al. (2015), I generate an aggregated panel and employ a difference-in-differences model to estimate the causal effect of TOST adoption on house values. In each market, I produce annually-averaged market-year-inside/market-year-outside pairs. By averaging house prices this way, I aggregate past individual housing attributes and to include observations that would be otherwise discarded due to missing variables.[14] I substantiate this analysis with a graphical event study to add validity to the difference-in-differences research design. Second, I control for time-invariant house attributes and changes in the characteristics of houses selling year-to-year with a repeat sales model. Again, I justify this method by plotting an event study. Finally, I employ a difference-in-differences estimation approach using all transactions with complete characteristic vectors to conduct regression analysis on a bundle of control attributes and local time trends.

Each approach uses TOST regulation boundaries to define treated units and untreated units. The use of geography to assign treatment status for difference-in-differences estimation is well-established in housing market literature (Currie et al., 2015; Davis, 2011; Muehlenbachs et al., 2015; Pope and Pope, 2015). These papers use geography to compare houses "near" a toxic plant, Walmart store, or power plant to those "far" away. I apply similar logic by assigning treatment to

[14]For example, traditional hedonic analysis requires a complete vector of attributes for controls so any houses missing data on one or more variables including bedrooms, bathrooms, square footage, age, or acreage would be discarded.

all OWS properties *inside* a regulated area. Then, within each market, I assign control status to all *outside* houses with OWS within a short distance of the regulated area. I use an inside/outside approach instead of the near/far approach of the authors above. This approach also overcomes the caveat that "When units experience treatment at different times, one cannot estimate [the traditional difference-in-differences equation] because the post-period dummy is not defined by control variables" (Goodman-Bacon, 2021, page 3).

1.5.1 Aggregated Panel Approach

In the first approach, I collapse all the arms-length transactions into a balanced panel of market-year pairs. The result is a transformed dataset of 283 market-year-inside/market-year-outside cells. The benefit of this strategy is using the maximum number of observations because the variable reporting requirements are lower than other approaches. The number of raw observations used to construct the counterfactuals each year grow as the buffer size increases: the 5-mile sample uses 54,353 raw observations, the 7.5-mile sample averages 68,201 observations, and 85,263 observations make up the 10-mile sample.

Once again, defining houses "inside" a regulatory area as those receiving policy treatment compared to houses "outside" the regulatory area, which serve as policy controls, I fit the econometric model:

$$\begin{aligned} P_{jmt} &= \beta_0 + \beta_1 \cdot 1[TOST]_{mt} + \beta_2 \cdot 1[Inside]_{jm} \\ &+\beta_3(1[TOST]_{mt} \times 1[Inside]_{jm}) + \eta_{jm} + \delta_{mt} + \varepsilon_{jmt} \end{aligned} \tag{1.1}$$

where P_{jmt} represents the natural log of average housing values where j denotes the area lying inside or outside market m in year t. Identification relies on the pairing of a regulated inside cell and an outside counterfactual cell within each market each year. The inside observation averages the prices of houses within the regulated area of market m while the outside observation averages the price of houses just outside the regulated area of market m.

The indicator variable $1[TOST]_{mt}$ is equal to 0 until TOST regulation implementation occurs in market m at time t and it switches to 1. Time invariant $1[Inside]_{jm}$ indicates whether an observation is treated for market m (lies with a TOST jurisdiction). Fixed effects, η_{jm}, control for time-invariant housing price differences inside and outside the regulated area of each market. The $1[Inside]_{jm}$ parameter cannot be identified because it is perfectly collinear with the location fixed effects. Time fixed effects δ_{mt} net out local market trends. As such, I do not estimate the $1[TOST]_{mt}$ effects which are perfectly collinear with the δ_{mt}. I consider two specifications for these fixed effects, a region-by-year specification considers Eastern, Central, Western, and Northwestern Michigan separately while finer market-by-year controls for hyper-local housing market trends.

The parameter of interest in equation (1.1) is the difference-in-differences coefficient β_3 which estimates the pecuniary effect of TOST regulated houses in a market against unregulated houses in that same area. The fixed effects that control for local drivers of housing prices, η_{jm} ensure that β_3 captures the effects of policy adoption by controlling for persistent intra-market differences. Put differently, β_3 obtains identification from the differences in average house values between houses inside the regulatory boundary of a market relative to those outside the same regulatory boundary during the same year of observation.

1.5.2 Repeat Sales Model Approach

Repeat-sales models provide another approach to identifying the causal effect of TOST policy enactment on housing values. These specifications require a sample of houses that sold at least twice during the study period so house-level fixed effects can be used to control for the property-specific, time-invariant unobservables. Further, a weakness in the average panel approach above is that it does not account housing stock changes over time. For example, if every house sold every year, I would be able to ignore changes in the differing characteristics of houses selling over time. Since houses are durable goods and tenure extends over several years, this is not necessarily the case, or at least has the potential to bias estimates by failing to control for differences in the sold stock year to year. To control for house characteristics, I specify the model:

$$\begin{aligned} P_{ijmt} &= \beta_0 + \beta_1 \cdot 1[TOST]_{mt} + \beta_2 \cdot 1[Inside]_{jm} \\ &+\beta_3(1[TOST]_{mt} \times 1[Inside]_{jm}) + \beta_4 \mathbf{X_{it}} + \rho_i + \delta_{mt} + \varepsilon_{ijmt} \end{aligned} \tag{1.2}$$

where P_{ijmt} denotes the natural log of house prices of house i, located in area j, of market m at time t. The coefficient of interest is β_3 and $1[TOST]_{mt} \times 1[Inside]_{jm}$ equals one for a house located inside j within the regulated area of market m if time t follows TOST program adoption. The time-varying attributes are collected into $\mathbf{X_{it}}$, which only contains age in my specifications. House-specific fixed effects control for time-invariant house characteristics while quarterly fixed effects δ_{mt} control for macroeconomic trends at the market or region level. They are perfectly collinear with $1[TOST]_{mt}$, which I do not estimate. House-specific dummy ρ_i captures time-invariant house attributes, and due to the fixed position of homes, $1[Inside]_{jm}$ also drops out of the specification.

1.5.3 Pooled Cross-Section Hedonic Price Model Approach

While the repeat sales model controls for time invariant house-level unobservables and assuage concerns of omitted variable bias, this approach also loses many observations because it includes only houses with multiple arms-length sales during the study period. The number of housing transactions lost are significant: only 37% of the arms-length transactions appear in the repeat sales model approach. This is not surprising as average United States home tenure exceeds 11 years, the period considered in this analysis (ACS, 2010). Further, during the timeline of this study, the median Michigan homeowner lived in their house between 10 and 20 years and roughly 20% of homeowners had lived in their house for at least 20 years (ACS, 2010). As result, houses that do not sell frequently may impact the estimates in a meaningful way. The final identification strategy considers all available house transactions to integrate such possibilities.

The following estimating equation captures the effect of TOST policy implementation:

$$\begin{aligned} P_{ijmt} &= \beta_0 + \beta_1 \cdot 1[TOST]_{mt} + \beta_2 \cdot 1[Inside]_{jm} \\ &+ \beta_3(1[TOST]_{mt} \times 1[Inside]_{jm}) + \beta_{\mathbf{4m}}\mathbf{X_i} + \gamma_i + \delta_{mt} + \varepsilon_{ijmt} \end{aligned} \tag{1.3}$$

where P_{ijmt} is the natural log of house value for house i located inside or outside j of market m at time t. Just as in the repeat sales model, the β_3 coefficient on $1[TOST]_{mt} \times 1[Inside]_{jm}$ captures the price effect of TOST adoption. Observed property-specific structural and spatial controls are collected into vector $\mathbf{X}_i$, and the associated coefficient, $\beta_{\mathbf{4m}}$, is allowed to vary regionally to capture differences in the hedonic gradient of structural attributes based on geography. Township fixed effects, γ_i, control for time-invariant community-level heterogeneity. Market-by-quarter or region-by-quarter fixed effects, δ_{mt} flexibly account for trends in housing values over time. $1[TOST]_{mt}$ and $1[Inside]_{jm}$ are presented for consistency but, once again, β_1 and β_2 are not estimated due to the inclusion of township and time fixed effects.

1.6 Results

1.6.1 Event Studies

I present event study graphs to justify the various difference-in-differences strategies employed to estimate the causal effect of TOST implementation on housing values. Such illustrations provide visual evidence that no trend in housing prices existed for houses that would become regulated in periods ahead of policy implementation. This is akin to the classic difference-in-differences parallel trends assumption in the context of a pooled analysis.

Event studies for the aggregated panel of market-by-proximity-by-year cells can be found in Figure 1.3. In this analysis, a pair of logged average housing values shows up for each market each year: one mean of houses inside the regulated market and one mean of the houses just outside the jurisdictional boundary. The graphs were generated from estimating a version of equation (1.2) which includes market-by-year fixed effects, market-by-inside fixed effects, market-by-outside fixed effects, and interactions of $1[Inside]_{jm}$ with event time. Event time is normalized to the time of TOST implementation. The date each regulated area implemented its TOST program marks the first day of year 0. The plots display point estimates for the event study parameters and their associated 95% confidence intervals.

Each panel of Figure 1.3 presents event study coefficients for the 5 years preceding TOST implementation and 6 years following TOST implementation. The plotted coefficients illustrate the time path of average house values inside the regulated portion of a market against the average house values outside the regulated area. The first panel restricts the houses outside the regulatory boundary to 5 miles of the regulated township or county, the second panel expands this region to 7.5 miles, and the bottom includes houses within 10 miles of the boundary. All three panels, representing expanding geographic distance, support the validity of the difference-in-differences approach because there is little evidence of differential trends between the average price of houses inside the regulatory boundary and the average price of unregulated houses in the years leading up to TOST program commencement. My use of never-treated buffer properties in the same market and inclusion of "market-time" fixed effects here, and in the analyses below, implies that I only compare treated properties to never-treated properties within each market. Thus, my approach is robust to the problems identified by Goodman-Bacon (2020) and Roth and Sant'anna (2021) when treatment timing varies across treated units: my first-treated areas never serve as controls for later-treated areas. There is, however, evidence that average house values fell following TOST ordinance enactment in all three plots.

Figure 1.4 shows event study analysis results for repeat sales models of housing values. The samples considered contain only houses that sold twice or more in the 13 in-study markets 5 years before or 6 years after policy enactment. These point estimates and confidence intervals correspond to regressions of equation (1.4) with time trends in the form of geography-specific year fixed effects and the interaction of event time with the indicator $1[Inside]_{jm}$. Once again, event time is normalized so year 0 begins at the time of TOST policy implementation and the plotted event study coefficients are normalized to the year before implementation, year -1.

The first column of Figure 1.4 presents the time path of TOST-regulated housing values compared to housing values just outside conditional on geographic year fixed effects. The first column shows the plotted coefficients when region-by-year-by-quarter fixed effects are used while the second column shows the plotted coefficients when the more localized market-by-year-by-quarter fixed effect are used. The lack of meaningful pre-TOST trend is consistent across the six panels and the downward trends following TOST implementation are similar in shape between the two columns.

Figure 1.5 similarly shows event study plots for the pooled cross section approach. Here, a full set of structural controls, spatial controls, township fixed effects, and time trends control for observables, unobservables at the township level, and local housing market trends. Standard errors are clustered at the township level, but two-way clustering at the market-year level does not impact the significance of the estimates. The first column demonstrates more consistent pattern: no discernible pre-regulation trend followed by a noticeable downward trend after regulation. The use of market-specific time trends results in a post-regulation downward trend but with a v-shape instead of a straight tail.

1.6.2 Aggregated Panel Approach

Table 1.3 reports estimates for the effect of TOST implementation on housing values for houses with OWS. Panel A displays the results from two specifications of equation (1.2). In this setting, identification comes from comparing average annual price of houses "inside" the regulated portion of a market to the average annual price of houses "outside" the market's regulated area. I present three samples to demonstrate how sensitive the estimated effects are to changes in how the counterfactuals are geographically constructed. The samples progressively increase the buffer distance for house "outside" the regulated portion of a market area from 5 miles to 10 miles.

For each sample, two sets of time controls are offered. The first column controls for housing market trends more broadly and aggregates the 13 markets in the study into four regions. Each region has a set of quarterly fixed effects to control for housing market fluctuations and macroeconomic trends. The second column controls for more localized trends and includes quarterly fixed effects for each of the 13 markets. For all models and samples the estimated coefficients and standard errors on $1[TOST]_{mt} \times 1[Inside]_{jm}$ are shown. The standard errors are two-way clustered by market and year. Following Currie et al. (2015), each cell is weighted by group-level cell size with groups defined at the market-location-year level (location indicates if a cell lies inside or outside the regulated jurisdiction).

The results presented in the first two columns of Panel A were produced from the 5-mile sample where "outside" cells are averages of transactions falling within 5 miles of regulatory boundaries. The coefficients are not statistically significant, and thus, comparing houses closest to the regulated areas suggests no policy effect. The 7.5-mile sample produces point estimates that are larger in magnitude, representing a 7.6 percent decline in housing values following TOST enactment.[15] The coefficients are significant at the 5 percent level with region-quarter fixed effects, but insignificant when the model instead employs more granular market-quarter fixed effects. Finally, the estimated parameters produced from the 10-mile sample are about 7 percent; very similar to the estimation results obtained from the 7.5-mile sample. Once again, the statistical significance observed from regional level fixed effects are not present when the market-by-quarter fixed effects are considered. These results suggest that the model is sensitive to the geography used to construct the counterfactuals and locality of time fixed effects. In addition, this aggregated data approach is probably not the best possible specification as if does not control for potential changes in attributes of homes or important difference in prices occurring across different months, which could bias the results.

1.6.3 Repeat Sales Model Approach

Panel B of Table 1.3 reports the estimated coefficients and standard errors of the repeat sales specifications described in equation (1.3). All six estimated $1[TOST] \times 1[Inside]$ parameters are much smaller in Panel B than the estimated effects obtained from the aggregated panel. The odd columns refer to regression results which include region-by-year-by-quarter fixed effects. The estimated effects are -3.3 percent, -4.1 percent, and -5.2 percent for the 5-, 7.5-, and 10-mile samples, respectively. Each coefficient is statistically significant at the 5% level.

However, including more localized time controls decreases the magnitude and significance of the estimated policy effect. Columns 2, 4, and 6 of Panel B display the estimation results for equation (1.3) using market-specific quarterly fixed effects. Relative to the regional fixed effects, these coefficients of interest are not only smaller in absolute value but also less significant. In particular, only the 10-mile sample coefficient of a 3.4 percent price decrease is statistically significant. These results suggest that controlling for house-specific and market-specific unobservables is critical to

[15] Coefficients must be transformed à la Halvorsen and Palmquist (1980) and therefore may be slightly different compared to Table 1.3. The required transformation is p=exp(x)-1 where x is the dummy coefficient and p is estimated percent change.

isolating the causal effect of TOST policy implementation. Failing to do so inflates the impact of TOST program adoption.

1.6.4 Pooled Cross-Section Hedonic Price Model Approach

Panel C of Table 1.3 shows estimated coefficients and their associated standard errors conditional on structural controls, spatial controls, township level fixed effects, and time trends. All estimates were produced following equation (1.4). The standard errors are clustered at the township level to ensure they are robust to heteroskedasticity at the smallest geographic level subject to regulation.

I present the results of two specifications for each sample. The first allows flexibility only regionally and includes structural, spatial, and year-by-quarter fixed effects for each of the four regions of lower Michigan (Eastern Michigan, Central, Western, and Northwestern Michigan). This allows for the hedonic gradients to vary at a level akin to a Metropolitan area or region. The more flexible model, allows the capitalization of structural characteristics and spatial attributes to vary across the 13 markets included in this study and specifies market-specific year-by-quarter fixed effects.

The results of Panel C are the smallest in magnitude and overall the least significant of the three presented in Table 1.3. Controlling for local, market-level time trends and estimating market-specific capitalization provides the strongest evidence that TOST implementation does not lower house prices. With the inclusion of regional controls, the story is widely the same, except in the case of the 10-mile sample which suggests a modest decline of 2.6 percent.

1.7 Discussion

Taken together, the results across the three specifications provide some evidence for a small price decline among OWS houses following TOST implementation. The repeat sales model—the most credible for identifying a causal effect—shows a consistent 3 percent to 5 percent price decline across the 5-, 7.5-, and 10-mile buffers when using region by quarter fixed effects. The magnitudes shrink by roughly half when including market by quarter fixed effects, remaining significant only in the 10-mile sample. Meanwhile, the aggregate panel approach generates somewhat larger effects, especially in the 7.5- and 10-mile samples, however these regressions do not control for home attributes and are therefore less trustworthy. Finally, the pooled cross-section results, which control for observed but not unobserved home attributes, show near-zero effects, with the exception of a 2.6 percent decline for the 10-mile buffer sample with region-year fixed effects.

There are several plausible explanations behind the findings that TOST programs do not drastically change the prices of houses with wells and septic systems. First, there may not be much additional information added from the inspections. In particular, Michigan's Seller Disclosure Act, which began well before the study period, requires homeowners to divulge their knowledge of well and septic system working order before home purchase. Additionally, most homebuyers elect to have a home inspection ahead of closing. While TOST program administrators emphasize the difference between standard housing inspections and TOST inspections, the marginal improvement in the information relevant to homeowners and buyers may be very small in reality. The housing market is highly organized and the additionality of TOST programs, on average, could be quite low. Some opponents of TOST programs have claimed that the policies are redundant for mortgaged homes because the inspections are so similar (Barry County, 2017). As such, it is possible that TOST compliant houses do not appreciate relative to the failing houses which must address OWS problems to comply with TOST regulations.

Second, this study focuses on the price effects TOST adoption. Given the structure of the data for this study, I am unable to study changes in the total number of OWS houses sold. Anecdotal evidence and the real estate literature suggest that mandatory disclosure policies can induce "mothballing" where homeowners with the lowest quality houses do not enter the housing market to avoid discovery. If the houses that would be most impacted by policy introduction self-select out of the purview of the regulation, I would not capture these behaviors in my analysis. This has important implications for regulators facing a variety of policy approaches to limiting the externalities associated with OWS because it would lead to the worst polluters becoming the least likely to repair or replace their systems. If the policy goal is to protect water quality and public health, TOST-induced mothballing makes discovery more difficult.

Third, a significant share of the costs of TOST programs may come in the form of transaction costs absorbed by real estate agents. Many of the transaction costs associated with residential property sales are borne by real estate agents through time-intensive activities like advertising properties, attending house visits with clients, and conducting negotiations (Levitt and Syverson, 2008). TOST programs generate additional real estate transaction costs by relying on real estate agents to ensure inspections occur and Health Department approval letters are obtained. Further, this can lengthen the time it takes to sell a house, leading to fewer overall sales and a lower total commission income because real estate agents typically earn a flat percentage of the final sale price of a home (Bian et al., 2016). These concerns are evidenced by real estate agent and stakeholder complaints about the costs, administrative hurdles, and delays in property sales due to inspections (Gallup, 2018; Interlochen Public Ratio, 2020). Taken together, if real estate agent workloads becomes heavier due to TOST adoption and TOST-regulated house values modestly decline, real estate agents will feel amplified cost shocks relative to other market participants. While my results suggest that house prices fall only a little, the costs passed on to real estate agents are important for regulators to consider. When real estate agents shoulder TOST compliance costs, they are more likely to drive campaigns against adopting or toward revoking TOST campaigns (McWhirter, 2019).

Next, there may be countervailing price effects that empirically confound one another. For example, if there is a price penalty for low average quality of the systems but an increase in the overall environmental quality of regulated areas, it would be difficult to disentangle the impacts absent additional information. However, this suggests that capturing changes in environmental quality is a worthwhile approach for estimating the policy effects of TOST programs. Unfortunately, given the structure of data collection across the State of Michigan, it was not possible for me to include water quality measurements in my analysis (Vissers, 2018). Opponents and champions of TOST regulations across Michigan have been unable to prove that TOST programs have improved environmental quality and have instead made claims about housing market outcomes. This study introduces much needed empirical evidence into the debate and suggests regulators can adopt TOST regulations without significantly suppressing OWS home values.

Finally, while the small magnitude of these findings may seem shocking given the market failures and externalities they are designed to address, another empirical study provides some insight into the sign and size of the effect identified here. In my second essay, I find that houses that require Health Department-mandated OWS repairs or replacement sell for roughly 10 percent less than compliant houses. Taking this finding in the context of a 15 to 30 percent failure rate leads to expected policy effects around 1.5-3 percent, almost precisely the coefficients identified in the localized repeat sales model.

For proponents of TOST programs who assert that environmental quality increases as a result of the policies, these findings are unexpected and perhaps worrying as house prices are not lifted by policy implementation. From a policymaking perspective, these results considered along with the long timeframe required to identify and repair troubled OWS systems through a TOST evaluation approach. Ingham County estimates that in the first 11 years of its TOST program only one third of all OWS were inspected and despite over a decade of policy administration, the Health Department believes that roughly 1,200 septic systems are at or near failure (Ingham County Health Department, 2018). Meanwhile, proposals to inspect OWS every three years have proved non-starters in the Michigan state legislature (Blakely, 2021). Untethering OWS evaluations from home sales through a state-wide regulation could decrease the time needed to find problematic OWS and relieve pressure on real estate agents. However, the costs of repairing and replacing the worst systems can reach into five figure range (Blakely, 2021). The timing of internalizing externalities is contentious. Divorcing OWS repairs and replacement from the time of a sale when negotiations can be made about who pays for repairs could impose a significant financial burden on homeowners and generate blowback and public outcry akin to that of Barry County ahead of the 2018 repeal of its TOST policy (Barry County, 2018).

1.8 Conclusion

This paper answers one of the most pressing, unanswered questions regarding Time-of-Sale-or-Transfer (TOST) regulations: do these policies cause housing prices to fall? I answer this question by analyzing how TOST policy implementation is capitalized into housing values. In the residential housing market, TOST regulations mandate well and septic system inspections, require information disclosure, and impose corrective actions for on-site water systems (OWS) with serious problems. Despite increasing use across Michigan and the United States more broadly, the impacts of TOST programs on housing market values are unknown.

I construct a dataset of housing transactions from MLS and Zillow data to estimate the causal impact of TOST adoption. I pursue three lines of econometric analysis using a difference-in-differences style approach and construct transformations and samples to fit each line of analysis. First, I aggregate up to construct a panel of average housing values and obtain identification from the differences between average house prices inside and outside the regulated jurisdiction within the same market-year. Taken alone, this approach presents weak evidence of a large decrease in housing values following TOST enactment. Second, to control for time-invariant housing characteristics, I estimate a repeat sales model and find smaller, but more significant policy effects. These estimates are highly sensitive to the geographic level of time fixed effects. Finally, by taking into account the long tenure of houses in Michigan and exploiting as many controls as feasible from the detailed house transaction data, I find the price decline following TOST implementation all but disappears and conclude that there is not strong evidence of a price decline larger than 4 percent.

The findings of this paper are important for regulators. Within the state of Michigan, initiatives towards adopting or repealing TOST programs occur frequently at the village, township, county, and even state level. While the average price declines are small, my next essay demonstrates that individual houses bear steep price penalties when TOST evaluations reveal OWS problems.

1.9 Acknowledgments

The author is grateful to the associations and boards of REALTORS® in Michigan that were willing to provide MLS data for sales of residential properties, including Ann Arbor Area Board of REALTORS®, Bay County REALTOR® Association, East Central Association of REALTORS®, Greater Lansing Association of REALTORS®, Greater Shiawassee Association of REALTORS®, Jackson Area Association of REALTORS®, Lenawee County Association of REALTORS®, Michigan Regional Information Center®, LLC (MichRIC®), Midland Board of REALTORS®, Northern Great Lakes REALTORS® MLS, LLC, RealComp II, Ltd., Saginaw Board of REALTORS®, Southeastern Border Association of REALTORS (formerly Monroe & Downriver Regional Association of REALTORS®, and Water Wonderland Board of REALTORS®. Without their cooperation, this study would not have been possible. The author also acknowledge the support of the Michigan State University Remote Sensing and Geographic Information Systems Research and Outreach Services (RS&GIS), which provided valuable geocoding services and spatial analysis services. Special thanks to Dr. Robert Richardson for support and collaboration on a related research project. All opinions expressed in this paper are those of the author and do not reflect the opinions or positions of the aforementioned entities.

APPENDICES

APPENDIX A: TABLES AND FIGURES

Table 1.1 Municipalities in Study

Name	Date Enacted	In Study?	Why Excluded	Region
Barry County	10/16/2007	Yes		Central Michigan
Benzie County	1990	No	Implementation too early	
Eaton County	10/16/2007	Yes		Central Michigan
Ingham County	6/9/2006	Yes		Central Michigan
Isabella County	9/19/2017	No	Implementation too late	
Kalkaska County	4/1/2009	Yes		Northwestern Michigan
Macomb County	8/1/2002	Yes		Eastern Michigan
Manistee County	4/1/2009	Yes		Northwestern Michigan
Ottawa County	6/1/1984	No	Implementation too early	
Shiawassee County	1/1/2002	No	Outside data area	
Washtenaw County	1/3/2000	Yes		Eastern Michigan
Wayne County	9/1/2003	Yes		Eastern Michigan
Milton Township	10/8/2012	Yes		Northwestern Michigan
Long Lake Township	5/1/2009	Yes		Northwestern Michigan
Glen Arbor Township	6/17/2014	Yes		Northwestern Michigan
Village of Empire	6/18/2013	No	Geographic area too small	
West Bloomfield Township	2/14/2002	Yes		Eastern Michigan
Brooks Township	6/28/2005	Yes		Western Michigan
Alcona Township	8/1/2009	No	Outside data area	
Caledonia Township	8/3/2008	No	Outside data area	
Village of Elk Rapids	2/20/2018	No	Implementation too late	
Cleveland Township	1/10/2019	No	Implementation too late	
Centerville Township	11/22/2020	No	Implementation too late	

Table 1.2 Property Specific Variable Descriptions

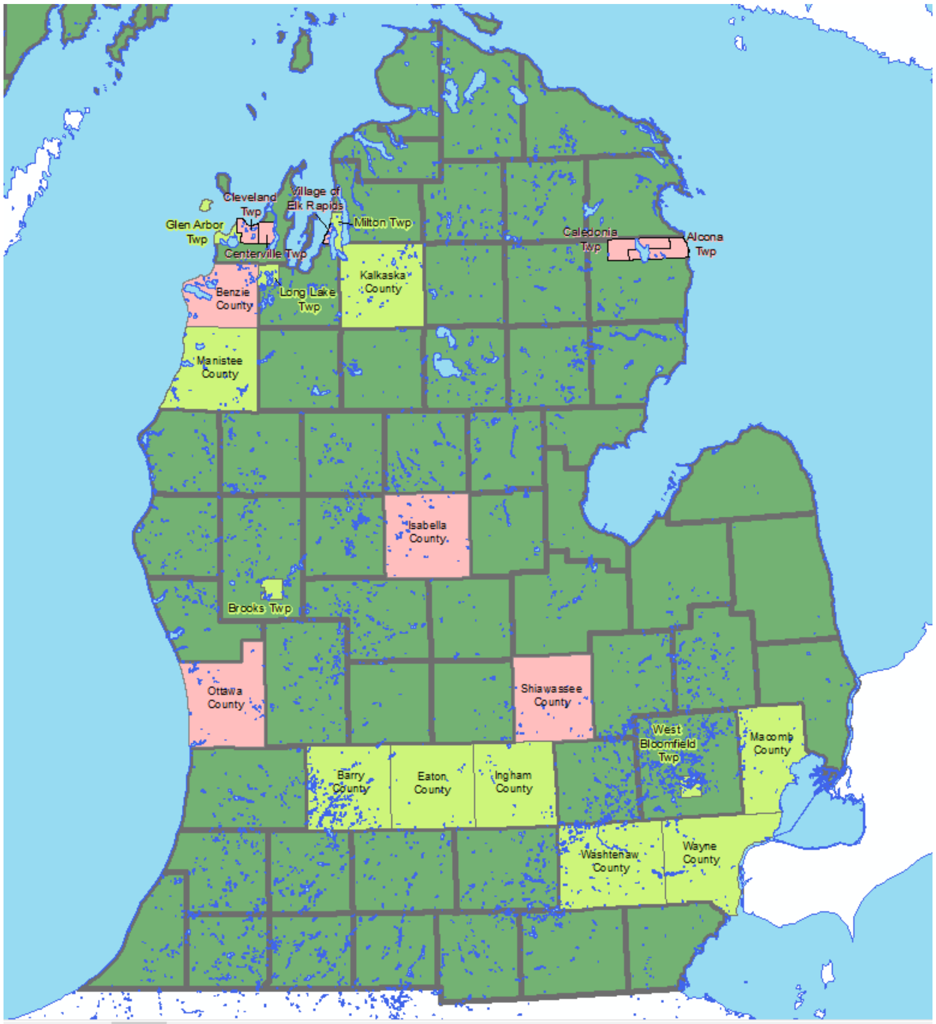
Variable	Type	Description
RealSalePrice	continuous	House sale price in 2015$
Age	continuous	House age (years)
Age_sq	continous	Square of house age (years)
Bathrooms	continuous	Number of bathrooms
Bedrooms	continuous	Number of bedrooms
DistanceHwyExit	continuous	Distance to nearest highway exit (miles)
DistanceRoad	continuous	Distance to nearest major state road (miles)
DistanceCity	continuous	Distance to nearest city; population > 10,000 people (miles)
Fireplace	indicator	Presence of fireplace = 1; otherwise = 0
Garage	indicator	Presence of garage = 1 ; otherwise = 0
GreatLakeFront	indicator	Located within one tenth of Great Lake = 1; otherwise = 0
LivingArea	continuous	Living space of house (square feet)
LotSize	continuous	Parcel size associated with house (acres)
LakeFront	indicator	Located within one tenth of inland lake = 1; otherwise = 0

Table 1.3 The Effect of Time-of-Sale Policy Implementation on Housing Values
5 Years Before and 5 Years After Implementation Year

	(1)	(2)	(3)	(4)	(5)	(6)
	5 Mile Buffer		7.5 Mile Buffer		10 Mile Buffer	
Panel A: Aggregated Panel						
1[TOST]	-0.045	-0.041	-0.079**	-0.075	-0.073*	-0.072
× 1[Inside]	(0.040)	(0.050)	(0.037)	(0.048)	(0.040)	(0.051)
Market × Inside/Outside FE	X	X	X	X	X	X
Region × Year FE	X		X		X	
Market × Year FE		X		X		X
R^2	0.930	0.956	0.936	0.960	0.931	0.956
N	283	283	283	283	283	283
Panel B: Repeat Sales Model						
1[TOST]	-0.034**	-0.013	-0.042***	-0.029	-0.053***	-0.035**
× 1[Inside]	(0.017)	(0.020)	(0.016)	(0.018)	(0.015)	(0.017)
Region × Year × Quarter FE	X		X		X	
Market × Year × Quarter FE		X		X		X
R^2	0.832	0.840	0.838	0.845	0.846	0.851
N	16,749	16,749	20,858	20,858	26,060	26,060
Panel C: Pooled Cross-Section						
1[TOST]	-0.008	0.006	-0.018	-0.006	-0.026**	-0.014
× 1[Inside]	(0.015)	(0.013)	(0.014)	(0.011)	(0.013)	(0.011)
Region × Structural Controls	X		X		X	
Market × Structural Controls		X		X		X
Region × Spatial Controls	X		X		X	
Market × Spatial Controls		X		X		X
Region × Year × Quarter FE	X		X		X	
Market × Year × Quarter FE		X		X		X
Township FE	X	X	X	X	X	X
R^2	0.599	0.616	0.604	0.621	0.608	0.623
N	44,908	44,908	55,875	55,875	69,280	69,280

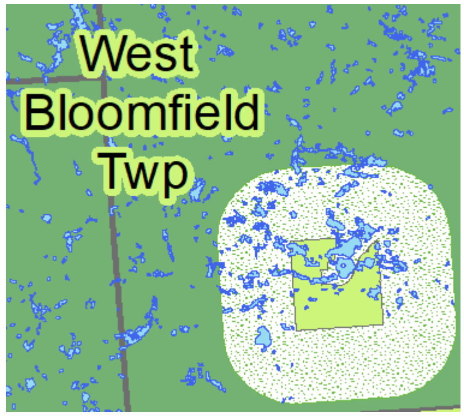
Notes: This tables reports regression coefficients from 18 separate regressions, 6 per panel. The dependent variable of each regression is the natural log of housing values. The samples used for estimation change moving left to right with a 5 mile buffer defining houses "outside" the regulatory boundary for columns 1 and 2, a 7.5 mile buffer for columns 3 and 4, and a 10 mile buffer for columns 5 and 6. Columns 1 and 2 compare the effect of TOST policy implementation on houses inside the regulated area to houses 5 miles from the border. In Panel A housing values are aggregated annually so each market has two cells for each event year: one inside the regulated area and one outside. The regressions in Panel A are weighted by group-level cell size. Robust standard errors are clustered at the municipality-year level. Panel B shows the same coefficient estimates as Panel A but uses a repeat sales model approach on houses selling twice or more in the event study time. Robust standard errors are clustered at the market-year level. Panel C reports results from a hedonic price model approach with structural and spatial controls. Robust standard errors are clustered at the township level (but significance is not meaningfully affected if the market-year level is considered). *** p<0.01, ** p<0.05, * p<0.1

Figure 1.1 Michigan Municipalities with Time of Sale Regulations



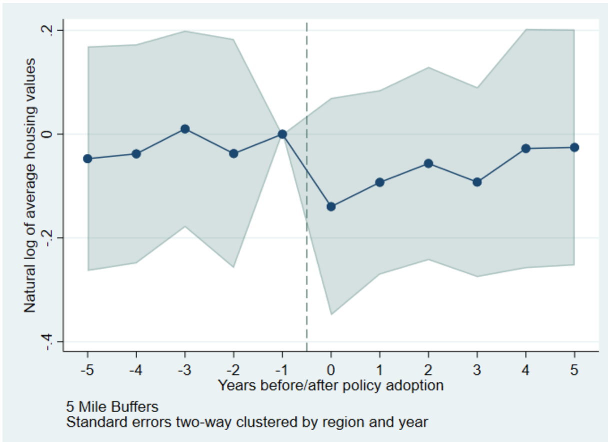
Notes: Above is a map of the lower peninsula of Michigan highlighting the counties, townships, and villages with Time of Sale or Transfer Programs. Jurisdictions in green are included in this study while pink areas are not. For a list of reasons for exclusion, please see Table 1.1.

Figure 1.2 Example of a Market - West Bloomfield Township

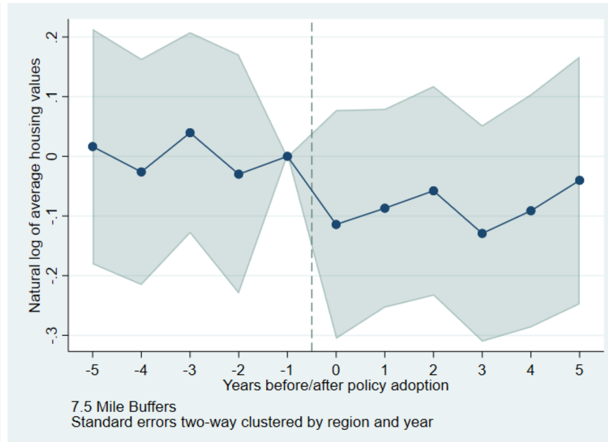


Notes: Above is a map of the geographic regions of the West Bloomfield Township market.
All houses located inside the light green interior are treated.
All houses in the speckled buffer serve as controls of the 5 mile sample. Taken together, the green interior and speckled outer band form the West Bloomfield Market.

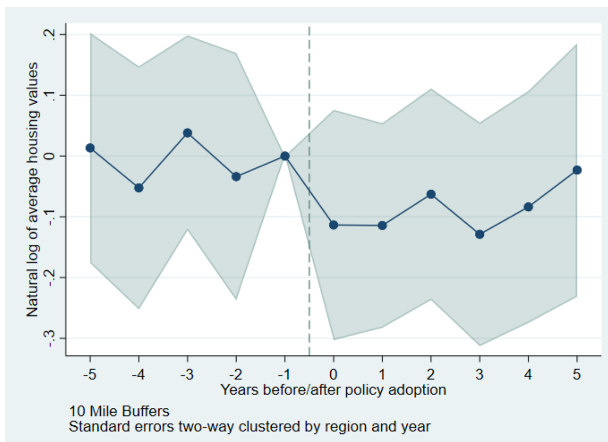
Figure 1.3 Balanced Panel Analysis Event Studies



(a) Five Mile Buffers



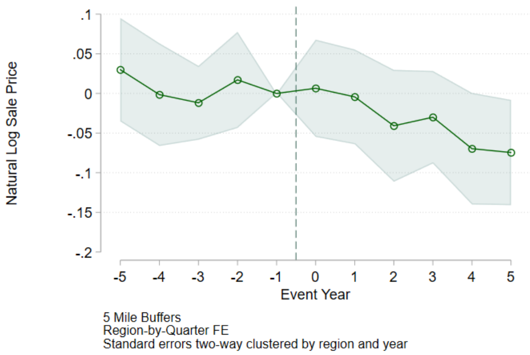
(b) Seven and a Half Mile Buffers



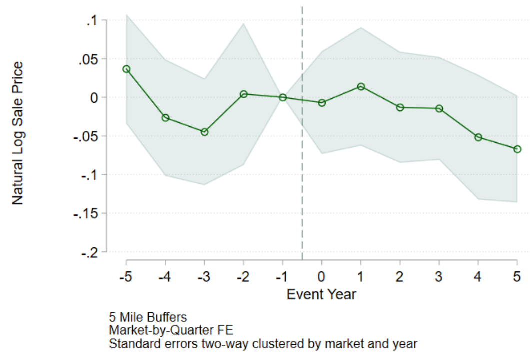
(c) Ten Mile Buffers

Notes: The coefficients plotted above are the results from three separate regressions of the natural log of average house sale price on a set of market-by-inside/outside fixed effects, time fixed effects, and the interaction of event time with an indicator variable $1[Inside]$ equal to 1 for the cells containing ever-regulated houses. All time trends are market-specific quarterly fixed effects. Event time is normalized to the date at which TOST implementation began in each market, thus $t = 0$ is the year immediately following implementation. The dots plot the time path of regulated houses relative to those 5, 7.5, and 10 miles outside the regulatory boundary. Shaded 95% confidence intervals are also shown above and below the point estimates. The coefficients are normalized to event time $t = -1$. The results are almost identical when region-by-year fixed effects are used in lieu of market-by-year fixed effects.

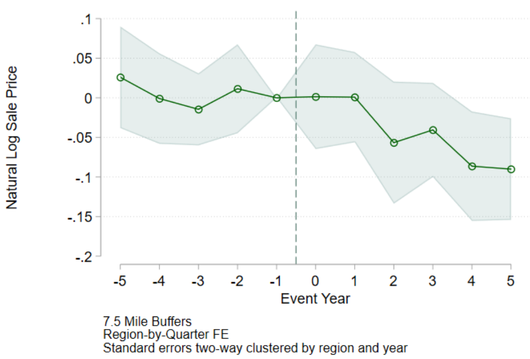
Figure 1.4 Repeat Sales Analysis Event Studies



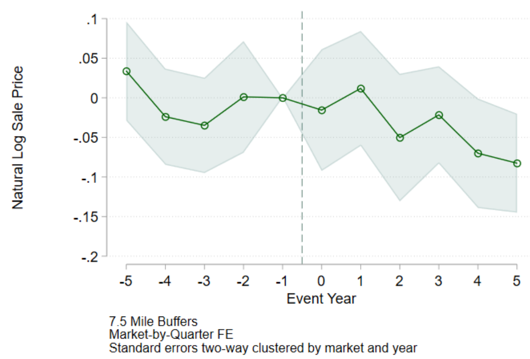
(a) 5 Mile Buffers; Region-by-quarter FE



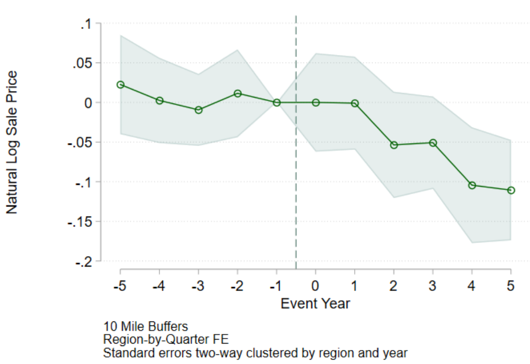
(b) 5 Mile Buffers; Market-by-quarter FE



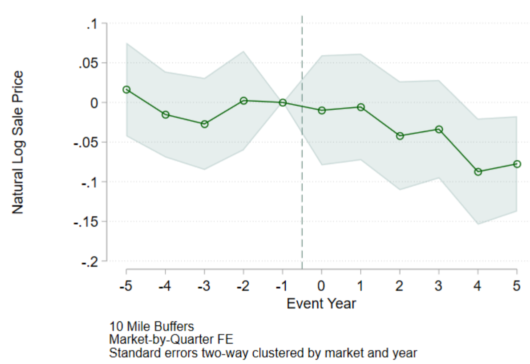
(c) 7.5 Mile Buffers; Region-by-quarter FE



(d) 7.5 Mile Buffers; Market-by-quarter FE



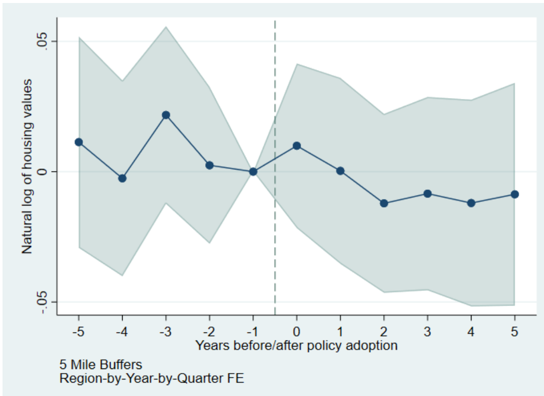
(e) 10 Mile Buffers; Region-by-quarter FE



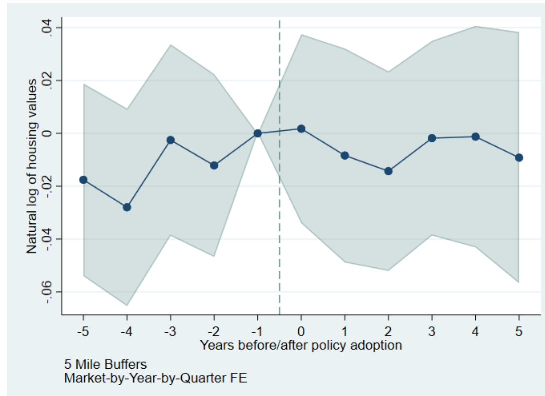
(f) 10 Mile Buffers; Market-by-quarter FE

Notes: The coefficients plotted above are the results from six separate regressions of the natural log of house sale price on a set of time fixed effects and the interaction of event time with an indicator variable $1[Inside]$ equal to 1 for the cells containing ever-regulated houses. All six regressions were performed on restricted sample of houses that sold at least twice in the five years before and six years after TOST regulation implementation. Event time is normalized to the date at which TOST implementation began in each market, thus $t = 0$ is the year immediately following implementation. The dots plot the time path of regulated houses relative to unregulated houses 5, 7.5, and 10 miles outside the regulatory boundary, respectively. 95% confidence intervals are also shown. The coefficients are normalized to event time $t = -1$. Column 1 presents results with region-by-year-by-quarter fixed effects while the second column the results of more localized market-by-year-by-quarter fixed effects. Standard errors are clustered at the region-year or market-year cell level.

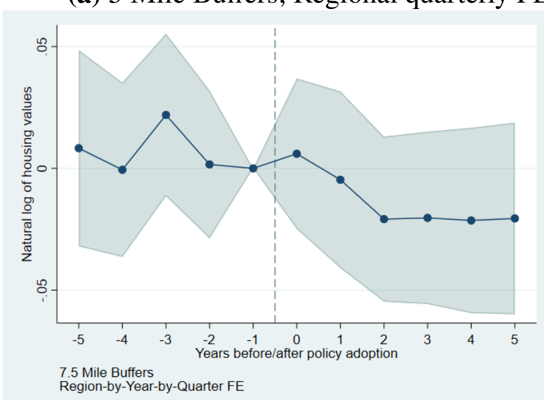
Figure 1.5 Pooled Cross Section Event Studies



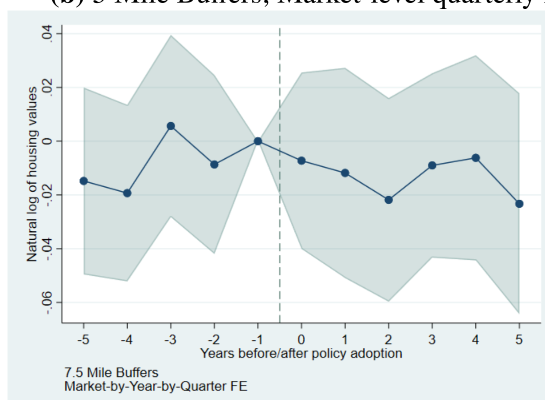
(a) 5 Mile Buffers; Regional quarterly FE



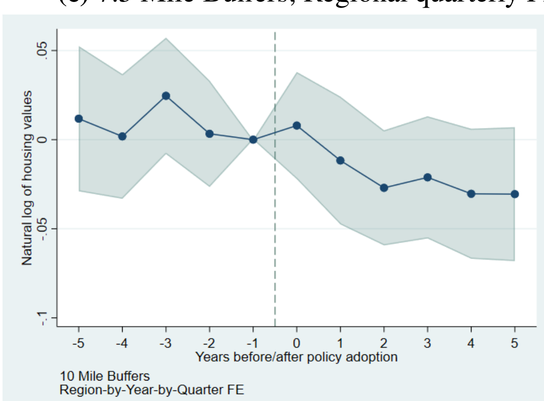
(b) 5 Mile Buffers; Market-level quarterly FE



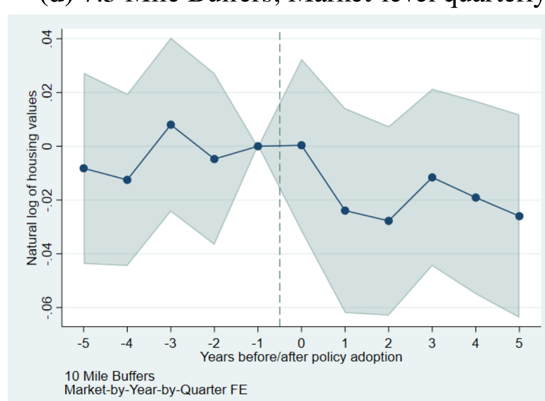
(c) 7.5 Mile Buffers; Regional quarterly FE



(d) 7.5 Mile Buffers; Market-level quarterly FE



(e) 10 Mile Buffers; Regional quarterly FE



(f) 10 Mile Buffers; Market-level quarterly FE

Notes: The coefficients plotted above are the results from six separate regressions of the natural log of average house sale price on a set of structural controls, spatial controls, year-by-quarter fixed effects at the regional or market level, township fixed effects, and the interaction of event time with an indicator variable $1[Inside]$ equal to 1 for the cells containing ever-regulated houses. Column 1 presents results with region-by-year-by-quarter fixed effects while column 2 specifies more local market-by-region-by-year fixed effects. Event time is normalized to the date at which TOST implementation began in each market, thus $t = 0$ is the year immediately following implementation. The dots plot the time path of regulated houses relative to those 5, 7.5, and 10 miles outside the regulatory boundary. Shaded 95% confidence intervals are also shown above and below the point estimates. The coefficients are normalized to event time $t = -1$. Standard errors are clustered at the township level, though the results are widely unchanged when two-way clustered at the market-year level.

APPENDIX B: SUPPLEMENTARY MATERIALS

Data Methodology

The foundation of the data for this paper are from Multiple Listing Services (MLS) across the state of Michigan. Zillow ZAsmt and ZTrax assessment and transaction data products serve as secondary sources of data. MLSs are responsible for compiling and distributing housing attribute and housing transaction data. They are maintained by associations of real estate agents and realtors. Through a confidential data use agreement, we obtained listing information from 15 MLSs. Similarly, a confidential data license with Zillow provided access to the ZAsmt and ZTrax packages.

To begin, every observation from an MLS was assigned a unique identification number. Then, property addresses were geocoded using the U.S. Census API (U.S Census Bureau, 2021). This allowed for all addresses to be standardized and coordinates to be obtained for the properties. This facilitated matching properties within the MLS data to one another based on identical standardized addresses and coordinates. To be clear, the interest of this study is to identify the causal impact of a jurisdiction-level (county, township, or village) level policy change on housing prices, so any calculated distances are serving as controls and not the variables of concern. The geocoding process reported standardized addresses, the county of the address, and latitude and longitude coordinates. (About 25 percent of raw observations were geocoded using Texas A&M's services (https://geoservices.tamu.edu/Services/Geocode/About/), and less than 2 percent came directly from MLS data or from ESRI. These observations didn't actually make it into the final analysis because those properties were dropped.)

Once the coordinates were obtained, the geospatial was uploaded into ArcGIS software for location processing. This was done using shapefiles from the state of Michigan's GIS Open Data portal (https://gis-michigan.opendata.arcgis.com/). Layers with data including county and townships, 2010 Census geography, and the location of the Great Lakes and inland lakes provided important identifiers and control variables. To ascertain property characteristics and capture as many transactions as possible, I employed four different approaches to join together the MLS data with the Zillow data. These approaches vary in the richness of the MLS and Zillow data available. I employed the approaches in order of their quality, with the first implying highest quality and the fourth lowest. First, I tried to merge them based on a formatted assessor parcel number (APN). An APN is used by a taxing authority to designate and identify parcels. APNs vary in length and construction from taxing authority to taxing authority. When formatting is present, the APN often contains dashes and the placement of the dashes matters; a misplaced dash will prevent a match from occurring. Second, I tried to merge the MLS properties to the Zillow properties based on unformatted APN. When formatting is not present, the APN consists of a string of numbers and this approach is more flexible because it does not require perfect dash placement to yield a match. In some instances, unformatted APNs will match when formatted APNs did not due to misplaced dashes. This approach will not, however, yield matches if one or both data sources have APNs with missing digits or dropped zeros.

Many of the MLSs did not, however, report APNs. In this case it was necessary to develop a strategy to pair MLS observations with Zillow observations based on some other identifying characteristics. I used address information to move away from an APN-reliant approach to identifying properties across MLS and Zillow observations. This method first matched MLS observations to Zillow observations by requiring two identical numbers: address street number and ZIP code. This generated a pool of candidate matches which were refined using string matching algorithms based on street name. I designed an algorithm to be sensitive to direction identifiers (this prevented, for example 100 S. Main St., Cityville, MI, 48888 from matching 100 N. Main St., Cityville, MI, 48888) and discard any low-confidence matches. This analysis performed conservatively to prevent mismatches from entering the dataset. The first run of merging based on addresses used the standardized addresses obtained from the U.S. Census geocoding API (U.S. Census, 2021) while the second run used the addresses directly provided by the MLS.

Once this was done, I had a large set of pairwise matches of MLS observations of a property and Zillow observations of the same property. The goal was to obtain a comprehensive list of all transactions recorded across the 15 MLSs and Zillow. I sorted the observations by the Zillow identifier and dropped any sales for which I had evidence of a non-arms-length transaction. This process removed any duplicate sales, pairs of sales which occurred within one calendar year of one another (often indicating flips), sales that occurred between family members, or transactions that involved extraordinary deed types.

Through the entire process I tried to keep things as "dirty" as possible. That is, I waited as long as sensible to drop duplicates, transactions that implied flips or non-arms-length sales, or observations that were not usable for estimation due to a lack of completeness on the control variables, etc. until the very end of the process. I used this strategy because I wanted to accumulate as much information about a property as possible before I decided what to do with it. This meant potentially keeping multiple listings and transaction records of the same property from different MLSs and from Zillow. For example, if there was information from the MLS that a property was single-family residential but Zillow had the property tagged as agricultural residential I threw the property, and all associated transactions with it, out. This is because I am not modeling the fertility or other agricultural attributes associated with agricultural land and needed to omit any transactions that would have critical omitted variables like that in them.

When matching properties by address, multiple issues can arise. Sometimes one address will have two entries in the Zillow data. Over time, some parcels are split. It is not rare to observe parent and child parcels from homesteads and farmland getting divided or changes in land use and ownership. In instances where an MLS observation merged to two property records with different APNs I discarded the observation. At this stage, I had to triage the quality of the observations. Despite the richness in data quality for many thousands of observations, MLSs are independently managed and maintained entities which serve different housing markets and vary greatly in standards and requirements for listing.

Figure 1.6 The Limitations of Common Inspection Dye Tests

Examples of when a dye test can be a useful tool and when a dye test is not a useful tool. Source: EPA Webinar, 2014

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CHAPTER 2

WHAT LIES BENEATH? AN ANALYSIS OF "TIME OF SALE OR TRANSFER" WELL AND SEPTIC INSPECTION FAILURES

2.1 Introduction

Houses require two important water systems: one bringing potable water to the house and one taking wastewater away. Most households in the United States are connected to municipal piped water and sewer lines and rely on public water utilities and managers for their water needs. In contrast, one in five Americans, mainly in suburbs and rural areas, rely on private wells and septic systems (US EPA, 2001). Wells and septic systems, also known as on-site water systems (OWS), provide safe, cost-effective water provision and wastewater disposal under proper maintenance and replacement cycles. Unfortunately, the quality of wells and septic systems vary widely. Malfunctioning systems pose significant threats to the health of households, communities, and ecosystems. For example, contaminants jeopardize human health in 20 percent of U.S. private wells (DeSimone et al., 2009). Similarly, failing septic systems account for five to 25 percent of all septic systems across the United States (US EPA, 2001). This level of malfunction is a serious health concern as poorly maintained septic systems cause 168,000 viral illnesses and 34,000 bacterial illnesses annually (US EPA, 2002). Further, the US EPA identified septic systems as the second greatest source of contamination to groundwater (US EPA, 1997). OWS performance is stochastic. Risk factors like age, ground composition, weather events, and maintenance affect the probability a system will fail (LaGro, 1996; Steffy and Kilham, 2004; Thomas, 2000). As wells and septic systems age, they generate additional risks to public and environmental health, most of which remain hidden to homeowners and environmental regulators. Compromised wells cannot effectively protect house residents from drinking water contamination and pollute groundwater through cracks or missing safeguards. Derelict septic systems can fail to treat wastewater, release partially treated wastewater into ground and surface water, and introduce pathogens into the environment.

Wells and septic systems are spread out geographically, typically in regions of low population density. Further, environmental contaminants rarely remain at their sources and can be difficult to trace. Non-point source pollution is notoriously challenging to identify and regulate.

Given the environmental health risks to residents and communities, regulators across the United States have adopted strategies to minimize OWS health risks. Many programs work to educate homeowners, while others involve permits, mandatory maintenance, and additional strategies (Halvorsen and Gorman, 2006; Mohamed, 2009). One instrument, frequently called a "Time of Sale or Transfer" (TOST) policy, focuses on housing transactions to address OWS performance problems. TOST regulations dually serve as information disclosure policies and minimum quality standards. Some U.S. states, including Arizona, Iowa, and Massachusetts, employ state-wide TOST programs. Most states have not adopted state-wide TOST policies. Michigan is one such state, however several counties, townships, and villages administer TOST programs across the lower peninsula.

TOST policies harness the structure of the housing market to mandate OWS-specific inspections. A registered inspector must evaluate any OWS on a property and file a report with the Health Department (HD). The HD then discloses its findings to the homeowner and potential buyer. Any deficiencies identified by the Health Department must be fixed before receiving approval for house sale closing.

Despite the use of TOST policies across the United States to preserve environmental quality and protect public health, the literature is almost entirely silent on the findings of the programs or their effects on housing markets. The impacts of TOST programs are particularly salient to regulators who have an array of policy instruments available in their efforts to minimize OWS risks. Only one study, the first essay of this dissertation, estimates the consequences of TOST adoption on housing values and finds evidence of a price decline no larger than 4 percent following TOST implementation. This paper builds on that study by focusing on houses that required repairs or replace by asking and answering two main questions: are the OWS problems uncovered by TOST inspections capitalized into housing prices and is there significant heterogeneity in the capitalization effects associated with TOST results?

To better understand the prevalence of TOST inspection failure I analyze ten years' worth of TOST inspections across three Mid-Michigan counties. Barry, Eaton, and Ingham Counties are geographically proximal, implemented their TOST programs about 16 months apart, and provide good proxies for urban, suburban, and rural communities across Michigan. I start with the universe of TOST inspections and I find 15 to 30 percent of TOST evaluations require mandatory remediation or replacement, depending on location, well or septic system, and vacancy status. Then, I link the well and septic system inspection records to housing transaction data to estimate the price impact of failing a TOST inspection. Using a log-linear hedonic regression approach, I find house prices decrease 7-10 percent following a failed TOST inspection. These results are large in magnitude, statistically significant, and relatively homogeneous across different classifications of inspection failure in terms of which system failed, risk severity, and program. Further, I investigate heterogeneity along the distribution of housing prices and find evidence that the negative price impacts are borne by the least valuable houses in the market. These findings are important to policymakers because they suggest that TOST program costs are borne largely by those least able to maintain their systems.

This study contributes to the environmental quality, environmental externality, and information disclosure literatures. A rich tradition in the environmental economics literature demonstrates the salience of environmental quality to homebuyers, especially in the context of water quality (Söderqvist, 1995; Leggett and Bockstael, 2000; Walsh et al., 2011; Wolf and Klaiber, 2017). These studies use non-market valuation to capture the effect of a change in environmental quality on housing prices and estimate the capitalization effects of such changes. Another related literature investigates the impact not of environmental quality, but environmental quality information through housing market disclosures. These include disclosures regarding flood zones (Pope, 2008a), airport noise (Pope, 2008b), lead paint (Bae, 2012; Billings and Schnepel, 2017) and contamination sites (Walsh and Mui, 2017). The policies studied in this paper blend the two literatures. First, TOST regulations feature minimum quality standards and directly change environmental quality. Second, the findings of TOST inspections must be shared with homeowners, homebuyers, and regulators, constituting information disclosure. This analysis differs from others like Boyle et al. (2010) where information disclosure occurs, but mitigation strategies are left to homeowners and homebuyers. Currently, no empirical work investigates how policies combining disclosure with remediation affect the housing market.

The remainder of the paper is as follows. First, the background and program overview sections provide the context and history behind TOST regulations. Second, I develop a simple model of a negative information shock during a house sale and connect this model to several empirical models and hypotheses. Third, I discuss the sources and structure of the data used in this study. Fourth, I present estimation results followed by robustness checks. Finally, I conclude with a discussion of policy implications.

2.2 Background and Program Overview

Michigan lacks statewide OWS construction and maintenance policies. As such, local governments retain the right to regulate these systems. Various counties, townships, and villages have adopted TOST policies requiring evaluations of OWS as a precondition of a legal housing transaction. However, the vast majority of Michigan municipalities use no such provision. The purposes of such programs are to ensure the safety of drinking water for homes with wells, confirm adequate treatment of sewage for homes with septic systems, protect the quality of water resources, and protect public health (Ingham County Health Department, 2018; Barry-Eaton District Health Department 2017). In addition, the programs identify performance standards for wells and septic systems, specify when inspections must be conducted, and provide the force of law to ensure corrective actions occur when inspections identify problems (Barry-Eaton District Health Department 2017).

Although counties write and approve their TOST regulations, county policies overlap substantially in layout and language. These similarities are artifacts of the propagation of TOST regulations across Michigan in the last thirty years. In the mid-1990's, a Federal water quality case against managers of the Rouge River Watershed in metropolitan Detroit drew significant attention to pollution in the area (Johnson et al., 2001). As a result, administrators in Wayne and Washtenaw counties targeted OWS contamination as one component of pollution in the watershed. Wayne County adopted a TOST regulation in Rouge River Watershed in 1999 and county-wide policy in 2003 (Johnson et al., 2001). Washtenaw County adopted a county-wide TOST program in 2000, and nearby Macomb and Shiawassee Counties followed in 2002.

In general, TOST policies are county, township, or village ordinances which include definitions for failure and non-conformance, an inspection checklist, criteria for inspectors, and consequences of non-compliance by property owners. In the context of this paper, local HDs serve as TOST program administrators. These departments handle the paperwork and record-keeping associated with TOST evaluations, issue formal letters regarding evaluation results, and track compliance. HDs also maintain public lists of approved inspectors for residents. The HDs are responsible for training, certifying, and registering private inspectors and some employ specialized staff to conduct inspections. All inspectors must demonstrate working knowledge of well and septic system functions, follow inspection guidelines, and risk de-certification for deviating from protocols. Private TOST evaluators are often professional home inspectors, sanitarians, or public health experts.

While home inspections are a common part of house transactions, TOST inspectors are typically selected and hired by the homeowner, not the homebuyer. Inspections require the evaluator to locate all the wells or septic systems on a property, conduct visual and physical inspection of these systems, and identify present and future public and environmental health risks. Inspection fees generally range between $500 and $700. Following inspection, evaluators submit their reports to the HD, which then reviews the report and to determine whether the OWS warrant repairs or replacements. The HD communicates its official conclusion in a letter to the owner. A compliance notification letter entitles the property owner to sell their house within one year.

The HD issues a corrective action letter if it concludes the OWS quality is below the minimum quality standard based on the evaluator report. Corrective actions range from minor requirements like drawing new water samples or pumping a septic tank to more major changes like replacing an entire well system or septic system (Barry-Eaton District Health Department, 2017). Additionally, if bad weather delays corrective actions (i.e., the ground is frozen in winter), a HD supervised escrow must be established at 1.5 times the estimated corrective action cost. As a result, the financial effects from a failed TOST inspection bind whether or not repairs occur before or after property sale closing.

TOST inspections differ from the inspections or appraisals mortgage lenders commonly require for homebuyers to secure a mortgage. In particular, these mortgage inspections do not imply policy compliance absent a TOST regulation for two reasons. First, mortgage inspections lack the rigor of TOST inspections. For example, lenders often require dye tests that introduce a brightly colored indicator dye into the septic tank and then observe whether the dye can be detected. While this test can identify surface discharges, they fail to provide information on underground leaks (Tooke et al., 2014). Second, the results of mortgage inspections are not regulated, administered, or reported to local authorities. This private transaction means the results are not public knowledge, the outcomes are not tracked, and HD officials do not prescribe the standards for the inspections. Thus, the nature of the information distribution is different when the entity imposing the inspection is a mortgage lender versus HD administrators.

This study focuses on three counties in mid-Michigan: Barry, Eaton, and Ingham. Figure 2.1 shows their locations within the Lower Peninsula of Michigan. The three counties are similar in size and shape, with Barry County furthest west, Ingham County furthest east, and Eaton County sandwiched in between. These three counties are ideal candidates for TOST policy analysis due to the similarity of their programs, their geographic proximity, and the organized record keeping and reporting of the Ingham County Health Department (ICHD) and Barry-Eaton District Health Department (BEDHD).

The Ingham County Board of Commissioners adopted its "Point-of-Sale" policy on April 25, 2006 and the ICHD started administration and enforcement June 9, 2006. The ICHD continues to oversee the program to this day and TOST inspections are required only for house sales. In contrast, Barry and Eaton Counties shared a TOST program between 2007 and 2018. The joint BEDHD

Board of Health adopted the policy on May 7, 2007 and enforcement began October 16, 2007. Like Ingham County's policy, the BEDHD policy required OWS inspections for traditional housing sales but also for most other types of property transfers. This provision meant that non-sale transfers, like a parent handing their house down to one of their children, would trigger a TOST evaluation inspection. On March 21, 2018, the BEDHD Board of Health voted to repeal the regulation.[1] The BEDHD stopped enforcing the TOST program May 5, 2018. Currently, there are no active TOST programs across Barry or Eaton Counties.

Table 2.1 presents composition and population demographics for Barry, Eaton, and Ingham counties and the state of Michigan. Ingham County, the most urban county, hosts Michigan State University and Michigan's capital, Lansing. It also has more houses, people, and racial diversity than either Barry or Eaton Counties and is similar in composition to other urban counties in Michigan. Barry County is much different and represents more rural counties: it has the highest rate of owner-occupied housing, median value of owner-occupied housing units, and surface water endowment. Eaton County falls between Barry County and Ingham County geographically and demographically, and reflects Michigan closest in terms of owner occupacy rate and median house value. Taken together, these three counties serve as a good proxy for the state of Michigan.

I obtained TOST inspection records from Ingham County's program from ICHD. These records report the address of the inspected property, an indicator of well presence, an indicator of septic system presence, the date of inspection, the date of non-conformance designation (failed inspection), the date of conformance designation, and reason(s) for non-conformance (failure) between the years 2006 to 2017. I similarly obtained TOST inspection records for Barry and Eaton Counties from BEDHD. These records include the address of the inspected property, a well indicator, a septic system indicator, an indicator for whether the property was vacant at the time of inspection, and the reason(s) for inspection failure between October 2007 and April 2018. Inspections from 2008 to 2017 are considered in this study to ensure each HD had fully rolled out its program and neither program faced repeal during the study period. During data collection, I met with administrators

[1] Citizens of Barry County disliked the fact property owners could not sell houses in "as-is" condition and claimed inspections delayed sales, cost too much, and were administered too strictly (wbch.com, 2018).

from both HDs. In meetings with BEDHD, it was suggested that low-income homeowners play an important role in the story of TOST policies. Specifically, homeowners short on funds may be less able to perform necessary maintenance on their wells and septic systems leading to more OWS problems for low-income owned houses relative to high-income houses. Therefore, it is likely that OWS problems identified through TOST inspections on low-income property owners could not be fixed by the homeowners left to their own devices due to capital constraints. Given the structure of TOST regulations, however, any HD mandated corrective actions must be taken whether or not the house sells. As such, homeowners without the financial means to repair problem systems need to sell their houses to cover these costs and shift the burden to the homebuyers, resulting in a fire sale or at least reducing the bargaining power of the homeowner. This would generate downward pressure on the house price because the capital-constrained homeowner cannot perform the repairs or replacements and relies on the buyer to complete them and foot the bill.

Each HD defined classifications for the most common reasons TOST inspections required repair, replacement, or remediation (ICHD, 2018; BEDHD, 2017). These categories are presented on Table 2.2 by OWS and risk severity. High risk reasons, such as coliform bacteria present in a well water sample, present significant public health or environmental health concerns while low risks do not present as high a level of immediate concern. No matter the level of risk severity, however, a HD could prevent property transfer until verifying the completion or escrowed plan of corrective actions.

Figure 2.2 presents the number of TOST well inspections performed between 2008 and 2017 by HD and the failure rate shows how many well inspection required repair or replacement. Overall, many more inspections occurred in Barry and Eaton Counties during the study period than Ingham County. This reflects the rurality of Barry and Eaton Counties as well as the BEDHD requirement of a TOST evaluation for any type of property transfer. Though more inspections occurred in Barry and Eaton, the failure rate was higher in Ingham County and trended up over time, starting near 20 percent and reaching over 40 percent by 2017. Barry and Eaton Counties also started around a 20 percent failure rate but this value remained flat for about 6 years before trending down to about percent.

Figure 2.3 shows the number of septic system inspections and failure rates for each program over the duration of the study period. Once again, Barry and Eaton Counties saw many more inspections that Ingham County, and fewer septic system inspections than well inspections. This difference in Barry and Eaton OWS inspections stems from many homes in Barry County having wells but not septic systems. In Ingham and Eaton Counties, however, most houses with wells also rely on septic systems. The failure rate for Barry and Eaton counties remained stable across the study period around 25 percent while it trended up in Ingham County.

Figure 2.4 shows how many inspections cited multiple reasons for inspection failure. A well could fail inspection for multiple reasons, such as a cracked casing and a contaminated water sample. The first panel presents the number of reasons provided for well inspection failure. Most failed inspections are the result of just one failure reason and no failure is the result of more than six violations. Similarly, the second panel of Figure 2.4 illustrates the number of reasons provided for septic system inspection failure by county. It is most common for a failed septic inspection to occur due to one or two reasons and uncommon for three or more reasons.

Figures 2.5 and 2.6 provides insight into the frequency of failures by type, highlighting the high-risk reasons HDs cited for required corrective action. These risk classifications, provided by BEDHD and ICHD, reveal that serious problems with both wells and septic system were uncovered at a higher rate in Ingham County than in Barry or Eaton Counties.

Motivated by conversations with HD officials, I decomposed TOST inspection failure rates by real house price. The failure rates are plotted by real house price decile in Figure 2.7. Consistent with expectations, houses on the low end of the price spectrum failed both well and septic system inspections more frequently than on the high end of the spectrum. The failure rate was roughly four times higher (40%) for the first decile than the tenth (10%). Despite the increased frequency of failure at the low end of the spectrum, it is unclear if the housing price spectrum also demonstrates heterogeneous capitalization effects. The methodology required to test this hypothesis is introduced in the next section.

2.3 Empirical Models

In economics, houses are considered differentiated products because they vary significantly in characteristics like square footage, age, plumbing system types, number of bedrooms, neighborhood amenities, distance to amenities, etc. Under a TOST regulatory regime, OWS-specific inspections provide information regarding well and septic system quality, in particular whether or not the well and/or septic systems met minimum quality standards at the time of inspection. A first-stage hedonic price model is used to identify the effect of TOST inspection results on housing values (Rosen, 1974).

Rosen's model considers a differentiated good composed of a vector of characteristics and decomposes its price into values for the individual characteristics of the good. In the context of the housing market, this vector should contain all the structural and community characteristics of the house salient to price. The model assumes that the housing market is populated by utility maximizing buyers and sellers. Buyers place bids on houses and homeowners choose whether to accept the bids. A sale occurs with a price determined by the highest bid acceptable to the seller. In Rosen's model, this price reflects an equilibrium between the buyer and seller.

To expound on this process, once a seller accepts a buyer's bid, the house goes under contract and a 30-60 day period follows during which a mortgage is secured, inspections take place, and negotiations occur based on new information. At the end of this closing period, the final house price is posted. In this context of this study, it is important to note that an empirical analysis of the timing of home sale dates and TOST inspections revealed that the norm in the markets studied is for TOST inspections to occur during closing. For better or worse, few homeowners get their OWS inspected before matching with a buyer. Figure 2.8 explains the stages of price formation when a TOST inspection uncovers a problem requiring costly corrective action. In the first stage, the buyer and seller agree on price $X and the house goes under contract. All else equal, this is the price we would observe absent a TOST program.

In the second stage, the house undergoes inspection. A registered TOST evaluator performs the inspection, submits their report to the HD, the HD makes the determination that repairs or replacement are necessary to achieve a minimum quality standard, and the parties are informed of the OWS quality problems through a formal letter. These repairs are valued at $\$r$, a unobserved value in this study.

Finally, in the third stage, we observe price $\$P \in [\$X{-}\$r{,}\$X]$. The observed price bears a discount \$d and is determined by the negotiating power of the two parties. Let β denote the negotiating power of the seller and $1-\beta$ be the negotiating power of the buyer. How the cost of repairs are split is based on the β value and the discount can be expressed $\$d = \beta * \$0 + (1-\beta)\$r$. If the buyer has absolute power in the negotiation, all repairs will be paid for by the seller and the posted price will be \$X-\$r. If the seller has all the market power, she will not pay for repairs and the house price will remain the same, \$X while the buyer pays for repairs such that no price effect can be observed. More likely is that the repairs will be paid for by one of the parties and the price of the house will be discounted to reflect the problems identified in the inspection. Empirically, the average discount, \$d, can be estimated as a hedonic intercept shifter. The portion that is paid by the buyer will be subtracted off the house value and reflected as a discount. The final posted price is the equilibrium price.

The equilibrium price is expressed in log-linear form as:

$$\ln P_{ijt} = \beta_0 + \beta_1 \mathbf{X}_i + \beta_2 \mathbf{Z}_j + \beta_3 \mathbf{T}_t + \beta_4 Fail_{it} + \varepsilon_{ijt} \tag{2.1}$$

where P_{ijt} is the price of house i located in community j at time t, $\mathbf{X}_i$ gives the structural attributes of house i, $\mathbf{Z}_i$ provides time-invariant community-level attributes, $\mathbf{T}_t$ indicates the time period of the sale, $Fail_{it}$ indicates the instance of a TOST inspection failure, and ε_{ijt} is an idiosyncratic error term. The vector β contains the parameters associated with each of the variables of the model. I investigate heterogeneity effects by decomposing $Fail_{it}$ along several dimensions including OWS, risk severity, and program administration.

The first specification considered decomposes TOST inspection failures into two types: well failures or septic system failures but imposes a uniform effect across the three sampled counties:

$$\ln P_{ijt} = \beta_0 + \beta_1 \mathbf{X}_i + \beta_2 \mathbf{Z}_j + \beta_3 \mathbf{T}_t + \beta_4 WellFail_{it} + \beta_5 SepticFail_{it} + \varepsilon_{ijt} \tag{2.2}$$

By including TOST inspection failure separately for both wells and septic systems the effect of a failed inspection can be capitalized differently for the different types of inspection failure. This also allows for testing between estimated parameters to investigate whether the effect of failing a well inspection differs from failing a septic inspection. TOST inspection failures can also be classified according to the severity of the problems discovered by inspection. The third specification decomposes well inspection failures and septic system inspection failures based on if inspection failure can be attributed to low-risk or high-risk problems. This can be modeled as:

$$\begin{aligned}\ln P_{ijt} =& \beta_0 + \beta_1 \mathbf{X}_i + \beta_2 \mathbf{Z}_j + \beta_3 \mathbf{T}_t + \beta_4 WellFailLowRisk_{it} + \beta_5 WellFailHighRisk_{it} \\ &+ \beta_6 SepticFailLowRisk_{it} + \beta_7 SepticFailHighRisk_{it} + \varepsilon_{ijt}\end{aligned} \tag{2.3}$$

where $WellFailLowRisk_{it}$ captures the capitalization effect of a well inspection failure for low risk reasons versus $WellFailHighRisk_{it}$ which reflects the capitalization effect of a high risk well inspection failure. These two categorizations are mutually exclusive because all well inspection failures occur for low risk reasons if they are not high risk. If multiple reasons for inspection failure are given, including both high and low risk reasons, the entire inspection is attributed to high-risk problems. This specification allows health risk and contamination affect house value differently than lower offenses. There is also reason to believe that the high risk problems may generate stigma or increased health concerns. Many different types of events and information disclosures have been shown to generate stigma in the housing market (Boyle et al., 2010; Gourley, 2019, Messer et al., 2006). It is possible that high-risk problems generate a lingering worry about contamination or foster feelings of disgust. This would cause the average price of houses with high-risk TOST information shocks to be lower than low-risk ones. One would expect, for example, that if an inspection reveals a leaking septic tank a larger price penalty than if the inspection revealed the septic tank merely needed a pumping. If, however, stigma or inconvenience are capitalized into the house price from any kind of failure, there may be no difference in these risk-based parameters.

The "Time of Transfer" program in Barry and Eaton Counties and Ingham County's "Point of Sale" program shared more similarities than differences during the study period. Despite the meaningful overlap in the programs, the idiosyncrasies of two different HDs administering two different regulations could have led to important differences reflected in house values, especially if one program was more stringent with minimum quality standards and rendering corrective actions. The fourth specification allows the impact of each type of failure to differ by Health Department by considering Barry and Eaton Counties separately from Ingham County:

$$
\begin{aligned}
\ln P_{ijt} = & \beta_0 + \beta_1 \mathbf{X}_i + \beta_2 \mathbf{Z}_j + \beta_3 \mathbf{T}_t \\
& + \beta_4 WellFail \times BarryEaton_{it} + \beta_5 WellFail \times Ingham_{it} \\
& + \beta_6 Septic \times BarryEaton_{it} + \beta_7 Septic \times Ingham_{it} + \varepsilon_{ijt}
\end{aligned} \tag{2.4}
$$

While augmenting the log-linear hedonic model in equation 2.1 with interaction terms can help analyze heterogeneity effects for OWS type, risk severity, and HD, this methodology is not suitable for estimating TOST failure impacts along the distribution of housing values.

To exploit the information in the house price distribution, I employ a methodology akin to that of Kuethe and Keeney (2012). Their study estimated the effects of proximity to concentrated agricultural feeding operations (CAFOs) on housing prices and employed a spatially lagged quantile regression approach to reveal that CAFOs only have a negative effect on houses at or above the conditional mean price. It would be reasonable to expect negative capitalization effects from failed TOST inspections lower end of the price distribution. For two reasons. First, problems with wells and septic systems would represent a larger portion of the value of a house in the lower end of the distribution. Second, low-income homeowners should have less market power when selling their homes than their buyers once an inspection shows problems requiring costly corrective action. This is because TOST programs require repairs or replacement even if the house doesn't sell and capital-constrained, low income homeowners would be forced to sell to cover the costs of mandated corrections. I test this hypothesis to better understand the negative capitalization effects uncovered in this study.

To motivate this analysis, first consider the standard spatial lag model

$$
\mathbf{y} = \rho \mathbf{W}\mathbf{y} + \mathbf{X}\beta + \varepsilon \tag{2.5}
$$

where y is the vector of house prices, $\mathbf{W}$ is the spatial lag matrix, ρ is the spatial autoregressive coefficient, $\mathbf{X}$ is the vector of housing attributes, and ε is the error vector (Anselin, 2003). This model can be estimated through ordinary least squares (OLS). When the spatial weights matrix is row normalized, the following transformation facilitates interpreting individual β coefficients:

$$\mathbf{y} = (1-\rho)^{-1}\mathbf{X}\beta + (1-\rho)^{-1}\varepsilon \tag{2.6}$$

Unlike (OLS) estimation, quantile regression produces decile-specific estimates to understand the impact of TOST inspection failure along the house price distribution. Though house value is an imperfect proxy for homeowner income, it is reasonable to expect that low house prices are correlated with low income. I specify the following spatial lag hedonic model

$$\mathbf{y} = \rho(\tau)\mathbf{Wy} + \mathbf{X}\beta(\tau) + \varepsilon \tag{2.7}$$

where all property-specific structural, spatial, and sale timing variables are collected into the $\mathbf{X}$ matrix and the spatial weights matrix, $\mathbf{W}$ is a row-normalized inverse-distance matrix of each property's ten nearest neighbors.[2] Taken together, $\mathbf{Wy}$ produces an n×1 vector of spatially lagged house prices. $\rho(\tau)$ is the decile specific spatial lag parameter and $\beta(\tau)$ is the decile-specific parameter vector for the house-level controls. Estimates were obtained through simultaneous quantile regression with standard errors produced by bootstrapping with 500 repetitions.

2.4 Data

Empirically analyzing the impacts TOST regulations on the housing values in a hedonic framework requires linking the HD inspection results with housing transaction records and property characteristics. As previously mentioned, the ICHD and BEDHD supplied TOST inspection data. The universe of records contains 17,078 property inspections between January 2008 and December 2017. I chose this period because it represents a time span when both HDs actively enforced their TOST policies and neither program was ramping up or winding down. I acquired the necessary

[2]The school district and census geography fixed effects cannot be used in this model because there are too many fixed effects which prevents bootstrapping from occurring. Instead, locations are controlled for with the spatial lags.

housing transaction and attribute data from two major sources: Michigan Multiple Listing Services (MLSs) and Zillow. These data include historic sales information and select structural characteristics for properties sold between January 2008 and December 2017. I connected the inspection records and sales records through the address and location identifiers common to each source.

Empirical analysis is restricted to single-family houses sold through arms-length transactions in the resale residential housing market. Arms-length transactions represent traditional home sales which result from buyers and sellers acting in their own self-interest. As discussed in the previous section, property owners seek to maximize the price they receive from buyers by posting asking prices to maximize the profit they earn from the house sale. Similarly, buyers try to minimize the amount of money they must pay by issuing counteroffers. The result is a market price posted when the buyer and seller agree on a price: this reflects the equalization of the house's value between the buyer and seller, a critical component of assuming the housing market is in equilibrium. Intra-family transfers and sales between business entities are classic examples of non-arms-length transactions (Taylor, 2017).

Limiting the sample to arms-length transactions involves significant data cleaning. Any transactions identified as intra-family transfers, tax exempt transfers, or representing a purchase of a second home (as opposed to primary residence) are omitted. This removes sales records that represent arrangements outside the conventions of the traditional housing market context. For example, an intra-family transfer may reflect a non-competitive "sweetheart deal" which violates the assumptions necessary for market equilibria. Further, to establish a sample representing the traditional housing market, any house sales flagged as foreclosures, repeat sales within one year, or vacant houses were removed. Once vacant properties were dropped, 58% of inspected wells 62% of inspected septic system inspections remained in sample.

The resulting full cleaned sample is mapped on Figure 2.7 below. Notice that cities are delineated in light, speckled orange, but inspection records do not often fall within their boundaries. This reflects the rural scope of the TOST regulated properties: houses in cities are generally connected to municipal sewerage and piped water while rural houses must provide their own water provision and sewage disposal systems.

Summary statistics for the cleaned sample of 6,956 housing transactions are displayed by county in Table 2.3. Descriptions of the variables presented in Table 2.3 are shown in Table 2.4. Observable housing characteristics are mostly consistent between the three counties sampled but Barry and Ingham Counties are most disparate. This is not too surprising because one is very rural and one is very urban, however, in this analysis, the three counties are combined to and treated as one market. Barry County represents the largest share of observations with 2,628 observations followed by Ingham County with 2,579 observations and Eaton County with 1,748 observations. On average, houses in Barry County sold for $12,000 more than houses in Ingham County and $6,000 more than houses in Eaton County. Houses in Ingham County are slightly older than houses in Barry and Eaton Counties. Table 2.5 provides a list of the spatial controls compiled for estimation. These spatial controls include census tract, census block group, and school district which allow fixed effects to be included in each model that control for community attributes shared at the local level. In addition to serving as a control for school quality, which has been shown to greatly impact house values (Black, 1999), the school district fixed effect also controls for differences in property taxes. These fixed effects are important because the land use, school quality, and public amenities vary greatly across the three counties in the sample. Additional spatial controls are included and relate each property to its nearest major recreation opportunities such as state parks, trout and salmon streams, and inland lakes. Finally, the nearest distance to a major road, highway exit, and city control for differences in access to commerce and centers of economic activity.

To contextualize the deciles used to perform quantile regression analysis, I present summary statistics for structural housing characteristics in Table 2.6. Each decile represents one tenth of the observations, sorted by sale price in 2015 $. The average price within each decile increases non-linearly along with several other variables including size in square feet and acreage, number of bedrooms, number of bathrooms, and presence of fireplace or garage. Meanwhile, the building age decreases between lower and higher deciles. These trends are expected because the housing attributes are important determinants of house value. Less valuable houses tend to be smaller and older while more valuable houses tend to be larger and newer.

2.5 Results

The results from the log-linear hedonic price model show large and statistically significant price effects when TOST inspections lead to mandatory corrective actions. However, when looking for heterogeneity effects, I cannot conclude that these capitalization effects differ by OWS type, risk severity, or HD administrator. The results of the spatially lagged quantile regression approach, however, provide strong evidence of heterogeneity along the house price distribution, with the largest effects accruing to the lower end of the spectrum.

Table 2.7 presents estimation results for three specifications of TOST inspection failure. The first specification follows the model illustrated in equation 2.2 above. Column 1 reports estimates from this model and pools TOST inspection results across the three counties reporting separate estimates for well and septic system inspection failures. The second specification breaks system problems into either high-risk or low-risk failures following equation 2.3 above. The third specification introduces heterogeneity based on the HD administering the TOST program, as in equation 2.4 above. All specifications include structural controls, spatial controls, and time controls. The spatial fixed effects include Census tract fixed effects to control for unobservable spatial heterogeneity while school district fixed effects control for school quality and educational opportunity. Quarterly fixed effects control for shifts in the hedonic equilibrium due to time-varying but spatially invariant factors like macroeconomic trends as well as the cyclical nature of the housing market. Standard errors are clustered at the Census tract level to allow for arbitrary heteroskedasticity and spatial and serial correlation among the errors of houses in the same Census tract.[3]

Column 1 presents estimates of inspection failure for wells and septic systems separately, but pools the effects over risk and administrative units. All else equal, houses that fail well inspections sell for 9.2 percent less than those that pass.[4] This effect is both large in magnitude and highly

[3]The statistical significance of estimates presented in Table 2.5 does not change when standard errors are clustered at the Census block level instead of Census tract.

[4]The different between the -0.097 coefficient in Table 2.7 and the interpreted coefficient is due to the transformation explained in Halvorsen and Palmquist (1980).

significant statistically. The coefficient corresponding to a failed septic system inspection represents a negative capitalization effect of 10.9 percent and is also large, negative, and statistically significant. A test of the difference between these two point estimates is presented in the first row of Table 2.8 below. I cannot reject a null hypothesis of equality for the two coefficients and conclude they are not statistically different.

High-risk and low-risk septic system inspection failures produce different point estimates that are not as close to one another in magnitude as the well inspections failures. A high-risk septic system inspection failure generates a 13 percent decline in house price while low-risk failures lead to an 9.3 percent decline. Although high-risk septic system inspection failures seem to evoke a steeper price penalty, their confidence intervals overlap and a test of their difference reveals these coefficients are not statistically different from one another. This test is presented as Test 3 on Table 2.8.

The final column of Table 2.7 presents estimates the effect of TOST inspection failures based on which HD administered the program during the study period. The point estimates for Ingham County are nearly identical to the point estimates from pooling Barry and Eaton Counties together for both well inspections and septic system inspections. This suggest that the only meaningful heterogeneity in price effects come from risk severity and even then, the differential is not statistically significant.

The quantile regression estimation results are presented in Table 2.9. I present select coefficients to focus on the price outcomes when well and septic system TOST inspections result in corrective actions. The spatial lag coefficient is reported to aid interpretation, and shows how much surrounding houses influence the price of a given house (Kuethe and Keeney, 2012). Given the row normalization of the spatial weights matrix, the well inspection failure coefficient requires two transformations for interpretation, one for the dummy variable and one for the spatial lag (Halverson and Palmquist, 1980; Anselin, 2003).[5] These transformations are applied and presented visually in Figure 2.9 in percentage terms. It is clear that the percent change in convex in housing prices: it is

[5] The Halvorsen and Palmquist (1980) is p=exp(x)-1 where x is the dummy coefficient and p is estimated percent change and the Anselin transformation is (1-l)xp.

significantly more negative at the low end of the house price distribution relative to the high end, where the effect tapers off. One would expect this convexity, however, if the costs of repairing and replacing OWS were uniform as they would represent larger shares of lower priced house values. Looking at the quantile regression results in levels, however, shows that this convexity persists, as shown in Figure 2.10. This implies that the costs, whether in logs or levels, are indeed higher at the lower end of the price spectrum. Put differently, less expensive houses incur greater price penalties when TOST inspections uncover problems requiring OWS repairs or replacement and confirms the hypothesis that the low end of the house value (a proxy for low income) accrues larger consequences than higher end houses.

2.6 Robustness Checks

The statistically significant and large negative estimates of the effect of a failed time-of-sale inspection raise an important question: could these estimates be biased by unobserved characteristics? If a house of generally low quality is more likely to fail a TOST inspection, and no variable reflecting the low overall house quality is included in the model, then the estimates produced by the model will demonstrate a negative bias. That is, the estimates of the negative effects of failing TOST inspections above would be too large in magnitude. It would be ideal to have a measure of overall building quality to include in the econometric model. Many house systems require regular maintenance to ensure performance over time and lengthen the systems' lifetimes. It is reasonable to believe a homeowner does not maintain her septic system may forego maintaining others, too. As a result, the quality of various systems in a house may be correlated and signal important information to potential homebuyers. A failed point-of-sale inspection, then allows a homebuyer to update their beliefs regarding the rest of the systems of the house. For example, a poor quality septic system might be correlated with a poor quality roof or a poor quality furnace. Or perhaps houses that ultimately fail TOST inspections have other, readily observable flaws. Unfortunately, the quality of the systems of a house are unobservable from a research perspective. Time varying, house-specific quality measures would provide a first-best opportunity to investigate the role of omitted variable bias in the presented results. Such measures are unavailable for the properties considered in this study, however two second-best options are available: a repeat sales model that controls for time-invariant house quality and a subsample with County Assessor Grade controls for time-invariant house quality.

2.6.1 Repeat Sales Model

The first approach controls for time-invariant unobservable heterogeneity by restricting analysis to houses that sold more than once under a TOST program. This strategy has both benefits and costs. The major benefit comes in the form of controlling for property-level unobservables that persist over time. Only time-varying variables can be included in analysis, such as building age and sale date. On the other hand, only houses that sold at least twice during the relatively short 2006-2017 time period are included.

Table 2.10 presents estimation results obtained from a subsample of the houses included in the sample from Table 2.5. This subsample has a longer temporal range, now from 1999 to 2017, to facilitate a repeat sales approach. This extended time period was necessary to compensate for the long tenure of houses in the sample. Only houses with at least two observed, arms-length transactions are included. This results in the sample size falling from 6,952 transactions to 2,607. There are several reasons this subsample is smaller. First, some houses only sold during the TOST regulation period. Second, some houses were built during the regulation period and only sold once thereafter, registering a single transaction in the resale market. Third, only houses with verifiable characteristics were retained, including bedrooms, bathrooms, square footage, lot size, etc. For the repeat sales model this includes, perhaps most importantly, age. Only observed time-varying characteristics are included in the fixed effects model. Time-invariant characteristics like number of bedrooms, square footage, etc., are not included in model because they are perfectly correlated with the property fixed effect. As a result, instead of structural controls and spatial controls, the models presented in Table 2.7 only employ house age and age squared controls.

The inspection failure estimates in the first column of Table 2.10 pool across the three counties and the ten year regulation period by system type. The point estimates are smaller in absolute value than the non-repeat specification presented in Table 2.7. This is consistent with expectations: unobserved property characteristics correlated with wells or septic system quality could bias the estimates of the first model downward, inflating the magnitude of the effect. Controlling for time-invariant property characteristics does not eliminate the negative and significant effects, though. A well inspection failure leads to a 7.4 percent decrease in housing values, all else equal, while a septic system inspection failure leads to a 8.5 percent reduction. Although the standard errors are larger, due to the reduction in sample size, the estimates of the first column are large in magnitude and statistically significant at the 1 percent level. Though the point estimates differ, a Wald test shows that I cannot reject that the coefficients are equal (Table 2.11).

The remaining columns of Table 2.10 diverge from the full sample estimates and tell a less consistent story. Column 2 presents estimates pooled across time and geography according to risk severity. Well inspection failures stemming from high risk problems lead to a significant 9.2 percent house price reduction while well inspection failures for low risk reasons incur no significant price effect. Conversely, inspection failures from low risk reasons yield a significant 10.3 percent house price reduction while high risk reasons have no significant effect. Statistically, it is not possible to reject a null hypothesis that the risk severity estimates are equal for well inspection failures and septic inspection failures, respectively, as shown in the Wald test results on Table 2.11.

Column 3 presents estimates pooled across time by system inspected and Health Department. Houses in Ingham County experience a 10.6 percent decrease in value following well inspection failures. In contrast, houses in Barry and Eaton Counties do not exhibit a statistically significant negative effect. The difference between these estimated effects is statistically significant at 5 percent level, as seen in row 4 of Table 2.11. This could be in part driven by wells on properties with municipal water, which is more common in Barry and Eaton Counties, but likely also has to do with the lowered power from splitting this smaller sample by HD. The estimates between the two TOST programs are statistically different, as shown in the fourth row of Table 2.10 below. Septic system inspection failures incur significant negative capitalization effects for houses under both programs: 7.5 percent in Ingham County and 9.7 percent in Barry and Eaton Counties. I cannot reject the equality of these price effects, and conclude that the effects are about the same.

2.6.2 Barry County Assessment Grades

Unfortunately, measures of house quality are often missing from MLS records or county assessor's evaluations. Some assessor's offices, however, seek to formally capture building quality using a metric or scale. The use of assessor assigned values for the physical condition of a house or the material and workmanship quality have been used in recent studies to control for house quality (Alzahrani and Collins, 2021).

In the context of this study, a large subsample of houses in Barry County can be matched to a building quality grade assigned by the Barry County Assessor's Office. Restricting the three-county sample to just Barry County observations with building quality grades results in 1,943 properties (74 percent of Barry County inspection-sale pairs from the full sample). Of these, 508 properties failed a TOST well or septic system inspection (26.1 percent). Figure 2.11 shows the number of Barry County subsample inspections by result for the five reported building quality grades (no houses received a A grade). The second panel shows the percent failure for inspections across the five grades. There are very few properties classified as B or B- quality with most houses classified as C, C-, or D. The shares of B or B- houses which fail inspection are significantly lower than the other grade levels, as demonstrated in the second panel.

The restricted estimation results from the graded Barry sample are presented in Table 2.12. The first column omits the grades from estimation to show the estimated results without controlling for building quality. This follows the same specification as equation 2.2 above and includes structural controls, spatial controls, census tract fixed effects, and quarterly fixed effects.[6] Both types of OWS TOST inspection failures produce statistically significant, large price penalties with wells associated with a 8.7 percent decrease and septic systems associated with a 6.7 percent drop.

[6] Once again, the results do not change meaningfully when the census tract fixed effects are replaced with census block group fixed effects.

The second column reports estimation results when the Assessor's Office grades are included in the specification. Each grade enters the regression as a dummy variable and D graded houses serve as the baseline omitted category. The results show that each grade is statistically significant, implying that C- graded houses sell for 15.1 percent more than D graded houses while B graded houses sell for 70.7 percent more. The R^2 value increases, demonstrating that the inclusion of building grades helps to explain the variation in observed housing prices. Importantly, however, the sign, relative size, and significance of the well and septic system failure coefficients shows that the price impact of a failed TOST inspection cannot be entirely accounted for by controlling for overall building quality. This suggests that the mechanism of information revealed through inspection drives a meaningful portion of the negative capitalization effect observed following inspections that expose OWS problems in need of corrective action.

2.7 Discussion

Estimation results from the models presented provide evidence of a strong negative price penalty associated with failed TOST inspections. Specifically, there a is negative and significant capitalization effect from failing either a well or septic system inspection and this effect persists even when failures are decomposed by risk severity or TOST jurisdiction. Further, these findings are not sensitive to a cross-sectional approach or time-series approach. It is not surprising that the effects of inspection failure under the two time-of-sale programs did not differ much when controlling for differences across geographic locations through spatial controls and location fixed effects, especially because the programs exhibited more similarities than differences during the study period.

Low-risk and high-risk inspection failure reasons carry different levels of risk with respect to public health and property contamination. It is surprising that inspections that fail for reasons that involve leaking sewage and elevated levels of bacteria in water samples do not induce a more negative penalty than other reasons for inspection failure in the repeat sales model. However, since repairs, remediation, or replacement are required by the policy, there may not be major differences in how these two tiers of risk are capitalized. Future work must focus on uncovering the mechanism behind the negative price effect of inspection failure and explain which characteristics of failure matter in equilibrium, if any.

The estimated effects of this study are quite large in magnitude. For example, a 10 percent price reduction represents a \$15,000 decrease for the average in-sample house. These large values are not, however, unprecedented in the disclosure literature. Currie et al. (2015) find that the opening of a toxic plant decreases property values about 11 percent (\$14,000) for houses within half a mile of the new plant. It is worth noting, however, that homeowners have much more control over the health risks and disamenities stemming from problematic wells and septic systems than nearby toxic plants. As such, it is more fitting to compare my findings to studies of private management of housing attributes. Billings et al. (2017) found that lead remediated houses in Charlotte, North Carolina sold for 32 percent or about \$26,000 more than those that did not. Put differently, forgoing lead remediation led to a \$26,000 price penalty. In the context of my study, this roughly corresponds to the most extreme price penalties under the quantile regression approach: the smallest decile is associated with a \$21,000 price decline for a failed well inspection and \$27,000 penalty for a failed septic system inspection. However, highly valued houses in the top deciles are not immune from price penalties, though magnitudes of the effects are smaller, as predicted.

2.8 Conclusion

The question of whether or not to implement TOST policies is an active one in the State of Michigan. Each year, several counties and health departments consider such policies as a way of protecting their water resources and public health. TOST policy proposals are often defeated based on public sentiment, but a dearth of empirical evidence prevents science-based policy making. This paper bridges that gap by combining inspection results with housing transaction records to estimate the price impact of failed TOST-mandated evaluations. My estimation results provide evidence of a strong negative price penalty associated with failed TOST inspections in the range of 7.5 to 10.5 percent. Further, I find these negative price effects using either a cross-sectional approach or time-series approach. These results show not only that well and septic system quality are capitalized into the market, but also present important recommendations for property owners and prospective buyers in the United States. Specifically, if a seller is uncertain about whether a septic system or well will pass a TOST inspection, on average, it is worth finding out ahead of time and remedying any system problems that would return a negative inspection report. The costs of hiring a private inspector, outside the scope of a TOST program, are low — typically a couple hundred dollars. Risk averse sellers may be advised that it is a good use of their money to learn of any problems well ahead of putting their house on the market. The challenges associated with increasing adoption of such inspections lie to behavioral economics, discounting, and risk aversion.

2.9 Acknowledgments

The author is grateful to the associations and boards of REALTORS® in Michigan that were willing to provide MLS data for sales of residential properties, including Ann Arbor Area Board of REALTORS®, Bay County REALTOR® Association, East Central Association of REALTORS®, Greater Lansing Association of REALTORS®, Greater Shiawassee Association of REALTORS®, Jackson Area Association of REALTORS®, Lenawee County Association of REALTORS®, Michigan Regional Information Center®, LLC (MichRIC®), Midland Board of REALTORS®, Northern Great Lakes REALTORS® MLS, LLC, RealComp II, Ltd., Saginaw Board of REALTORS®, Southeastern Border Association of REALTORS (formerly Monroe & Downriver Regional Association of REALTORS®, and Water Wonderland Board of REALTORS®. Without their cooperation, this study would not have been possible. The authors also acknowledge the support of the Michigan State University Remote Sensing and Geographic Information Systems Research and Outreach Services (RS&GIS), which provided valuable geocoding services and spatial analysis services. All opinions expressed in this paper are those of the author and do not reflect the opinions or positions of the aforementioned entities.

APPENDIX

APPENDIX: TABLES AND FIGURES

Table 2.1 Characteristics of Counties in Study

	Barry County	Eaton County	Ingham County	Michigan
Population Estimates	60,540	109,456	290,587	9,965,265
Population, Census 2010	59,173	107,759	280,895	9,883,640
Housing Units	27,586	47,558	123,570	4,596,198
Households	24,296	44,480	112,840	3,935,041
Owner Occupied Housing Unit Rate	83.5%	72.3%	58.5%	71.2%
Median Value of Owner-Occupied Housing Units	$158,400	$155,000	$135,600	$154,900
Median Household Income (2019)	$64,490	$64,348	$52,872	$57,144
Land area in square miles, 2010	553.09	575.18	556.12	96,716
Population per square mile, 2010	107	187.3	505.1	102.2
Persons 65 years and over, percent	18.0%	17.9%	13.1%	16.7%
White alone, not Hispanic or Latino, percent	96.3%	86.4%	74.3%	78.4%
Black or African American alone, percent	0.7%	6.8%	11.7%	13.8%
Hispanic or Latino, percent	3.0%	5.4%	7.8%	5.1%
Foreign born persons, percent	1.7%	4.0%	9.9%	6.9%
Land in agriculture*, percent, 2017 NASS estimates	41.6%	55.1%	48.0%	26.0%
Area Water, percent	4.2 %	0.7%	0.8%	-

Source: U.S. Census Bureau, 5-year American Community Survey Estimates Vintage 2019, except where noted by *

Table 2.2 Time of Sale or Transfer Policy Reasons for Remediation and/or Repair

Program	System	Risk Severity	Issue
Barry and Eaton Counties	Well	High	Cross plumbing connection
			Coliform bacteria in water sample
			Nitrates exceed 10 ppm
			Flooded well
		Low	Substantial construction deficiency
			Substantial isolation deficiency
			Unplugged, abandoned well
			Non-functioning/incapable well
			Other
	Septic System	High	Illicit discharges or connections
			Sewage backup
			Sewage on ground
			No system found
		Low	Septic tank structure
			Maintenance flaws
			Unrecognizable system
			Dilapidated system
Ingham County	Well	High	Elevated arsenic sample
			Positive bacteria sample
			Well in disrepair
			Cross plumbing connection
			Yard hydrant
		Low	Well pit or dug well
			Unprotected suction line
			Not functional
			Unabandoned well
			Improper isolation distance to septic
			Missing samples
			Other
	Septic System	High	System at or near failure
			Tank in disrepair
			Illicit discharge to farm tile
			Illicit discharge through plumbing
		Low	Missing pump report
			Missing alternative maintenance agreement
			Septic tank insufficient size
			Unabandoned septic tank
			Components in disrepair
			Other

Table 2.3 Property-Specific Variable Summary Statistics

	Barry County				Eaton County				Ingham County			
Variable	Mean	St. Dev	Min	Max	Mean	St. Dev	Min	Max	Mean	St. Dev	Min	Max
Real Sale Price (2015, $1,000's$)	161.55	78.33	19.38	404.96	155.32	61.09	23.72	403.33	150.14	74.44	18.98	404.3
Building Area (sqft, 1,000's)	1.91	0.68	0.8	3.78	2.02	0.66	0.8	3.74	2	0.68	0.8	3.78
House Age (years)	37.82	29.87	5	137	38.8	29.48	5	137	41.23	29.36	5	137
Number of Bedrooms	3.2	0.76	2	5	3.22	0.63	2	5	3.24	0.65	2	5
Number Full Bathrooms	1.86	0.68	1	3	1.83	0.64	1	3	1.83	0.63	1	3
Number Half Bathrooms	0.65	0.76	0	2	0.63	0.71	0	2	0.52	0.62	0	2
Fireplace (0/1)	0.92	0.27	0	1	0.71	0.45	0	1	0.92	0.28	0	1
Forced Air (0/1)	0.97	0.18	0	1	0.96	0.19	0	1	0.87	0.34	0	1
Garage (0/1)	0.91	0.28	0	1	0.98	0.13	0	1	0.98	0.12	0	1
Parcel Lot Acreage	3.65	5.72	0.13	40	3.73	5.65	0.14	40	3.76	4.89	0.16	40
Well Water (0/1)	0.97	0.17	0	1	0.98	0.12	0	1	0.97	0.18	0	1
Septic System (0/1)	0.79	0.41	0	1	0.83	0.38	0	1	0.93	0.25	0	1
Well Failure (0/1)	0.15	0.36	0	1	0.09	0.29	0	1	0.31	0.46	0	1
Septic Failure (0/1)	0.16	0.37	0	1	0.12	0.33	0	1	0.27	0.44	0	1
N	2,629				1,748				2,579			

Table 2.4 Property-Specific Variable Descriptions

Variable	Description
RealSalePrice	Real sale price, in 2015$(1,000's)$
BuildingArea	Structural square footage (1,000's)
Age	Age of the house, years
Bedrooms	Total number of bedrooms
FullBathrooms	Total number of full bathrooms
HalfBathrooms	Total number of half bathrooms
Fireplace	Indicator variable of fireplace
ForcedAir	Indicator variable of forced air system
Garage	Indicator variable for garage
LotAcres	Parcel acreage
WellWater	Indicator of a well on property
SepticSystem	Indicator of a septic system
WellFailure	Indicator of failed well inspection on property
SepticFailure	Indicator of failed septic inspection

Table 2.5 Spatial Controls and Sources

Spatial Variable	Description	Source	Spatial Layer
dist_major_road	Straightline distance to nearest major road (km)	All Roads (v17a) (MI GIS Open Data)	Road Lines
CensusTract2010	U.S. Census Tract	Census Tracts (MI GIS Open Data)	2010 Census Tract Polygons
BlockGroup2010	U.S Census Block Group	Block Groups (MI GIS Open Data)	2010 Census Block Group Polygons
dist_great_lake	Straightline distance to nearest Great Lake (km)	Great Lakes Shapefile (MSU RS & GIS Lab)	Great Lakes Polygons
schooldistrict	Geographically assigned school district	School Districts (v17a) (MI GIS Open Data)	School District Boundary Polygons
dist_fish_stream	Straightline distance to nearest fishable stream (km)	Trout and Salmon Inland Stream Regulation Types (MI GIS Open Data)	Fishable Stream Polygons
dist_hwy_exit	Straightline distance to nearest highway exit (km)	U.S. and Canada Highway Exits (Tele Atlas North America, Inc)	Highway exit points
dist_1_ha_lake	Straightline distance to nearest inland lake $\geq$ 1 hectare	All Lakes 1ha (LAGOS-NE)	Lakes Polygons
dist_4_ha_lake	Straightline distance to nearest inland lake $\geq$ 4 hectares	All Lakes 4ha (LAGOS-NE)	Lakes Polygons
dist_state_park	Straightline distance to nearest state park (km)	State Parks (v17a) (MI GIS Open Data)	State Parks Polygons
dist_city	Straightline distance to nearest city (km)	Cities (MI GIS Open Data)	Michigan Cities Polygons

Table 2.6 Summary Statistics by Decile

Variable	Decile (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Real Sale Price ($ 2015, 1,000's)	46.54	82.01	105.97	124.21	139.42	154.80	171.97	194.80	231.41	306.32
	(13.95)	(7.60)	(6.06)	(4.53)	(4.36)	(4.48)	(5.69)	(8.33)	(13.03)	(39.19)
Build Area (sqft, 1,000's)	1.45	1.54	1.65	1.74	1.87	1.95	2.10	2.28	2.43	2.70
	(0.47)	(0.51)	(0.52)	(0.51)	(0.54)	(0.58)	(0.54)	(0.60)	(0.61)	(0.65)
Build Age (years)	59.22	49.62	45.57	41.87	40.02	34.80	34.42	30.91	29.94	26.89
	(36.16)	(33.01)	(29.94)	(29.23)	(28.66)	(24.74)	(26.25)	(23.90)	(24.40)	(20.94)
Bedrooms	2.89	2.96	3.05	3.13	3.19	3.23	3.32	3.40	3.45	3.58
	(0.67)	(0.63)	(0.64)	(0.60)	(0.61)	(0.65)	(0.67)	(0.68)	(0.69)	(0.73)
Full Baths	1.41	1.48	1.50	1.67	1.75	1.87	1.99	2.12	2.21	2.41
	(0.52)	(0.53)	(0.57)	(0.58)	(0.58)	(0.59)	(0.59)	(0.58)	(0.54)	(0.59)
Half Baths	0.46	0.48	0.55	0.55	0.53	0.57	0.59	0.67	0.75	0.81
	(0.76)	(0.74)	(0.73)	(0.69)	(0.66)	(0.69)	(0.65)	(0.68)	(0.65)	(0.62)
Fireplace (0/1)	0.78	0.82	0.80	0.82	0.85	0.87	0.90	0.93	0.94	0.94
	(0.42)	(0.39)	(0.40)	(0.38)	(0.35)	(0.34)	(0.30)	(0.26)	(0.25)	(0.23)
Forced Air (0/1)	0.89	0.93	0.92	0.93	0.95	0.93	0.93	0.94	0.94	0.90
	(0.31)	(0.26)	(0.27)	(0.25)	(0.21)	(0.25)	(0.25)	(0.24)	(0.23)	(0.30)
Garage (0/1)	0.89	0.92	0.95	0.97	0.96	0.98	0.98	0.98	0.98	0.98
	(0.32)	(0.28)	(0.22)	(0.18)	(0.19)	(0.15)	(0.14)	(0.14)	(0.15)	(0.12)
Acreage	2.54	2.64	2.65	2.89	2.90	3.12	3.88	4.45	5.65	6.39
	(3.53)	(3.84)	(3.81)	(4.11)	(4.40)	(4.70)	(5.21)	(5.80)	(7.17)	(7.95)
Well Water (0/1)	0.93	0.96	0.96	0.97	0.97	0.98	0.98	0.99	0.99	0.98
	(0.26)	(0.19)	(0.19)	(0.17)	(0.16)	(0.15)	(0.13)	(0.12)	(0.08)	(0.13)
Septic System (0/1)	0.89	0.88	0.87	0.84	0.86	0.85	0.87	0.86	0.84	0.77
	(0.31)	(0.33)	(0.34)	(0.37)	(0.35)	(0.35)	(0.34)	(0.35)	(0.37)	(0.42)
Well Failure (0/1)	0.41	0.26	0.21	0.20	0.17	0.17	0.15	0.15	0.12	0.11
	(0.49)	(0.44)	(0.41)	(0.40)	(0.37)	(0.38)	(0.35)	(0.36)	(0.33)	(0.31)
Septic Failure (0/1)	0.40	0.26	0.20	0.20	0.18	0.17	0.17	0.14	0.11	0.09
	(0.49)	(0.44)	(0.40)	(0.40)	(0.38)	(0.38)	(0.38)	(0.34)	(0.31)	(0.29)
N	699	697	698	705	691	699	703	699	694	695

Decile-specific means and standard deviations presented. Standard deviations in parentheses.

Table 2.7 Time-of-sale Inspection Failure Effects on House Prices for Three Michigan Counties, 2008-2017

VARIABLES	(1) Inspection Type	(2) Risk Severity	(3) Type and Health Department
Well Inspection Failure	-0.097***		
	(0.014)		
Well Inspection Low Risk		-0.101***	
		(0.019)	
Well Inspection Failure High Risk		-0.095***	
		(0.019)	
Well Inspection Failure Ingham			-0.100***
			(0.023)
Well Inspection Failure Barry Eaton			-0.094***
			(0.014)
Septic Inspection Failure	-0.115***		
	(0.015)		
Septic Inspection Failure Low Risk		-0.098***	
		(0.021)	
Septic Inspection Failure High Risk		-0.139***	
		(0.030)	
Septic Inspection Failure Ingham			-0.116***
			(0.026)
Septic Inspection Failure Barry Eaton			-0.114***
			(0.017)
Observations	6,952	6,952	6,952
R-squared	0.592	0.592	0.592
Structural Controls	YES	YES	YES
Spatial Controls	YES	YES	YES
School District FE	YES	YES	YES
Census FE	Tract	Tract	Tract
Time FE	Year× Quarter	Year× Quarter	Year× Quarter
Standard Error Clusters	Tract	Tract	Tract
Number of Clusters	63	63	63

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.8 Tests of Estimation Result Relationship: Full Model

Test	H_0	H_1	Test Statistic	p-value
1	$\beta_{WellFailure} - \beta_{SepticFailure} = 0$	$\beta_{WellFailure} - \beta_{SepticFailure} \neq 0$	F(1, 66) = 0.61	0.44
2	$\beta_{WellHighRisk} - \beta_{WellLowRisk} = 0$	$\beta_{WellHighRisk} - \beta_{WellLowRisk} \neq 0$	F(1, 66) = 0.05	0.82
3	$\beta_{SepticHighRisk} - \beta_{SepticLowRisk} = 0$	$\beta_{SepticHighRisk} - \beta_{SepticLowRisk} \neq 0$	F(1, 66) = 1.04	0.31
4	$\beta_{WellFailureBarryEaton} - \beta_{WellFailureIngham} = 0$	$\beta_{WellFailureBarryEaton} - \beta_{WellFailureIngham} \neq 0$	F(1, 66) = 0.05	0.3
5	$\beta_{SepticFailureBarryEaton} - \beta_{SepticFailureIngham} = 0$	$\beta_{SepticFailureBarryEaton} - \beta_{SepticFailureIngham} \neq 0$	F(1, 66) = 0.00	0.95

Table 2.9 Spatially Weighted Quantile Regression Results

	Decile								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Well Inspection Failure	-0.197 ***	-0.132 ***	-0.118 ***	-0.098 ***	-0.081 ***	-0.074 ***	-0.065 ***	-0.042 ***	-0.011
	(0.042)	(0.026)	(0.021)	(0.015)	(0.013)	(0.011)	(0.012)	(0.011)	(0.014)
Septic System Inspection Failure	-0.265 ***	-0.218 ***	-0.147 ***	-0.095 ***	-0.068 ***	-0.041 ***	-0.030 ***	-0.031 ***	-0.031 ***
	(0.039)	(0.028)	(0.022)	(0.016)	(0.013)	(0.011)	(0.012)	(0.01)	(0.012)
Lag ($\rho(\tau)$)	0.425***	0.381***	0.356***	0.314***	0.284***	0.269***	0.260***	0.245***	0.224***
	(0.028)	(0.028)	(0.023)	(0.019)	(0.017)	(0.014)	(0.016)	(0.014)	(0.017)
Structural Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Spatial Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Nearest Neighbors	10	10	10	10	10	10	10	10	10
Pseudo R^2	0.3932	0.3859	0.3807	0.3816	0.3884	0.3985	0.4102	0.4239	0.4259

Results presented according to real sale price (2015$) decile. The spatial weight matrix used for spatial lags was a row-normalized for each observation with non-zero cells for each observation's 10 nearest neighbors and zeroes elsewhere.

Table 2.10 Repeat Sales Model Time-of-Sale Inspection Failure Effects on House Prices, 3 Michigan Counties

VARIABLES	(1) Failure by Type	(2) Failure by Risk Severity	(3) Failure by Health Department
Well Failure	-0.077***		
	(0.018)		
Well Low Risk		-0.048	
		(0.031)	
Well High Risk		-0.097***	
		(0.022)	
Well Failure Ingham			-0.109***
			(0.021)
Well Failure x Barry Eaton			-0.013
			(0.040)
Septic Failure	-0.089***		
	(0.027)		
Septic Low Risk		-0.109***	
		(0.034)	
Septic High Risk		-0.059	
		(0.040)	
Septic Failure Ingham			-0.078***
			(0.026)
Septic Failure x Barry Eaton			-0.094*
			(0.047)
Observations	2,607	2,607	2,607
R-squared	0.398	0.399	0.400
Number of Houses	1,251	1,251	1,251
House Age Controls	YES	YES	YES
Time FE	Year × Quarter	Year × Quarter	Year × Quarter
Standard Error Clusters	CensusTract	CensusTract	CensusTract
Number of Clusters	60	60	60

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.11 Tests of Estimation Result Relationship: Repeat Sales Model

Test	H_0	H_1	Test Statistic	p-value
1	$\beta_{WellFailure} - \beta_{SepticFailure} = 0$	$\beta_{WellFailure} - \beta_{SepticFailure} \neq 0$	F(1, 59) = 0.10	0.75
2	$\beta_{WellHighRisk} - \beta_{WellLowRisk} = 0$	$\beta_{WellHighRisk} - \beta_{WellLowRisk} \neq 0$	F(1, 59) = 1.50	0.23
3	$\beta_{SepticHighRisk} - \beta_{SepticLowRisk} = 0$	$\beta_{SepticHighRisk} - \beta_{SepticLowRisk} \neq 0$	F(1, 59) = 0.97	0.33
4	$\beta_{WellFailureBarryEaton} - \beta_{WellFailureIngham} = 0$	$\beta_{WellFailureBarryEaton} - \beta_{WellFailureIngham} \neq 0$	F(1, 59) = 4.10	0.05
5	$\beta_{SepticFailureBarryEaton} - \beta_{SepticFailureIngham} = 0$	$\beta_{SepticFailureBarryEaton} - \beta_{SepticFailureIngham} \neq 0$	F(1, 59) = 0.00	0.97

Table 2.12 Inspection Failure Effects on House Prices, Barry County Michigan, 2008-2017

	(1) Building Grades Omitted	(2) Building Grades Included
Well Failure	-0.091***	-0.074***
	(0.019)	(0.020)
Septic Failure	-0.069**	-0.074**
	(0.022)	(0.024)
B		0.535***
		(0.071)
B Minus		0.478***
		(0.049)
C		0.325***
		(0.058)
C Minus		0.141**
		(0.046)
Observations	1,944	1,944
R-squared	0.640	0.671
Structural Controls	YES	YES
Spatial Controls	YES	YES
Census FE	Tract	Tract
Time FE	Year × Quarter	Year × Quarter
Standard Error Clusters	Tract	Tract
Number of Clusters	11	11

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 2.1 Locations of Barry, Eaton, and Ingham Counties in Michigan

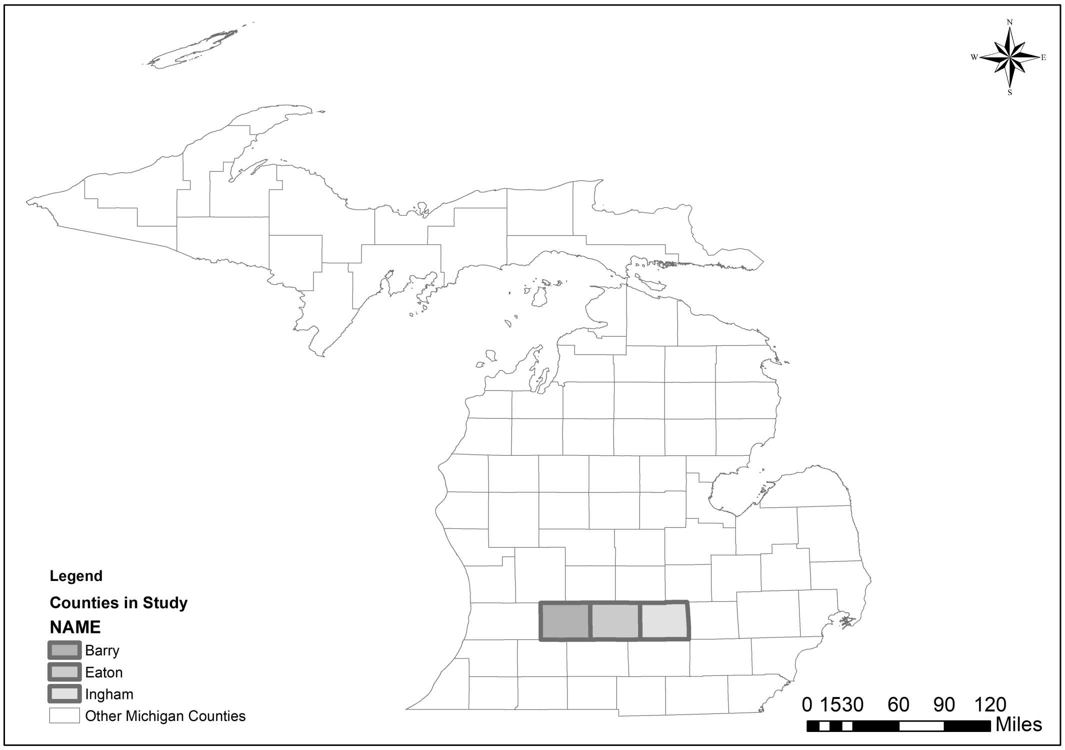
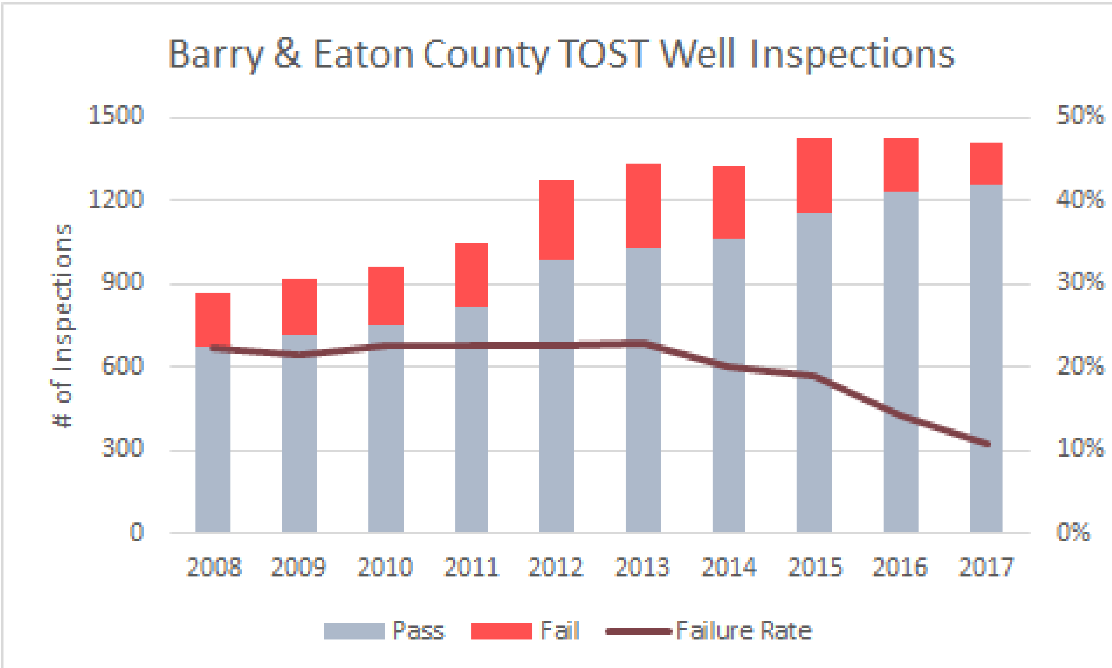
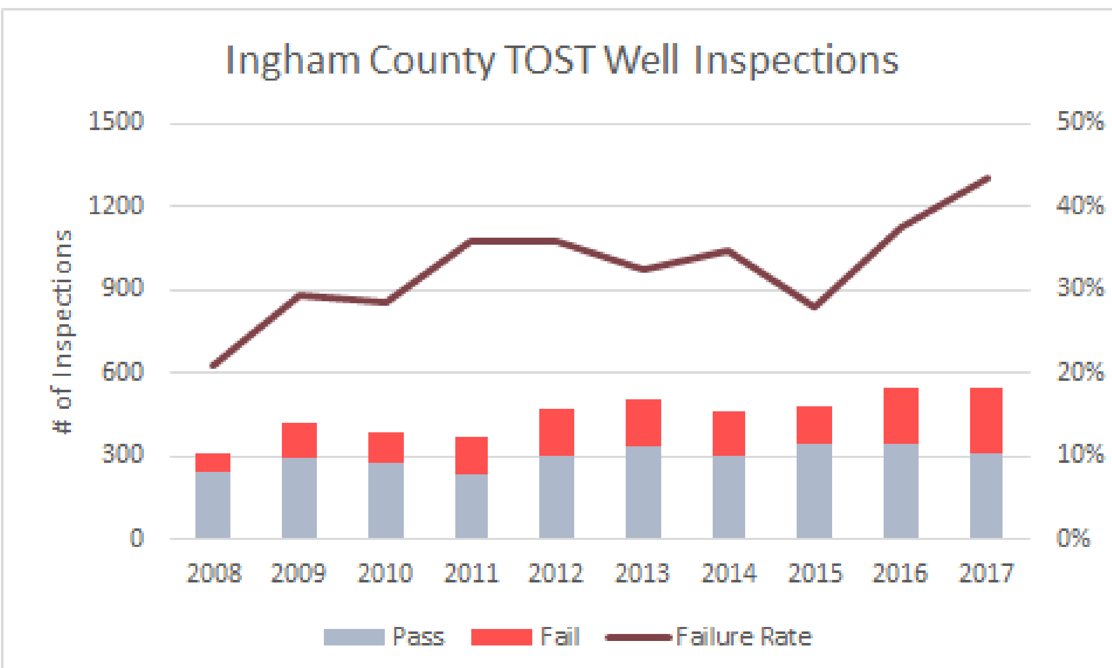


Figure 2.2 Well Inspection Results by Health Department and Year

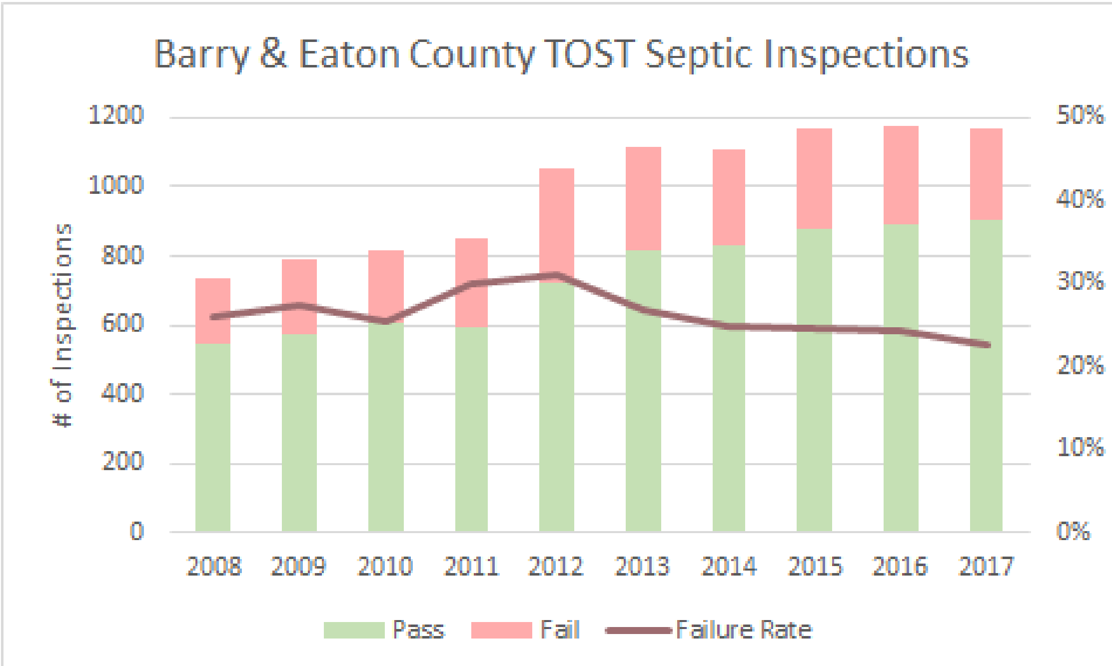


(a) Barry and Eaton County Well Inspections

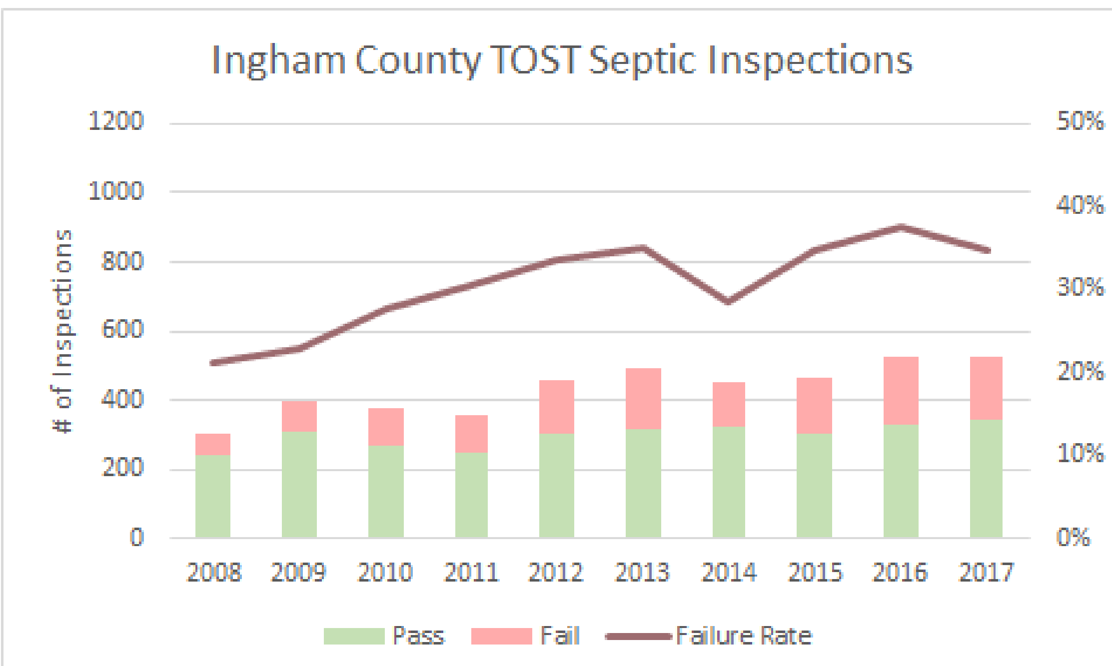


(b) Ingham County Well Inspections

Figure 2.3 Septic Inspection Results by Health Department and Year

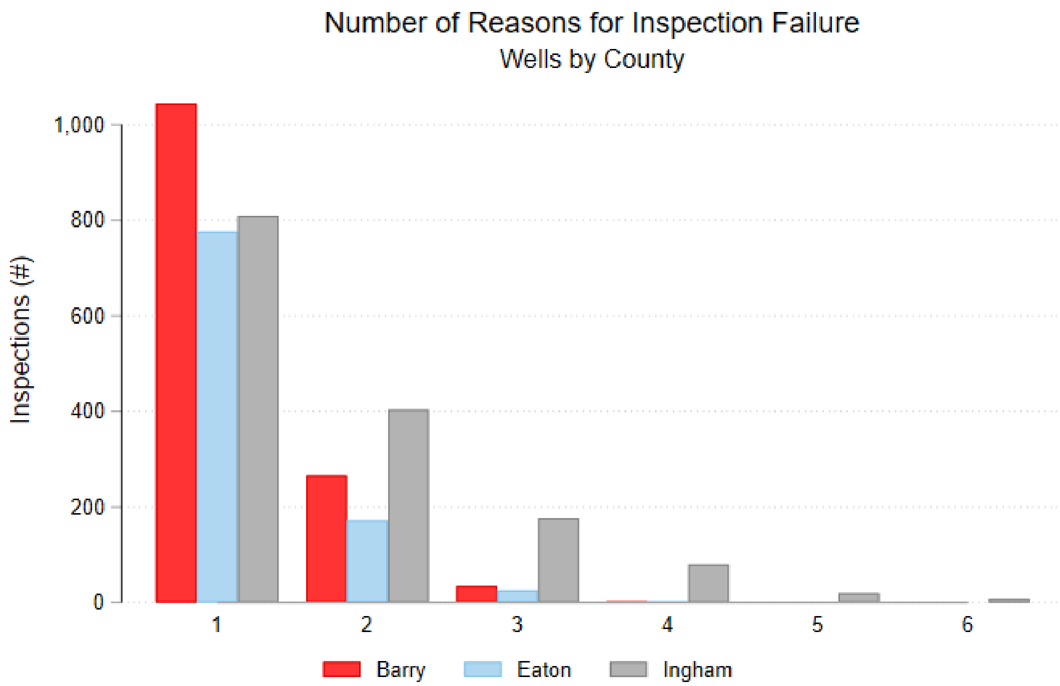


(a) Barry and Eaton County Well Inspections

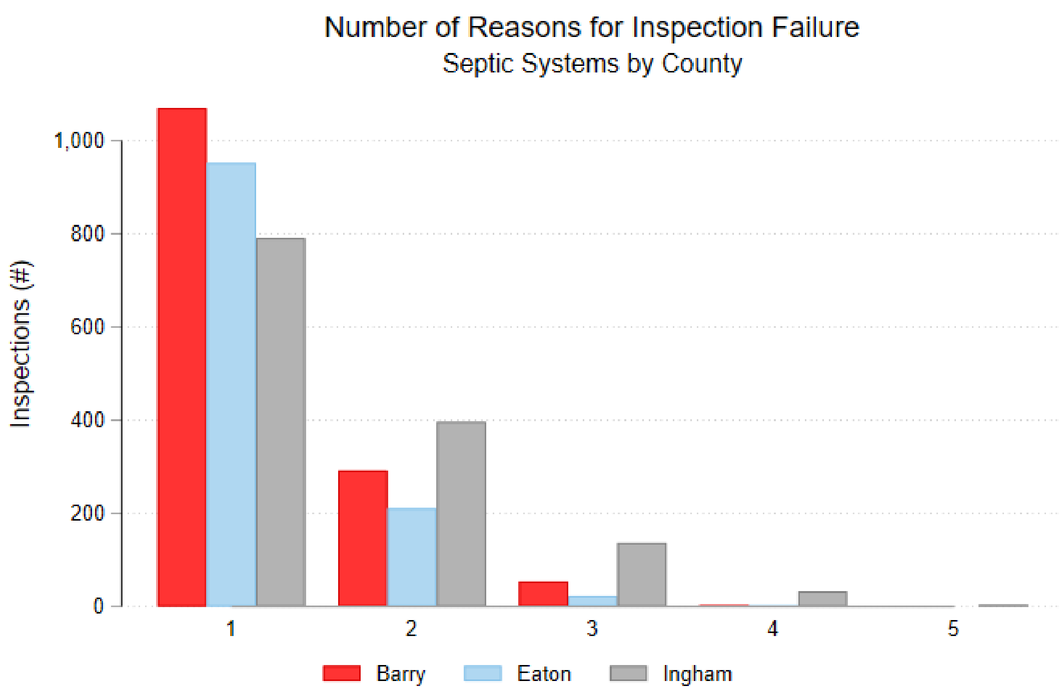


(b) Ingham County Well Inspections

Figure 2.4 Number of Reasons Given for Inspection Failure

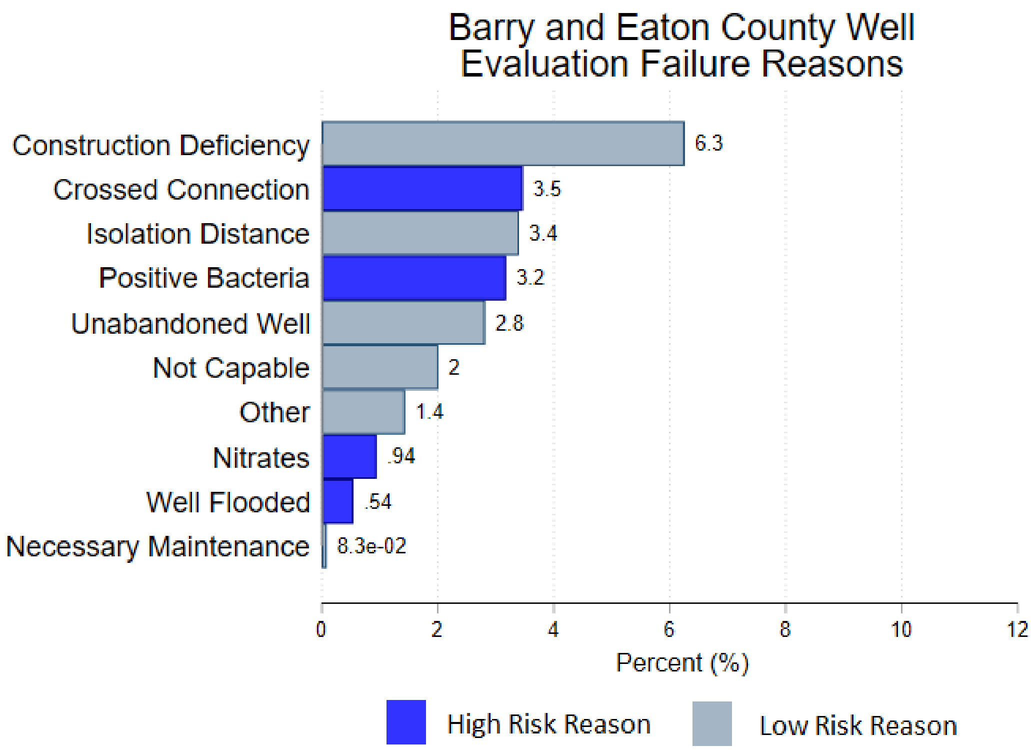


(a) Well Inspections

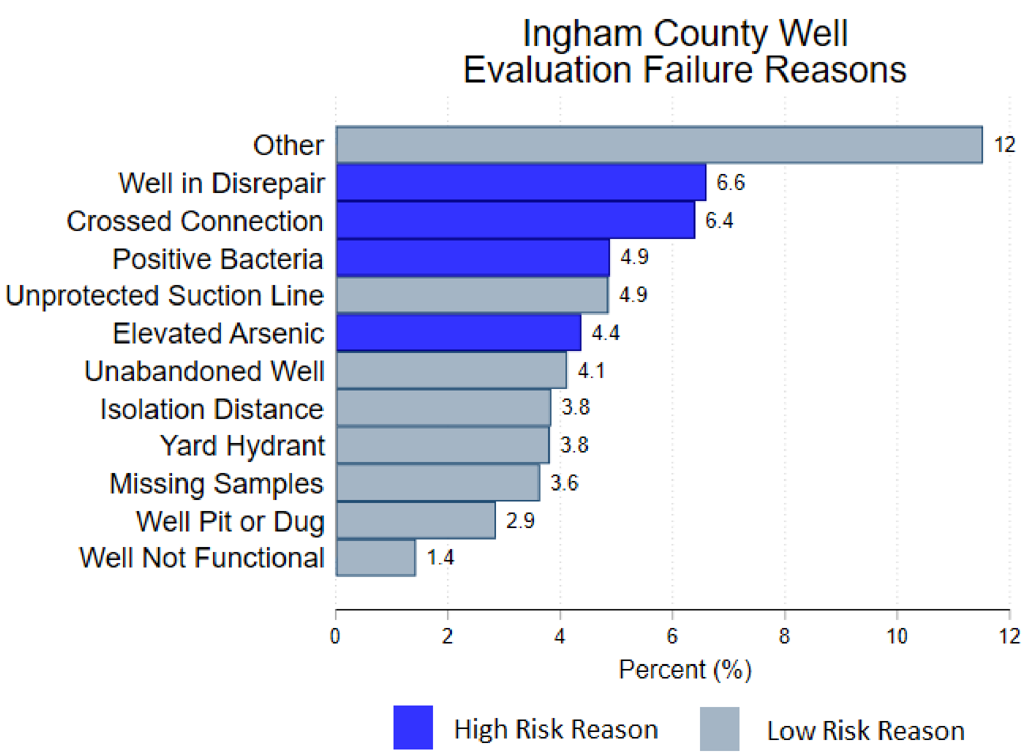


(b) Septic System Inspections

Figure 2.5 Well Inspection Failure Reasons by Health Department

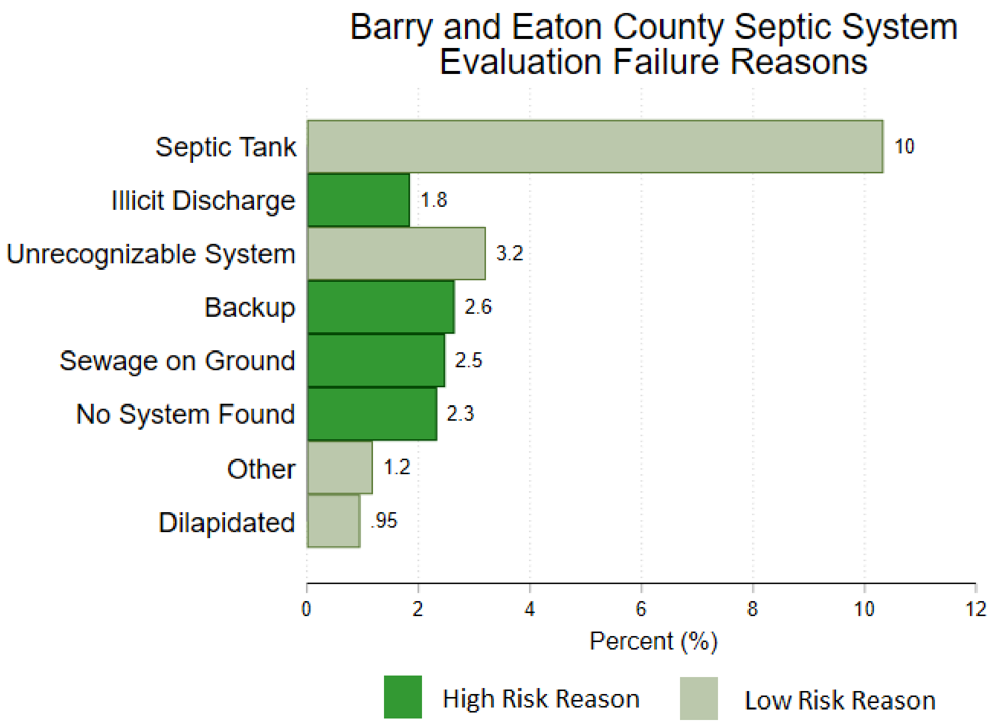


(a) Barry Eaton District Health Department

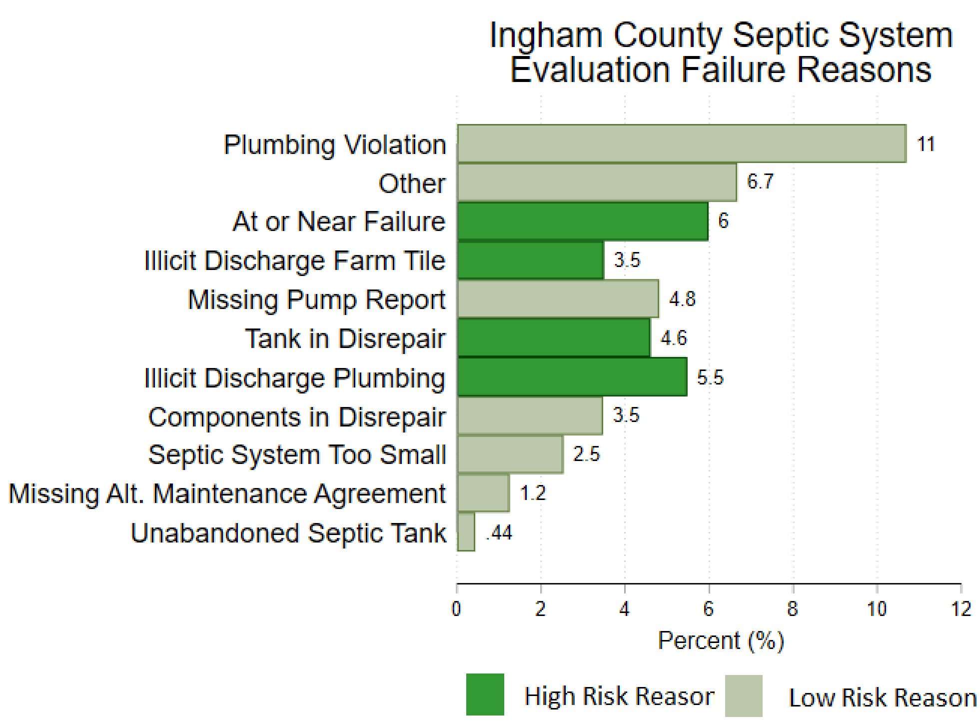


(b) Ingham County Health Department

Figure 2.6 Septic System Inspection Failure Reasons by Health Department



(a) Barry Eaton District Health Department



(b) Ingham County Health Department

Figure 2.7 TOST Inspection Rate Failures by Decile & OWS Type

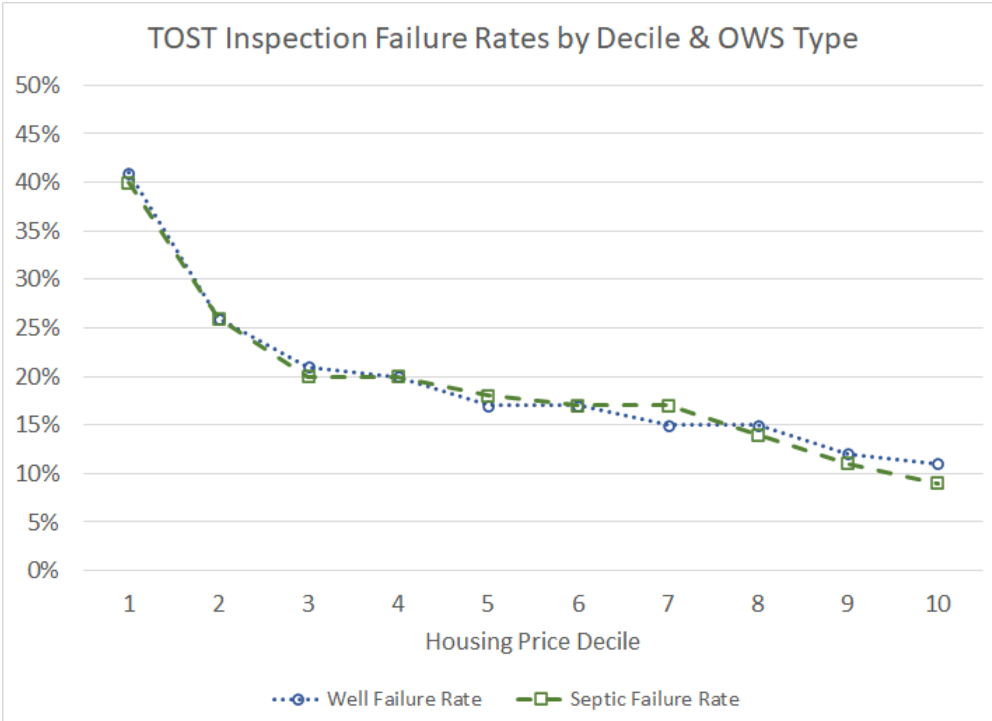


Figure 2.8 Model of House Price Formation under TOST Regime with Inspection Failure

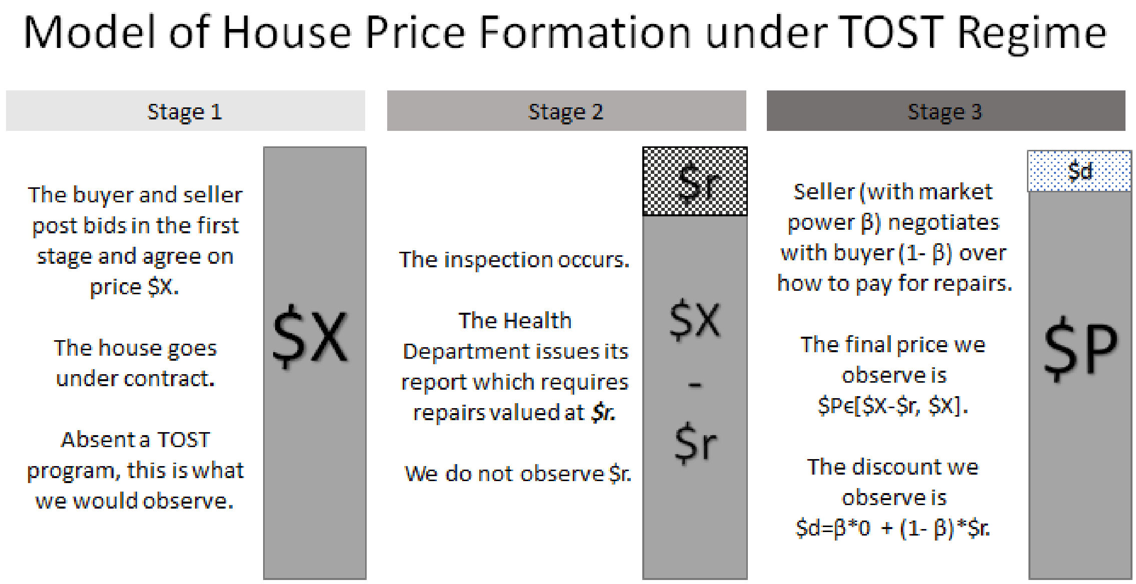


Figure 2.9 Quantile Regression Results in Percentage Change

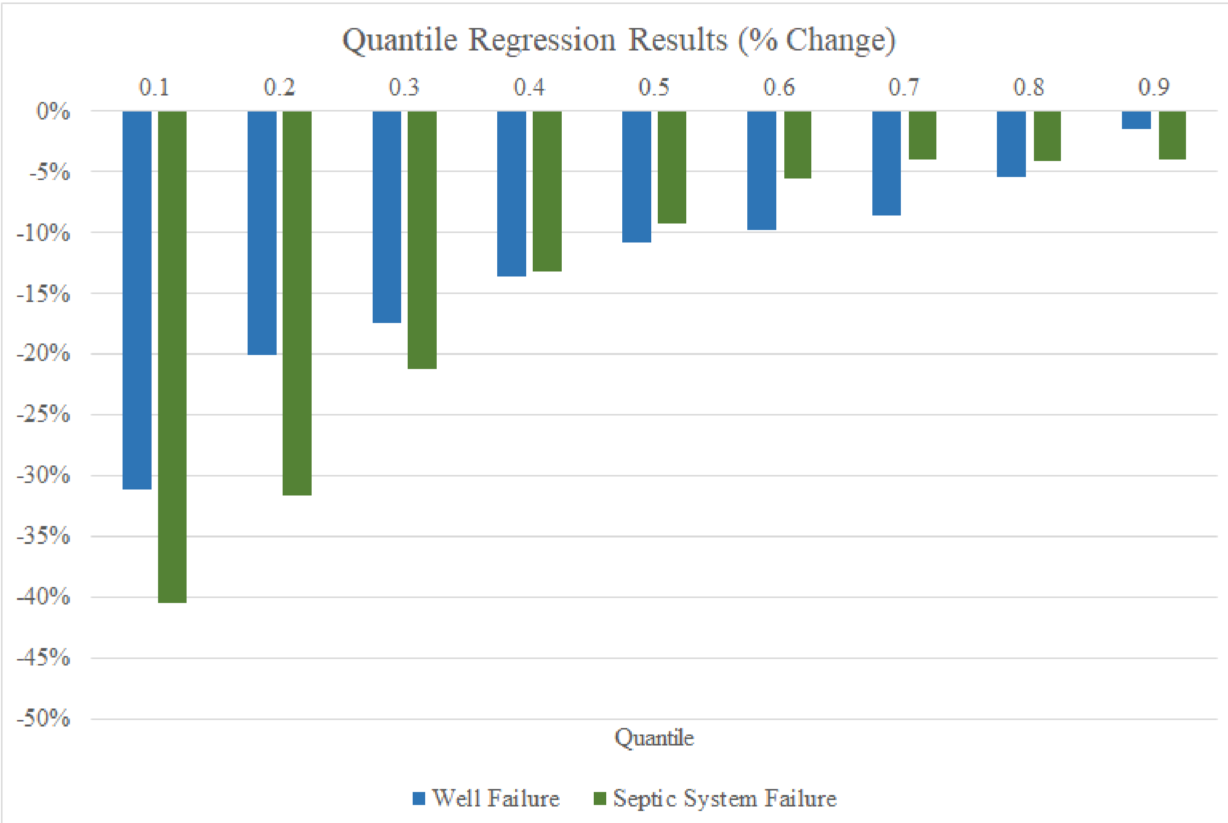
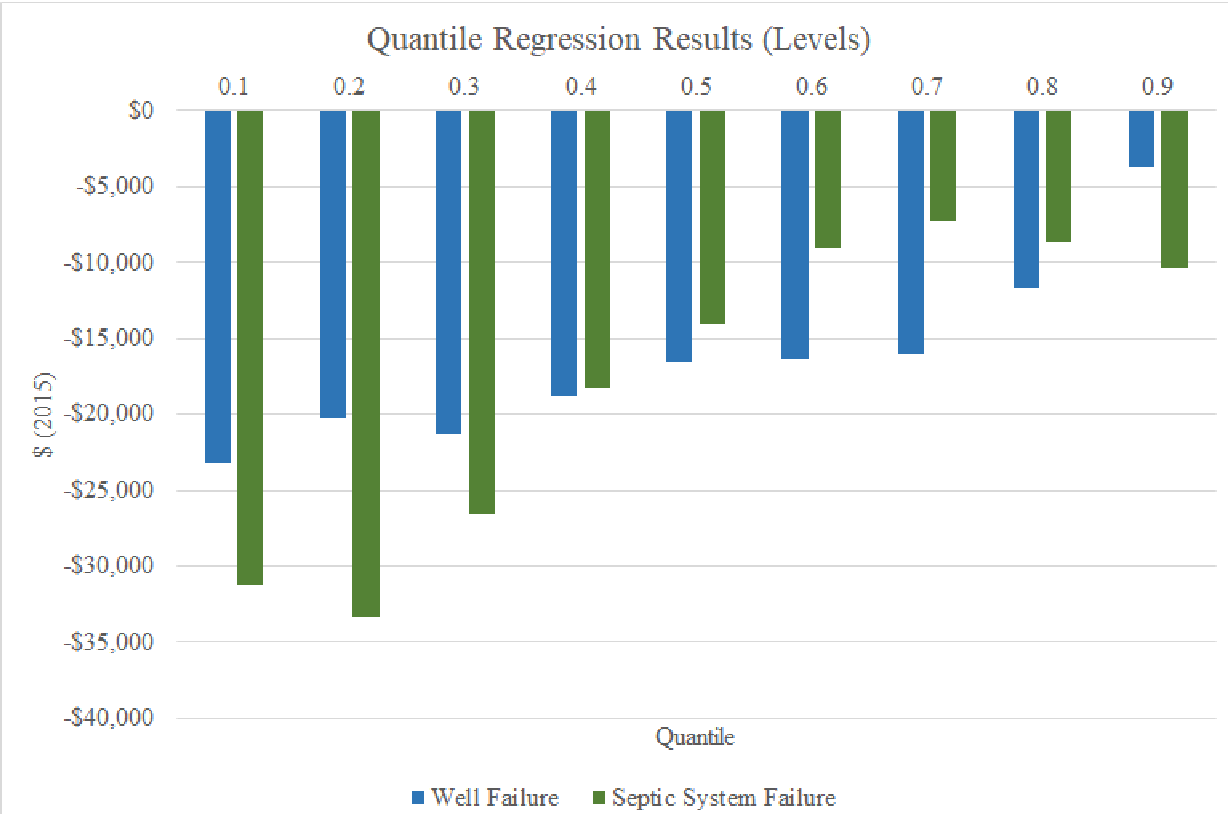


Figure 2.10 Quantile Regression Results in Levels



Each decile-specific coefficient was multiplied by the house price which corresponds to its percentile.

Figure 2.11 Barry County Inspection Failures by Grade

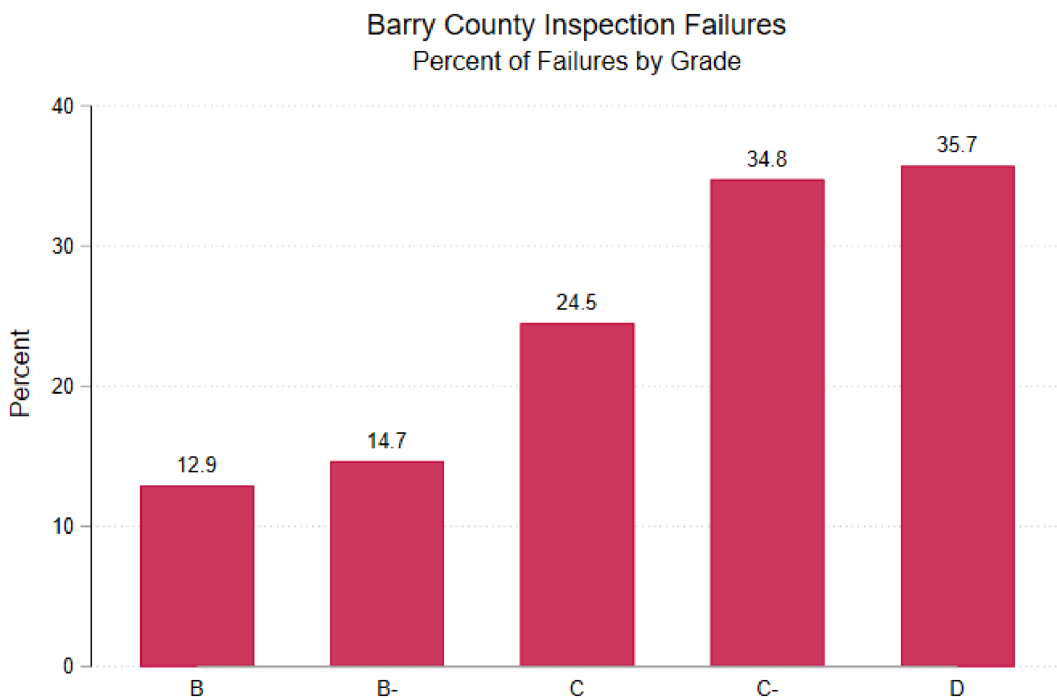
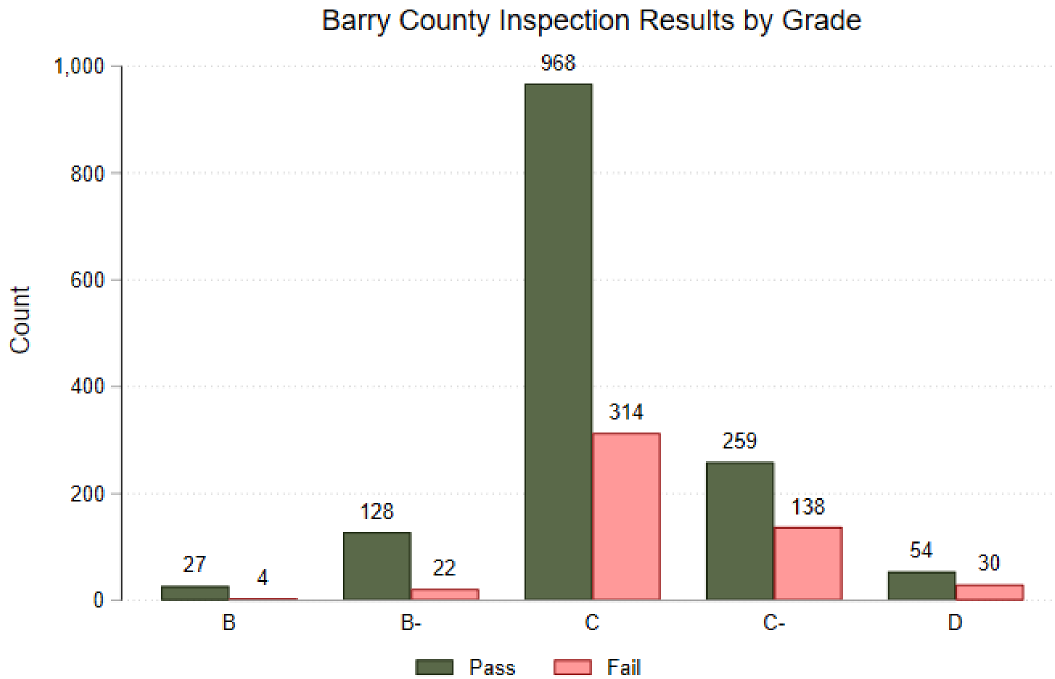


Figure 2.12 Barry County Inspection Results by Grade



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CHAPTER 3

U.S. CONSUMER PREFERENCES AND WILLINGNESS TO PAY FOR SELECT GREAT LAKES FISH

3.1 Introduction

Global seafood consumption and aquaculture production expanded greatly in the past 50 years, doubling world per capita fish consumption (FAO, 2020). Given this increase, seafood has become one of the most highly traded food types globally (Anderson et al., 2018). Worldwide per capita seafood consumption reached a record high of 45.2 lbs. in 2018 (FAO, 2020). Similarly, the United States experienced an increase in seafood consumption, posting an all-time high of 19.2 lbs. per capita in 2019 (National Marine Fisheries Service, 2021). Market reports attribute the growing U.S. demand for seafood to consumers' increasing preferences for healthy proteins, particularly during the COVID-19 pandemic (Roberts, 2021). Other concerns relate to sustainability, particularly among younger consumers. These concerns are especially relevant since fisheries are susceptible to overfishing and limited in their ability to sustainably provide larger volumes. In response, retailers are partnering with suppliers to increase sustainable seafood offerings.

Despite this growing domestic demand, U.S. aquaculture has not kept pace. Aquaculture production in the United States grew from 866 million pounds in 1996 to 1.3 billion pounds in 2004, but then contracted to 875 million pounds in 2011 (FAO, 2020). Despite this reduction, the U.S. aquaculture industry shows signs of recovery and produced approximately 1 billion pounds in 2018 (FAO, 2021). However, this improvement still falls well below 2004 levels, and the domestic seafood market relies heavily on imports. The current gap in seafood trade can be attributed to capture fisheries reaching sustainable levels while domestic fisheries and the aquaculture industry concomitantly struggle to compete with import prices (FAO, 2020). Between 70 percent and 85 percent of U.S. current seafood consumption is imported, making the United States the world's second-largest fish importing market after the European Union (National Marine Fisheries Service, 2021; Gephart et al., 2019). Currently, the United States ranks 17th among aquaculture-producing nations in the world.

Geographically, most aquaculture operations are concentrated in the Southern region of the United States. The smallest region, in terms of aquacultural production, is the North Central Region (NCR), shown in Figure 3.1. The NCR accounts for fewer than 10 percent of U.S. fish farms and produces less than 4 percent of sales (Figure 3.2). Proximal to the Great Lakes, the twelve NCR states host favorable climate conditions and abundant water resources for producing food fish and supplying the growing U.S demand for cold-water species, including rainbow trout (*Oncorhynchus mykiss*) and cool-water species such as walleye (*Sander vitreus*) and yellow perch (*Perca flavescens*). However, the region underperforms relative to other regions, presenting an opportunity for development and expansion.

The increase in U.S. consumer demand for fish has also been unevenly distributed—with respect to species. Salmonids, including Atlantic salmon, Pacific salmon, and trout, grew from 57 percent of food fish imports by volume in 2013 to 72 percent in 2018 (USDA ERS, 2019). As a result, salmon leads grocery store retail sales by volume and accounted for 185 million pounds in 2019 (Goldschmidt, 2020). Rainbow trout followed a similar trend with a 79 percent increase in import volume between 2014 and 2018 (USDA ERS, 2019). Domestically, trout production and total national sales increased over 30 percent between 2005 and 2018 (USDA, 2019; USDA 2014). The 2018 Census of Aquaculture reported a 22 percent increase in the volume of trout sales by NCR aquacultural producers. Though the NCR produces roughly three percent of the fish farmed in the United States, producers in the region are particularly poised to meet the growing need for fish due to their unique geography and access to fresh water. However, information about the marketability and demand for NCR-produced fish are needed to justify expanding aquacultural production in the region.

This paper seeks to fill this knowledge gap and support the NCR aquaculture industry by helping producers, processors, and retailers target U.S. fish consumers. In particular, we investigate whether U.S. consumers value fish produced in the NCR, if they are willing to buy farm-raised fish, and which species and attributes they seek. Our analysis relies on the primary survey data collected from U.S. adult fish consumers. Since no NCR-specific label exists in the marketplace, we conduct a hypothetical discrete choice experiment (DCE) to estimate consumers' willingness to pay (WTP) for an NCR source label, an indicator of consumer demand. We also measure consumer WTP for wild-caught fish and fresh fillets to see which harvesting methods and preparations U.S fish consumers seek when they shop for fish. To facilitate this analysis, we vary attributes over rainbow trout, walleye, and yellow perch in a simulated purchasing experience. Our analysis focuses on these three species given the prominence of each to the regional tradition of fish production, NCR gastronomic culture, biological adaptation to the region's climate, and pronounced trade imbalances. In particular, the yellow perch market faces significant shortages while most domestically consumed walleye is imported from Canada with limited Native American commercial harvest from the U.S. Great Lakes.

This paper also addresses a gap in the literature concerning variation in regional preferences for these specific species and important seafood attributes. The current literature reports either transnational or nationally aggregated consumer purchasing behavior and preferences for other finfish and shellfish species or considers a limited geographic extent. Other studies focus on a different selection of seafood products and species (Bouchard et al., 2021; Brayden et al., 2018; Tien et al., 2021), different regions (Bouchard et al., 2021; Printezis et al., 2019), only one state (Tian et al., 2021; Quagrainie et al., 2008), or only one city (Fonner and Sylvia, 2015). Further, many of these studies limit their analysis to products of aquaculture alone (Quagrainie et al., 2008; Runge et al., 2021). We estimate WTP at the national level, as well as WTP for the NCR alone. Specifically, this split-sample analysis fills a knowledge gap concerning NCR and national consumer preferences for increasingly popular cool and cold-water fish in the domestic markets. We provide information for a wide variety of producers by considering wild-caught and farm-raised alternatives, fillets sold fresh or frozen at retail points, and "localness" encompassing the whole NCR.

The next section of the paper describes the current structure of the NCR aquaculture industry, including farms and species produced. The following section describes U.S. consumer fish preferences. We then outline our consumer survey instrument, including the discrete choice experiment specifically tailored for NCR species. Results and discussion follow.

3.2 The NCR Aquaculture Industry

The NCR spans from the Great Lakes Region to the Great Plains, has plentiful water resources, and experiences a seasonally cold climate. The region produces a wide variety of seafood species (Batterson, 2013) and some states are more specialized than others (USDA ERS, 2019). Overall, the NCR reports strength in the food fish production of trout, catfish, yellow perch, tilapia and carp, and sport fish production of largemouth bass, which is also sold as food fish, and walleye (Table 3.1). Other species produced in the region include hybrid striped bass, crawfish, shrimp (saltwater), prawns (freshwater), ornamental fish, and baitfish. Most NCR trout farms are in Wisconsin, Michigan and Nebraska, but trout farms can be found in all other NCR states except North Dakota. Catfish farms are predominantly located in Ohio, Illinois, and Missouri. Yellow perch production is strong in Ohio and Wisconsin, but it is also produced in Michigan and Minnesota. The NCR contributes small shares of the overall U.S. harvest of tilapia and carp, representing 2 percent and 5.2 percent of the national sales, respectively.

Rainbow trout (*Oncorhynchus mykiss*), though non-native, is an important species in the NCR. It is a typical cold-water fish that thrives in the climatic conditions of the Great Lakes region (Kinnunen, 2000; Hinshaw et al., 2004). In 2005, the NCR accounted for 28 percent of all U.S. trout farms and 9 percent of national sales (USDA, 2006), but regional production contracted modestly to 23 percent of total farms and 7 percent of national sales in 2018 (USDA, 2019) and nationally, trout generated $12.4 million dollars in exports in 2018 (USDA ERS, 2019). Presently, the NCR produces less than 8 percent of total domestic trout value (USDA ERS, 2019). In contrast, the NCR boasts 90.2 percent of U.S. walleye (*Sander vitreus*) production and 81.3 percent of U.S. yellow perch (*Perca flavescens*) production (USDA Aquaculture Census 2018). Once abundant in the Great Lakes, commercial fisheries serviced the large domestic demand for yellow perch and walleye during the middle of the 20th century and solidified the two species in the gastronomic traditions of the region (Malison, 2003; Riepe, 1999; Summerfelt et al., 2019).

With a relatively high market value, walleye is considered an opportunity for the NCR aquaculture industry's growth and development (Summerfelt et al., 2019; Riepe, 1999). As such, walleye received the NCR priority species designation for financial support and research funding through the 1990s (Riepe, 1999). Yellow perch is another historically important species in the Great Lakes region and it also bears the NCR priority species designation.

Like walleye, yellow perch is particularly adapted to the seasonal cycle of the lower NCR temperate systems (Hokanson, 1977; Linkenheld, 2019) making it an ideal candidate for aquacultural development in the region. During the twentieth century, the international supply of yellow perch came from capture fisheries in the Great Lakes region of the U.S and Canada (Malison, 2003). Wild catch exceeded 33 million lbs. annually in the 1950s and 1960s but fell significantly to 11-18 million lbs. in the late 20th century (Malison, 2003). With its natural population in decline since the 1980s, aquaculture and the Canadian Lake Erie commercial fishery currently service U.S yellow perch demand. Canadian imports alone accounted for 155 metric tons in 2020, the equivalent to $4.2 million dollars (USDA FAS, 2021). On a smaller scale, there is a limited U.S. state-licensed commercial fishery for yellow perch in Lake Huron's Saginaw Bay and Lake Michigan's Green Bay in addition to Native American commercial fisheries in Michigan.

3.3 U.S. Consumer Preferences for Fish

The American population rose 7 percent between 2009 and 2019 while U.S. per capita seafood consumption grew 10.3 percent over the same period (National Marine Fisheries Service, 2021). Most of this growth can be attributed to an increase in the consumption of fresh and frozen seafood while per capita consumption of canned and cured seafood products remained constant (National Marine Fisheries Service, 2021). With increasing frequency, consumers choose to meet their protein needs with seafood given the combination of low fat content and high levels of Omega-3 fatty acids (de Boer et al., 2020; Runge et al., 2021). For example, 2017 market research showed

82 percent of respondents purchased fish or shellfish (Averbook, 2018).

Consumer preferences and consumption trends ultimately reflect individual definitions of quality, which in turn is a multidimensional attribute constructed from perceptions of a combination of traits (Wirth et al., 2011). As a result, retail seafood products may be thought of as "bundles of characteristics" composed of many search, experience, and credence attributes (Ahmad and Anders, 2012; Ward et al., 2008). Consumers can readily verify 'search' attributes at the moment of purchase, while 'experience' attributes require an interaction, such as eating, to discern. 'Credence' attributes are most difficult to verify, even after handling or consumption, and are imparted through labels. In the case of seafood, search attributes include species, price, and form of the product (such as fresh or frozen). The latter, if taken as a search attribute, subdivides into a range of possible attributes such as convenience and appearance. Nevertheless, choices between fresh and frozen can be associated with individuals' previously experienced taste, blurring the lines that separate this classification of attributes. However, flash-freezing technology has improved the quality of frozen fish in comparison to fresh fish, rendering attributes such as fresh (not previously frozen) and frozen imperceptible and therefore credence attributes. In blind taste tests, consumers prefer flash-frozen samples to never-frozen-fresh samples (Cox et al., 2017; Kinnunen and Pisitis, 2007). Such developments in fish preservation may change consumer perceptions of quality.

At present, whether fish is sold fresh or frozen plays an important role in framing consumer fish choices. As a result, our choice experiment presents the form of fish at retail, a search attribute, as either fresh fillets or frozen fillets. Consumers face many forms of fish products at seafood retail counters and freezer cases. Niche live markets coexist alongside grocery stores, specialty stores, and big box retailers providing a wide range of forms of fish from live, undressed whole to processed frozen fillets. Consumers perceive fresh fish to be more nutritious and thus, these alternatives command a price premium relative to frozen fish choices (Averbook, 2018). Frozen fish, while also considered nutritious, is perceived to be easier to prepare, more convenient, and more affordable than fresh alternatives. Despite these associations, actual consumption rates are higher for frozen fish products than fresh ones. National scanner data shows most seafood expenditures go to frozen products with just 18 percent spent on fresh seafood products (Gorstein and Larkin, 2014). Fresh fish is considered least affordable based on consumer perceptions and cost is the most influential attribute for consumer purchasing decisions (42 percent of respondents), followed closely by taste (41 percent) and healthfulness (30 percent) (Averbook, 2018). In some instances, the preference for fresh seafood over frozen are specific to a geographical region or species. For example, when U.S. consumers were presented with fresh tilapia versus previously frozen tilapia, consumers in Colorado exhibited a $2.67/lb. lower willingness to pay (WTP) while consumers in Florida showed a $4.47/lb. WTP premium (Meas and Hu, 2014). Both consumer groups showed species-specific indifference about product form regarding salmon and tuna (Meas and Hu, 2014). More recently, consumers report purchasing equal shares of fresh fish and frozen fish and viewing frozen foods as equally nutritious to their counterparts (Averbook, 2018). Prior studies have shown preferences across fresh fillets and frozen fillets (as well as fresh fillets, frozen fillets, and smoked) vary geographically (Foltz et al., 1999).

Similarly, whether fish was wild-caught or farm-raised can be considered a credence attribute because it cannot be consistently perceived or identified by consumers in the absence of a label (Sogn-Grundvåg et al., 2014). WTP estimates for wild-caught fish are neither widespread nor uniform in the literature and evidence shows geographic heterogeneity in preferences for production method (Davidson et al., 2012; Jaffry et al., 2004; Rickertson et al., 2017; Uchida et al. 2014). Nationwide, consumer surveys show that 36 percent of consumers report searching for wild-caught fish while only 14 percent report seeking out farm-raised fish, but the equal shares of regular buyers of seafood buy farm-raised and wild-caught fish (Averbook, 2018; Kraushaar, 2014). For example, Hawaiian consumers are willing to pay a premium for wild-caught fish (Davidson et al., 2012). A 2012 study of consumers in Colorado and Florida found no positive WTP for wild-caught salmon or tuna relative to farm-raised, a $2.98/lb. discount for wild-caught or farm-raised Salmon, and a $6.69/lb. discount for wild-caught tuna (Meas and Hu, 2014). Other studies have focused on those in Europe and China, where per capita seafood consumption is much higher (Menozzi et al., 2020; Zheng et al., 2021). The number of studies estimating WTP for wild-caught or farm-raised fish, especially those of U.S.-based consumers, are few but indicate a positive WTP for wild-caught fish that may vary across species (Maesano et al., 2020) or seafood product (Brayden et al., 2018).

Consumers sometimes associate health and environmental impacts with the two forms of production. In part, wild-caught preferences can be attributed to the perception of wild-caught fish as more "natural" and better quality, consumer apprehension regarding the environmental impact of aquaculture farms, and lack of trust in farm production systems (Claret et al., 2014; Runge et al., 2021; Whitmarsh and Palmieri, 2011). In contrast, the Aquaculture Stewardship Council reports more than half of seafood consumers are indifferent between wild-caught and farm-raised fish, if production is environmentally and socially responsible (Holland, 2020). Moreover, 69 percent of respondents in this report stated they bought both farmed and wild-caught products or did not know which production method was used. This international survey reported respondent consensus prioritizing responsibly produced food. Further, 29 percent of respondents believed purchasing farm-raised fish provides positive ecological impacts by preserving wild stocks, and 40 percent agreed that significantly more farm-raised seafood should be consumed globally. In the U.S., consumers report growing trust in fish farmers and government regulatory agencies and understand aquaculture reduces pressure on wild stocks (Runge et al., 2021). Aquaculture standards and fishery management practices have improved steadily over the last decade, which has catalyzed a worldwide movement to demystify the "wild versus farmed" debate to benefit both capture fisheries and aquaculture industries (Hill, 2020).

Given the prominence of trout as a domestically farmed commodity, the familiarity of NCR residents with walleye as a sport fish, and evidence of consumer non-attendance toward wild-caught fish, one could expect our estimates to vary compared to the localized studies of the extant literature. The two production alternatives presented to consumers are wild-caught or farm-raised. Ultimately, the ability of NCR and U.S. aquaculture to serve domestic demand rests on the willingness of consumers to purchase farm-raised products. A strong preference for wild-caught fish would imply further reliance on landings from Canada.

Another example of a credence attribute is “locally sourced”, which is often sought due to concerns about health, nutrition, and food safety (Wirth et al., 2011). Fish products sold in the U.S. must bear a country-of-origin label, but these labels do not necessarily convey state or region of production in the U.S (Agricultural Marketing Board, 2013). Labels indicating the fish geographic origin or source are known to affect consumer seafood preferences (Brayden et al., 2018). Some studies show consumers find it only "somewhat" important to purchase locally produced or farm-raised fish (Gvillo et al., 2013; Runge et al., 2021), indicating the term "locavore" has yet to cross over from beyond terrestrial food products to seafood. More recently, supply chain disruptions during the COVID-19 pandemic were especially severe for meat products and seafood (Arita et al., 2021), expanding the benefits of local production beyond healthy and food safety concerns to food security. Stated preferences for locally sourced food fish have been previously reported in Europe (Altintzoglou et al., 2010; Risius et al., 2017) and have been elicited more recently in the U.S. (Runge et al., 2021). A survey of Wisconsin-based seafood consumers identified preferences for fish sourced locally or in the U.S. relative to imported alternatives (Runge et al., 2021; Shaw et al., 2020). While certain regions in the U.S. hold strong historical affinities for certain seafood species, evolving attitudes regarding the health and welfare of seafood have changed the landscape nationally. We capture the consumer WTP for NCR state sourced fish compared with non-NCR sourced fish through our choice experiment design. Within the NCR, the NCR-sourced designation serves as a proxy for local production or landing.

As the lines between search, experience, and credence attributes change for fish and seafood due to farm production and preservation technology improvements, the consumer preferences for these attributes should also adjust. This paper estimates consumers' WTP for fish search attributes including species and fresh versus frozen fillets, as well as wild-caught versus farmed. We produce national and NCR-specific WTP estimates using a hypothetical choice experiment of trout, walleye, and yellow perch to identify whether these attributes attract premia.

3.4 Consumer Survey

3.4.1 Data

We collected the data for this analysis by constructing and distributing an online survey instrument using QualtricsXM in the fall of 2020. The sampling frame included American adult consumers who reported preparing fish at home. The choice experiment designed for this study, described below, asked respondents to consider a hypothetical purchasing scenario typical of a fish retailer and this required us to screen respondents who prepared and ate fish at home as opposed to those who only dined on fish away from home. This designation of fish consumers, as opposed to seafood consumers, removes those who eat only crustaceans and/or mollusks from the sample, an important distinction because shrimp is one of the most consumed seafood products. The survey featured screening questions, a consequentiality statement (Zheng et al., 2021), a discrete choice experiment, and a demographics section. A pilot-study of 106 respondents preceded the full survey release to provide a quality check on the suitability of the questions, survey flow, and display logic. We discarded any respondents who fell outside the sampling frame, did not complete the survey, failed a speed test, or submitted multiple survey responses from the final sample.

After screening and quality control, the final sample consisted of 876 respondents. Summary statistics for the demographics of the respondents are presented in Table 3.2. According to the 2019 American Community Survey, one in five Americans lives in the NCR and our sample is proportionate in composition (U.S. Census Bureau, 2020). Our sample skews slightly more female, younger, and lower on the income spectrum than is nationally representative.

3.4.2 Discrete Choice Experiment

In the discrete choice experiment (DCE) portion of our survey, respondents viewed a map of the states of the NCR before facing a series of hypothetical purchasing choice scenarios (Figure 3.3). The choice scenarios presented attributes across alternatives to force respondents to make tradeoffs between species and attributes, facilitating estimation of WTP for these species and attributes.

Each choice scenario included a framing prompt to consider buying one pound of fish by choosing among three labeled alternatives (trout, yellow perch, walleye) or choosing not to purchase any of the presented options (a no-buy option) to simulate a real purchasing situation (Lusk and Schroeder, 2004; Scarpa et al., 2005). Given the differences in the taste, texture, and size of each species' fillets, we expect respondents to derive species-specific utility associated with each species, necessitating a labeled design (Holmes et al., 2017). The no-buy option encompasses all outside options and we remain agnostic about all of the classifications of substitutes respondents may have envisioned.

Each alternative included a picture of species-specific fillets. Attributes varied over the alternatives according to levels presented in Table 3.3. Prices ranged from $9 to $16 in dollar increments for each alternative, producing eight price levels. We chose price levels conservatively to avoid biasing WTP results up due to large magnitude price vectors (Glenk et al., 2019). The two production methods considered were farm-raised and wild-caught. Each alternative was labeled as "NCR sourced" or "Not NCR sourced" to differentiate fish originating inside or outside the region. This grouping of non-NCR but U.S.-sourced fish with imported fish is like the categorization used in the analysis of Brayden et al. (2018). Each alternative bore a "Fresh Filets" or "Frozen Filets" label to reflect the availability of different forms at retail.

The combination of four labeled alternatives, eight prices, two regions of origin, two production methods, and two product forms yielded an untenable number of choice tasks under a full factorial design: 262,144 (83*23*23*23) different choice tasks. To address this dimensionality, we employ a simultaneous orthogonal factorial design and subdivide the resulting 24 choice scenarios into four blocks. Each respondent faced just six choice scenarios randomly assigned from the four blocks to combat respondent fatigue (Hanley, Wright, and Koop, 2002). This design achieved orthogonality within and across the attribute levels of alternatives to ensure pairs of attributes are uncorrelated while every pair of attributes occurred equally often to attain balance. The *ex ante* multinomial logit efficiency measures and full design are found in the appendix.

3.5 Conceptual Framework

Our conceptual framework follows McFadden's random utility model (RUM) (McFadden, 1974), widely popularized by Train (Train, 2003). The utility of consumer n for fish alternative j can be decomposed into two components: observed component V_{nj} and unobserved component ε_{nj}

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{3.1}$$

This model forms the foundation of multinomial logit model assuming the unobserved utility component is identically and independently (i.i.d.) distributed following an extreme value type 1 distribution. Under this assumption, the probability of consumer n choosing fish alternative j is

$$P_{nj} = Prob[V_{nj} + \varepsilon_{nj} > V_{ni} + \varepsilon_{ni}] \; \forall \; i \neq j \tag{3.2}$$

$$= Prob[\varepsilon_{nj} > V_{ni} - V_{nj} + \varepsilon_{ni}] \; \forall \; i \neq j \tag{3.3}$$

which is to say that the unobserved component of utility for every unchosen fish alternative i must be smaller than the differences between the observed component n and observed component for fish alternative i plus the unobserved component of fish alternative j.

$$P_{nj} = \sum_{i \neq j} \exp[-\exp(-(V_{ni} - V_{nj} + \varepsilon_{ni}))] \int (\varepsilon_{nj}) \exp[\exp(-\varepsilon_{nj})] d\varepsilon_{nj} \tag{3.4}$$

Under the assumption of independence between unobserved utility components, we can multiply the probability for all $i \neq j$ to obtain the probability of individual n choosing alternative i and integrate the conditional probability over all possible ε_{nj} values. Equation (3.4) may be expressed in closed form as

$$P_{nj} = \frac{\exp(\beta' x_{nj})}{\sum_i \exp(\beta' x_{ni})}. \tag{3.5}$$

The multinomial logit has several limitations due to the strong assumptions required to obtain equation (5) (Train, 2003). These include an inability to model random taste variation, the imposition of independence of irrelevant alternatives (IIA) property, and state independence. These challenges can be addressed with more flexible models like universal logit models, heteroskedastic extreme value models, multinomial probit models, random parameters (mixed) logit models, and error components models (Lusk and Schroeder, 2004; Scarpa et al., 2005; Scarpa et al., 2007). Error component logit models augment the multinomial logit framework with random effects. One can model the utility of consumer n for fish alternative j at time t as

$$U_{njt} = \beta' x_{njt} + \theta_j E_{nj} + \epsilon_{njt} \tag{3.6}$$

The innovation comes from decomposing the unobserved component of utility from equation (1), ε_{njt}, into standard normal error component, E_{nj}, and an i.i.d extreme value type 1 idiosyncratic error term ϵ_{njt}. The error components account for time and choice task invariant individual-alternative-level variation with alternative-specific standard deviation θ_j. This changes the probability of individual n choosing alternative j to

$$P_{nj|E_{n1},...,E_{nj}} = \frac{\exp(\beta' x_{nj} + \theta_j E_{nj})}{\sum_i \exp(\beta' x_{ni} + \theta_i E_{ni})} \tag{3.7}$$

Since significant preference heterogeneity can be present in a population, it is often unreasonable to impose parameter homogeneity. For example, we expect some consumers to prefer NCR-sourced fish, a wild-caught label, and fresh fillets more than others based prior studies of preference heterogeneity with respect to sourcing labels, production method labels, and form at purchase. Random parameter logit (RPL) models (also known as mixed logits) specify the parameters within the observed component of utility as random variables drawn from a continuous mixing distribution to allow parameter heterogeneity. The probability of individual n choosing fish alternative j is found by integrating the standard multinomial logit probabilities of the density of the mixing distribution

$$P_{nj} = \int L_{nj}(\beta) f(\beta) d\beta \quad \text{where } L_{nj}(\beta) = \frac{\exp(V_{nj}(\beta))}{\sum_i \exp(V_{ni}(\beta))} \tag{3.8}$$

so when utility follows a linear specification equation (3.8) may be rewritten as

$$P_{nj} = \int \frac{exp(\beta' x_{nj})}{\sum_i exp(\beta' x_{ni})} f(\beta) d\beta \tag{3.9}$$

This makes it possible for individual utilities to be affected differently by an attribute, but overall the parameters are drawn from the same distribution. RPL models also permit relaxing the zero correlation assumptions between alternatives and between time periods. These types of correlation can arise from the unobserved component of utility and do not conflict with the assumptions of the model. However, since RPL model probabilities are composed of integrals, the "cancellation" of denominators observed in a multinomial logit cannot occur and simulation methods are necessary for estimation.

Building on the ability to model correlation between the utilities of different alternatives, the error component model (ECM) provides desirable innovations on the RPL model by allowing covariance between the random parameters of labeled alternatives (Scarpa et al., 2005, Scarpa et al., 2007). A random parameter logit with error component model (RPLEC) decomposes equation (3.1) into three components:

$$U_{nj} = \alpha' x_{nj} + \mu_n' z_{nj} + \varepsilon_{nj} \tag{3.10}$$

where x_{nj} and z_{nj} are observed attribute vectors for fish alternative j, α represents fixed coefficients, μ represents random coefficients with zero means, and ε_{nj} is the i.i.d. extreme value type 1 unobserved portion of utility (Train, 2009). The random part of the utility specification is thus $\eta_{nj} = \mu_n' z_{nj} + \varepsilon_{nj}$ and this portion can demonstrate correlation over alternatives for individual n. In the case of non-zero error components consider individual n facing alternative i and alternative k:

$$Cov(\eta_{ni}, \eta_{nk}) = E(\mu_n' z_{ni} + \varepsilon_{ni})(\mu_n' z_{nk} + \varepsilon_{nk}) = z_{ni}' W z_{nj} \tag{3.11}$$

where W is the covariance of μ_n. Through these error component terms, utilities U_{ni} and U_{nk} are correlated so the utility of individual n is correlated across alternatives. In the hypothetical choice experiment context of this paper, we prefer error component random parameters logit models to handle heteroskedasticity emerging from correlation between the labeled fish species alternatives. We expect respondents to experience labeled alternatives differently than the no-buy option.

3.6 Empirical Estimation

Assuming equation 3.10 is linear in parameters, the utility of consumer n for fish species j in choice scenario t is

$$Choice_{njt} = \alpha_j + \beta_1 Price_{njt} + \beta_2 NCRSourced_{njt} + \beta_3 WildCaught_{njt} + \beta_4 Fresh_{njt} + \varepsilon_{njt} \tag{3.12}$$

where j = trout, yellow perch, and walleye; α_j is the alternative specific constant for fish type j relative to the "no buy" option; $Price_{njt}$ is the continuous price of alternative j for consumer n; $NCRSourced_{njt}$ is an indicator variable taking a value of 1 for NCR state origin; $WildCaught_{njt}$ is an indicator variable taking a value of 1 when alternative j is labeled wild-caught; and $Fresh_{njt}$ is an indicator variable taking a value of 1 when alternative j is labeled fresh fillets. This estimating equation rests on strong assumptions such as a lack of correlation across utilities and fixed alternative specific constant parameters for each species.

To relax these constraints, we choose a panel logit specification with random parameters and error component to formally account for correlation between choices and alternatives. This allows the choice model to exhibit more realistic substitution patterns, correlation between the utilities of the fish species, and correlation across the utilities given repeated choices by the same individual. The random parameters and latent random effects may covary between the labeled alternatives but not between labeled alternatives and the no-buy option. This is modelled as

$$\begin{aligned} Choice_{njt} = \alpha_{nj} + \beta_{n1}Price_{njt} + \beta_{n2}NCRSourced_{njt} + \\ \beta_{n3}WildCaught_{njt} + \beta_{n4}Fresh_{njt} + \eta_{nj} + \varepsilon_{njt} \end{aligned} \tag{3.13}$$

where the first five parameters vary across individuals. The zero-mean normal error η_{nj} represents the error component and is included in utilities for the three fish species but omitted from the no-buy option. If we collect all parameters into vector β, the random parameters (alternative specific constants and attributes) are random variables $\beta_{nj} = \bar{\beta}_j + \sigma_j\tilde{\beta}_{nj}$ with population mean $\bar{\beta}_j$, standard deviation σ_j, and individual-specific i.i.d. distributed standard normal disturbance $\tilde{\beta}_{nj}$. Both correlation across utilities and random parameter introduce stochasticity into the model which prevents a closed-form solution for the log-likelihood of the choice probability (Train, 2009). Due to this computational necessity, we employed a simulated maximum likelihood estimation strategy to perform integration and estimate probabilities. We used NLogit (Version 6.0, Econometric Software, Inc) to perform all estimation and simulation.

The estimates obtained from equations 3.12 and 3.13 may be used to derive and compare WTP values for the fish attributes in the DCE. The WTP for attribute j is defined as

$$\text{WTP}_j = -\frac{\beta_j}{\beta_{price}} \tag{3.14}$$

where WTP_j is the willingness-to-pay for the j^{th} attribute, β_j is the coefficient associated with the j^{th} attribute, and β_{price} is the price coefficient. In the context of this study, the WTP measures for the dummy variables $WildCaught$, $Fresh$, and $NCRSourced$ are relative to the base level, or converse label. They are thus interpreted as farm-raised to wild-caught, frozen fillets to fresh fillets, or not NCR-sourced to NCR-sourced (Holmes et al., 2017). Further, all the species-specific WTP estimates are relative to the no-buy option because we normalize the utility of no-buy option to zero.

Marginal WTP estimates facilitate comparing the WTP values between different attributes. This is a useful option, for example, when investigating whether one label commands a higher premium than another.

$$\text{WTP}_{j,k} = -\frac{\beta_j - \beta_k}{\beta_{price}} \tag{3.15}$$

We model each of the random attribute parameters using a normal distribution $\beta_{nj} \sim N(\bar{\beta}_j, \sigma_j)$. As such, the WTP estimates for attributes (and alternatives) also follow normal distributions. Since this study seeks to identify the WTP estimates for attributes and species pertinent to NCR aquacultural production, the distributions provide illustrations of consumer valuation beyond mean WTP estimates. We use Krinsky and Robb's bootstrapping approach (Krinsky and Robb, 1986; Lusk and Schroder, 2004; Henscher et al., 2005) with 1,000 simulated draws to obtain the parameters of these distributions.

3.7 Results

Our results demonstrate U.S. consumers are on average willing to pay premia for NCR-sourced fish, wild-caught fish, and fresh fillets. Further, we find significant, regionally varying heterogeneity in the WTP estimates for these attributes. We also find NCR-based consumers have similar WTP for trout, yellow perch, and walleye while non-NCR fish consumers strongly prefer trout to walleye and yellow perch.

The simulated maximum likelihood estimation results from the correlated random parameter logit (RPL) and random parameters with error component logit (RPLEC) are shown in Table 3.4 below. Consistent with consumer theory, the *Price* coefficient is negative and statistically significant at the one percent level in all specifications. The difference in prices between the NCR-specific sample and the non-NCR sample suggests that NCR fish consumers are more price sensitive than other U.S. fish consumers. The mean coefficients for the other three attributes are also statistically significant and provide empirical evidence that U.S. fish consumers value these factors when buying fish. In keeping with previous studies documenting the importance of sourcing labels, the coefficients on the NCR-specific label are positive and highly significant. Though the signs are the same, the sizes of the *Fresh*, *NCRSourced*, and *WildCaught* coefficients differ across the two geographic samples, reflecting regional taste and preference variation.

In addition to positive, statistically significant mean estimates for *Fresh*, *NCRSourced*, and *WildCaught*, the estimated standard deviation for these three attributes are also highly statistically significant (except in the case of NCR sample RPLEC *Fresh* value). This provides evidence of significant variation in the utility U.S. consumers derive from each of these attributes. In each case, the estimated standard deviations exceed the means. As such, some consumers gain utility from the presence of an attribute, while others derive utility from that attributes's counterpart. For example, a portion of U.S. consumers get positive utility from a wild-caught label while another portion get positive utility from a farm-raised label. Nationally, the NCR-source label is associated with the largest standard deviation, suggesting consumers are not aligned in their appreciation of such a label. This is not too surprising given the hypothetical nature of this label: consumers have never seen this option before and may not have strong, unified preferences with respect to it.

The means of the alternative specific constants presented in Table 3.4 for *Trout*, *Yellow Perch*, and *Walleye* are positive and statistically significant across all samples. As such, consumers across the United States obtain significantly more utility from each of the choice set species relative to forgoing purchasing from the three options (the utility of the no-buy option is normalized to zero). The species-specific mean and standard deviation estimates vary by specification but largely tell the same story. Within the NCR, the utilities associated with *Walleye* and *Yellow Perch* do not exhibit statistically significant standard deviations. In contrast, the estimated standard deviation for *Trout* is not statistically significant outside the NCR. Therefore, consumers within and outside the NCR demonstrate heterogeneity for different species.

In terms of model performance, we prefer the RPLEC specification for several reasons. First, the no-buy option is the only presented alternative which respondents can realistically experience: they pay nothing and receive nothing in return. As such, the utilities between the imagined alternatives are more likely to be correlated with one another than the no-buy alternative (Scarpa et al., 2005). We find evidence supporting such correlation due to the statistical significance of the estimated standard deviation of the error components for all three samples presented in Table 3.4. Statistically, the RPLEC model performs better in terms of fit than the RPL model, as evidenced by the lower adjusted Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC). Moving forward, we focus on results from the RPLEC model because it allows for more realistic correlation between the species alternatives, produces a better fit, generates estimates closer to observed prices in the market, and the standard deviation of the error component is statistically significant. Taken with the observed variation in price estimates, we forgo discussing the raw, unscaled maximum likelihood coefficients any further and instead proceed with comparing and interpreting the WTP estimates those coefficients produced from the RPLEC model.

Table 3.5 displays WTP estimates constructed from the RPLEC coefficients from Table 3.4 through Krinsky-Robb simulation (Krinsky and Robb, 1986). Nationally, consumers demonstrated price premia for all three studied attributes. The highest value is associated with *WildCaught* with an average \$1.97/lb premium relative to farmed fish. The standard deviation is substantial, at \$6.01, suggesting a largely positive, but wide WTP distribution for this label. The *NCRSourced* mean WTP estimate is a little smaller at \$1.64/lb. and the estimated standard deviation is significantly smaller at \$2.82. U.S. consumers valued fresh fillets just \$0.84/lb. more than frozen fillets, but the large standard deviation (\$2.82) reflects the heterogeneity in these values. The relatively small premium and wide distribution of WTP for $Fresh$ relative to frozen fillets could be due to the convenience of frozen fillets, advances in freezing technologies, or a popular perception that frozen fish can improve food safety while reducing food waste, an understanding often encouraged by retailers (O'Donnell et al., 2021).

The WTP estimates for *Fresh* are geographically uniform while the price premia for wild-caught fish represent an important difference between consumers in the NCR and consumers outside the region. Wild-caught is valued more outside the NCR than within the region. Non-NCR consumers are willing to pay $1.71/lb. on average for wild-caught fish compared to average NCR consumers who are willing to pay $1.46/lb. NCR fish consumers value an NCR Sourced label, confirming our "locavore" predictions from previous studies of localness (Brayden et al., 2018; Runge et al., 2021; Tien et al., 2021). Further, the mean WTP for NCR production is higher beyond the NCR, indicating an appreciation for NCR-sourced fish beyond the region.

Taking the U.S. as one market, $Trout$ commands the highest mean WTP at $19.99/lb. trailed by $Walleye$ at $17.37/lb. and $YellowPerch$ at $15.89/lb. There is strong evidence of heterogeneity in the WTP estimates for each species given the significance of the alternative specific constant standard deviations. A large amount of this heterogeneity is regional. In particular, the mean WTP for all three species was significantly higher in the NCR; each species commanded over $20.00/lb. $Walleye$ topped NCR consumer WTP at $24.79/lb., followed by $24.04/lb. for trout and $23.00/lb. for yellow perch. Outside the NCR, mean WTP estimates for trout, yellow perch, and walleye are much smaller. The geographic heterogeneity is most pronounced with respect to Walleye and Yellow Perch, as the mean WTP estimates are about $10 less per pound and bear significant standard deviations. Outside the NCR, the highest WTP estimate is $Trout$, and the value is stable with an insignificant standard deviation.

An alternative approach to interpreting WTP estimates comes in the form of analyzing marginal means. Studies combining hypothetical DCE with real choice experiments have shown that marginal WTP estimates from hypothetical DCEs show less hypothetical bias than mean WTP estimates (Lusk and Schroeder, 2012). Marginal means and marginal standard deviations provide distributional evidence for comparing species and attributes within regions (Table 3.6). Under the national approach, both an NCR label and wild-caught label are more valuable than fish in fresh fillets form. Within the NCR market, however, there was no statistical significance between the estimated mean WTP for $Fresh$, $NCRSourced$, or $WildCaught$. Most notably, there is no significant premium for an NCR-source label relative to a wild-caught label across all three samples.

On average, U.S. fish consumers value trout significantly more than walleye or yellow perch. The premia for trout over walleye and trout over yellow perch were \$2.62/lb. and \$4.10/lb., respectively. In the NCR market, the three species were valued much more similarly, with only $Walleye$ valued significantly \$1.79/lb. more than *Yellow Perch*. Trout, which is much more valued outside the NCR, is equally valued to walleye and yellow perch within the region.

3.8 Discussion

Our results present several important implications for producers, distributers, and retailers marketing yellow perch and walleye in the NCR. First, and most importantly, we find strong evidence that U.S. seafood consumers prefer, and are willing to pay for, domestically produced fish sourced from NCR states. Remarkably, residents in the NCR show a slightly lower WTP for NCR-sourced fish than those outside the area. However, the geographic heterogeneity in the value of localness is not unprecedented (Printezis et al., 2019). For example, NCR residents, who consume walleye and yellow perch more regularly, may be more familiar with or indifferent to Canadian imports. Further, non-NCR residents may, on average, have stronger preferences for U.S. products than those in the NCR. We take this as evidence that fish-related "locavore" preferences extend beyond state lines and regions.

Consumer preferences for wild-caught fish vary significantly across the United States. Specifically, seafood consumers outside the NCR strongly prefer wild-caught to farm-raised fish with an average WTP of \$1.73/lb. Inside the NCR, however, the estimated consumer mean WTP is \$0.99/lb. This variation in WTP for wild-caught is consistent with previous studies that show WTP estimates for wild-caught change depending on the specific context of the choice task, alternatives, attributes, and respondent base. However, for NCR producers, the important take away is that an

NCR-sourced label is not enough to offset the preference most U.S. fish consumers demonstrate toward wild-caught fish over products of aquaculture. Increasing consumer WTP for farm-raised fish is critical to increasing demand for aquacultural producers, and evidence of consumer indifference regarding harvest method under environmentally and socially responsible production suggests one way to use marketing to overcome this gap (Holland, 2020).

Next, preferences for fresh or frozen fish options were rated the least important in the choice experiment compared to the location of origin or harvest method. Nevertheless, we obtained positive, significant WTP across all three samples for fresh fillets, suggesting a preference for the health benefits of fresh fish over convenience frozen alternatives. Nationally, consumer WTP is $0.84/lb. for fresh filleted fish compared to frozen fillets, and the most uniformly valued attribute across the NCR and non-NCR samples. This finding suggests consumers value the convenience and safety of frozen fish options. More, freshness may not play as large a role in ascertaining quality for consumers as it once did, especially when compared to source and production methods. That allows flexibility for the NCR seafood industry to expand the distribution of traditional NCR-sourced species to their loyal local demand and a wider captivated national demand.

Finally, U.S. fish consumers at large demonstrate a clear preference for trout over walleye and yellow perch. These finding suggest that aquaculture producers should focus on marketing walleye and yellow perch within the NCR as WTP is highest in the region. However, the greater takeaway is that NCR fish producers should intensify production of trout: it is as valuable in the NCR as walleye and yellow perch and much more valuable outside the NCR.

3.9 Conclusion

Per capita U.S consumption of seafood products and finfish has increased in recent decades, with demand met by an ever-growing supply of imported products. In the face of these changes, we analyze consumers' preferences for three fish species: trout, yellow perch, and walleye in a random utility model framework. We designed and distributed a hypothetical discrete choice experiment and obtained responses from 876 Americans from a nationally representative sample of seafood consumers. Using a maximum simulated likelihood estimation approach, we estimated fixed and random parameters with a panel logit with random parameters and error components to compare preferences for species and fish attributes nationally, in the North Central Region (NCR), and in non-NCR states.

Trout, yellow perch, and walleye are each important species to Great Lakes cultural traditions. A strong demand for these species endures in the NCR despite profound restructuring to the supply chain for yellow perch and walleye due to regulatory changes. Possibly led by this persistent gastronomic culture, we identified a pronounced preference for yellow perch and walleye in the NCR. Specifically, NCR consumers show statistically indistinguishable WTP for trout relative to yellow perch or for trout compared walleye. Meanwhile, trout is nationally most preferred, commanding a \$4.10/lb. premium over yellow perch and a \$2.62/lb. premium over walleye. No matter the region, though, walleye is preferred over yellow perch, with a national average premium of \$1.48/lb. for walleye over yellow perch. American seafood consumers are willing to pay an average \$19.99/lb. for trout, \$17.37/lb. for walleye, and \$15.89/lb. for yellow perch.

This study presented a national sample of seafood consumers with three fish species alternatives bearing different sources, forms, and growth environments. While the survey instrument presented respondents with various attributes, the attribute levels considered were relatively general given various production technologies currently available or in development for future use. For example, respondents faced hypothetical choice scenarios for alternatives defined as "fresh fillets" or "frozen fillets." In reality, fish processors employ various processing, packaging, freezing, and thawing technologies which can affect the palatability, texture, and other product quality cues (Nagarajarao, 2016). Our choice of terminology, too, differs from other surveys where researchers have made the distinction between "chilled" and "fresh" presentations (Zheng et al., 2021). Further, there may be a contingent of consumers keen on the differences between fresh never frozen, previously frozen, and frozen. Our analysis instead presents forms consumers face at retail. Finally, our study includes neither consumer experience with different preservation technologies nor knowledge and attitudes regarding the safety of fresh versus frozen fish alternatives. This omission suggests an opportunity for future research to augment this study.

Our analysis contributes to the active debate regarding consumer preferences for wild and farmed seafood. Consistent with many previous studies, we identified price premia for wild-caught fish for U.S. markets within and outside the NCR. This analysis assumes wild harvesting constitutes a credence attribute; consumers cannot reliably perceive it through search or experience activities. If consumers can discern production methods based on their senses, one might expect that the presence of a label would be insignificant. Due to the magnitude and significance of our estimates, however, it appears the inclusion of wild-caught or farm-raised labels provides relevant, valuable information to consumers. However, what is less clear are the consumer beliefs, attitudes, and experiences negatively associated with farm-raised fish. In particular, if consumers view farm-raised labels as a heuristic for lower quality, producers may wish to employ other marketing strategies to connect high-quality cues with farm-raised products. We find NCR residents value wild-caught fish less than other Americans, but analysis of the drivers of these regional differences remains open for future research.

3.10 Acknowledgments

This study was funded by the by USDA-NIFA through the North Central Regional Aquaculture Center Award 2016-38500-25753. I would like to acknowledge my wonderful co-authors in this study: Dr. Simone Valle de Souza, Dr. Kwamena Quagrainie, Dr. Chinonso Etumnu, Dr. William Knudson, Dr. Ronald E. Kinnunen, and Mr. Paul Hitchens. Many thanks also to the industry liaisons and Board members of the North Central Regional Aquaculture Center who provided productive comments and support on this project. All opinions expressed in this paper are those of the authors and do not reflect the opinions or positions of the aforementioned entities.

APPENDICES

APPENDIX A: TABLES AND FIGURES

Table 3.1 Total number of farms and sales reported by NCR Aquaculture

Fish Type	Number of Farms	Annual Sale ($1,000's)	Percent Total U.S. Sales
Food Fish			
Rainbow trout	78	8,689	7.4
Catfish	44	1,238	0.3
Yellow perch	52	898	81.3
Tilapia	28	785	2.0
Carp	34	541	5.2
Sport Fish			
Largemouth bass	73	4,189	15.3
Walleye	38	2,630	90.2

Source: 2018 USDA Aquaculture Census

Table 3.2 Summary of Respondent Demographics

Category	Sample (%)	U.S. (ACS)(%)
Origin		
North Central Region States	22.3	20.6
Non-North Central Region States	77.7	79.4
Gender		
Female	57.6	48.7
Male	42.6	51.3
Age (Years)		
18-24	10.3	11.8
25-34	27.2	17.9
35-44	25	16.5
45-54	14.5	15.9
55-64	14	16.6
65+	9.4	21.2
Income (Annual)		
<24, 999	21	18.1
25, 000−49,999	28.5	20.3
50, 000−74,999	20.9	17.4
75, 000−99,999	12.2	12.8
100, 000−149,999	12.9	15.7
150, 000+	4.2	15.7
Race/Ethnicity [2]		
Asian	5.5	5.7
Black	8.2	12.8
Hispanic	10	18.4[2]
Native American	1	1.1
Other	1.3	5
White	74	72
Sample Size	876	—

[1] Source: American Community Survey 2019 1-Year Estimates
[2] Due to differences in the classification of race and ethnicity the national race statistics do not sum to one and "Hispanic" overlaps with other categories.

Table 3.3 Choice Experiment Attributes and Levels

Attribute	Attribute Levels
Species (Alternative Specific Constants)	Trout Yellow Perch Walleye
Price (Continuous)	\$9/lb. \$10/lb. \$11/lb. \$12/lb. \$13/lb. \$14/lb. \$15/lb.
Form (Indicator)	Fresh fillets Frozen fillets
Source (Indicator)	NCR sourced Not NCR sourced
Production System (Indicator)	Farm-raised Wild-caught

Table 3.4 RPL and RPLEC Model Coefficients

		Random Parameters Logit			Error Component Random Parameters Logit		
		National	NCR	Non-NCR	National	NCR	Non-NCR
Price		-0.224***	-0.284***	-0.210***	-0.227***	-0.292***	-0.213***
		(0.011)	(0.028)	(0.014)	(0.010)	(0.025)	(0.012)
Fresh Fillets	Mean	0.186***	0.233*	0.217***	0.191***	0.254*	0.187**
		(0.063)	(0.134)	(0.076)	(0.064)	(0.147)	(0.073)
	Std. Dev.	0.609***	0.874***	0.576***	0.669***	0.966	0.593***
		(0.230)	(0.200)	(0.124)	(0.176)	(0.805)	(0.168)
NCR-Sourced	Mean	0.334***	0.227*	0.378***	0.447***	0.426***	0.364***
		(0.063)	(0.129)	(0.078)	(0.080)	(0.152)	(0.099)
	Std. Dev.	0.596***	0.698***	0.657***	1.365***	0.999***	1.462***
		0.114	(0.232)	(0.113)	(0.169)	(0.239)	(0.343)
Wild-caught	Mean	0.522***	0.491***	0.563***	0.371***	0.288**	0.370***
		(0.081)	(0.143)	(0.099)	(0.062)	(0.137)	(0.077)
	Std. Dev.	1.392***	0.975***	1.471***	0.639***	0.764***	0.697***
		(0.138)	(0.217)	(0.115)	(0.114)	(0.280)	(0.108)
Trout	Mean	4.238***	6.486***	3.529***	4.539***	7.011***	3.957***
		(0.270)	(0.852)	(0.268)	(0.269)	(0.928)	(0.285)
	Std. Dev.	4.450***	6.039***	4.510***	1.627***	2.396***	0.485
		(0.241)	(0.794)	(0.274)	(0.222)	(0.533)	(0.365)
Yellow Perch	Mean	3.336***	6.213***	2.496***	3.608***	6.706***	2.879***
		(0.276)	(0.831)	(0.276)	(0.276)	(0.875)	(0.29)
	Std. Dev.	4.641***	5.686***	4.649***	2.421***	0.526	1.285***
		(0.258)	(0.765)	(0.280)	(0.331)	(0.736)	(0.223)
Walleye	Mean	3.655***	6.749***	2.763***	3.942***	7.229***	3.192***
		(0.282)	(0.857)	(0.284)	(0.284)	(0.880)	(0.301)
	Std. Dev.	4.908***	6.036***	4.894***	2.811***	1.262	1.740***
		(0.270)	(0.790)	(0.293)	(0.347)	(0.788)	(0.346)
Error Component	Std. Dev.				2.804***	4.777***	4.219***
					(0.361)	(1.076)	(0.301)
N		5,256	1,170	4,086	5,256	1,170	4,086
Log Likelihood		-6,071.14	-1,317.75	-4,733.41	-5,491.27	-1,197.98	-4,258.05
AIC/N		2.314	2.27	2.322	2.101	2.099	2.099
BIC/N		2.326	2.313	2.337	2.15	2.157	2.156

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5 WTP Estimates

		National	NCR	Non-NCR
Fresh Fillets	Mean	$0.84***	$0.87*	$0.88**
(vs. Frozen Fillets)		($0.30)	($0.53)	($0.35)
	Std. Dev.	$2.95***	$3.31	$2.78***
		($0.79)	($2.68)	($0.79)
NCR-Sourced	Mean	$1.64***	$0.99**	$1.73***
(vs. Non NCR-Sourced)		($0.28)	($0.46)	($0.40)
	Std. Dev.	$2.82***	$2.62***	$3.27***
		($0.54)	($0.97)	($0.52)
Wild-caught	Mean	$1.97***	$1.46***	$1.71***
(vs. Farm-raised)		($0.36)	($0.54)	($0.48)
	Std. Dev.	$6.01***	$3.43***	$6.85***
		($0.82)	($0.92)	($1.67)
Trout	Mean	$19.99***	$24.04***	$18.56***
(vs. No-Buy)		($1.04)	($3.10)	($1.09)
	Std. Dev.	$7.17***	$8.22***	$2.28
		($1.06)	($2.02)	($1.76)
Yellow Perch	Mean	$15.89***	$23.00***	$13.50***
(vs. No-Buy)		($1.07)	($2.97)	($1.12)
	Std. Dev.	$10.66***	$1.80	$6.03***
		($1.54)	($2.61)	($1.14)
Walleye	Mean	$17.37***	$24.79***	$14.97***
(vs. No-Buy)		($1.09)	($2.98)	($1.16)
	Std. Dev.	$12.38***	$4.33	$8.16***
		($1.66)	($2.76)	($1.69)

[1] Displayed WTP estimates obtained from RPLEC specification with 500 Halton draws.
[2] Standard errors are bootstrapped using the Krinsky-Robb method.
[3] Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6 RPLEC Marginal WTP Estimates

	National	NCR	Non-NCR
NCR vs. Fresh Fillets	$0.79**	$0.12	$0.86*
	($0.38)	($0.60)	($0.48)
NCR vs. Wild-caught	$0.33	$-0.47	$0.03
	($0.45)	($0.69)	($0.53)
Wild-caught vs. Fresh Fillets	$1.13**	$0.59	$0.83
	($0.45)	($0.72)	($0.55)
Trout vs. Walleye	$2.62***	$-0.75	$3.59***
	($0.52)	($0.84)	($0.66)
Trout vs. Yellow Perch	$4.10***	$1.05	$5.05***
	($0.45)	($0.98)	($0.59)
Walleye vs. Yellow Perch	$1.48***	$1.79**	$1.46***
	($0.47)	($0.86)	($0.56)

[1] Displayed WTP estimates obtained from RPLEC specification with 500 Halton draws.
[2] Standard errors are bootstrapped using the Krinsky-Robb method.
[3] Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7 Estimated p-values for WTP by Sample

	National	NCR	Non-NCR
Fresh Fillets	0.376	0.098†	0.362
NCR-Sourced	0.262	0.326	0.283
Wild-caught	0.364	0.322	0.391
Trout	0.000	0.000	0.000†
Yellow Perch	0.047	0.000†	0.000
Walleye	0.058	0.000†	0.013

[1] P-values constructed from the percent of simulated WTP estimates in the Krinsky-Robb 95% confidence interval less than or equal to $0.00 .
† No statistically significant standard deviations were obtained for these WTP estimates. The p-value shown refers to the mean WTP estimate.

Figure 3.1 North Central Region Aquaculture Center States

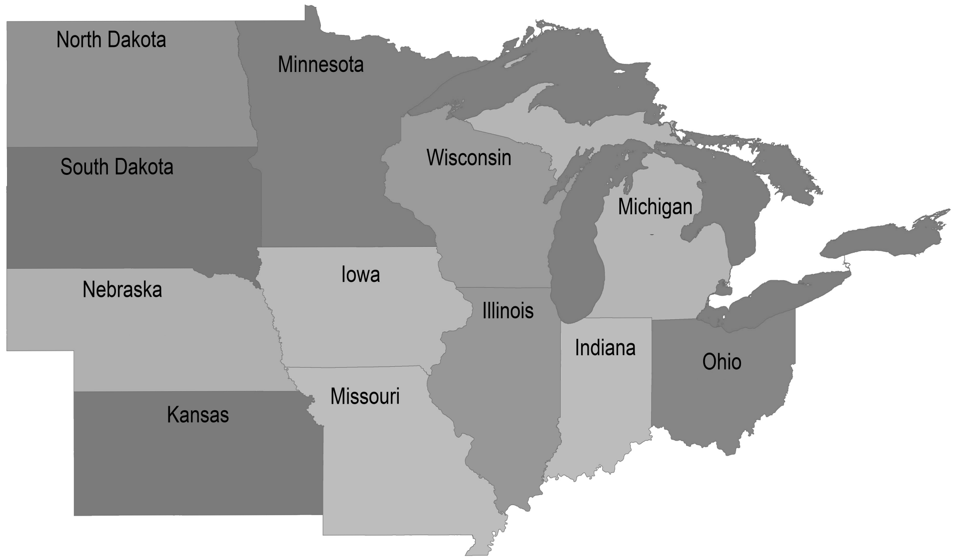
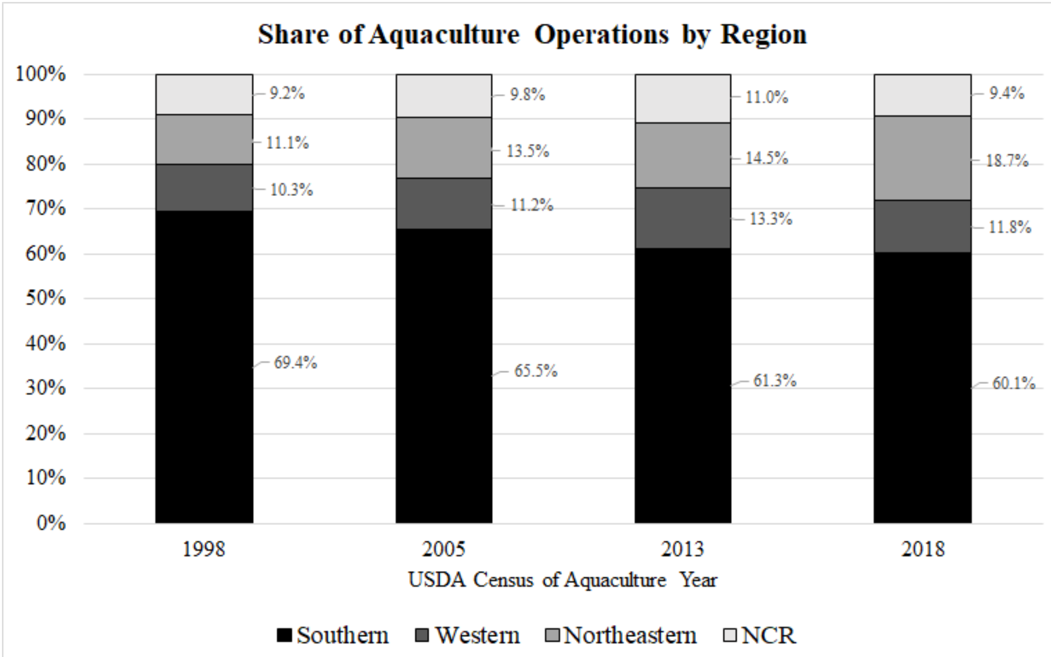
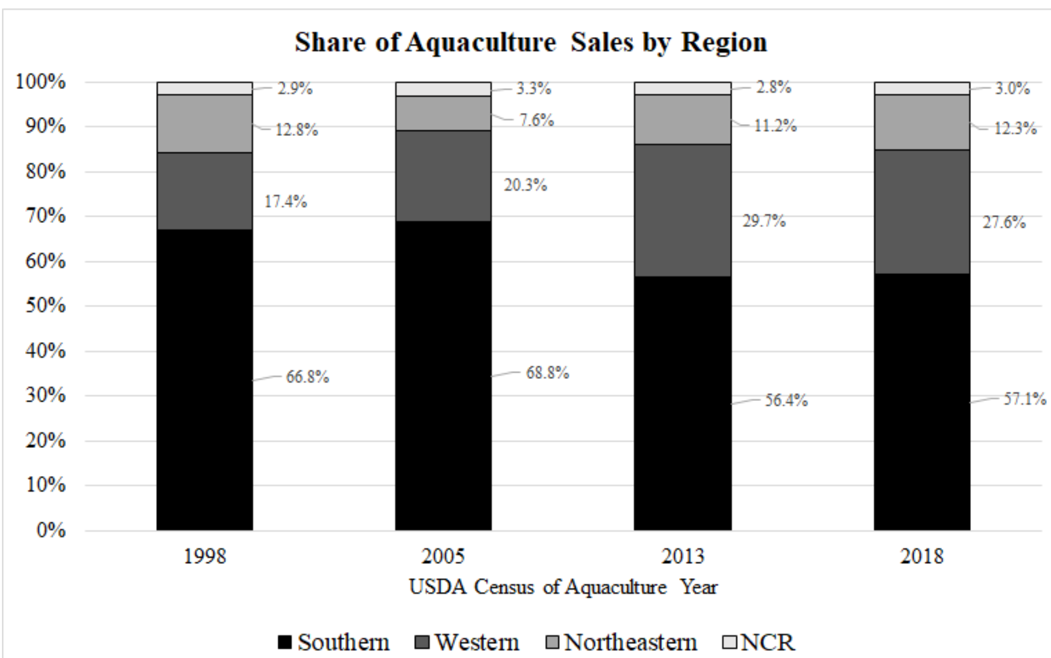


Figure 3.2 U.S. Aquaculture Production by Region

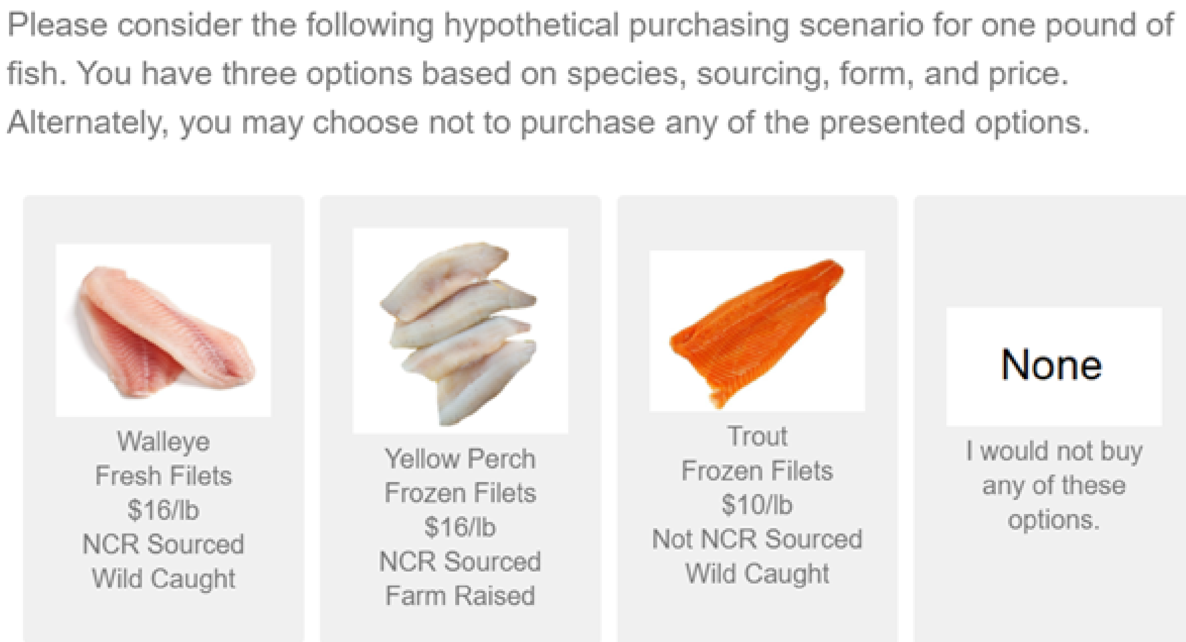


(a) Share of Aquaculture Operations by Region



(b) Share of Aquaculture Sales by Region

Figure 3.3 Example of a Choice Task



Note: Respondents either clicked their preferred alternative with a mouse (computer) or touched it with their finger (mobile device).

APPENDIX B: SUPPLEMENTARY MATERIALS

Table 3.8 Total number of farms and sales reported by NCR Aquaculture

Measure	Value
D Error	0.138
A Error	0.226
B Estimate	100
S Estimates	0

Table 3.9 Full Experimental Design — Choice Tasks by Block

			Walleye				Yellow Perch				Trout			
Block	Question	Choice Scenario	Form	Price ($/lb.)	Origin	Source	Form	Price ($/lb.)	Origin	Source	Form	Price ($/lb.)	Origin	Source
1	1	5	Fresh Fillets	16	NCR Sourced	Wild Caught	Frozen Fillets	16	NCR Sourced	Farm Raised	Frozen Fillets	10	Not NCR Sourced	Wild Caught
1	2	12	Fresh Fillets	13	Not NCR Sourced	Wild Caught	Fresh Fillets	11	Not NCR Sourced	Farm Raised	Frozen Fillets	15	Not NCR Sourced	Farm Raised
1	3	14	Fresh Fillets	10	Not NCR Sourced	Wild Caught	Fresh Fillets	15	Not NCR Sourced	Wild Caught	Fresh Fillets	9	NCR Sourced	Wild Caught
1	4	22	Frozen Fillets	11	NCR Sourced	Farm Raised	Fresh Fillets	16	NCR Sourced	Wild Caught	Frozen Fillets	15	NCR Sourced	Wild Caught
1	5	23	Frozen Fillets	14	Not NCR Sourced	Wild Caught	Frozen Fillets	10	NCR Sourced	Farm Raised	Fresh Fillets	16	NCR Sourced	Wild Caught
1	6	24	Frozen Fillets	9	NCR Sourced	Farm Raised	Frozen Fillets	9	NCR Sourced	Farm Raised	Frozen Fillets	9	NCR Sourced	Farm Raised
2	1	2	Fresh Fillets	11	NCR Sourced	Wild Caught	Fresh Fillets	10	Not NCR Sourced	Farm Raised	Fresh Fillets	12	NCR Sourced	Farm Raised
2	2	4	Frozen Fillets	13	Not NCR Sourced	Farm Raised	Frozen Fillets	16	Not NCR Sourced	Wild Caught	Fresh Fillets	14	NCR Sourced	Farm Raised
2	3	8	Fresh Fillets	12	Not NCR Sourced	Farm Raised	Frozen Fillets	14	Not NCR Sourced	Farm Raised	Frozen Fillets	13	Not NCR Sourced	Farm Raised
2	4	9	Frozen Fillets	16	NCR Sourced	Wild Caught	Fresh Fillets	13	NCR Sourced	Wild Caught	Fresh Fillets	15	Not NCR Sourced	Farm Raised
2	5	20	Frozen Fillets	14	NCR Sourced	Farm Raised	Fresh Fillets	9	Not NCR Sourced	Wild Caught	Frozen Fillets	10	Not NCR Sourced	Wild Caught
2	6	21	Fresh Fillets	11	Not NCR Sourced	Farm Raised	Frozen Fillets	11	NCR Sourced	Wild Caught	Fresh Fillets	12	Not NCR Sourced	Wild Caught
3	1	3	Frozen Fillets	12	Not NCR Sourced	Farm Raised	Fresh Fillets	11	NCR Sourced	Farm Raised	Fresh Fillets	14	Not NCR Sourced	Farm Raised
3	2	11	Fresh Fillets	15	NCR Sourced	Farm Raised	Fresh Fillets	13	Not NCR Sourced	Farm Raised	Fresh Fillets	14	NCR Sourced	Wild Caught
3	3	13	Fresh Fillets	13	Not NCR Sourced	Farm Raised	Fresh Fillets	14	NCR Sourced	Wild Caught	Frozen Fillets	12	Not NCR Sourced	Farm Raised
3	4	16	Frozen Fillets	12	Not NCR Sourced	Wild Caught	Frozen Fillets	13	Not NCR Sourced	Wild Caught	Frozen Fillets	12	NCR Sourced	Farm Raised
3	5	18	Frozen Fillets	15	NCR Sourced	Wild Caught	Frozen Fillets	12	Not NCR Sourced	Wild Caught	Fresh Fillets	9	Not NCR Sourced	Farm Raised
3	6	19	Fresh Fillets	10	NCR Sourced	Farm Raised	Frozen Fillets	10	Not NCR Sourced	Wild Caught	Fresh Fillets	15	Not NCR Sourced	Wild Caught
4	1	1	Fresh Fillets	14	NCR Sourced	Farm Raised	Frozen Fillets	15	NCR Sourced	Farm Raised	Fresh Fillets	11	NCR Sourced	Farm Raised
4	2	6	Fresh Fillets	10	NCR Sourced	Wild Caught	Fresh Fillets	12	NCR Sourced	Wild Caught	Frozen Fillets	14	NCR Sourced	Farm Raised
4	3	7	Frozen Fillets	16	Not NCR Sourced	Farm Raised	Fresh Fillets	12	Not NCR Sourced	Farm Raised	Frozen Fillets	11	NCR Sourced	Wild Caught
4	4	10	Fresh Fillets	15	Not NCR Sourced	Wild Caught	Frozen Fillets	9	NCR Sourced	Wild Caught	Frozen Fillets	13	NCR Sourced	Wild Caught
4	5	15	Frozen Fillets	9	Not NCR Sourced	Wild Caught	Fresh Fillets	14	NCR Sourced	Farm Raised	Fresh Fillets	9	Not NCR Sourced	Wild Caught
4	6	17	Frozen Fillets	9	NCR Sourced	Wild Caught	Frozen Fillets	15	Not NCR Sourced	Farm Raised	Frozen Fillets	16	Not NCR Sourced	Wild Caught

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