

# Three Policies: Nonfiler Tax Enforcement, Renewable Fuel Credits, and Leverage Requirements

by

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## DEDICATION

This doctoral dissertation is dedicated to Terry Shuch and Neal Meiselman.

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## ABSTRACT

Three Policies: Nonfiler Tax Enforcement, Renewable Fuel Credits, and Leverage Requirements

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This dissertation comprises three research papers, each of which examines a public policy.

**Chapter 1.** Many people who owe income tax fail to file a timely tax return. In communication with these “ghosts,” what messages from the tax authority are effective for eliciting a return? This is the first study to address message content in communication with income tax nonfilers. I assess the efficacy of messages related to penalty salience, punishment probability, compliance cost, and civic pride by evaluating the response to experimental mailings distributed by Detroit to 7,142 suspected resident nonfilers. The penalty salience message was the most effective. Relative to a basic mailing that requested a return, penalty salience mailings that

stated the statutory penalty for failing to file a return tripled response rates from 3% to 10%, increased the number of back-year returns filed per response from 0.08 to 0.27, and raised the fraction of filed returns that admitted tax due from 39% to 52%. Compliance cost mailings that enclosed a blank tax return and punishment probability mailings that stated the recipient's federal income also raised response rates relative to the basic mailing, but civic pride mailings did not. Mailings were more effective in eliciting returns from older, higher-income, and first-time nonfilers. I investigate the impact of treatment mailings on the behavior of untreated neighbors and find no evidence of geographic network effects.

**Chapter 2.** Two peculiar features of the market for renewable fuel are essential for understanding the welfare consequences of the Renewable Fuel Standard (RFS). First, the 10% limit on ethanol in E10 gasoline—the blendwall—makes the total renewable fuel mandate more costly. Second, the linkage among prices of different categories of renewable energy credits—RINs—makes the total renewable fuel mandate less costly. I simulate policy experiments in a model that captures both of these features. In the short run, I find that reducing carbon emissions using the RFS imposes welfare costs of more than \$300 per metric ton of CO<sub>2</sub>.

**Chapter 3.** The financial crisis focused attention on policies for managing systematic risk. One policy tool for managing systematic risk is bank leverage requirements, yet existing models do not consider the contribution of leverage to the frequency of financial crises. This paper develops a criterion for optimal leverage requirements when bank leverage makes financial crises more likely. Despite the contribution of leverage to systematic risk, it is optimal to tolerate leverage because

it helps banks create liquidity. I provide illustrative calculations that show current requirements are too low.

## CHAPTER I

# Ghostbusting in Detroit: Evidence on nonfilers from a controlled field experiment

### 1.1 Introduction

Tax authorities want to know what messages induce compliance from noncompliant taxpayers. Relative to other enforcement mechanisms like audits or site visits, the marginal cost of written communication is low. Even better, the marginal cost of making communication more effective is zero; the postage cost of mailing a letter that gets filed in the dustbin is the same as the postage cost of mailing a letter that induces additional timely compliance. Tax authorities want to send a message that works.

One common form of noncompliance is failure to file a tax return. For the U.S. federal individual income tax, Erard et al. (2014) estimate that 6.1% of required tax year 2012 returns were not filed on time. Nonfiling is a much bigger problem for Detroit's individual income tax, for which I estimate that 48% of required tax year 2014 returns were not filed on time. Controlled experiments are becoming more common in the literature on the determinants of tax compliance, most of which examines underreporting or underpayment. Several papers have examined corporate tax

and profits tax nonfiling (Kettle et al. 2016; Brockmeyer et al. 2016), but individual income tax nonfilers have been the focus of only one such empirical paper, which examined the effect of repetition and reminders on filing rates (Guyton et al. 2016).

This paper provides the first evidence from a controlled experiment about message content in communication with income tax nonfilers. The experiment was designed and conducted by the author in collaboration with the City of Detroit. Detroit’s income tax division sent mailings in April through June 2016 to 7,142 suspected “ghosts”—people who owed tax but did not file a tax year 2014 return. Each mailing contained one of several experimental messages, related variously to penalty salience, punishment probability, compliance cost, or civic pride. From the population of suspected ghosts with at least \$350 in estimated tax liability, nonfilers were randomly selected into experimental treatments and sent the same message in two mailings: a postcard, and then a certified letter one week later.

I compare the effectiveness of the various experimental messages for inducing taxpayer compliance. The main outcome of interest is the response rate, the rate at which mailings elicited a tax return from suspected resident nonfilers in the sample. I also evaluate response quality, including the amount of remittances, the likelihood of claiming a refund rather than admitting tax due, and the number of back-year returns accompanying the tax year 2014 return. I examine whether taxpayer behavior differed across treatments in ways that can be attributed only to messages on the postcard, such as the rate at which taxpayers accepted the letters, which required a signature for delivery. I identify taxpayer characteristics, including age and income, that were associated with higher response rates to the experimental messages. I investigate geographic network effects—the response rates of untreated neighbors to experimental mailings.

In communication with nonfilers, the penalty salience message was the most ef-



fective at inducing compliance. Mailings that stated the statutory penalty for failing to file elicited a tax return from 10.1% of intended recipients, more than triple the response rate to the contact-only control mailings and more than any other treatment mailings. Taxpayers in the penalty salience treatment were most likely to file back-year returns, most likely to admit tax due, and most likely to remit payment. Taxpayers responded more promptly to the penalty salience message, sometimes after receiving just the postcard, before the letter was even delivered.

The compliance cost mailings were also effective at raising response rates relative to a contact-only control, but the response quality was lower than the penalty salience mailings. Whereas all other treatment mailings differed only by one or two sentences in a prominent box on the postcard or letter, the compliance cost treatment letter also enclosed a blank tax form and return envelope. The response rate to the compliance cost mailings was 6.2%, double the response rate to the contact-only control mailings. However, the returns that were filed in response to the compliance cost mailings were more likely to claim refunds and less likely to admit tax due than the returns filed in response to the penalty salience mailings. Taxpayers also filed fewer back-year returns in response to compliance cost mailings.

Adding to the penalty salience message a punishment probability message that informed nonfilers that the city tax authority knew their 2014 federal income dampened response rates relative to the penalty salience message by itself. The idea behind the punishment probability message is that revealing the nonfiler's federal income demonstrates that the tax authority has the ability to monitor taxpayer behavior and therefore raises the perceived probability of punishment. On its own, the punishment probability message raised response rates relative to the contact-only control. If the punishment probability and penalty salience messages both operated exclusively through their intended channels, we would expect that including both

messages would raise response rates relative to one or the other by itself (Erard and Ho 2001). However, when mailings included both the punishment probability message and the penalty salience message, the response rate was lower than the response rate to mailings with just the penalty salience message. This surprising result may be a consequence of limited taxpayer attention, supporting the conclusions from prior literature that simplicity is important in communication with taxpayers (Bhargava and Manoli 2015).

This is the first controlled experiment to test the effectiveness of a civic pride message on city taxpayers, and the response rate was statistically indistinguishable from the contact-only control. The civic pride message reminded taxpayers that the collection of taxes is essential to the successful resurgence of the City of Detroit. Kettle et al. (2016) found no impact of a “national pride” message on payment rates among Guatemala corporations. Prior tax experiments have tested the efficacy of other moral appeals: public service, fairness, and compliant majority messages. Consistent with the results of this experiment, most prior literature finds that moral appeals are not as effective as messages about the probability of being caught and the penalty if caught (Slemrod 2015).

I find no evidence of geographic network effects. Network effects can be important even when per-neighbor effects are very small because treated individuals can have many neighbors. To investigate geographic network effects, I compute the distance between every treated nonfiler and every untreated taxpayer who filed a return within 90 days of the first postcard in the experiment. The effect of treatment mailings on filing rates of taxpayers within 100 meters of treated nonfilers was not statistically significant, and this finding was robust to alternative distances. If there are network effects from treatment, they are likely through family or coworkers rather than geographic neighbors.

I assess the revenue and welfare effects of the experimental mailings. I estimate that the penalty salience treatment raised marginal revenue net of administrative costs by \$8 per letter. A back-of-the-envelope application of marginal net revenue to the population of 42,754 nonfilers who fit the sample selection criteria implies that the penalty salience mailings could have generated net revenue of \$342,000. Accounting for the private costs to taxpayers of foregone consumption and compliance costs, the baseline estimate finds that even the most effective treatment had a negative effect on social welfare. However, the welfare estimate is sensitive to assumptions about the social value of public spending and the cost of compliance.

If collecting revenue is valued highly relative to private compliance costs, then net welfare can be improved relative to the penalty salience treatment by refining the sample selection criteria. Taxpayers with higher income, older taxpayers, and taxpayers who were identified as nonfilers for the first time in tax year 2014 were more responsive to all treatments including penalty salience. The effects of age, income, filing history, and treatment status appear to be positive even when they are all at play. Higher income taxpayers are also likely to have larger tax liability net of compliance costs. Relative to applying the penalty salience treatment to the entire population of interest, net welfare could be improved by focusing on a smaller population with higher response rates and higher expected liability net of compliance costs.

Section 1.2 gives background on the income tax system, the decision to file, and the estimated number of nonfilers in Detroit. Section 1.3 presents the design of a controlled field experiment. Section 1.4 presents the results of the field experiment. Section 1.5 conducts a normative analysis. Section 1.6 discusses the results in the context of prior literature. Section 1.7 concludes.

## 1.2 Background

### 1.2.1 Tax system

The City of Detroit levies an income tax on local residents and local workers. Regardless of where they work, residents owe 2.4% of income, with an exemption of \$600 per filer, spouse, or dependent. People who work in Detroit but reside elsewhere owe 1.2% of income earned in Detroit with the same exemption levels. Detroit imposes other taxes such as property tax, but my focus here is on the income tax.<sup>1</sup>

Whether the worker or the firm remits income tax to Detroit depends on worker classification and firm location. A firm must classify workers as either employees or contractors.<sup>2</sup> A firm located in the city must withhold from employees and remit income tax to Detroit. However, a firm located outside the city is not required to withhold Detroit income tax from employees, even if the employees owe Detroit income tax because they are Detroit residents.<sup>3</sup> A firm never remits income tax on behalf of contractors, regardless of the firm's location. City tax administrators believe one reason remittances by firms have fallen is that an increasing share of the workforce is classified as contractors.<sup>4</sup>

Reporting requirements also depend on worker classification and firm location. Firms issue forms that summarize annual income to all workers—a Form W2 for

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<sup>1</sup>Many localities levy income tax. Appendix Table 1.11 reports a count of localities by state.

<sup>2</sup>Generally, workers who receive benefits and over whom the firm has control are employees. The IRS has guidelines for distinguishing employees from contractors: <https://www.irs.gov/businesses/small-businesses-self-employed/independent-contractor-self-employed-or-employee>.

<sup>3</sup>State legislation may soon require firms outside the city to withhold and remit income tax on behalf of Detroit residents. See House Bill 4829 of 2015: <http://legislature.mi.gov/doc.aspx?2015-HB-4829>.

<sup>4</sup>“Detroit Chief Financial Officer John Hill blamed the [revenue] shortfall on a reduction in income tax withholding by employers in the city. In February, he told the Financial Review Commission, the state board overseeing Detroit’s fiscal affairs post-bankruptcy, that he believes a fair number of the new workers downtown are contract workers.” *Detroit Free Press*, March 7, 2015.

employees and a Form 1099 for contractors. A taxpayer must include a copy of W2s and 1099s she received when she files a tax return with the city. A firm located in Detroit must report to the city the income and withholding information from any W2 or 1099 forms it issues. A firm located outside Detroit is not required to report income earned by Detroit residents.

Tax enforcement in Detroit is severely limited by administrative capacity. Detroit struggles just to process returns submitted on time by compliant taxpayers.<sup>5</sup> Around the time of Detroit's bankruptcy in July 2013, lawyers for the city who wanted to sue taxpayers with known tax due were limited by the court, which had insufficient staff to process more than five such cases per week. Prior to tax year 2015, Detroit did not accept electronic returns; taxpayers were required to mail a paper return to a post office box or deliver a paper return in person to the municipal center.<sup>6</sup>

Within these limits, Detroit does audit tax returns, but not the same way as the IRS. For tax year 2014, Detroit contracted with Chase Bank to scan and manually key tax returns into a data file, which was then loaded into proprietary software called CityTax. City auditors can check information from returns in CityTax against information on federal income tax returns that are shared with Detroit by the IRS.<sup>7</sup> Whereas IRS audits often independently verify information supplied by a taxpayer, the vast majority of Detroit audits currently go no further than comparing the information in the city return to the information in the federal return. Information on

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<sup>5</sup>"Taxpayers often wait months or even years before their refund checks arrive." *Detroit Free Press*, March 7, 2015.

<sup>6</sup>Detroit's tax administration is changing. In recognition of capacity constraints, Detroit turned over primary responsibility for processing city returns to the state beginning with tax year 2015. Even as Detroit ceded some responsibility to Michigan, the city maintained its own compliance and enforcement apparatus. The sample in this paper is for tax year 2014, for which the city retained full responsibility.

<sup>7</sup>The IRS shares federal tax information with state and local governments for the purpose of tax enforcement. Third party information reporting is an important mechanism of tax enforcement, as noted by, for example, Erard and Ho (2004) and Pomeranz (2015). This context is somewhat unusual because the "third party" is another level of government.

the federal return is treated as verification.

Michigan gives cities legal tools for income tax enforcement. A city tax authority is permitted to examine records that will help it to assess tax liability, including the tax liability of individuals who did not file a return but are believed to owe income tax. The city does not have automatic subpoena power over records, but it can sue noncompliant individuals in court to compel documents. Willful failure to file a return, remit tax owed, or permit the tax authority to examine records is a misdemeanor.<sup>8</sup>

Detroit has two available pathways for pursuing identified individuals who have not filed a tax return. The first pathway is to send a “proposed assessment” to the taxpayer based on the city’s belief of what the taxpayer owes. If the taxpayer receives and does not dispute the proposed assessment, the tax debt becomes official. If the taxpayer then does not remit the tax debt, Detroit sends the debt to a collection agency. The second pathway is a criminal procedure. The city can charge an individual who fails to file a tax return with a misdemeanor. For many years, Detroit has used the first pathway exclusively—issuing proposed assessments and forwarding unpaid tax debt to a collection agency.

As part of the proposed assessment pathway, the city must be able to prove that the taxpayer received the proposed assessment in order for the tax debt to become official. There is no such notification requirement for the city to charge taxpayers with a misdemeanor. To be courteous and reduce enforcement costs, city administrators prefer to communicate with taxpayers prior to charging them with a misdemeanor, but Detroit is under no legal obligation to do so. The city’s burden of ensuring the taxpayer is notified when it pursues the proposed assessment pathway may have led

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<sup>8</sup>City Income Tax Act of 1964, Act 284 at 141.673 and 141.699: <https://legislature.mi.gov/documents/mcl/archive/2014/May/mcl-Act-284-of-1964.pdf>.

taxpayers to believe that they could avoid getting in trouble by refusing to accept the treatment letter, which was sent via certified mail and therefore required a signature for delivery.

### 1.2.2 Filing decision

The logic of the standard model of income reporting can be naturally extended to the decision whether to file a return. In the standard model of Allingham and Sandmo (1972), taxpayer reports depend on the probability of audit and the penalty for a false report. In an extension by Erard and Ho (2001), taxpayer choice of whether to file a return depends on the probability of detection and the penalty for nonfiling. One suspects that Detroit residents and workers correctly perceive that the probability of punishing nonfilers is low. However, the statutory penalty for failing to file an income tax return is substantial: a fine of up to \$500 and up to 90 days in jail.

The extended model of filing a return includes compliance costs, which appear to be important in Detroit. Many workers who are owed a refund from the city, because they have income tax withheld from their paychecks exceeding tax liability, still fail to file a return. The standard model cannot explain this behavior. It is possible that some of these workers decide not to claim a refund as a form of “donation” to the city, but it seems likely that compliance costs are more important. Compliance costs should be at least as large for taxpayers with tax due as it is for taxpayers who are owed a refund. So taxpayers with tax due are discouraged from filing a return both by the prospect of remitting tax and by the compliance costs.

There may also be nontax reasons to avoid truthfully reporting residence. For instance, car insurance rates are particularly high in Detroit, higher than in districts immediately adjacent to the city.<sup>9</sup> A resident of downtown Detroit would save money

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<sup>9</sup>According to [carinsurance.com](http://carinsurance.com), the average annual auto insurance rate was \$1,400 higher

on car insurance by claiming residence at a suburban address. Workers may believe their true residence is more likely to be detected by the car insurance company if it is truthfully reported on an income tax return. To the extent that truthfully reporting residence is necessary for renters or homeowners insurance, desire for those insurance services could act in the opposite direction. So the decision not to file a return may be jointly determined by considerations of the probability of detection by the tax authority, the penalty for detection, compliance costs, and nontax reasons for claiming residence in a particular location.

It is also possible that failure to file a return is not the result of a conscious decision or optimizing behavior. Some taxpayers may mistakenly believe that they filed a city return electronically. Many taxpayers file federal and state returns electronically, but Detroit did not accept city tax returns electronically prior to tax year 2015. If taxpayers use tax preparation software, they may think they are done with all of their federal, state, and local returns when they click the submit button, but that is not true if they owe Detroit income tax. Detroit only processes income tax returns that are mailed to a post office box or hand delivered. Furthermore, some Detroit residents and workers, especially those new to the area, may honestly be unaware that Detroit has an income tax.<sup>10</sup>

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in central Detroit than in selected suburbs adjacent to Detroit. Reported auto insurance rates are averages by zip code for a 2014 Honda Accord for a single 40-year-old male with a clean record and good credit. The average rates in central Detroit were \$4,846 in Downtown (zip code 48226), \$5,025 in Midtown (48201), \$4,945 in New Center / North End (48202), \$4,827 in Downtown (48207), and \$4,636 in Corktown / Woodbridge (48216). The average rates in selected suburbs were \$3,491 in Southfield (48075), \$3,489 in Oak Park (48237), \$2,621 in Ferndale (48220), \$3,139 in Grosse Pointe (48230), and \$4,256 in Dearborn (48126).

<sup>10</sup>Awareness of Detroit's income tax seems comparable to awareness of city income tax in Ohio cities Cincinnati and Columbus, judging by an index of search interest from Google Trends. See Appendix Figure 1.7. Hoopes, Reck, and Slemrod (2015) discuss tax enforcement with uninformed taxpayers.



### 1.2.3 Nonfiler population size

In designing a tax enforcement approach to nonfilers, it would be helpful to know how many nonfilers there are. That would be easy for a tax administrator to calculate if she knew who is in the tax base and who filed tax returns. The identity of filers is known, but the identity and size of the tax base is unknown. Detroit's income tax base consists of residents and workers whose income exceeds the exemption amount.<sup>11</sup>

I estimate the number of people who owed Detroit income tax for tax year 2014 to be approximately 387,000. To calculate this figure, I use the Current Employment Statistics (CES) program of the Bureau of Labor Statistics to estimate the number of people who work in Wayne County and the number of employed Wayne County residents. I then utilize Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics from the Census Bureau to estimate Detroit's share of workers in Wayne County and Detroit's share of employed residents of Wayne County. Table 1.1 shows that the estimated income tax base of Detroit was 387,000 people when these shares from LEHD are applied to the workforce of Wayne County from CES.

For a given tax year, the population of nonfilers shrinks over time because many individuals file city tax returns months or years late. The population of nonfilers for a given tax year is thus a moving target. For example, Detroit received 155,000 tax year 2011 returns on time by April 2012, 42,000 additional tax year 2011 returns over the next 12 months by April 2013, 12,000 additional tax year 2011 returns by April 2014, and 3,000 additional tax year 2011 returns by April 2015. Filing patterns are similar for other tax years. For the purpose of cross-year comparisons, it is therefore important to specify the date on which the population is being measured.

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<sup>11</sup>The exemption amount is \$600 per filer, spouse, and dependent.

Table 1.1: Estimated Detroit Tax Base

Year	Detroit residents who work in Detroit	Detroit residents who work elsewhere	Nonresidents who work in Detroit	Total
2012	68,970	191,878	121,542	382,389
2013	66,468	191,176	123,256	380,901
2014	67,562	194,144	125,398	387,103

Note: Estimates of Detroit resident-workers, nonresident workers, and worker nonresidents are obtained by applying Detroit shares of Wayne County workers and employed residents to the workforce of Wayne County. Detroit shares of Wayne County workers and employed residents are from the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics from the Census Bureau. Wayne County workforce is from the Current Employment Statistics (CES) program of the Bureau of Labor Statistics.

As of April 2016, when the field experiment began, I estimate the number of people who were Detroit nonfilers for tax year 2014 to be 179,000. The estimate comes from subtracting the actual number of people in the tax base who filed returns from the estimated total number of people in the tax base. That estimate implies that 46% of individuals who were required to file Detroit tax returns failed to file a return. Assuming 40% of joint returns have two earners, as in Table 1.2, and that 17.3% of nonfilers would file joint returns, there were 167,000 missing returns, equal to 48% of required returns.<sup>12</sup>

A notable source of uncertainty is the number of joint filers who earned income. When all income is reported by third parties to the tax authority on Form W2 for employees and Form 1099 for contractors, then the tax authority knows whether one or both individuals in a couple filing jointly are among the 387,000 individuals in the tax base. However, for income with no third-party reporting, there is no way to know whether each individual is in the tax base. Table 1.2 shows the computation of nonfilers by subtracting the number of people in the tax base who filed returns

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<sup>12</sup>Erard et al. (2014) estimate there were 7.6 million federal individual income tax nonfilers in 2012 (6.1% of required returns). Among suspected resident nonfilers identified from federal income tax returns, 17.3% filed joint federal returns.

from the number of people in the tax base.

This section provided context for the controlled field experiment by describing the income tax system in Detroit, identifying factors that influence the failure of a taxpayer to file a return, and estimating the size of Detroit’s nonfiler population. The next section explains the design of the experiment.

## **1.3 Design of a controlled field experiment**

### **1.3.1 Sample**

A sample of 9,523 individuals for the field experiment was randomly selected from the population of 42,754 suspected nonfilers who met the following sample selection criteria: (1) The IRS identified the individual as a federal taxpayer with a Detroit residence and income taxable to Detroit in tax year 2014. (2) Detroit had no record of the individual filing a 2014 city income tax return as of April 2016. (3) Detroit estimated the individual had 2014 tax due to the city of at least \$350. (4) Detroit had no record of the individual passing away or filing for bankruptcy. (5) The individual’s address appeared to be valid.<sup>13</sup> Of the 185,137 taxpayers who met the first two criteria, approximately 135,000 were eliminated from consideration by the third criterion because Detroit estimated the individual had 2014 tax due to the city of less than \$350.

Detroit estimates tax due from nonfilers using an algorithm that includes federal income information from the IRS and local withholding information from city employers. The city’s algorithm for estimating tax due is correct within \$15 of reported tax due for 70% of taxpayers who file both local and federal returns. Incomplete

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<sup>13</sup>To avoid pursuing individuals who were not actually Detroit residents, addresses were excluded if they had a zip code that is shared between Detroit and another city (e.g. Highland Park). To reduce the nondelivery rate, addresses were excluded if they had a street name that was not shared by other federal taxpayers, on the grounds that it was likely to be an erroneous address.

Table 1.2: Estimated Detroit Nonfilers

Year	Individuals in Detroit tax base	Returns filed	Joint returns	Joint returns with two earners	Nonfilers
2012	382,389	205,275	82,046	32,135	144,979
2013	380,901	193,455	77,084	31,133	156,313
2014	387,103	178,859	72,843	28,847	179,397

Note: Individuals in Detroit tax base (column 2) is author’s estimate explained in the text and Table 1.1. Returns filed (column 3) includes resident, non-resident, and partial-year returns. A return is considered to be a joint return (column 4) if it was marked as such by the taxpayer. A return is considered to be a joint return with two earners (column 5) if there was a W2 associated with the “secondary” social security number. Nonfilers (column 6) is equal to the size of the tax base (column 2) less the number of returns (columns 3) and the number of joint returns with two earners (column 5).

withholding information from employers causes discrepancies between Detroit’s estimation of tax due and actual tax due. Detroit’s estimation of tax due is too high for nonfilers with employers who did not submit W2s to the city electronically.<sup>14</sup> Two sources of income—active duty military pay and pension income—also cause discrepancies between Detroit’s estimation of tax due and actual tax due. Detroit’s estimation of tax due is too high for nonfilers with these types of income.<sup>15</sup>

Detroit excluded taxpayers with addresses that were likely to be invalid. For prior tax years, Detroit sent tens of thousands of letters to nonfilers, thousands of

<sup>14</sup>Detroit accepts W2s from employers in electronic (online or CD) and paper format. Around 4% of the 12,700 employers who file an annual report with individual income tax withholding do so electronically. If an employer submitted a W2 electronically, then Detroit used the withholding amount for the nonfiler to estimate tax due. W2s that were submitted in paper form only were not digitized or used to estimate individual income tax due. By dollar value, around 20% of tax prepayments reported on city returns, including employer withholding and estimated payments from business income, are visible to the tax division and able to be connected to the taxpayer before receiving the city return.

<sup>15</sup>Active duty military pay appears as wage (W2) income on a federal 1040. It is taxable income to the federal government, but it is not taxable income to Detroit. Detroit cannot systematically distinguish between active duty military pay and other wage income, although it can request that information for individual taxpayers. Similarly, pension income appears as other (1099-MISC) income on a federal 1040. It is taxable income to the federal government, but it is not taxable income to Detroit. As with military pay, Detroit cannot systematically distinguish between pension income and other income from a 1099-MISC, although it can request that information for individual taxpayers.

which were returned as undeliverable. For tax year 2014, Detroit used a filter on addresses that marked about 7% of IRS addresses as likely to be invalid prior to sample selection. The United States Postal Service contracts with private vendors to offer paid address verification services, but Detroit does not pay for those services.

Table 1.3 reports summary statistics for individuals who filed a federal return in tax year 2014 with a Detroit address by local filing status, sample eligibility, and sample selection. Among federal filers, individuals who failed to file a city return were younger on average and more likely to file as a head of household. Local nonfilers had lower income, and they were much more likely to have been identified by Detroit as a nonfiler for a tax year prior to 2014. Around 84% of nonfilers in the sample were also identified as a nonfiler for a prior year.

### **1.3.2 Experimental treatments**

Taxpayers in the sample were sent two separate mailings in sequence, one week apart. The first mailing was a postcard, and the second mailing was a letter.<sup>16</sup> The postcard listed the types of income that are taxable by Detroit and directed taxpayers where to find tax forms and filing instructions. The letter informed the nonfiler that Detroit believes they had taxable income and failed to file a city tax return for tax year 2014. Taxpayers were randomly assigned to a treatment status, which varied the content of a prominent box in both the postcard and the letter. Table 1.4 reports the message associated with each treatment status. Examples of postcards and letters are in Appendix Figure 1.8.<sup>17</sup>

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<sup>16</sup>To track delivery, the letters were sent via United States Postal Service certified mail. Certified mail requires a signature for delivery, either in person or on a card left by the letter carrier.

<sup>17</sup>This study was submitted for approval to the University of Michigan Health Sciences and Behavioral Sciences Institutional Review Board. The IRB determined that this study had a status of “Not Regulated”.

Table 1.3: Summary Statistics (TY 2014)

	Filer		Nonfiler		Population		Sample	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Age	50.2	15.4	44.8	17.5	39.6	12.0	39.6	12.0
FS = single (%)	46.4	49.9	43.4	49.6	39.4	48.9	39.2	48.8
FS = married filing jointly (%)	26.9	44.3	17.3	37.8	10.6	30.8	10.8	31.0
FS = head of household (%)	24.3	42.9	37.9	48.5	48.6	50.0	48.6	50.0
Years identified as nonfiler	3.5	2.2	4.1	2.4	4.3	2.5	4.3	2.5
Filed in 2012 or 2013 (%)	82.4	38.1	15.2	35.9	23.3	42.2	22.4	41.7
Total income (\$ 000s)	57.0	91.6	40.1	175.3	33.9	42.6	33.4	24.7
Wage income (\$ 000s)	44.4	61.3	27.5	80.2	31.4	23.3	31.3	23.7
Log total income	10.3	0.7	10.0	0.5	10.3	0.5	10.3	0.5
Nonzero nonwage income (%)	36.4	48.2	42.9	49.5	29.5	45.6	29.5	45.6
Observations	61,632		185,342		42,754		9,523	

Note: This table reports means and standard deviations of taxpayer characteristics from administrative tax data. “Filers” are taxpayers identified by the IRS as Detroit residents who filed both a federal return and a city return for tax year 2014. “Nonfilers” are taxpayers identified by the IRS as Detroit residents who filed a federal return but not a city return for tax year 2014. “Population” is the subset of Nonfilers who met all five sample selection criteria, including estimated tax due of at least \$350. “Sample” is the subset of Population that was randomly selected for the experiment.

*Penalty salience.* One treatment status tested whether penalty salience affects tax compliance. The boxed message stated that failure to file a tax return is a misdemeanor, and the statutory penalty for the misdemeanor is a fine of up to \$500 and 90 days in jail. Absent this treatment, the statutory penalty was almost certainly unknown by the vast majority of Detroit residents. The city had not prosecuted anyone under the misdemeanor provision for many years. The message in this treatment status was not phrased as a threat, but it is comparable to other field experiments that test “threats” of various sorts.<sup>18</sup>

*Punishment probability.* Another treatment status was intended to affect the perceived probability of punishment. The boxed message revealed that Detroit knew the recipient’s total federal income, which is among the information provided by the IRS to Detroit. The rationale for this treatment is that a taxpayer will feel punishment is more likely if the tax authority reveals that it has relevant information. Revealing this information is intended to raise the perceived probability of punishment, rela-

<sup>18</sup>The “threat” treatment in Chirico et al. (2015) actually uses threatening language. Most other threat treatments are based on the threat of auditing a return, rather than the threat of punishment if no further action is taken.

Table 1.4: Experimental treatments

Treatment	Intervention	Message in prominent box on letter <sup>a</sup>
Penalty salience	Postcard and letter	Failure to file a tax return is a misdemeanor punishable by a fine of \$500 and 90 days in jail.
Punishment probability	Postcard and letter	Our records indicate you had federal total income of \$X for tax year 2014. <sup>a</sup>
Compliance cost	Postcard and letter, form and return envelope enclosed with letter	For your convenience, City Income Tax Form D-1040(R) is enclosed with this letter. <sup>a</sup>
Civic pride	Postcard and letter	Detroit's rising is at hand. The collection of taxes is essential to our success.
Penalty salience × Punishment probability	Postcard and letter	Our records indicate you had federal total income of \$X for tax year 2014. Failure to file a tax return is a misdemeanor punishable by a fine of \$500 and 90 days in jail. <sup>a</sup>
Contact-only (control)	Postcard and letter	None
No-contact (control)	None	N/A

Note: This table describes the experimental treatments. 1,200 taxpayers were assigned to each experimental treatment other than the no-contact control, to which 2,400 taxpayers were assigned.

<sup>a</sup> The boxed message was exactly the same on the postcard and the letter within each treatment other than the punishment probability treatments and the compliance cost treatment. In the punishment probability treatments, the boxed message on the postcard was, "The letter you receive will indicate how much taxable income you had in tax year 2014." In the compliance cost treatment, the boxed message on the postcard was, "For your convenience, City Income Tax Form D-1040(R) will be enclosed with the letter."

tive to the letters that do not reveal that Detroit has information about the taxpayer other than name and address.

*Compliance cost.* The cost to the taxpayer of filing a return was reduced by a treatment status that enclosed a blank tax form and a return envelope. The enclosed return was for Detroit residents for tax year 2014, Form D-1040(R).<sup>19</sup> The boxed message referred to the tax form as being provided for the convenience of the recipient. Although the monetary cost of the form and envelope is small, the nonmonetary cost could be substantial, including the time and effort to find the form online or retrieve it from the Coleman A. Young Municipal Center in downtown Detroit.

*Civic pride.* One set of mailings tested the effect of an appeal to civic pride. The boxed message proclaimed the importance of tax collection to the resurgence of Detroit. This is the first moral appeal of its kind, but it is not the only type of moral appeal that is potentially relevant in communication with taxpayers. In similar tax enforcement field experiments, moral appeals to taxpayers have (1) reminded taxpayers of services provided by tax dollars, (2) informed taxpayers about the compliance rate of their neighbors, and (3) referred to a general principle of equity or fairness.

*Penalty salience  $\times$  punishment probability.* The messages in the penalty salience treatment status and the punishment probability treatment status were combined in a separate treatment group. The boxed message stated the taxpayer's income first, then the penalty. Standard theory about the decision to file suggests that the interaction between penalty salience and punishment probability should be important. If the other treatments are effective and operate through the intended channel of raising the perceived penalty and probability of punishment, then we would expect

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<sup>19</sup>The individual income tax form for nonresidents, Form D-1040(NR), was sent to some nonfilers in the experiment in place of the tax form for residents.



the interaction treatment to elicit a higher response than either by itself.

*Control.* Two groups of nonfilers were assigned to “control” groups. One group received no contact at all, and the other group was sent mailings with the prominent box omitted from both the postcard and the letter. There is considerable evidence that taxpayers respond to any kind of contact from the tax authority, probably because it alerts the taxpayer that the tax authority can monitor their behavior, so it is important to isolate the effect of the contact-only mailings from the effect of the particular messages in the other treatment groups.<sup>20</sup>

From the population of 42,754 nonfilers that met the sample selection criteria, 1,200 individuals were randomly selected for each of the 6 treatment groups that received letters (including the contact-only control group), and 2,400 individuals were randomly selected to be in a no-contact control group. To stay within the limits of the Detroit tax division’s administrative capacity, the postcards and letters were sent in staggered batches.<sup>21</sup> Each batch had an approximately equal number of nonfilers from each treatment group. Individuals in the no-contact group were assigned to batches as if they were being sent postcards and letters. There were 119, 581, 2,160, 2,160, and 2,160 individuals in batches one through five, respectively.<sup>22</sup> The treatment groups are not exactly the same size because the city’s address filter was refined shortly before sending the second batch. Also, individuals were removed from the sample if they filed a city tax return between the time the sample was selected and the time the postcards were mailed. Individuals removed from the

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<sup>20</sup>Chirico et al. (2015) and Fellner, Sausgruber, and Traxler (2013) describe field experiments that used similar contact-only letters to isolate the response to particular messages from the response to contact from the tax authority.

<sup>21</sup>The tax division reports that it was unable to handle the phone calls that resulted from large batches (tens of thousands) of similar letters to nonfilers in past years. That likely dampened response rates and the effectiveness of contact. Therefore, in this field experiment, postcards and letters were dispersed in batches.

<sup>22</sup>Postcards were sent on April 18, May 2, May 16, June 1, and June 13-15. Letters were sent on April 25, May 9, May 24-26, June 9, and June 23.

sample were replaced with other individuals randomly selected from the population of nonfilers whenever possible. Appendix Table 1.12 reports summary statistics by treatment status.

This field experiment was accompanied by another change that may have affected response rates. The State of Michigan took responsibility for processing individual City of Detroit income tax returns for tax year 2015. The state did not take any responsibility for past returns, so there is no direct impact on tax year 2014 returns. The shift to processing tax returns by the state was not directly related to this experiment, although both were motivated by a desire by city administrators to improve the efficiency of tax enforcement. There is no reason to think that nonfilers in one treatment status had a different level of exposure to this change than nonfilers with a different treatment status.

## 1.4 Results

Table 1.5 summarizes the response of nonfilers to mailings in the field experiment. Of the 7,142 taxpayers in the sample to whom mailings were sent, 450 taxpayers (6.3%) responded by filing a return within 75 days of the initial mailing. Even though the mailings only mentioned tax year 2014 specifically, many taxpayers filed returns for multiple years, such that the number of returns per filer was 1.16.<sup>23</sup>

Inclusion in the sample was conditional on the city estimating tax due above \$350, but 34% of returns nevertheless claimed a refund.<sup>24</sup> Of returns claiming refunds, the average refund size was \$75. About half of the returns that were filed admitted tax

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<sup>23</sup>When a taxpayer calls or visits the tax division, staff instruct the taxpayer to file returns for all missing years.

<sup>24</sup>The most common discrepancy between estimated and actual tax due is withholding that Detroit did not connect with an individual taxpayer. However, many individuals claimed a refund without enclosing a W2 to prove withholding, and without a W2 the city does not issue a refund.

Table 1.5: Summary of response

	Contact only	Penalty salience	Punishment probability	Compliance cost	Civic pride	Saliency x Probability	All letters	No contact
Sample size	1,185	1,191	1,191	1,189	1,195	1,191	7,142	2,381
Filers	36	120	58	74	46	116	450	7
Returns filed	39	153	69	83	50	129	523	7
Claiming refund	16	44	19	34	21	41	175	5
Admitting tax due	15	80	37	30	18	62	242	2
Remitting payment	10	44	19	16	10	36	135	1
Total claimed (\$)	758	3,092	834	3,367	1,276	3,782	13,109	297
Total admitted (\$)	6,183	33,413	11,494	9,388	11,804	19,360	91,642	1,720
Total remitted (\$)	5,046	17,237	4,353	2,157	4,278	9,641	42,712	1,690
Filed % of sample	3.0	10.1	4.9	6.2	3.8	9.7	6.3	0.3
Returns per filer	1.08	1.27	1.19	1.12	1.09	1.11	1.16	1.00
Refund % of returns	41.0	28.8	27.5	41.0	42.0	31.8	33.5	71.4
Tax due % of returns	38.5	52.3	53.6	36.1	36.0	48.1	46.3	28.6
Payment % of returns	25.6	28.8	27.5	19.3	20.0	27.9	25.8	14.3
Avg refund claimed (\$)	47.38	70.27	43.89	99.03	60.76	92.24	74.91	59.40
Avg due (\$)	412.20	417.66	310.65	312.92	655.78	312.26	378.68	860.00
Avg remittance (\$)	504.60	391.75	229.11	134.81	427.80	267.81	316.39	1690.00
Claim per letter (\$)	0.64	2.60	0.70	2.83	1.07	3.18	1.84	0.12
Due per letter (\$)	5.22	28.05	9.65	7.90	9.88	16.26	12.83	0.72
Remit per letter (\$)	4.26	14.47	3.65	1.81	3.58	8.09	5.98	0.71

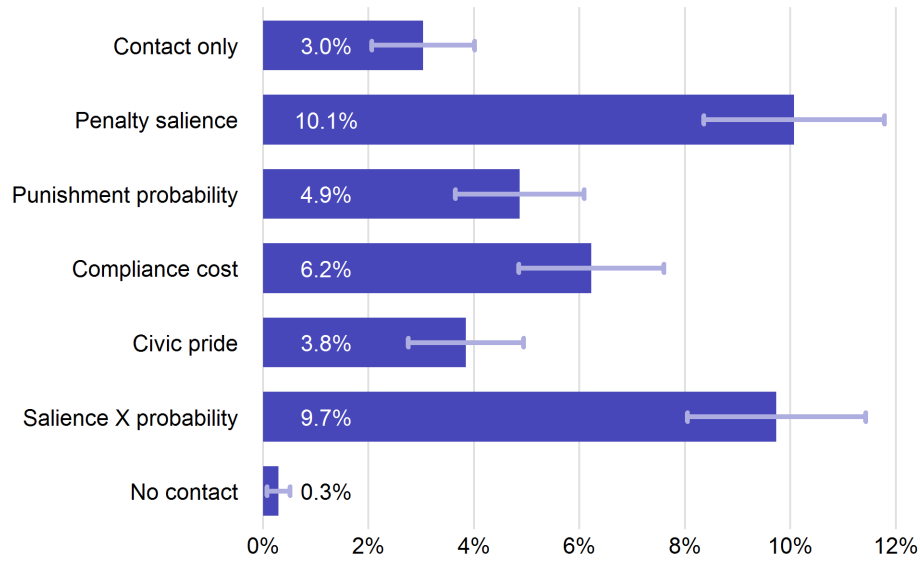
Note: This table reports summary statistics for responses within 75 days of sending the postcard. It includes information from returns received through the income tax division's post office box and returns processed by Chase Bank. Initially, 1,200 taxpayers were selected to be sent each of the treatment mailings. A few taxpayers were removed without being replaced because the city refined its address validity criteria, and a few taxpayers were removed without being replaced because they filed a tax return shortly before the postcard would have been sent.

due, and on returns that admitted tax due the average due was \$379. Taxpayers are instructed to remit payment along with the return, but only 56% of returns that admitted tax due were accompanied by a remittance. The average remittance was \$316. The sum of refunds claimed by taxpayers who received mailings was \$13,109, the sum of tax due admitted was \$91,642, and the sum of payments remitted was \$42,712.

### 1.4.1 Response to mailings

Figure 1.1 shows the fraction of sampled suspected resident nonfilers who filed a return within 75 days of the initial mailing. The penalty salience mailing elicited the

Figure 1.1: Response rate by treatment status



Note: This figure shows response rates by treatment status, where a response is filing a return within 75 days of the initial mailing. Standard error bars show 95% confidence intervals. Appendix Table 1.12 reports summary statistics by treatment status.

highest response rate (10.1%), followed by penalty salience  $\times$  punishment probability (9.7%), compliance cost (6.2%), punishment probability (4.9%), civic pride (3.8%), and contact-only (3.0%) mailings. The individuals in the no-contact control group, of course, did not receive a letter, and the “response” rate of filers as a percent of the no-contact sample was 0.3%. Each individual in the no-contact control was assigned to a batch of outgoing postcards, so a return from a no-contact individual is considered to be a response if it is received within 75 days of the date the postcards were sent to that batch, just as if the individual had been sent a postcard.

Table 1.6 reports the estimated effects of sending experimental mailings on response rates. In this experiment, estimating the effect of sending experimental mailings on filing behavior is straightforward because suspected resident nonfilers were randomly selected into treatments. To control for other characteristics that may impact response rates, treatment effects are estimated using the linear probability

model

$$\mathbb{P}[\text{response}_i = 1] = \alpha + \sum \beta^j \text{treatment}_i^j + \gamma X_i, \quad (1.1)$$

where indicator variables denoting treatment status  $j$  ( $\text{treatment}_i^j$ ) predict the probability that taxpayer  $i$  filed a return, with  $\text{response}_i$  equal to one if the taxpayer filed a return and zero otherwise. A vector of taxpayer characteristics  $X_i$  includes age, filing status, filing history, log income, and a dummy indicator for the presence of nonwage income. Treatment effects are estimated relative to the excluded no-contact control condition, in which taxpayers were not sent any mailings. In Table 1.6, the dependent variable is scaled by a factor of 100 so that coefficients can be read in percentage points.

Column 5 of Table 1.6 reports the response rate to treatment mailings with the full set of controls. A mailed penalty salience letter raised response rates by 9.9 percentage points relative to the no-contact control, about 3.5 times the effect of the contact-only letter, which raised response rates by 2.8 percentage points. A mailed penalty salience  $\times$  punishment probability letter raised response rates by 9.5 percentage points, the compliance cost letter by 5.8 percentage points, the punishment probability letter by 4.6 percentage points, and the civic pride letter by 3.4 percentage points.

Filing history was a significant determinant of response rates. Taxpayers who had filed a tax year 2012 or 2013 return were 6.5 percentage points more likely to respond to treatment mailings by filing a return. However, taxpayers who had previously been identified as suspected resident nonfilers were less likely to respond to treatment mailings. For each additional year of identification as a suspected resident nonfiler, the conditional expectation of the response rate was 0.5 percentage points

Table 1.6: Response by experimental intervention, linear probability model

	(1)	(2)	(3)	(4)	(5)
	Filed	Filed	Filed	Filed	Filed
<b>Treatments</b>					
Penalty salience	9.78*** (0.88)	9.78*** (0.87)	9.96*** (0.86)	9.76*** (0.87)	9.94*** (0.86)
Punishment probability	4.58*** (0.63)	4.70*** (0.63)	4.55*** (0.63)	4.57*** (0.63)	4.66*** (0.63)
Compliance cost	5.93*** (0.71)	5.92*** (0.70)	5.83*** (0.70)	5.97*** (0.71)	5.86*** (0.70)
Civic pride	3.56*** (0.57)	3.64*** (0.57)	3.34*** (0.56)	3.60*** (0.56)	3.43*** (0.56)
Penalty X punishment	9.45*** (0.87)	9.46*** (0.86)	9.46*** (0.85)	9.52*** (0.86)	9.49*** (0.85)
Contact only	2.74*** (0.51)	2.80*** (0.51)	2.81*** (0.51)	2.79*** (0.51)	2.84*** (0.51)
<b>Other variables</b>					
Age		0.20*** (0.02)			0.16*** (0.02)
FS = single		2.59*** (0.45)			1.47*** (0.47)
FS = married filing jointly		4.75*** (0.92)			2.60*** (0.97)
Years nonfiler			-0.38*** (0.08)		-0.52*** (0.09)
Filer in 2012 or 2013			7.98*** (0.70)		6.35*** (0.69)
Log income				4.32*** (0.55)	1.65*** (0.58)
Nonwage income dummy				1.64*** (0.50)	0.93* (0.50)
Mean of dependent variable	4.80	4.81	4.80	4.80	4.81
Observations	9,523	9,508	9,523	9,523	9,508
$R^2$	0.027	0.048	0.056	0.040	0.072
Batch fixed effects		X	X	X	X
<b>p-value of F-test on:</b>					
Civic pride = Contact only	0.28	0.26	0.47	0.27	0.42
Penalty salience = Sal x Prob	0.78	0.79	0.67	0.84	0.70
Fixed effects joint significance		0.16	0.09	0.14	0.08

Note: This table estimates the response of nonfilers to experimental treatments using ordinary least squares regressions. The dependent variable is a dummy indicator (scaled by 100) for whether the suspected resident nonfiler filed a city income tax return within 75 days of the initial mailing. Mailings were sent in five batches in April–June 2016. Age is not observed for 0.2% of taxpayers in the sample. Heteroskedasticity robust standard errors in parentheses. Coefficients are significantly different from zero at the \*10%, \*\*5%, or \*\*\*1% significance level.

lower.

Income was positively associated with response rates. For each point of log income, taxpayers were 1.6 percentage points more likely to respond. Taxpayers with nonzero nonwage income were 0.9 percentage points more likely to respond. Because a large portion of tax liability attributable to wage income had withholding, taxpayers with nonwage income are more likely to have net liability substantially different from zero. Taxpayers with negative nonwage income are likely to be owed a refund, and taxpayers with positive nonwage income are likely to have tax due. A higher response rate of taxpayers with nonzero nonwage income is consistent with an attitude that filing taxes is more important when there is a substantial net obligation.

#### **1.4.2 Letter delivery and response to postcard**

Many intended recipients never received the treatment letter. Table 1.7 reports the delivery status according to the USPS tracking website six months after the letters were sent. Across all treatments, 55.3% of letters had a status of delivered, 25.8% were listed as unclaimed, 11.5% were listed as undeliverable, and 7.3% were listed as in transit. The volume of letters that were still listed in some stage of transit six months after the letters were sent is an indication of reporting error. Letters with a status of delivered or unclaimed had valid addresses or active forwarding addresses and were capable of being delivered. Letters with a status of undeliverable had invalid addresses or inactive forwarding addresses.

A potentially interesting treatment effect is the impact of *receiving* a treatment message, but estimation of this effect is not straightforward. Because the letter was sent via certified mail, we know the subsample of taxpayers to whom the letter was reported on the USPS tracking website as delivered. However, treated taxpayers were first sent a postcard and then a letter via certified mail, so they had an oppor-

Table 1.7: Nonfiler letter delivery rates

Treatment status	Delivered		Unclaimed		Delivery status				Total	
					Undeliverable	In transit				
Contact only	662	55.9%	285	24.1%	149	12.6%	89	7.5%	1,185	100.0%
Penalty salience	670	56.3%	294	24.7%	136	11.4%	91	7.6%	1,191	100.0%
Punishment probability	658	55.2%	334	28.0%	132	11.1%	67	5.6%	1,191	100.0%
Compliance cost	621	52.2%	311	26.2%	168	14.1%	89	7.5%	1,189	100.0%
Civic pride	643	53.8%	343	28.7%	128	10.7%	81	6.8%	1,195	100.0%
Saliency X probability	697	58.5%	279	23.4%	110	9.2%	105	8.8%	1,191	100.0%
Total	3,951	55.3%	1,846	25.8%	823	11.5%	522	7.3%	7,142	100.0%

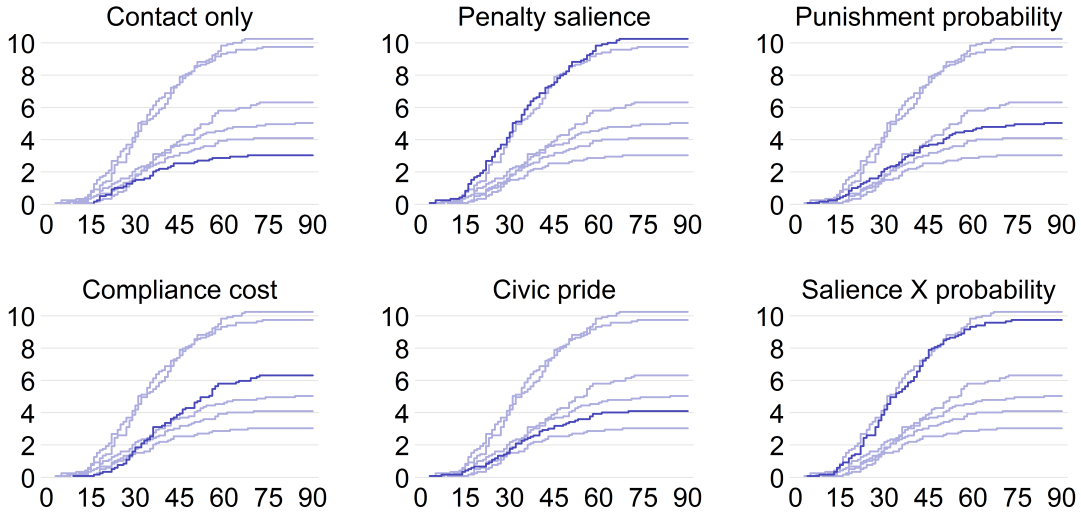
Note: This table reports the delivery status of certified letters according to the USPS tracking website. The F-statistic for equality of delivery rates (delivered % of sample) is 2.24, which is significant at the 5% level. Appendix Table 1.13 reports summary statistics by delivery status.

tunity to decline to authorize delivery of the letter after viewing the postcard, which also had the treatment message and may have induced selection into the delivered subsample. The F-statistic for equality of delivery rates is 2.24, rejecting the null of equal delivery rates at the 5% level. In consideration of possible selection into receipt of the treatment letter, I focus on the effect of an intent to treat, meaning the response rate among the entire sample of suspected resident nonfilers. This can be interpreted as a lower bound on the effect of receiving a treatment message.

In addition to its influence on the rate at which taxpayers authorized delivery of the treatment letter, the postcard also influenced taxpayer behavior directly. The cumulative response rate over time in Figure 1.2 shows that some taxpayers responded to the postcard by filing a return almost immediately, even before the letter was sent a week later. Most returns were filed between 15 and 60 days after the postcard was sent, and very few returns were filed after 75 days. The time pattern of responses was similar across treatment groups, except for the returns filed in response to the compliance cost mailings. The cumulative response rate to the compliance cost mailings was the lowest of all treatment mailings until about 30 days after the postcard was sent, then it rose over the following 15 days to be the third highest response rate. This is likely because the compliance cost postcard announced that the letter would



Figure 1.2: Cumulative response by treatment status



Note: These graphs show the cumulative percent of taxpayers who filed returns. The vertical axis is percent of sample, and the horizontal axis is days elapsed since the date on which the postcard was sent.

enclose a blank tax form, and some taxpayers waited for the blank tax form to be delivered before taking action to respond. The contact-only response rate was zero until a full two weeks after the postcard was sent. This suggests people may not have read or seen the postcard, because the only responses were after the letter arrived. That was the only treatment without a boxed message on the postcard and letter, so it is possible that the box itself, regardless of the content, attracted attention.

### 1.4.3 Response quality

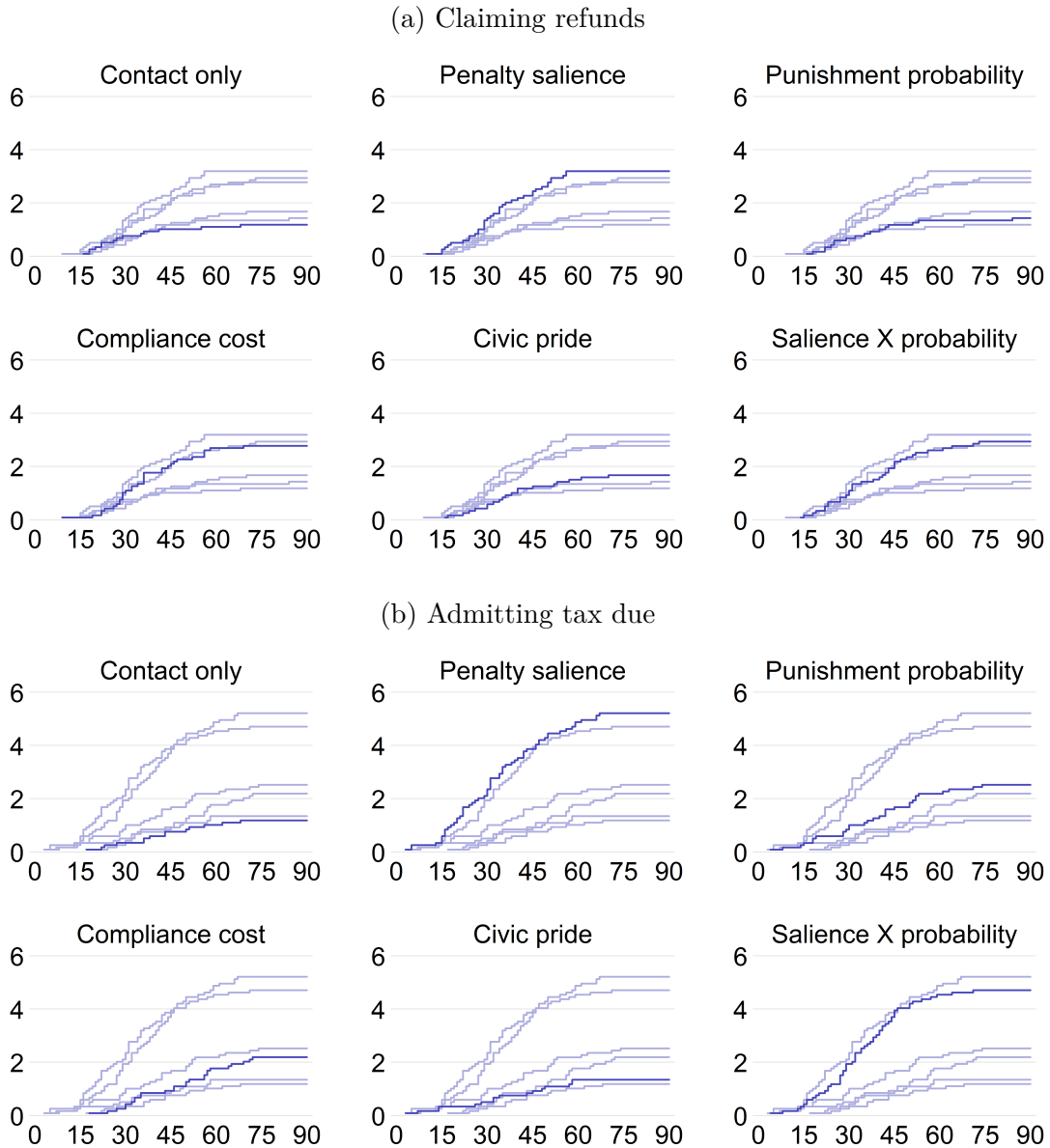
Some types of responses are better than others from an enforcement perspective. For example, a filed return accompanied by a remittance is better for net revenue from enforcement efforts than a filed return that claims a refund. This section reports treatment effects along several dimensions of response quality: the propensity of a filed return to claim a refund or admit tax due, the number of returns per filer, and the dollar amount of net tax due.

Figure 1.3 decomposes cumulative response rates by treatment according to whether the taxpayer had negative or positive net tax due. For the subgroup with positive net tax due, there is a large gap between the two treatments that included the penalty salience message and the four treatments that did not. However, for the subgroup that claimed a refund, the compliance cost treatment elicited nearly the same response rate as the penalty salience treatments. This was likely a composition effect: The compliance cost treatment was as effective as the penalty salience treatment among taxpayers who were owed a refund, but the compliance cost treatment was no more effective than the punishment probability treatment among taxpayers who had tax due.

The penalty salience mailings elicited more returns per filer and more remitted dollars than other treatments. Table 1.5 shows that the penalty salience mailing elicited 1.27 returns per filer, whereas the other mailings elicited just 1.08 to 1.19 returns per filer. The number of returns per filer may have been mediated by direct contact with the tax authority. Taxpayers in the penalty salience treatment group were relatively more likely to call or visit the tax division, and taxpayers who called or visited the tax division were instructed by staff to file all delinquent returns including for tax years other than 2014.

Table 1.5 also shows that taxpayers admitted tax due of \$28.05 on average in response to the penalty salience mailings but just \$5.22 to \$16.26 in response to the other mailings. Similarly, taxpayers remitted \$14.47 on average in response to the penalty salience mailings but just \$1.81 to \$8.09 in response to the other mailings. The difference in remittances and admitted tax due is largely attributable to the difference in response rates. However, the penalty salience  $\times$  punishment probability mailings elicited nearly the same response rate as the penalty salience mailings but still had substantially lower remittances. The average dollar figures are sensitive to

Figure 1.3: Cumulative response by treatment status and net tax due



These graphs show the cumulative response rate. The vertical axis is percent of sample, and the horizontal axis is days elapsed since the date on which the postcard was sent. Panel (a) shows the cumulative percent of taxpayers who filed returns claiming a refund. Panel (b) shows the cumulative percent of taxpayers who filed returns admitting tax due.

outliers, so the response rates are measured more precisely.

#### 1.4.4 Heterogeneity of response

A particular treatment message could be effective for eliciting a return from some taxpayers and not others. Similarly, nonfiler letters overall could be well-suited as an enforcement tool for some taxpayers and poorly-suited for others. To inform the welfare and policy discussion, this section examines heterogeneous response to treatment with respect to filing history, age, and income.<sup>25</sup>

Taxpayers who were identified as nonfilers from federal returns in more years were less likely to respond to experimental mailings. Figure 1.4 shows that this pattern holds across treatments, and it is more pronounced in the treatments that elicited higher response rates.

Older taxpayers responded to experimental mailings at higher rates than younger taxpayers. This was true across all treatments, and the gap was larger for the more effective mailings. To examine the heterogeneity by age, Figure 1.5a plots a fractional polynomial regression of response rate on age within each treatment.<sup>26</sup> Taxpayers under age 40 had a response rate below 10% for the penalty and penalty salience  $\times$  punishment probability treatments and below 5% for the other treatments. Response rates appear to be convex in age, such that response rates increase from age 40 to 50 and increase by even more from age 50 to age 60. By age 70, more than 20% of mailings elicit a return.<sup>27</sup>

Income is highly correlated with age, so it is not surprising that response rates

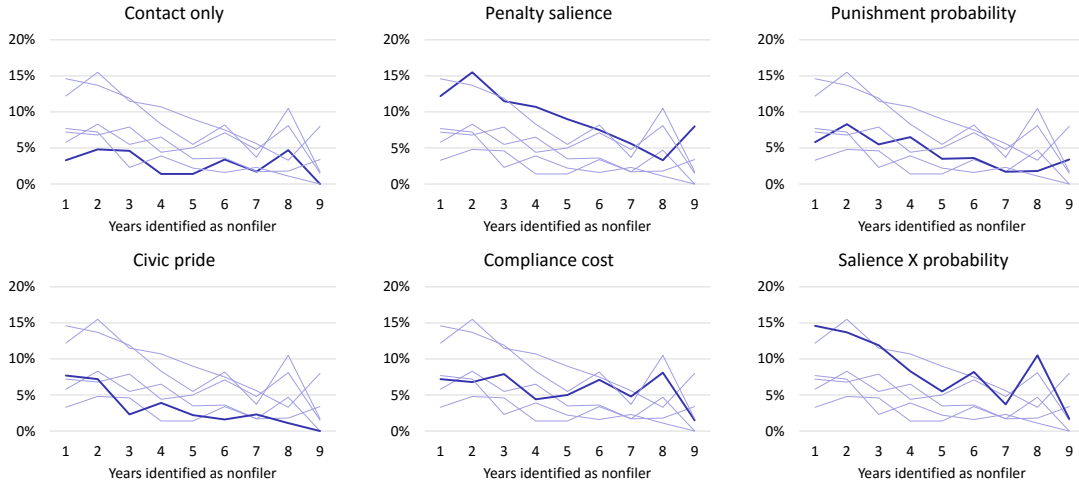
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<sup>25</sup>Appendix Table 1.14 reports response rates by history, age, income, filing status, and treatment batch.

<sup>26</sup>Fractional polynomial regressions find the best fitting polynomial from a predefined set of powers that includes noninteger powers (Royston and Altman 1994). I use the predefined set of powers  $\{-2, -1, -.5, 0, .5, 1, 2, 3\}$ .

<sup>27</sup>Pension income is not taxable for Detroit city income tax. Some taxpayers over age 65 are pensioners, but others are among the highest active earners.

Figure 1.4: Response rate by filing history and treatment

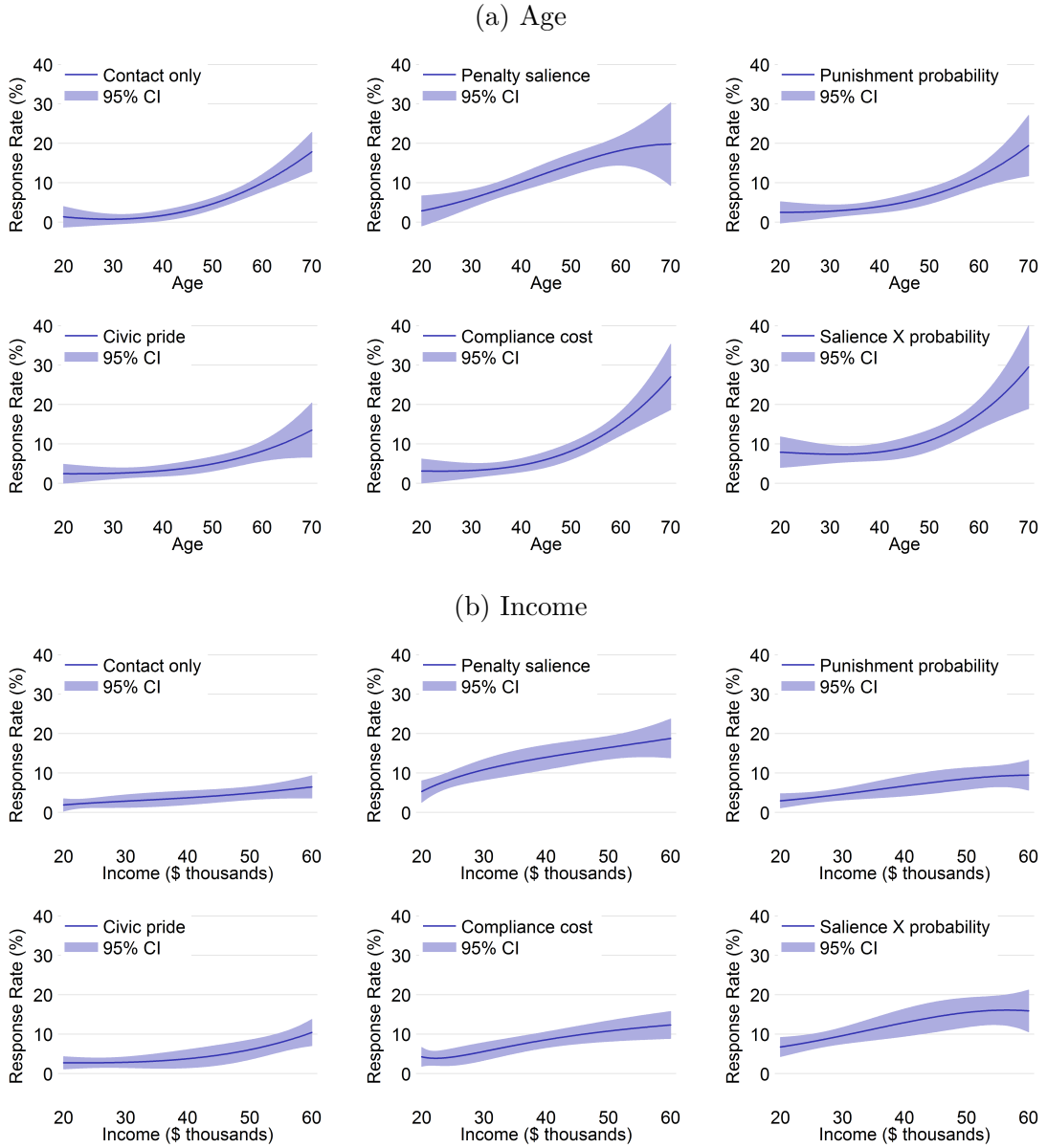


Note: This figure estimates response rate by income using a fractional polynomial regression of response on income.

are higher for taxpayers with higher incomes. This is again true across treatment groups but more pronounced in the more effective treatments. Figure 1.5b plots response rates by income for each of the mailing treatments. The penalty and penalty salience  $\times$  punishment probability treatments elicited higher response rates even from taxpayers earning less than \$30K, whereas most of the gains from the compliance cost and punishment treatments came among taxpayers earning more than \$40K, and the civic pride treatment only raised response rates considerably above \$50K. The contact-only letter was not much more effective with higher-income taxpayers than with lower-income taxpayers.

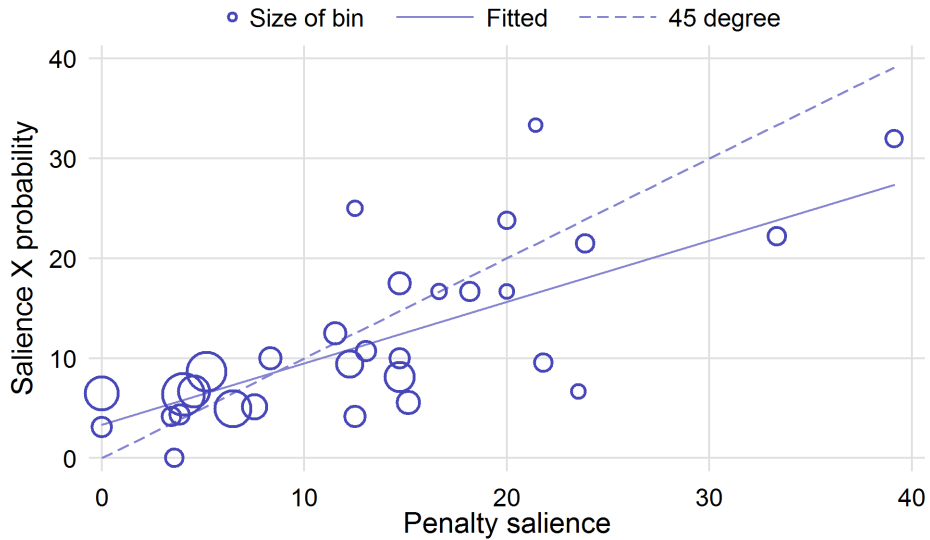
The penalty salience message was the most effective overall, and it was also the most effective within most identifiable subgroups. Figure 1.6 compares the response rates to the penalty salience mailings with the response rates to the penalty salience  $\times$  punishment probability mailings within age-income-filing history bins. The penalty salience message tended to elicit higher response rates in the same bins as the penalty salience  $\times$  punishment probability message. A bubble above the 45 degree line

Figure 1.5: Heterogeneity of response



This figure shows heterogeneity of response rates with respect to age and income. Panel (a) plots a fractional polynomial regression of response rate on age within each treatment. Panel (b) plots a fractional polynomial regression of response rate on income within each treatment. The fractional polynomial regressions find the best fitting polynomial from the predefined set of powers  $\{-2, -1, -.5, 0, .5, 1, 2, 3\}$ .

Figure 1.6: Response rate by age-income-filing history bin



Note: This figure compares response rates to the penalty salience mailings with response rates to the penalty salience  $\times$  punishment probability mailings within age-income-filing history bins. Appendix Figure 1.10 shows the analogous comparison with other treatments. Appendix Table 1.15 reports response rates by treatment and age-income-filing history bin. For defining bins, the three age categories are below 30, 30–50, and above 50. The four income categories are below \$25K, \$25K–\$35K, \$35K–\$50K, and above \$50K. The three filing history categories are 1–2 years, 3–5 years, and 6–9 years identified as a suspected resident nonfiler.

indicates a bin for which the penalty salience  $\times$  punishment probability message was more effective than the penalty salience message. Those bins are candidates for message targeting by demographics. However, the bins for which the response rate is substantially above the 45 degree line are small and thus less precisely measured. The large bins above the 45 degree line are still pretty close to the 45 degree line, so there is not a strong case for using the interaction message with some bins rather than the penalty salience message. The analogous comparisons in Appendix Figure 1.10 lead to the same conclusion, that the penalty salience message is better with most bins and never substantially worse than any of the other treatment messages.

The effects of age, income, filing history, and treatment status appear to be positive even when they are all at play. The response rates by age-income-filing

history bin reported in Appendix Table 1.15 are higher for older taxpayers, higher-income taxpayers, and taxpayers with less history of nonfiling. The highest response rate by a bin to a treatment, 39% to the penalty salience treatment, was by the bin of taxpayers with all three of those characteristics: over age 50 with more than \$50K income who had been identified as a suspected resident nonfiler fewer than three times. The tax authority could thus raise response rates above what was achieved in the sample for any experimental treatment by refining the criteria it uses to contact nonfilers.

#### 1.4.5 Network effects

This section investigates behavioral responses of untreated taxpayers to the experimental mailings. The mailings could have influenced the behavior of untreated taxpayers if, for example, recipients of experimental mailings told their neighbors, relatives, or coworkers that they had been contacted by Detroit’s income tax division. Even a small effect per neighbor can add up to a substantial impact if treated taxpayers have many network connections. In other enforcement contexts, network effects like this appear to be important.<sup>28</sup>

I find weak evidence of a negative geographic spillover effect from penalty salience and punishment probability mailings. For each treated nonfiler, including the no-contact control group, I calculate the number of untreated neighbors within 50 meters who filed a return between May 2 and August 27, from 15 days after the first experimental postcard was sent until 75 days after the final experimental postcard was sent. I geocoded the addresses of all treated taxpayers and all untreated

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<sup>28</sup>Drago, Mengel, and Traxler (2015) find that, when a sample of potential evaders of TV license fees were sent a letter, their untreated neighbors who did not receive a letter were more likely to comply with the fee. Boning et al. (2016) examine network effects of enforcement letters and site visits among firms, where the networks are defined by geography or common tax preparers.



Table 1.8: Untreated neighbor responses to treatment

	(1)	(2)	(3)
	<25m	<50m	<100m
Contact only	0.036 (0.154)	0.021 (0.120)	0.041 (0.083)
Penalty salience	-0.097 (0.158)	-0.122 (0.123)	-0.025 (0.085)
Punishment probability	-0.124 (0.163)	-0.117 (0.126)	0.074 (0.084)
Compliance cost	0.060 (0.153)	0.017 (0.120)	0.009 (0.084)
Civic pride	0.076 (0.157)	0.049 (0.121)	-0.027 (0.086)
Salience $\times$ probability	-0.302* (0.165)	-0.221* (0.127)	-0.129 (0.087)
Pseudo- $R^2$	0.0015	0.0010	0.0005
Observations	9,274	9,274	9,274

Note: This table reports results from a negative binomial regression of the number of untreated neighbors who filed a return from an address within  $x$  meters of an individual in the sample on the treatment dummies. Heteroskedasticity robust standard errors in parentheses. Coefficients are significantly different from zero at the \*10%, \*\*5%, or \*\*\*1% significance level.

taxpayers who filed a return during the relevant time period, then computed the distance between every treated nonfiler-untreated taxpayer pair. I then regress the count of untreated taxpayers who filed during the relevant time period on treatment dummies, where an observation is a treated nonfiler. Table 1.8 shows that most of the estimated coefficients on treatment dummies were not statistically different from zero. The penalty salience  $\times$  punishment probability treatment is significant at the 10% level, but significance is not robust to alternative distances. I repeated the procedure for a variety of distances, including 25, 50, and 100 meters. If taxpayers told their neighbors that they received mailings from the tax division, neighbors may have interpreted that as a sign that they would be warned by mail prior to receiving any sort of punishment.

## 1.5 Normative analysis

Would it be worthwhile for Detroit to send mailings to one additional suspected resident nonfiler? In this section I estimate that the direct expected welfare effect of nonfiler mailings is negative for all treatments, conditional on the exact selection criteria in the experiment. I then discuss the sensitivity of the direct welfare estimate to parameter assumptions and identify modifications to the selection criteria that would make mailings welfare-enhancing.

A tax authority that aims to maximize welfare should consider the effect of enforcement actions on the private well-being of individual taxpayers. Tax revenue is assumed to be spent on public goods that are valued by individual taxpayers. However, when the tax authority collects tax from an individual taxpayer, that taxpayer faces private compliance costs and also loses the ability to use the collected tax for private consumption. The tax authority should compare the expected marginal benefit of public goods to taxpayers with the expected marginal private costs to individual taxpayers. This welfare analysis therefore combines three components: expected marginal revenue net of administrative costs, expected marginal private cost, and the marginal social value of public spending.

Adapting the optimal enforcement condition from Keen and Slemrod (2016) to the present context, a tax authority should send mailings to a nonfiler if the expected change in welfare is positive:

$$\phi \left[ \Delta \text{Revenue} - \Delta \text{Administrative cost} \right] - \Delta \text{Private cost} > 0 \quad (1.2)$$

The expression inside the brackets is expected marginal revenue net of administrative costs. The marginal social value of public spending, expressed by the parameter

$\phi$ , converts tax-authority dollars to privately-held dollars. If collecting tax is ever worthwhile, then one dollar held by the tax authority has more social value than one dollar held by an individual taxpayer, so  $\phi > 1$ . The expression for net welfare therefore weights administrative costs more heavily than private costs. Note that foregone consumption appears twice—once as revenue and once as a component of private cost.

One assumption in this framework is that the individual marginal utility per dollar is constant across individual taxpayers. It would be natural to consider an alternative model with heterogeneous individual marginal utility per dollar, for example with high marginal utility per dollar for low income taxpayers and low marginal utility per dollar for high income taxpayers. However, such a model would require additional assumptions to map income onto marginal utility. Furthermore, if the tax base and rates were chosen optimally, then they would already incorporate considerations of heterogeneous marginal utility. For transparency and simplicity this welfare analysis equates marginal utility per dollar across taxpayers.

A second assumption is that the marginal social value of public spending is constant. The social value of spending is the sum of the valuations of individual taxpayers. Again, there is a natural alternative assumption, that there are diminishing marginal returns to public spending, i.e. that the social value of spending is concave. Constant marginal social value of public spending is a reasonable local approximation that simplifies the analysis.

Expected net welfare per mailing is estimated in Table 1.9 separately for each experimental treatment. Remittances are a large and important part of marginal revenue, but not the only part. They are offset by refunds, which are issued when withholding exceeds tax liability. Also, some tax debt which is not remitted with a tax return will eventually be recovered as a result of these mailings. Overall, marginal

Table 1.9: Net welfare

		Contact- only	Penalty salience	Punishment probabi- lity	Compliance cost	Civic pride	Saliene × proba- bility
Remit per letter	[1]	4.26	14.47	3.65	1.81	3.58	8.09
Tax debt recovered	[2]	0.19	2.72	1.20	1.22	1.26	1.63
Refund issued	[3]	0.51	2.08	0.56	2.27	0.85	2.54
Marginal revenue	[4] = [1] + [2] - [3]	3.94	15.11	4.29	0.76	3.99	7.19
Cost of mailings	[5]	4.70	4.70	4.70	4.70	4.70	4.70
Processing responses	[6]	0.73	2.41	1.17	1.49	0.92	2.33
Net revenue	[7] = [4] - [5] - [6]	-1.49	8.00	-1.57	-5.43	-1.64	0.15
Social value	[8] = $\phi \times [7]$	-2.23	12.00	-2.36	-8.14	-2.45	0.23
Private cost	[9]	7.74	27.71	10.38	8.54	8.80	19.36
Net welfare	[10] = [8] - [9]	-9.97	-15.71	-12.74	-16.68	-11.25	-19.13

Note: All units are dollars per mailing. Refunds that are claimed are not always paid, e.g. if the taxpayer does not submit a W2, so refund issued is assumed to be 80% of claimed refund per letter. Similarly, admitted tax debt is not always collected, so tax debt recovered is assumed to be 20% of admitted due per letter that is not remitted with the return. Marginal revenue is equal to remit per letter plus tax debt recovered minus refund issued. Net revenue is equal to marginal revenue minus the cost of mailings per nonfiler (\$4.70, details in Appendix Table 1.16) and the cost of processing responses (one hour per taxpayer valued at \$23.95 per hour). Social value of spending is equal to the marginal value of public spending ( $\phi$ ) times net revenue, with  $\phi = 1.5$  in the baseline estimate. Private cost is calculated as foregone private consumption (equal to marginal revenue) plus compliance costs of \$125 per filer. Net welfare is social value minus private cost.

revenue is equal to remittance plus recovered tax debt minus refunds issued.

Marginal administrative costs include (1) the cost of mailings and (2) the cost of processing responses. The marginal cost of mailings per nonfiler is estimated to be \$4.70. Appendix Table 1.16 shows the components of the marginal cost of mailings, including materials, time, and postage. The administrative cost of processing returns is assumed to be one hour per taxpayer who files a return, with time valued at \$23.95 per hour, the hourly equivalent of the top annual salary of a Detroit tax examiner.<sup>29</sup> The postage and staff time required for sending the letters via certified mail was about 80% of the marginal cost of mailings per nonfiler.

Marginal net revenue per nonfiler is positive in the penalty salience treatment and the penalty salience  $\times$  punishment probability treatment. The row of Table 1.9 labeled net revenue subtracts the marginal cost of mailings per nonfiler from col-

<sup>29</sup>The amount of processing time per taxpayer is based on conversations between the author and tax division staff. The salary of a Detroit tax examiner is from the following publication: *White Book, 2016-2017 Salary and Wage Adjustments*, March 2016, page 63, available at <http://www.detroitmi.gov/how-do-i/view-city-of-detroit-reports>.

lections net of administrative costs. Net revenue is \$8.00 per nonfiler in the penalty salience treatment, \$0.15 per nonfiler in the penalty salience  $\times$  punishment probability treatment, and negative for the other treatments.

The marginal social value of public spending  $\phi$  is the economic return to public spending, excluding administrative and compliance costs. Cellini, Ferreira, and Rothstein (2010) estimate this parameter is 1.5 for infrastructure spending in public school districts in California, arguing that school infrastructure is a local public good that ought to be reflected in home prices. In a jurisdiction with limited fiscal capacity such as Detroit, the marginal social value of public spending could be much higher if budget constraints force the city to forego projects that would be highly valued by constituents. I use 1.5 in my baseline estimate of welfare and perform alternative calculations with 1.1 and 4.5.

Marginal private cost includes foregone private consumption and compliance costs. Foregone private consumption is equal to net revenue, which is positive for a taxpayer who remits tax, negative for a taxpayer who receives a refund, and positive on average for all treatments. Compliance costs are not directly observed. The city income tax form for Detroit residents, Form D-1040(R), is comparable in length and complexity to federal Form 1040EZ, which the IRS estimates imposes an average burden of 5 hours and \$40 per taxpayer.<sup>30</sup> The baseline estimate of welfare assumes the compliance costs for the city income tax form are equal to that IRS estimate of compliance costs for Form 1040EZ: \$125 per taxpayer who files a return, equal to 5 hours at \$17 per hour—the hourly equivalent of the average annual income in the sample—plus \$40.

The baseline estimate of \$125 per taxpayer could overstate or understate true

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<sup>30</sup>The IRS burden estimate is in *1040a Instructions 2015*, available at <https://www.irs.gov/pub/irs-pdf/i1040a.pdf>.

compliance costs. The \$125 estimate would overstate compliance costs if income is earned at a lower wage rate by working more hours, or if the marginal compliance burden is lower because there is a fixed cost of tax preparation that was already paid in order to file a federal return. The \$125 estimate would understate compliance costs if income is earned by a part-time worker or if preparing tax forms is more unpleasant and psychologically costly than typical work, as argued by Benzarti (2015) in the context of itemizing federal deductions. In addition to the \$125 per taxpayer baseline, I perform alternative welfare calculations with \$25 and \$250 as the compliance cost per taxpayer who files a return.

Net welfare is estimated to be negative for all treatments under the baseline assumptions. The net effect was between minus \$10 and minus \$20 per letter. The social value of net revenue is not large enough to offset foregone private consumption and compliance costs. If compliance costs are truly as large as in the baseline estimate, then even for an average taxpayer who responds by filing a return, the net effect on welfare is negative. The welfare effect estimated here is direct in the sense that it considers mailings in isolation rather than simultaneously with other enforcement tools and in the sense that it does not consider specific or general deterrence effects.

The effect of mailings on net welfare is sensitive to assumptions about certification, the marginal social value of public spending, and compliance costs. Certification may have raised response rates if recipients took the letter more seriously, but certification may have reduced response rates if fewer intended recipients received the letter. It is therefore informative to consider a scenario in which certification was neutral and the same response rates could be obtained at lower cost without certification. Table 1.10 reports welfare calculations per letter for each treatment excluding the cost of certification and using alternative assumptions about the marginal social

Table 1.10: Net welfare under alternative assumptions

Parameters		Treatments					
Marginal social value	Compliance cost	Contact only	Penalty salience	Punishment probability	Compliance cost	Civic pride	Salience $\times$ probability
$\phi = 1.1$	\$25	-2.23	-4.71	-3.13	-4.18	-2.63	-5.34
$\phi = 1.1$	\$125	-5.27	-14.79	-8.00	-10.40	-6.47	-15.08
$\phi = 1.1$	\$250	-9.07	-27.37	-14.09	-18.19	-11.28	-27.26
$\phi = 1.5$	\$25	-1.33	-0.02	-2.27	-4.85	-1.79	-3.78
$\phi = 1.5$	\$125	-4.37	-10.09	-7.14	-11.08	-5.63	-13.52
$\phi = 1.5$	\$250	-8.17	-22.68	-13.23	-18.87	-10.43	-25.70
$\phi = 4.5$	\$25	5.42	35.20	4.21	-9.92	4.54	7.89
$\phi = 4.5$	\$125	2.38	25.13	-0.66	-16.15	0.70	-1.85
$\phi = 4.5$	\$250	-1.42	12.54	-6.75	-23.94	-4.10	-14.03

Note: This table reports welfare estimates in units of dollars per mailing using the procedure from Table 1.9 with alternative parameter assumptions. Three assumptions are changed. First, the cost of certification is removed from the cost of mailings, so that the cost of mailings is \$0.96. Second, the marginal social value of spending is assumed to be 1.1, 1.5, or 4.5, as indicated in column 1. Third, the compliance cost per taxpayer is assumed to be \$25, \$125, or \$250, as indicated in column 2.

value of public spending ( $\phi = 1.1, 1.5, 4.5$ ) and compliance costs (\$25, \$125, \$250). In the most optimistic scenario, with  $\phi = 4.5$  and compliance costs of just \$25, each penalty salience mailing raised welfare by \$35.20.

This analysis omits two potentially important channels by which nonfiler mailings could affect welfare. First, sampled taxpayers may comply at a higher rate in the future (specific deterrence). Second, other taxpayers may comply at a higher rate if they infer that Detroit is increasing its enforcement capability (general deterrence). If the mailings have a specific or general deterrence effect, then the estimates of marginal revenue and marginal compliance cost are too low.

If the most effective treatment, the penalty salience treatment, had been applied to the entire population of nonfilers that fit the sample selection criteria, then the city would have collected net revenue of \$342,000. This is inferred from a simple back-of-the-envelope calculation multiplying the number of taxpayers who fit the sample selection criteria (42,754) by the net revenue per letter (\$8.00). If the marginal social value of public spending is sufficiently high, then mailings sent to nonfilers who fit the selection criteria also improve welfare. Under the baseline assumptions,

nonfiler mailings using the selection criteria from this experiment did not improve welfare. However, the income threshold can be refined such that mailings would generate expected marginal revenue that is high enough to outweigh administrative and compliance costs and thereby to improve welfare.

Large administrative and compliance costs set a high bar for the expected marginal revenue required for a worthwhile intervention. Suppose that all suspected resident nonfilers respond to nonfiler mailings by filing a return. Rearranging Equation 1.2 and substituting the baseline assumptions, a welfare-improving enforcement action must collect tax of

$$\begin{aligned} \Delta\text{Revenue} &> \left(\frac{\phi}{\phi-1}\right)\Delta\text{Administrative cost} + \left(\frac{1}{\phi-1}\right)\Delta\text{Compliance costs} \\ &> (3)(4.70 + 23.95) + (2)(125) = 335.95. \end{aligned}$$

This condition provides a benchmark *expected marginal revenue threshold* for welfare-improving nonfiler mailings. Adjusting the benchmark for a 10% response rate, so that the administrative cost also includes the cost of mailings that do not elicit responses, the expected marginal revenue threshold is \$462.85.

Under these assumptions, nonfiler mailings sent to taxpayers with sufficiently high income improve welfare. The income level that corresponds to the expected marginal revenue threshold is higher to the extent that taxpayers remit only a fraction of net liability and to the extent that withholding is imperfectly observed. For most taxpayers, Gross liability =  $t(Y - 600 \cdot \text{Exemptions})$ , where  $Y$  is income and  $t$  is a tax rate of 2.4% for residents. If withholding is zero, then net liability is equal to gross liability, and net liability of \$463 corresponds to an income level of \$20,492 for a taxpayer with two exemptions. Among taxpayers who filed a return in response to treatment mailings, marginal revenue was 64% of net liability, so income of \$32,019



would be required to generate expected marginal revenue of \$463. For welfare-improving mailings, this would be a reasonable income threshold for taxpayers with only nonwage income and no withholding.

However, taxpayers with wage income are likely to have withholding, so a larger income threshold is required to generate the same level of expected marginal revenue. Among taxpayers who filed a return in response to treatment mailings and had only wage income, net liability was 22% of gross liability. For suspected resident nonfilers with only wage income, an income level of \$145,540 would therefore correspond to expected marginal revenue of \$463. The decomposition here,  $\text{Expected marginal revenue}_i = \frac{\text{Marginal revenue}}{\text{Net liability}} \cdot \frac{\text{Net liability}}{\text{Gross liability}} \cdot t(Y_i - 600 \cdot \text{Exemptions}_i)$ , highlights the difference between net and gross liability for taxpayers who earned wage income and were likely to have unobserved withholding.

Response rates are an important component of administrative costs with additional potential for refining selection criteria. As noted earlier in the discussion of the expected marginal revenue threshold, the administrative cost of sending letters is effectively higher if many letters go unanswered. When letters elicit a 10% response rate, eliciting one response requires postage for sending 10 letters. The population examined by the field experiment included taxpayers who the city estimated owed at least \$350, without regard to age, income level, income composition, or filing history. My analysis suggests that the city could reduce administrative costs by focusing on higher-yield demographics. Older taxpayers, higher-income taxpayers, and taxpayers who had been identified fewer times as nonfilers had higher response rates. These effects appear to operate even when they are all present, such that taxpayers with all of the higher-response characteristics have particularly high response rates.

## 1.6 Discussion

This paper is part of a rapidly expanding literature that uses controlled field experiments to improve tax compliance.<sup>31</sup> These experiments are motivated by the twin recognitions that (1) rationality is limited in its ability to describe actual human behavior (DellaVigna 2009; McCaffery and Slemrod 2006) and (2) controlled field experiments are the best available method for understanding tax compliance behavior (Angrist and Pischke 2010; Slemrod and Weber 2012; Hallsworth 2014).

*Deterrence parameters.* Traditional deterrence parameters are the basis for many tax experiment treatments, yet even those treatments are behavioral. In the canonical model of Allingham and Sandmo (1972), taking the tax rate as given, the tax authority needs only to set a penalty and a probability. However, in addition to those deterrence parameters, actual taxpayer behavior is mediated by the salience of the tax (Finkelstein 2009; Chetty, Looney, and Kroft 2009), the salience of the penalty, and beliefs about the probability of being caught (Alm 2012). Furthermore, nonfinancial penalties like shaming are clearly grounded in the traditional deterrence parameters but rely on social preferences that are outside the scope of strict rationality (Perez-Truglia and Troiano 2015).

The response to the penalty salience message in this experiment suggests that compliance can be induced by a threat even if that threat is merely implicit. Based on evidence that taxpayers in other contexts—filers, delinquents, corporations—respond to threats, it would have been reasonable to guess that income tax nonfilers would respond to a message about the penalty for failing to file a tax return. The penalty salience message in this experiment is typically understood as an implicit threat: If you do not file a return, you will be fined or sent to jail. However, the message

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<sup>31</sup>Mascagni (2016) reviews tax experiments and develops a taxonomy of tax treatments which I adopt.

itself did not actually promise any action; it stated a fact about a legal statute that had not been enforced in many years. That contrasts with “threat” treatments in other recent experiments that explicitly promise action against the taxpayer (Fellner, Sausgruber, and Traxler 2013; Castro and Scartascini 2015; Chirico et al. 2015). Tax administrators might prefer the somewhat more “courteous” frame of information salience if the two messages are equally effective, although the potency of the message may depend on whether the information is perceived as a threat.

*Information reporting.* The second deterrence parameter, the probability of being caught, is closely linked with third-party information reporting. In Detroit, the “third party” that enabled the tax authority to tailor the punishment probability message with information about the individual nonfiler’s federal income was the Internal Revenue Service. Information reporting has been linked to the ability of taxpayers to evade and the effectiveness of enforcement (Kleven et al. 2011; Naritomi 2013; Pomeranz 2015).

This experiment is one of a handful that attempts to influence the perceived probability of punishment by referring to information the tax authority has about the taxpayer. Brockmeyer et al. (2016) and Bott et al. (2014) both found that informing taxpayers—nonfiling firms or individuals with misreported foreign income, respectively—that the tax authority uses third-party information to identify sources of income had a positive effect on compliance even when the information itself was not revealed. It is possible that the punishment probability message in this experiment could have been even more effective by referencing the existence and source of information—the taxpayer’s federal income according to the IRS—rather than revealing the information. Haynes et al. (2013) found that text messages to a fine-owing delinquent were more effective with an amount than just a reminder, but that including the delinquent’s name in the text message was even better than the name and

amount together. This is in some ways parallel to the results from this experiment in Detroit, where the penalty salience message elicited a response rate that was above but not statistically different from the penalty salience and punishment probability messages combined.

*Compliance costs.* Compliance costs are almost certainly large (Benzarti 2015; Guyton et al. 2003) and just as closely related to traditional economic incentives as deterrence parameters (Erard and Ho 2001), but they have not received much experimental attention. Hasseldine et al. (2007) found no effect of offering assistance to sole proprietors, which they attribute to the fact that most sole proprietors use paid tax preparers. The finding in Detroit that providing a blank tax form and return envelope raises response rates of nonfilers, but with lower quality responses than other treatments, is the first of its kind. However, several tax experiments have attempted to reduce compliance costs in other ways. Guyton et al. (2016) found that reminders raise compliance rates. Bhargava and Manoli (2015) found that reducing the complexity of informational mailings improved takeup of the Earned Income Tax Credit, but attempts to reduce program stigma failed to improve takeup.

*Moral appeals.* This experiment adds to the bulk of the evidence against the effectiveness of moral appeals. I include in this category messages about a “compliant majority” of other taxpayers, messages about the “public services” that taxes fund, and messages that refer to general principles of equity or fairness. Most of these messages do not appear to be as effective as messages related to deterrence parameters. The only similar message to the civic pride message in this experiment was a “national pride” message tested by Kettle et al. (2016) on corporate and profits nonfilers in Guatemala. They also found no impact on the rate of payment. Perhaps people with whom a message about civic pride would succeed had already filed their tax returns. Against accumulating evidence to the contrary, Hallsworth et al. (2014)

find that certain moral appeals *do* enhance tax compliance. With the benefit of a very large sample, they tested many fairly similar messages. I interpret their findings as strong evidence that small changes in wording—seemingly insignificant, with no relationship to traditional economic incentives—can have a surprisingly large impact on behavior, probably through framing or reference effects. For instance, Hallsworth et al. (2014) found that, all else equal, replacing “nine out of ten” with “88%” raised a response rate to a compliant majority message by two percentage points.

*Social learning.* The social learning literature has provided ample theoretical and empirical grounds for expecting diffusion of technology and allocation of jobs (Glaeser 1999; Conley and Udry 2010; Mobius and Rosenblat 2014), but there is relatively little evidence of social learning about tax. Drago, Mengel, and Traxler (2015) found that letters about television license fees to households in rural Austria improved compliance behavior of geographically proximate untreated households. Failure to find spillover effects in Detroit could be attributed to differences in rural and urban communication norms; people in an urban setting like Detroit might learn from coworkers, friends and family rather than geographic neighbors. Or Detroit residents might not be discussing tax at all. Social workers and journalists seem to think it is self-evident that people are reluctant to discuss money (Trachtman 1999; Taylor 2014; Kadlec 2016), although Duflo and Saez (2003) do find social learning through coworkers in the context of retirement saving. There could be stigma associated with failure to pay income tax that is not present for retirement saving.

*Fiscal capacity.* The success of targeted messaging for improving tax compliance would be particularly helpful for tax authorities like Detroit with constrained fiscal capacity. Constrained fiscal capacity is particularly common in developing economies (Besley and Persson 2013). Finding effective, low-cost enforcement tools, like the penalty salience message in this experiment, could be a boon to tax administration

with constrained fiscal capacity. However, it is possible that the lessons learned in Detroit might not be generalizable to all taxpayers or all fiscally constrained tax authorities. The City of Detroit has unusual challenges of tax administration, including with income tax and also property tax (Hodge et al. 2016). The fact that higher-income taxpayers in Detroit had higher response rates in the experiment suggests that the lessons learned here may be more applicable to taxpayers in higher-income jurisdictions than in fiscally-constrained jurisdictions with lower-income taxpayers.

## 1.7 Conclusion

This paper tested the efficacy of messages related to penalty salience, punishment probability, compliance cost, and civic pride for improving tax compliance among income tax nonfilers. Informing taxpayers of a statutory penalty for failing to file a return elicited higher filing rates, more returns per filer, more admitted tax due, and more remittances than any other message. Even though both penalty salience and punishment probability were individually effective relative to the contact-only mailings, interacting these two treatments was no more effective, indeed less effective, than the penalty salience message by itself. This is inconsistent with the theoretical prediction that penalty salience and punishment probability should have a positive interaction. The interaction may have exhibited no improvement over penalty salience by itself because (1) the effectiveness of the penalty salience message depended on its simplicity, or (2) the penalty salience message had already exhausted the channel of affecting taxpayer behavior through perceived probability of punishment. Enclosing a blank tax form and return envelope was effective in eliciting higher response rates, but the quality of responses to the compliance cost treatment was lower in the sense that taxpayers were more likely to claim a refund and less likely to admit tax due.

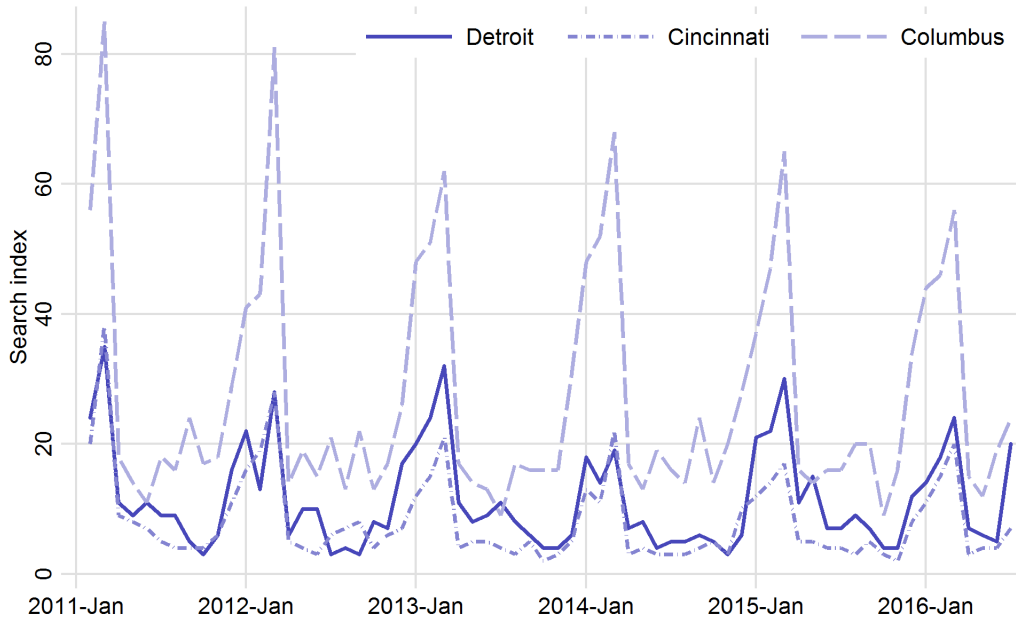
The response rate to the civic pride treatment was not statistically different from the contact-only control group.

Controlled experiments are the best available method for evaluating behavioral responses to tax enforcement. Many tax experiments have attempted to influence the perception of standard deterrence parameters: penalty and probability. The controlled experiment described in this paper tested the response to similar deterrence parameter treatments by income tax nonfilers, who have received relatively little attention in the literature. This experiment provides the first evidence about civic pride among city taxpayers, and it tests a novel approach to addressing compliance costs—providing a blank tax form.

I find that a single sentence, strategically placed in mailings to attract attention, can have an economically meaningful impact on tax filing behavior. Tax experiments like this one are helping to build an understanding of compliance behavior. However, even subtle treatment differences can affect taxpayer responses, and techniques that are individually effective can interact in surprising ways. Building experimental variation into tax enforcement is a valuable way of exploring compliance behavior and making enforcement more efficient, which should be particularly helpful for tax authorities with limited fiscal capacity.

## 1.8 Appendix

Figure 1.7: Google Trends search index for Detroit, Columbus, and Cincinnati income tax



Source: Google Trends.

Note: This figure compares search interest in “Detroit income tax” to corresponding search terms for Columbus and Cincinnati. Columbus has approximately the same population as Detroit but a much smaller metropolitan area. Cincinnati has a larger population in the city proper and about half of the population in the metropolitan area.



Figure 1.8: Example postcard and letter

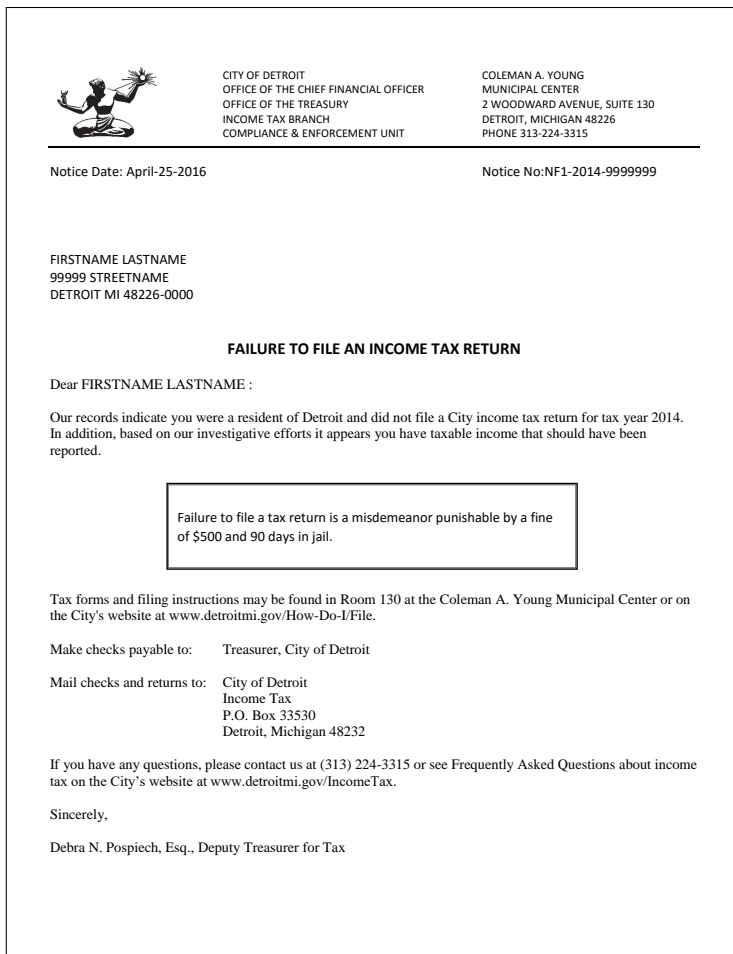
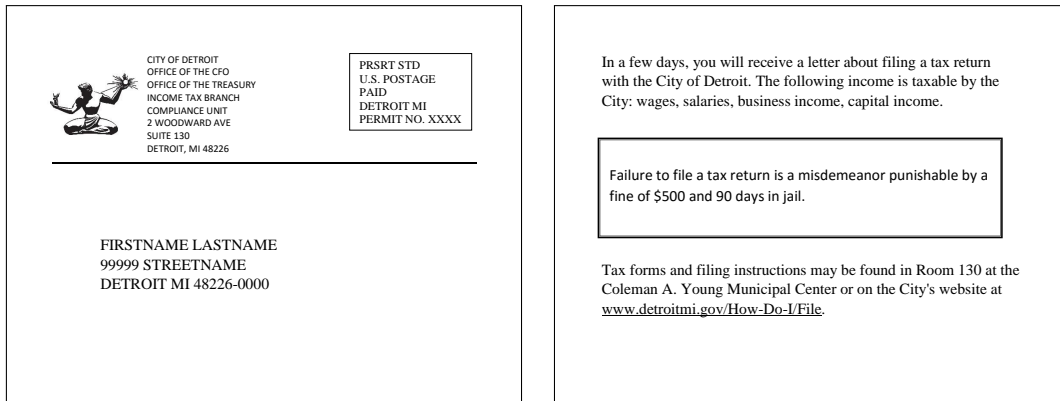
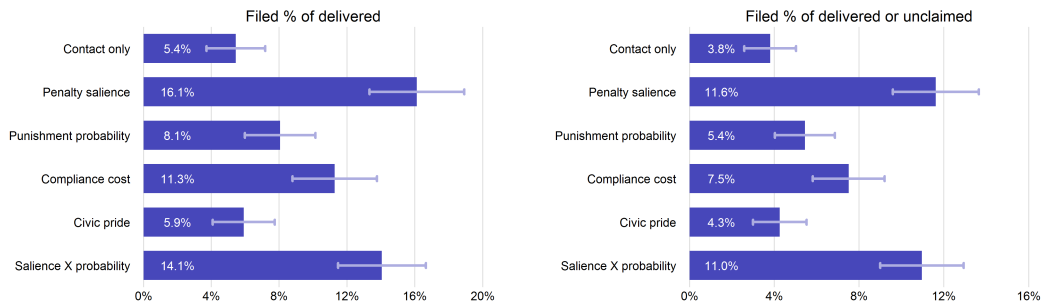
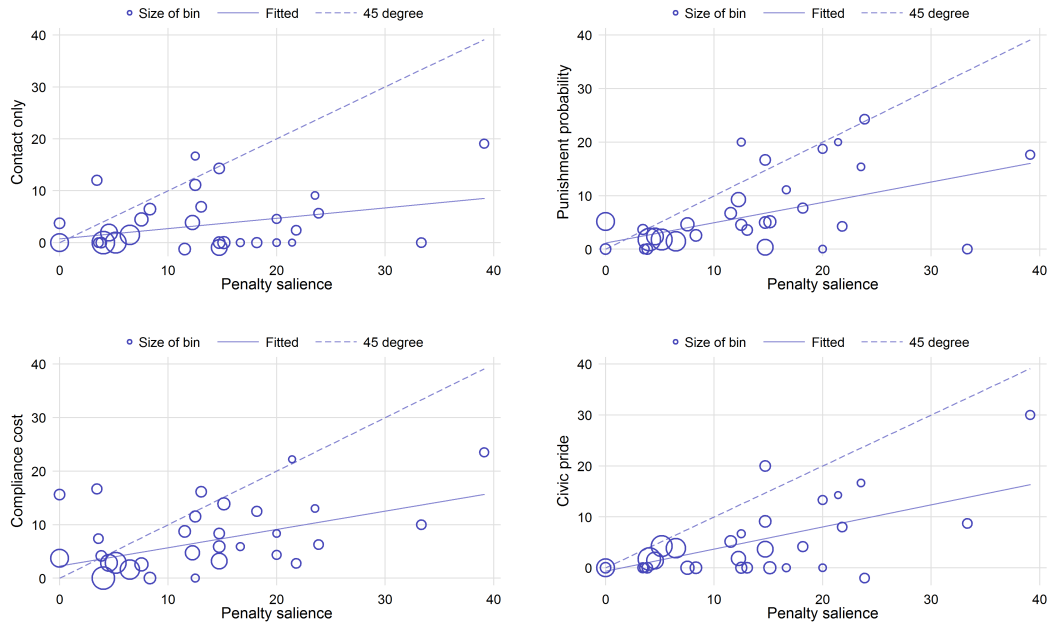


Figure 1.9: Response rates by treatment status



Note: This figure shows response rates by treatment status. The left panel restricts attention to taxpayers for whom the treatment letter was listed as delivered on the USPS tracking website. The right panel restricts attention to taxpayers for whom the treatment letter was listed as delivered or unclaimed on the USPS tracking website. Standard errors show 95% confidence intervals.

Figure 1.10: Response rates by age-income-filing history bin



Note: This figure compares response rates to the penalty salience mailings (horizontal axis) with response rates to other treatments (vertical axis) within age-income-filing history bins. Appendix Table 1.15 reports the raw response rates by treatment and age-income-filing history bin.

Table 1.11: States with local income tax

State	Localities	State	Localities
Alabama	4	Michigan	22
California	1	Missouri	2
Colorado	3	New Jersey	1
Delaware	1	New York	4
Indiana	91	Ohio	774
Iowa	297	Oregon	2
Kansas	535	Pennsylvania	2,961
Kentucky	218	West Virginia	3
Maryland	24		

Source: Tax Foundation

Note: The types of localities that levy income tax vary widely. In Michigan the localities that levy income tax are cities. In Maryland all 23 counties and one city, Baltimore, levy income tax. In Pennsylvania 2,492 municipalities and 469 school districts levy income tax.

Table 1.12: Summary Statistics (TY 2014) by treatment status

	Contact only		Penalty salience		Punishment probability		Compliance cost		Civic pride		Saliency × Probability		No contact	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Age	39.7	12.2	39.8	11.9	39.5	12.0	39.7	12.0	39.6	12.1	39.7	12.0	39.5	11.9
FS = single (%)	40.6	49.1	38.8	48.7	40.1	49.0	41.1	49.2	38.9	48.8	38.7	48.7	38.5	48.7
FS = joint (%)	10.3	30.4	10.9	31.2	10.4	30.5	10.0	30.0	10.9	31.2	10.5	30.7	10.9	31.2
FS = Head of household (%)	47.6	49.9	49.1	50.0	48.1	50.0	47.2	49.9	48.8	50.0	49.5	50.0	49.1	50.0
Years identified as nonfiler	4.3	2.5	4.3	2.4	4.2	2.4	4.2	2.5	4.2	2.4	4.3	2.5	4.3	2.5
Filed in 2012 or 2013 (%)	22.8	42.0	23.2	42.2	23.4	42.4	23.6	42.5	23.7	42.5	23.0	42.1	23.2	42.2
Total income (\$ 000s)	33.7	28.8	33.5	22.6	33.7	23.6	33.7	24.8	34.1	42.8	33.6	25.3	34.3	69.1
Wage income (\$ 000s)	31.3	26.9	31.4	21.6	31.4	22.0	31.1	21.6	31.2	23.8	31.4	22.8	31.6	23.5
Log total income	10.3	0.5	10.3	0.5	10.3	0.5	10.3	0.5	10.3	0.5	10.3	0.5	10.3	0.5
Nonzero nonwage income (%)	29.5	45.6	29.2	45.5	30.3	46.0	29.9	45.8	29.3	45.5	29.7	45.7	29.1	45.4
Observations	5,399		5,274		5,350		5,313		5,476		5,342		10,617	

Note: This table reports means and standard deviations of taxpayer characteristics from administrative tax data.

Table 1.13: Summary Statistics (TY 2014) by delivery status

	Delivered		Unclaimed		Undeliverable		Transit	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Age	40.3	12.2	38.7	11.4	37.4	11.2	39.8	11.7
FS = single (%)	39.7	48.9	41.6	49.3	36.5	48.2	39.3	48.9
FS = married filing jointly (%)	12.8	33.4	8.4	27.7	6.2	24.1	11.6	32.1
FS = head of household (%)	46.3	49.9	48.4	50.0	56.3	49.6	47.1	50.0
Years identified as nonfiler	4.2	2.5	4.3	2.4	4.3	2.5	4.2	2.4
Filed in 2012 or 2013 (%)	25.0	43.3	20.8	40.6	14.6	35.3	24.2	42.9
Total Income (\$ 000s)	34.3	27.4	32.9	20.3	28.9	16.1	35.2	24.6
Wage Income (\$ 000s)	31.8	24.5	31.4	19.6	27.1	16.7	33.0	22.7
Log total income	3.4	0.5	3.4	0.5	3.3	0.4	3.4	0.5
Nonzero nonwage income (%)	31.9	46.6	27.6	44.7	24.8	43.2	29.6	45.7
Observations	3,980		1,852		824		524	

Note: This table reports means and standard deviations of taxpayer characteristics from administrative tax data.

Table 1.14: Heterogeneity of response

	Treatment status					Saliency × Probabi- lity	All letters	N
	Contact only	Penalty saliency	Punishment probability	Compliance cost	Civic pride			
Age								
Age ≤ 30	0.9%	4.8%	2.1%	3.8%	1.8%	6.9%	3.3%	1,919
30 < Age ≤ 40	0.9%	8.3%	3.9%	2.7%	3.5%	8.3%	4.6%	2,042
40 < Age ≤ 50	3.5%	10.0%	4.8%	7.9%	4.0%	8.2%	6.5%	1,704
50 < Age ≤ 60	5.1%	20.4%	8.6%	8.2%	6.9%	14.3%	10.7%	1,061
60 < Age	15.9%	16.7%	15.2%	23.3%	7.8%	23.1%	17.1%	403
Filing status								
Single	4.5%	9.6%	5.0%	6.6%	5.4%	13.3%	7.3%	2,846
Joint	4.4%	23.1%	13.8%	11.1%	3.7%	15.6%	12.3%	765
Head of Household	1.4%	7.5%	2.5%	4.8%	2.7%	5.7%	4.1%	3,434
Other	7.7%	0.0%	11.1%	8.7%	0.0%	13.3%	7.2%	97
Years nonfiler								
1 year	3.3%	12.2%	5.8%	7.2%	7.7%	14.6%	8.3%	1,115
2 years	4.8%	15.5%	8.3%	6.8%	7.2%	13.7%	9.5%	1,116
3 years	4.6%	11.5%	5.5%	7.9%	2.3%	11.9%	7.2%	937
4 years	1.4%	10.7%	6.5%	4.4%	3.9%	8.3%	6.0%	873
5 years	1.4%	9.0%	3.5%	5.0%	2.2%	5.5%	4.2%	756
6 years	3.4%	7.5%	3.6%	7.1%	1.6%	8.2%	5.4%	747
7 years	1.7%	5.6%	1.7%	4.8%	2.3%	3.7%	3.3%	646
8 years	4.7%	3.3%	1.8%	8.1%	1.1%	10.5%	5.0%	581
9 years	0.0%	8.0%	3.4%	1.5%	0.0%	1.7%	2.7%	371
City returns filed								
Filed 2012	2.0%	18.3%	6.5%	4.7%	7.8%	14.9%	8.8%	605
Filed 2013	6.7%	29.9%	6.5%	10.2%	8.6%	11.7%	12.3%	446
Both	14.3%	35.7%	16.8%	22.3%	16.1%	36.2%	23.2%	547
Neither	1.9%	5.8%	3.3%	4.2%	1.7%	6.4%	3.9%	5,544
Income (\$ 000s)								
Income ≤ 20	2.2%	4.3%	1.7%	5.2%	1.9%	5.9%	3.5%	1,846
20 < Income ≤ 30	1.9%	8.5%	5.2%	3.3%	3.6%	8.6%	5.2%	2,557
30 < Income ≤ 40	4.2%	13.6%	2.9%	8.5%	2.4%	9.7%	6.8%	1,157
40 < Income ≤ 50	2.6%	14.9%	9.4%	8.6%	4.2%	15.0%	9.2%	612
50 < Income ≤ 60	6.3%	11.8%	10.7%	11.5%	10.0%	16.4%	11.0%	353
60 < Income	6.7%	21.7%	8.8%	11.5%	10.4%	16.5%	12.6%	617
Treatment batch								
Batch 1	0.0%	15.0%	0.0%	15.0%	0.0%	10.0%	6.7%	119
Batch 2	2.1%	16.5%	11.2%	7.1%	3.1%	11.6%	8.6%	580
Batch 3	2.8%	9.5%	6.7%	7.0%	4.2%	8.4%	6.4%	2,151
Batch 4	3.6%	11.5%	3.4%	5.0%	3.9%	10.3%	6.3%	2,149
Batch 5	3.1%	7.3%	3.1%	5.9%	3.9%	10.1%	5.6%	2,143
Total	3.0%	10.1%	4.9%	6.2%	3.8%	9.7%	6.3%	7,142

Note: This table shows heterogeneity in response.

Table 1.15: Response rate by age-income-filing history bins

Years nonfiler	Contact only	Penalty salience	Treatment status			Salience × Probability	All letters
			Punishment probability	Compliance cost	Civic pride		
age ≤ 30, inc ≤ 25K							
1-2 years (N = 867)	0.0%	5.2%	1.8%	2.9%	4.3%	8.7%	3.8%
3-5 years (N = 618)	0.0%	0.0%	5.2%	3.8%	0.0%	6.5%	2.6%
6-9 years (N = 186)	0.0%	3.6%	0.0%	7.4%	0.0%	0.0%	2.0%
Total	0.0%	3.2%	2.8%	3.8%	2.3%	6.8%	3.1%
age ≤ 30, 25K < inc ≤ 35K							
1-2 years (N = 273)	6.5%	8.3%	2.6%	0.0%	0.0%	10.0%	4.0%
3-5 years (N = 218)	0.0%	3.8%	0.0%	4.2%	0.0%	4.3%	1.9%
Total	3.4%	6.0%	1.5%	1.5%	0.0%	7.5%	3.1%
age ≤ 30, 35K < inc ≤ 50K							
1-2 years (N = 110)	0.0%	20.0%	0.0%	8.3%	0.0%	16.7%	6.9%
Total	0.0%	20.0%	0.0%	8.3%	0.0%	16.7%	6.9%
30 < age ≤ 50, inc ≤ 25K							
1-2 years (N = 401)	3.8%	12.2%	9.3%	4.8%	1.8%	9.4%	6.9%
3-5 years (N = 730)	2.6%	7.6%	2.6%	2.7%	5.0%	6.1%	4.5%
6-9 years (N = 973)	0.0%	4.0%	1.8%	0.0%	1.7%	6.4%	2.3%
Total	1.7%	6.8%	3.7%	1.7%	3.0%	6.9%	4.0%
30 < age ≤ 50, 25K < inc ≤ 35K							
1-2 years (N = 273)	0.0%	14.7%	5.0%	5.9%	9.1%	17.5%	9.0%
3-5 years (N = 470)	0.0%	15.7%	1.4%	4.2%	4.6%	9.1%	5.4%
6-9 years (N = 564)	1.9%	4.5%	2.4%	2.9%	1.4%	6.7%	3.4%
Total	0.8%	10.6%	2.5%	4.0%	4.2%	10.0%	5.3%
30 < age ≤ 50, 35K < inc ≤ 50K							
1-2 years (N = 208)	0.0%	18.2%	7.7%	12.5%	4.2%	16.7%	10.3%
3-5 years (N = 290)	0.0%	15.2%	5.1%	13.9%	0.0%	5.6%	6.2%
6-9 years (N = 349)	4.4%	7.5%	4.7%	2.6%	0.0%	5.1%	4.4%
Total	1.9%	12.0%	5.6%	9.3%	1.0%	8.6%	6.5%
30 < age ≤ 50, 50K < inc							
1-2 years (N = 221)	14.3%	14.7%	16.7%	8.3%	20.0%	10.0%	13.9%
3-5 years (N = 264)	0.0%	12.8%	8.0%	10.0%	6.5%	13.8%	8.6%
6-9 years (N = 221)	3.7%	0.0%	0.0%	15.6%	0.0%	3.1%	4.1%
Total	5.7%	9.8%	8.4%	11.2%	9.1%	8.6%	8.9%
50 < age, inc ≤ 25K							
1-2 years (N = 158)	4.5%	20.0%	18.8%	4.3%	13.3%	23.8%	13.4%
3-5 years (N = 229)	6.9%	13.0%	3.6%	16.1%	0.0%	10.7%	8.0%
6-9 years (N = 240)	11.1%	12.5%	4.5%	11.5%	0.0%	4.2%	7.5%
Total	7.7%	14.3%	7.6%	11.3%	2.5%	12.3%	9.2%
50 < age, 25K < inc ≤ 35K							
1-2 years (N = 117)	9.1%	23.5%	15.4%	13.0%	16.7%	6.7%	14.3%
3-5 years (N = 177)	4.3%	23.8%	6.3%	4.8%	10.0%	11.5%	10.2%
6-9 years (N = 201)	12.0%	3.4%	3.7%	16.7%	0.0%	4.2%	7.1%
Total	8.5%	14.9%	7.1%	12.2%	7.7%	7.7%	9.9%
50 < age, 35K < inc ≤ 50K							
1-2 years (N = 101)	0.0%	21.4%	20.0%	22.2%	14.3%	33.3%	19.7%
3-5 years (N = 132)	16.7%	12.5%	20.0%	0.0%	6.7%	25.0%	13.5%
6-9 years (N = 128)	0.0%	16.7%	11.1%	5.9%	0.0%	16.7%	9.7%
Total	7.9%	16.7%	16.3%	9.8%	7.7%	23.9%	14.0%
50 < age, 50K < inc							
1-2 years (N = 165)	19.0%	39.1%	17.6%	23.5%	30.0%	32.0%	27.6%
3-5 years (N = 174)	7.7%	25.9%	26.3%	8.3%	0.0%	23.5%	15.2%
6-9 years (N = 179)	0.0%	33.3%	0.0%	10.0%	8.7%	22.2%	10.7%
Total	8.7%	32.3%	12.7%	14.3%	11.9%	26.1%	17.7%

Note: This table shows response rate by age, income, and filing history. Only age-income-history bins with at least 100 observations are shown. The three age categories are below 30, 30–50, and above 50. The four income categories are below \$25K, \$25K–\$35K, \$35K–\$50K, and above \$50K. The three filing history categories are 1–2 years, 3–5 years, and 6–9 years identified as a suspected resident nonfiler.

Table 1.16: Marginal cost of mailings per nonfiler

	Dollars	Source / Description
Materials		
Card stock	0.017	$\frac{\$17}{250 \text{ sheets}} \times \frac{1 \text{ sheet}}{4 \text{ postcards}}$
Envelopes	0.044	$\frac{\$22}{500 \text{ envelopes}}$
Ink	0.040	pcworld.com estimate
Paper	0.014	$\frac{\$7}{500 \text{ sheets}}$
Time		
Printing	0.033	$\frac{3 \text{ hours}}{2,160 \text{ letters}} \times \frac{\$23.95}{\text{hour}}$
Stuffing	0.033	$\frac{3 \text{ hours}}{2,160 \text{ letters}} \times \frac{\$23.95}{\text{hour}}$
Certifying	0.444	$\frac{40 \text{ hours}}{2,160 \text{ letters}} \times \frac{\$23.95}{\text{hour}}$
Applying postage	0.033	$\frac{3 \text{ hours}}{2,160 \text{ letters}} \times \frac{\$23.95}{\text{hour}}$
Postage		
Postcard	0.270	USPS permit imprint
Letter	0.465	USPS metered postage
Certification	3.300	USPS metered postage
Total	4.698	

Note: Staff time is valued at \$23.95 per hour, the hourly equivalent of the top annual salary of a Detroit tax examiner. *White Book, 2016-2017 Salary and Wage Adjustments*, March 2016, page 63, available at <http://www.detroitmi.gov/how-do-i/view-city-of-detroit-reports>. Marginal cost of mailings per nonfiler was a bit higher for the compliance cost group because the compliance cost letters enclosed a blank tax form and a return envelope. Also, the stuffing machine was less likely to stuff the outgoing envelope successfully, which required staff time to correct.

## CHAPTER II

# Breaching the blendwall: RINs and the market for renewable fuel

### 2.1 Introduction

The Renewable Fuel Standard (RFS) is one of many potential policy tools for fighting climate change. The RFS requires American drivers to consume a minimum amount of renewable fuel as a method of displacing petroleum-based fuel with biomass-based fuel and thereby reducing carbon emissions. The RFS minimum volume requirement that was scheduled by law in 2007 is reevaluated annually by the Environmental Protection Agency (EPA). The EPA can stick with the original RFS schedule or reduce the RFS volumes by some amount.

This paper simulates policy alternatives with a real-world policy tool controlled by the EPA—the RFS minimum volume requirement—in a model that captures two important features of the market for renewable fuel: the blendwall, and the RFS linkage between ethanol and biodiesel. These two features are typically absent from welfare analysis of renewable fuel mandates.<sup>1</sup> With the linkage between ethanol and

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<sup>1</sup>De Gorter and Just (2009), Lapan and Moschini (2012), Cui et al. (2011), Holland et al. (2013), and Chen et al. (2014) all performed welfare analysis on renewable fuel mandates without incorporating the blendwall or the RFS linkage between ethanol and biodiesel.



biodiesel, marginal increases in the RFS mandate beyond the blendwall are filled by a combination of biodiesel and E85. I find that both biodiesel and E85 are expensive methods of reducing carbon emissions.

Through its implementation of the RFS, the EPA currently requires American drivers to consume more renewable fuel than can be blended into the most common gasoline blend. The 10% limit on ethanol in E10 gasoline is called the blendwall. The infrastructure for distributing and consuming regular gasoline cannot accommodate a blend with more than 10% ethanol because ethanol is more corrosive than petroleum-based gasoline. When the RFS minimum volume requirement was below the blendwall, meeting the requirement was easy because it could be done simply by adding more ethanol to E10 gasoline.

Now that the RFS requirement exceeds the blendwall, the only way to meet the requirement is by increasing consumption of renewable fuels other than ethanol in E10 gasoline. The RFS makes distinctions among good and better renewable fuels. It sets minimum volumes in four separate categories, each of which has its own renewable energy credit (RIN). The RFS allows “better” renewable fuels—like biodiesel—to satisfy requirements in place of “good” renewable fuels—like corn ethanol. So even though the minimum volume requirement for ethanol exceeds 10% of E10 gasoline, that requirement can be met with biodiesel or other gasoline blends.

The model includes salient features of markets related to renewable fuel. Consumers demand diesel, gasoline, and nonfuel corn. Producers supply renewable and nonrenewable blending components for gasoline and diesel. Fuel blenders combine blending components into blended fuel. The RFS requirements are modeled by incorporating RIN prices into the decision problem of blenders. I solve for a perfectly competitive equilibrium.

I calibrate the model to make the simulations empirically relevant. I use supply

and demand elasticities estimated from prior literature, and I use data to calibrate remaining parameters. The calibrated model does a good job matching untargeted moments.

The simulation indicates the RFS is a costly method of reducing carbon emissions in the short run. I find that reducing carbon emissions using the RFS imposes welfare costs of more than \$300 per metric ton of CO<sub>2</sub>. The linkage between ethanol and biodiesel mitigates the cost of reducing emissions with the RFS relative to a world in which the entire reduction occurred through E85. However, both biodiesel and E85 are expensive ways to reduce carbon emissions.

Biodiesel is an expensive way to reduce carbon emissions because (1) it has a steep supply curve and (2) as an input it is a very good substitute with petroleum-based diesel. The blender cost of petroleum diesel must rise along with the blender cost of biodiesel in order for biodiesel to remain competitive as an input, and the blender cost of petroleum diesel is not easily moved. E85 is an expensive way to reduce carbon emissions because (1) consumers require a substantial discount to substitute E85 for E10 consumption and (2) ethanol is a modest reduction in emissions relative to BOB, the fuel it displaces. Corn ethanol emits almost as much carbon as petroleum-based gasoline, so the reduction in carbon emissions is small relative to the welfare loss from distorting consumption of food and fuel.

The RFS is not a good tool for reducing carbon emissions in the short run, but it might be a good tool in the long run. Legislators hoped the RFS would support a massive expansion in cellulosic ethanol, which is a large reduction in carbon emissions relative to petroleum-based gasoline. The RFS could be useful as a tool for developing cellulosic ethanol technology and expanding infrastructure for consuming cellulosic ethanol in E85. However, the dynamic effects of the RFS are beyond the scope of this paper.

Section 2.2 gives background on the institutional features of the RFS and the markets for blended fuel. Section 2.3 presents a model that incorporates those features. Section 2.4 tests price predictions of the model. Section 2.5 calibrates the model. Section 2.6 presents the results of policy simulations using the model. Section 2.7 concludes.

## 2.2 Institutional context

### 2.2.1 Blended fuel

Transportation fuel is a blend of renewable and nonrenewable fuel. Gasoline is a blend of ethanol (renewable) and petroleum-based gasoline (nonrenewable). Similarly, diesel is a blend of biodiesel and petroleum-based diesel. Blenders combine these blending components into blended fuels. Three blended fuels are important for understanding the Renewable Fuel Standard (RFS): E10 gasoline, which contains 0% to 10% ethanol; E85 gasoline, which contains 51% to 85% ethanol; and blended diesel.<sup>2</sup>

**Gasoline**—Ethanol is an imperfect substitute for petroleum-based gasoline, also called blendstock for oxygenate blending or BOB when it is an input into blended gasoline, because it has a lower energy content and a higher octane rating. Octane is a measure of the compression a fuel can withstand before detonating. If two fuels have equal energy content but one has a higher octane rating, the one with a higher octane rating performs better, in the sense that it gets more miles per gallon.

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<sup>2</sup>It would be more precise to say that E85 contains at most 83% ethanol, because in high blends at least 2% of the ethanol portion must be denaturant (Alternative Fuels Data Center 2013b). According to the EPA, the average ethanol fraction in E85 is 71%. In some seasons and regions of the country, the practical limit on ethanol is substantially below 85% to avoid cold start problems. Other blends of gasoline exist but are unlikely to be relevant to policy in the near term. For example, E15 gasoline contains 15% ethanol. As of January 2014, there were only 59 stations in the United States vending E15 (Renewable Fuels Association 2014).

Octane improves fuel performance with diminishing returns. Adding ethanol into a gasoline blend with low octane improves performance because the high-octane effect dominates the low-energy effect. Adding ethanol into a gasoline blend with high octane hinders performance because the low-energy effect dominates the high-octane effect. Gasoline is required to have an octane rating above the octane rating of BOB. If BOB is not blended with ethanol, other octane-boosting liquids must be added to BOB in order to comply with the minimum octane rating.<sup>3</sup>

Ethanol is also different from BOB because ethanol is more corrosive. Containers designed for petroleum gasoline, including underground tanks at gas stations and gas engines in light-duty vehicles, do not need to be modified to use E10. E85 can damage those containers and cause leaks.

Demand for E85 and demand for E10 are derived from demand for vehicle miles traveled. The relative demand for E85 depends on the rate at which drivers substitute E85 for E10. This substitution can be made safely by drivers of flex fuel vehicles (FFVs). FFVs accept a wide range of gasoline blends including both E10 and E85. Most gasoline-powered vehicles can be converted to accept E85 for \$200-\$400,<sup>4</sup> but the current fleet of 226 million vehicles includes just 12 million FFVs.<sup>5</sup> As a result of the differences in octane and energy content between ethanol and BOB, a car travels farther on one gallon of E10 than on one gallon of E85.

All else equal we expect consumers to choose the blend that enables more miles per dollar, but miles per dollar is not the only consideration. The lower energy content of E85 requires drivers to fill their tanks more frequently. The three thousand E85

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<sup>3</sup>In the 1990s and early 2000s, many suppliers raised the octane rating of gasoline by adding methyl-tertiary butyl ether (MTBE). Because ethanol also raises the octane rating of gasoline, it is a substitute for the energy content of BOB and the octane rating of MTBE. Ethanol blending jumped in 2006 as a result of the ban on MTBE (Anderson and Elzinga 2014).

<sup>4</sup>Change2e85.com sells conversion kits for 4- and 6-cylinder engines for \$199 and \$325.

<sup>5</sup>Energy Information Administration, Annual Energy Outlook, 2013, Table 58: "Light-Duty Vehicle Stock by Technology Type".

stations in the United States are much sparser than the hundreds of thousands of E10 stations, so filling a gas tank with E85 is often inconvenient. Some FFV owners are not even aware their vehicles accept E85. Yet drivers purchased E85 in small volumes even when E85 was more expensive than E10 per gallon and far more expensive per mile.

**Diesel**—Biodiesel is an excellent substitute for petroleum-based diesel. The energy content of biodiesel is nearly as high as the energy content of petroleum-based diesel. Biodiesel may reduce performance if it is stored in high blends for long periods in cold weather, but for most drivers, the performance of blends with 5% biodiesel or less is the same as 100% petroleum-based diesel. The average blend of biodiesel in diesel has always been below 3%.

Biodiesel production is limited by competition with petroleum-based diesel as an input into blended diesel. Diesel blenders choose a blend composition that minimizes cost. Because blends with low biodiesel content are nearly perfect substitutes and the average blend of 2% in 2013 includes both biodiesel and petroleum-based diesel, the blender cost of biodiesel must nearly equal the blender cost of petroleum-based diesel. The blender cost of components includes explicit and implicit taxes and subsidies, including those from the RFS.

### **2.2.2 The Renewable Fuel Standard**

The Energy Independence and Security Act of 2007 (EISA) set a schedule of aggregate minimum volume requirements for annual consumption of renewable fuel. The minimum volumes in EISA and their implementation by the Environmental Protection Agency (EPA) are called the Renewable Fuel Standard (RFS). Every year, the EPA translates the RFS minimum volume requirement into an obligation on individual refiners in proportion to the volume of nonrenewable fuel they refine. For

example, if the RFS minimum renewable volume was 10 billion gallons, and non-renewable fuel consumption was expected to be 100 billion gallons, then the EPA would require refiners to prove use of 0.1 gallon of renewable fuel for every gallon of nonrenewable fuel they refined.<sup>6</sup> That fraction, 0.1, is the policy tool controlled by the EPA. It expresses the obligation faced by a refiner per gallon of nonrenewable fuel.

To keep track of RFS compliance, the EPA created Renewable Identification Numbers (RINs). RINs are renewable energy credits “generated” when renewable fuel is added to a fuel blend, meaning the EPA gives RINs to the blender. RINs generated by blenders are the supply of RINs, and RFS obligations on refiners are the demand for RINs. A blender who generates RINs can sell them to a refiner, who must submit RINs to the EPA to prove compliance with the RFS. Thus a RIN is received from the EPA by a blender, sold to a refiner, and submitted back to the EPA. Figure 2.1 illustrates the flow of blending components to the blender, the flow of blended fuel to the consumer, and the flow of RINs.

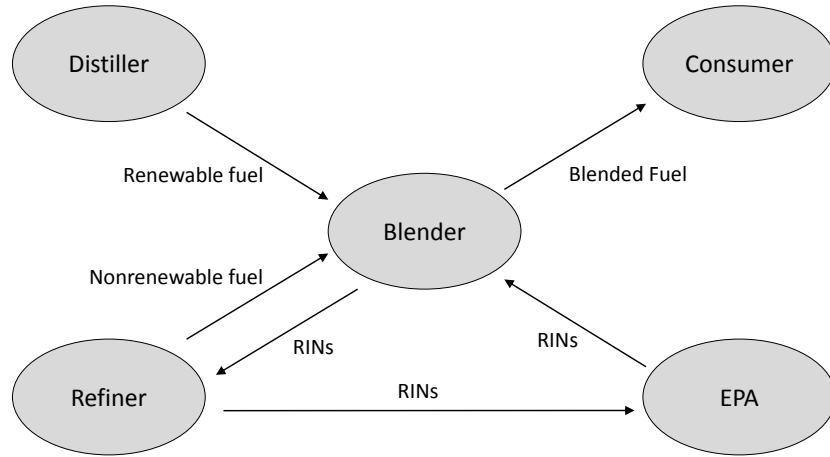
The treatment of a gallon of renewable fuel under the RFS depends on the raw material—feedstock—that is used to produce that gallon. There are four renewable fuel categories under the RFS: cellulosic, biodiesel, advanced, and renewable. The eligibility of a feedstock for a RIN category depends on the EPA’s assessment of the life cycle greenhouse gas emissions of renewable fuel produced from that feedstock relative to the nonrenewable fuel it displaces.<sup>7</sup> There are four categories of RINs corresponding to the four categories of renewable fuel under the RFS. One ethanol-

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<sup>6</sup>In the example, the fraction 0.1 is equal to  $\frac{10 \text{ billion gallons of renewable fuel}}{100 \text{ billion gallons of nonrenewable fuel}}$ .

<sup>7</sup>The EPA determined that the life cycle greenhouse gas emissions from grain corn ethanol are 20% below petroleum-based gasoline, so grain corn ethanol is eligible to produce renewable RINs. The reduction thresholds for the EPA to allow an ethanol feedstock to generate advanced and cellulosic RINs are 50% and 80% relative to petroleum-based gasoline. To produce a biodiesel RIN, a biodiesel feedstock must reduce life cycle greenhouse gas emissions 50% relative to petroleum-based diesel.

Figure 2.1: Flow of fuel and RINs



Note: Renewable fuel includes ethanol and biodiesel. Nonrenewable fuel includes BOB and petroleum-based diesel. Blended fuel includes E10, E85, and B5. The EPA gives RINs to a blender when the blender adds renewable fuel to a blend. The blender sells RINs to a refiner. The refiner submits RINs back to the EPA to demonstrate compliance with the RFS.

equivalent gallon is the standard unit of RINs. For one gallon of grain corn ethanol, the blender generates one RIN. Other renewable fuels generate different volumes of ethanol-equivalent gallons; one gallon of biodiesel produces 1.5 ethanol-equivalent RINs. Cellulosic and biodiesel are mutually exclusive subsets of advanced, and advanced is a subset of renewable.

A gallon of petroleum-based gasoline incurs the same obligation as a gallon of petroleum-based diesel. For each gallon of nonrenewable fuel, a refiner must submit a fraction of a RIN from all four RIN categories: a fraction of a cellulosic RIN ( $\rho_3$ ), a fraction of a biodiesel RIN ( $\rho_4$ ), a fraction of an advanced RIN ( $\rho_5$ ), and a fraction of a renewable RIN ( $\rho_6$ ). Because cellulosic and biodiesel are subsets of advanced, the fraction  $\rho_5$  is the *residual* fraction of an advanced RIN. If a refiner submits biodiesel RINs in excess of the biodiesel fraction, it has less residual obligation. Similarly,  $\rho_6$  is the *residual* fraction of a renewable RIN. The subscripts on the  $\rho$  fractions correspond to the labels typically used by the EPA to denote the four renewable fuel

categories.

The mandate fractions ( $\rho_3, \rho_4, \rho_5, \rho_6$ ) are the policy tool controlled by the EPA. In an RFS rule released annually, the EPA calculates the mandate fractions as the renewable volume requirements in EISA divided by total nonrenewable volume forecast by the Energy Information Administration. EISA grants waiver authority to the EPA to adjust this calculation under some circumstances.<sup>8</sup> The main policy adjustment I consider is the renewable volume requirement ( $\rho_6$ ).

RINs can be traded and stored, but there are some constraints on storage. An RFS obligation may only be filled with RINs generated in the same year and one year prior, and at most 20% may be filled with prior-year RINs. However, the aggregate stock of RINs is estimated to be around 2.6 billion, well below 20% of the total renewable mandate, so the restriction to prior-year RINs just means that the existing stock of prior-year RINs should be used for compliance and exhausted before tapping into current-year RINs. RINs of different vintages are thus good substitutes.

The RFS minimum volumes are based on the 2007 law and adjusted by the EPA to accommodate unforeseen circumstances. In 2013, the EPA reduced the cellulosic volume from 1 *billion* gallons, as scheduled back in 2007 by EISA, to 6 *million* gallons in recognition of inadequate supply. The capacity to produce cellulosic fuel has lagged far behind the timetable set in EISA.

The EPA computes the RIN obligation per gallon of nonrenewable as a fraction, where the numerator is the minimum renewable volume and the denominator is the expected volume of nonrenewables forecast by the Energy Information Administration (EIA). In 2013, the EPA set the minimum total renewable volume (including cellulosic, biodiesel, and advanced) at 16.55 billion ethanol-equivalent gallons. The

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<sup>8</sup>In the past, some RFS rules exempted certain nonrenewable producers from obligations under the mandate. Other RFS rules reduced the cellulosic volume requirement in recognition of inadequate domestic supply.



Table 2.1: Renewable fuel mandated by RFS

RIN obligation per gallon of nonrenewable						
Year	Cellulosic	Biodiesel	Advanced	Subtotal	Renewable	Total
2010	0.00%	0.62%	0.00%	0.63%	7.62%	8.25%
2011	0.00%	0.69%	0.08%	0.78%	7.24%	8.01%
2012	0.00%	0.91%	0.30%	1.21%	8.02%	9.23%
2013	0.00%	1.12%	0.48%	1.60%	8.03%	9.63%
2014	0.01%	1.16%	0.16%	1.33%	7.87%	9.20%

Note: This table shows the fraction of a RIN an obligated party must submit per gallon of nonrenewable. The fraction for advanced is a residual eligible to be filled by non-cellulosic, non-biodiesel advanced. Similarly, the fraction for renewable is a residual eligible to be filled by non-advanced renewable. Fractions for 2013 and earlier are from final EPA rules. 2014 fractions are from the EPA notice of proposed rulemaking. The 2012 cellulosic fraction was reduced to zero by court order. The biodiesel fraction from the final 2010 rule is distributed partially to 2009. Schnepf and Yacobucci (2013).

EIA forecast nonrenewable volume of 172 billion gallons. So the total renewable mandate fraction was 9.63% ( $= \frac{16.55}{172}$ ), which is the fraction of ethanol-equivalent RINs that must be submitted by a refiner for each gallon of nonrenewable.<sup>9</sup> Table 2.1 shows the actual RFS fractions from 2010 to 2013 and the proposed fractions for 2014.

### 2.2.3 RIN prices

The prices of the four categories of RINs are related through several mechanisms. The price of an advanced RIN should be at least as high as the price of a renewable RIN. This is because, under the RFS, an advanced RIN can be used to satisfy the renewable obligation. If advanced RINs were cheaper than renewable RINs, an obligated party would be better off purchasing advanced RINs to satisfy its renewable obligation. Similarly, the price of an advanced RIN should be no higher than the price of a biodiesel RIN. This inequality is not an explicit rule; it is a logical consequence. The RFS places complex constraints on the price of cellulosic RINs. They are usually

<sup>9</sup>In 2013, a refiner that produced 100,000 gallons of BOB would be in compliance with the RFS mandate if it submitted 3 cellulosic RINs generated from 3 gallons of switchgrass ethanol; 1,120 ethanol-equivalent biodiesel RINs generated from 747 gallons of biodiesel; 480 advanced RINs generated from 480 gallons of sugarcane ethanol; and 8,030 renewable RINs generated from 8,030 gallons of grain corn ethanol.

pinned to the price of advanced RINs plus 25 cents.

Most renewable RINs are produced by blending domestic corn ethanol. Most advanced RINs are produced by blending sugarcane ethanol from Brazil. Brazilians are indifferent between sugarcane ethanol and corn ethanol because the performance of fuel made from the two feedstocks is identical, but American blenders are not indifferent because the price of a sugarcane ethanol RIN can differ from the price of a corn ethanol RIN. The transportation cost of a round trip to exchange American corn ethanol for Brazilian sugarcane ethanol is around 40 cents per gallon. Therefore, arbitrage constrains the amount by which the price of advanced RINs can exceed the price of renewable RINs to 40 cents.

The price of RINs changes the blender cost of components. When a blender purchases a gallon of ethanol, it also gets to sell the RIN it generates from blending that gallon. The blender cost of ethanol is the price the blender pays for the ethanol minus the price it receives for selling the RIN. In this way, RINs act like a subsidy to renewable fuel because a blender earns revenue from selling a RIN. Similarly, the blender cost of BOB is higher than the world price of BOB because RINs act like a tax on BOB in the United States.<sup>10</sup>

#### **2.2.4 The blendwall**

I will use the term “blendwall” to mean 10% of blended gasoline. This differs slightly from the typical meaning of blendwall—the volume of ethanol that “can” be

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<sup>10</sup>Lade, Lin, and Smith (2015) explain the following benchmark for RIN prices: “RIN prices equal the weighted difference between the cost of the marginal ... renewable fuel used to meet each mandate and the marginal cost of the cheaper fossil fuel it displaces.” This benchmark for RIN prices can be violated through the linkage between the price of a cellulosic RIN and an advanced RIN, the arbitrage relationship between the price of an advanced RIN and the price of a conventional RIN, and the technical constraint on blending ethanol into E10.

incorporated into the fuel supply as a component of blended gasoline.<sup>11</sup> This typical meaning of blendwall is not well defined. The volume that is incorporated into blended gasoline is sensitive to prices and infrastructure, both of which are changing in response to the RFS. Expectations about the RFS influence the decision to vend E85 at a gas station or to buy a flex fuel vehicle.<sup>12</sup> This definition of blendwall thus depends on the policy we are trying to analyze. A benchmark of 10% of gasoline consumption provides a stable point of reference, so I use this definition of blendwall.

In 2013, the minimum RFS volume exceeded the blendwall.<sup>13</sup> Until 2013, RFS compliance could be achieved by increasing the fraction of ethanol in E10 gasoline.<sup>14</sup> That method of compliance has reached its limit; renewable fuel must be added to the fuel supply in some way other than increasing the fraction of ethanol in E10. There are four options for generating additional RINs once the ethanol fraction of E10 gasoline has reached its limit: increase the volume of E10 gasoline, increase the ethanol fraction in E85 gasoline, increase the volume of E85 gasoline, and increase the biodiesel fraction in blended diesel.

The response of the market to the tension between the blendwall and RFS volumes hinges on demand for E85 gasoline and supply of biodiesel. We know a little bit about the demand for E85 from prior literature.<sup>15</sup> However, the quantity of E85

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<sup>11</sup>A less common meaning of blendwall is the highest EPA-permitted blend fraction, which the EPA lifted from 10% to 15% in 2010 for most vehicles. Qiu, Colson, and Wetzstein (2014) use this definition.

<sup>12</sup>Babcock (2013) simulates the response of investment in E85 infrastructure to the RFS. Du and Carriquiry (2013) examine the impact of expanding the share of FFVs on ethanol price dynamics. Du and Li (2015) examine the impact of E85 fueling stations on the market share of FFVs.

<sup>13</sup>14.63 billion gallons were eligible to be satisfied by ethanol. Even if the 132.8 billion gallons of gasoline consumption forecast by the EIA included 10% ethanol, the volume of ethanol consumed would still fall 1.35 billion gallons short of satisfying the mandate.

<sup>14</sup>Appendix Table 2.6 shows that from 2006 to 2013, the average blend in E10 increased from 4% to 10%. Appendix Figure 2.8 shows that the mandate schedule passes the blendwall because it follows the trajectory of gasoline consumption that was expected when the law passed in 2007.

<sup>15</sup>Du and Carriquiry (2013) and Du and Li (2015) examine the impact of expanding the share of FFVs and the number of E85 fueling stations. Anderson (2012) uses fuel-station level data in Minnesota to estimate a discrete choice model in which consumers value E85 directly in addition to

and the quantity of biodiesel are in uncharted territory, and if the mandate increases according to its schedule, they will continue to break new ground.

## 2.3 Model

I build a model to serve as a laboratory for experimenting with policy options available to the Environmental Protection Agency (EPA) for implementing the Renewable Fuel Standard (RFS). The blender buys blending components from suppliers and sells blended fuel to consumers. The RFS mandate is incorporated into the blender's decision problem.

There is one biofuel in the model for each of the three categories of RINs that are produced in quantities large enough to affect the blendwall: biodiesel generates biodiesel RINs, sugarcane ethanol generates advanced RINs, and corn ethanol generates renewable RINs. The price of cellulosic RINs is set equal to the price of advanced RINs plus 25 cents.

### 2.3.1 Consumers

Utility is quasilinear in three goods: gasoline miles ( $G$ ), diesel miles ( $BX$ ), and bushels of nonfuel corn ( $C$ ), each of which has a constant elasticity of demand ( $\epsilon_i$ ). Consumers have a standard budget constraint with income  $Y$ , and the price of the numeraire ( $Z$ ) is normalized to 1. Diesel miles are traveled using a single average diesel blend. Gasoline miles are traveled using a combination of E10 gasoline and E85 gasoline. The elasticity of substitution between E10 and E85 is  $\frac{\sigma}{1-\sigma}$ , and the demand share of E10 is  $\alpha$ .

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its use for vehicle miles traveled. Liu and Greene (2013) and Pouliot and Babcock (2014) estimate similar discrete choice models.

$$\begin{aligned}
& \max_{Q_{E10}, Q_{E85}, Q_{BX}, Q_C, Q_Z} \phi_G \frac{\left[ (\alpha)(Q_{E10})^{\frac{1}{\sigma}} + (1 - \alpha)(\gamma Q_{E85})^{\frac{1}{\sigma}} \right]^{(\sigma)(1 - \frac{1}{\epsilon_G})}}{1 - \frac{1}{\epsilon_G}} \\
& \quad + \phi_B \frac{Q_{BX}^{1 - \frac{1}{\epsilon_B}}}{1 - \frac{1}{\epsilon_B}} + \phi_C \frac{Q_C^{1 - \frac{1}{\epsilon_C}}}{1 - \frac{1}{\epsilon_C}} + Q_Z \\
& \text{s.t.} \quad P_{E10}Q_{E10} + P_{E85}Q_{E85} + P_{BX}Q_{BX} + P_CQ_C + Q_Z = Y \quad (2.1)
\end{aligned}$$

Because there is a numeraire good, there is no income effect of price changes in fuel and nonfuel corn. The first order conditions imply the relative demand of E85 is a function of the relative price of E85. Consumers demand more E85 when it is cheaper relative to E10.

$$\frac{Q_{E85}}{Q_{E10}} = \left( \frac{P_{E85}}{P_{E10}} \right)^{\frac{\sigma}{1-\sigma}} \left( \gamma \right)^{\frac{1}{\sigma-1}} \left( \frac{1}{\alpha} - 1 \right)^{\frac{\sigma}{\sigma-1}} \quad (2.2)$$

Nonfuel corn is included in the model to facilitate calibration. It permits use of outside estimates of the elasticity of supply for corn and the elasticity of demand for corn, so that the elasticity of supply for corn as fuel arises endogenously through the decision of the corn producer.<sup>16</sup> In the model, nonfuel corn is sold directly by the corn producer to consumers, whereas fuel passes through blenders of E10, E85, and diesel. The first order conditions imply demand curves for gasoline, diesel, and

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<sup>16</sup>An alternative approach would be to leave nonfuel corn out of the model and use an outside estimate of the elasticity of ethanol supply, such as by Luchansky and Monks (2009). Because corn ethanol is such a large part of the RFS and the market for corn, I believe the benefit of explicitly modeling the tradeoff with nonfuel corn is worth the added complexity. Several studies have gone further in this direction to examine the effect of the biofuel mandates on food and fuel prices. Wu and Langpap (2015) find that the RFS raised corn prices substantially with a small positive impact on food prices overall and a small negative impact on gasoline prices. McPhail and Babcock (2012), who model the blendwall, find that the RFS increases price variability.

nonfuel corn.

$$P_{E10} = \phi_G [(\alpha)(Q_{E10})^{\frac{1}{\sigma}} + (1 - \alpha)(\gamma Q_{E85})^{\frac{1}{\sigma}}]^{\sigma - \frac{\sigma}{\epsilon_G} - 1} Q_{E10}^{\frac{1-\sigma}{\sigma}}(\alpha) \quad (2.3)$$

$$P_{BX} = \phi_B Q_{BX}^{-\frac{1}{\epsilon_B}} \quad (2.4)$$

$$P_C = \phi_C Q_C^{-\frac{1}{\epsilon_C}} \quad (2.5)$$

### 2.3.2 Suppliers

**Supply of corn ethanol and nonfuel corn**—The corn producer maximizes profit by choosing ethanol ( $E100$ ) and nonfuel corn ( $C$ ). Nonfuel corn can be converted to ethanol at a fixed ratio  $\mu$ . Costs are an increasing function of the number of bushels of corn required to produce the ethanol and nonfuel corn ( $Q_C + \mu Q_{E100}$ ). The first order condition for corn gives the corn supply curve with constant supply elasticity  $\eta_C$ . The first order condition for ethanol implies a relationship between the price of ethanol and nonfuel corn.

$$\max_{Q_C, Q_{E100}} P_C Q_C + (P_{E100} - \nu_C) Q_{E100} - \theta_C \frac{(Q_C + \mu Q_{E100})^{1 + \frac{1}{\eta_C}}}{1 + \frac{1}{\eta_C}}$$

$$\text{FOCs imply: } P_C = \theta_C (Q_C + \mu Q_{E100})^{\frac{1}{\eta_C}} \quad (2.6)$$

$$P_{E100} = \mu P_C + \nu_C \quad (2.7)$$

$\nu_C$  is the markup of the price of ethanol over the price of corn inputs. It reflects the cost of distillation and the revenue received from byproducts of distillation like dried distillers grains.

**Supply of petroleum-based gasoline and diesel**—The petroleum gasoline refiner chooses the quantity of gasoline blendstock for oxygenate blending ( $E0$ ) to

maximize profit. The first order condition implies a supply curve with intercept  $\theta_G$  and constant elasticity  $\eta_G$ .

$$\begin{aligned} \max_{Q_{E0}} \quad & P_{E0}Q_{E0} - \theta_G \frac{Q_{E0}^{1+\frac{1}{\eta_G}}}{1 + \frac{1}{\eta_G}} \\ \text{FOC implies:} \quad & P_{E0} = \theta_G Q_{E0}^{\frac{1}{\eta_G}} \end{aligned} \tag{2.8}$$

The diesel refiner's problem is parallel to the gasoline refiner's problem. The petroleum diesel refiner chooses the quantity of petroleum-based diesel ( $B0$ ) to maximize profit. The first order condition implies a supply curve with intercept  $\theta_D$  and constant elasticity  $\eta_D$ .

**Supply of biodiesel**—The biodiesel refiner chooses the quantity of biodiesel ( $B100$ ) to maximize profit. The biodiesel refiner pays a constant marginal cost ( $\nu_B$ ) for the biodiesel feedstock, and faces increasing marginal costs of refining. The biodiesel refiner's first order condition implies a supply curve.

$$\begin{aligned} \max_{Q_{B0}} \quad & P_{B100}Q_{B100} - \nu_B Q_{B100} - \theta_B \frac{Q_{B100}^{1+\frac{1}{\eta_B}}}{1 + \frac{1}{\eta_B}} \\ \text{FOC implies:} \quad & P_{B100} = \nu_B + \theta_B Q_{B100}^{\frac{1}{\eta_B}} \end{aligned} \tag{2.9}$$

**Supply of sugarcane ethanol**—The sugarcane ethanol supplier chooses the quantity of sugarcane ethanol ( $Q_{E100}^S$ ) to maximize profit. The sugarcane ethanol supplier's first order condition implies a supply curve.

$$\begin{aligned} \max_{Q_{E100}^S} \quad & P_{E100}^S Q_{E100}^S - \theta_S \frac{(Q_{E100}^S)^{1+\frac{1}{\eta_S}}}{1 + \frac{1}{\eta_S}} \\ \text{FOC implies:} \quad & P_{E100}^S = \theta_S (Q_{E100}^S)^{\frac{1}{\eta_S}} \end{aligned} \tag{2.10}$$

### 2.3.3 Blender

The blender of E10 gasoline chooses the quantity of E10 gasoline and the fraction of ethanol in each blended gallon ( $F_{E10}$ ) to maximize profit. I use the shorthand  $\rho$  as a row vector of mandate fractions and  $P_{RIN}$  as a column vector of RIN prices such that the obligation per gallon in dollars is  $\rho P_{RIN}$ :  $\rho P_{RIN} \equiv \rho_3 P_{R3} + \rho_4 P_{R4} + \rho_5 P_{R5} + \rho_6 P_{R6}$ .<sup>17</sup>

$$\begin{aligned} \max_{Q_{E10}, F_{E10}} \quad & Q_{E10} \left[ P_{E10} - F_{E10} (P_{E100} - P_{R6}) - (1 - F_{E10}) (P_{E0} + \rho P_{RIN}) \right] \\ \text{s.t.} \quad & 0 \leq F_{E10} \leq 0.1 \end{aligned}$$

Profit is equal to the volume of E10 gasoline times the difference between the price received by the blender ( $P_{E10}$ ) and the blender cost of components. The wholesale price of ethanol is offset by the generation and sale of a RIN, so the blender cost of ethanol is  $P_{E100} - P_{R6}$ . The wholesale price of BOB is augmented by the cost of RFS compliance, so the blender cost of BOB is  $P_{E0} + \rho P_{RIN}$ .

The quantity first order condition expresses an arbitrage condition that relates the price of blended E10 gasoline to the cost of components.<sup>18</sup> The fraction first order condition says that, if the blend fraction is at an interior solution above 0% and below 10%, then the blender cost of ethanol must equal the blender cost of BOB. The blender of E85 gasoline and blended diesel face analogous problems. Their quantity and fraction first order conditions express parallel relationships between price and

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<sup>17</sup>Fractions and RIN prices are indexed by numbers 3 to 6, which the EPA associates with cellulosic, biodiesel, advanced, and renewable RINs.

<sup>18</sup>When the model is calibrated in Section 2.4, the arbitrage condition will also include a wedge between the price of blended fuel and the blender cost of components to account for transportation costs and taxes.



blender cost, and between the cost of one component and the other.<sup>19</sup>

$$P_{E10} = F_{E10}(P_{E100} - P_{R6}) + (1 - F_{E10})(P_{E0} + \rho P_{RIN}) \quad (2.11)$$

$$P_{E100} - P_{R6} = P_{E0} + \rho P_{RIN} \quad (2.12)$$

If biodiesel and petroleum-based diesel are both included in the diesel blend, then the blender cost of biodiesel and the blender cost of petroleum-based diesel must be equal.

Gasoline blenders have a third choice variable, the fraction of ethanol that is sugarcane ethanol. This term was omitted from the profit function above for simplicity. It results in the following condition relating the blender cost of corn ethanol to the blender cost of sugarcane ethanol. The price of cellulosic RINs is set equal to the price of advanced RINs plus 25 cents.

$$P_{E100} - P_{R6} = P_{E100}^S - P_{R5} \quad (2.13)$$

### 2.3.4 Market clearing conditions

The market-clearing condition for renewable RINs is that the generation of corn ethanol RINs, sugarcane ethanol RINs, and ethanol-equivalent biodiesel RINs equals RFS obligations. For each gallon of BOB or petroleum diesel, a refiner must submit

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<sup>19</sup>Appendix section 2.8.2.2 includes the E85 and diesel blender quantity and fraction conditions, as well as a more precise statement of the blender's problem including the choice of sugarcane ethanol.

RINs from all four RIN categories.

$$Q_{E100} + Q_{E100}^S + 1.5Q_{B100} = (Q_{E0} + Q_{B0})(\rho_3 + \rho_4 + \rho_5 + \rho_6) \quad (2.14)$$

$$Q_{E100}^S + 1.5Q_{B100} \geq (Q_{E0} + Q_{B0})(\rho_3 + \rho_4 + \rho_5) \quad (2.15)$$

$$1.5Q_{B100} \geq (Q_{E0} + Q_{B0})(\rho_4) \quad (2.16)$$

The volume of ethanol in gasoline ( $Q_{E100} + Q_{E100}^S$ ) is equal to the volume of RINs generated by blending ethanol into gasoline. The lefthand side of equation 2.14 is thus the supply of RINs, including 1.5 ethanol-equivalent RINs per gallon of biodiesel. Current RFS obligations are the volume of nonrenewable fuel times the RIN obligation per gallon. Nonrenewable fuel is the sum of petroleum-based gasoline ( $Q_{E0}$ ) and petroleum-based diesel ( $Q_{B0}$ ). The market-clearing conditions for advanced RINs and biodiesel RINs are similar. These are inequality constraints because excess advanced RINs can be used to meet the renewable mandate.

When markets clear, the production volume of blending components will be equal to the volume used by blenders in blended fuel. The market clearing conditions for blending components—ethanol, blendstock for oxygenate blending, biodiesel, and petroleum diesel—are:

$$Q_{E100} + Q_{E100}^S = F_{E10}Q_{E10} + F_{E85}Q_{E85} \quad (2.17)$$

$$Q_{E0} = (1 - F_{E10})Q_{E10} + (1 - F_{E85})Q_{E85} \quad (2.18)$$

$$Q_{B100} = F_{BX}Q_{BX} \quad (2.19)$$

$$Q_{B0} = (1 - F_{BX})Q_{BX} \quad (2.20)$$

## 2.4 Testing and estimating price relationships

The model is designed for performing policy experiments with RFS minimum volumes, and it also makes predictions about the relationships among prices of RINs, blending components, and blended fuels. This section has two goals. One goal is to show that the predicted price relationships are observed in the data, as a method of supporting the empirical relevance of the model. The other goal is to inform the calibration of model parameters for taxes and transportation costs.

**RIN prices**—The model predicts a hierarchy of RIN prices: in descending order, biodiesel, advanced, renewable ( $P_{R4} \geq P_{R5} \geq P_{R6}$ ). Figure 2.2 shows that this has been the case. For most of 2011 and 2012, there were large gaps between the three prices, and then in 2013 the prices converged. The model predicts that the prices will converge if excess biodiesel RINs are being used to satisfy the renewable mandate. RIN price changes should be attributed to changes in expectations, which I do not explicitly model.<sup>20</sup>

**Price and blender cost of E10**—The model predicts that the retail price of E10 will equal the blender cost (BC) of components.<sup>21</sup> For the empirical test, I include the cost to the blender of octane-boosting additives (OBA), which was omitted from the exposition of the model for simplicity. I assume that octane-boosting additives are added in proportion to BOB above 90% at a price equal to 15% of the price of BOB.<sup>22</sup>

Figure 2.3 shows that the retail price of E10 exceeds the blender cost of components. This makes sense because the retail price includes components that were

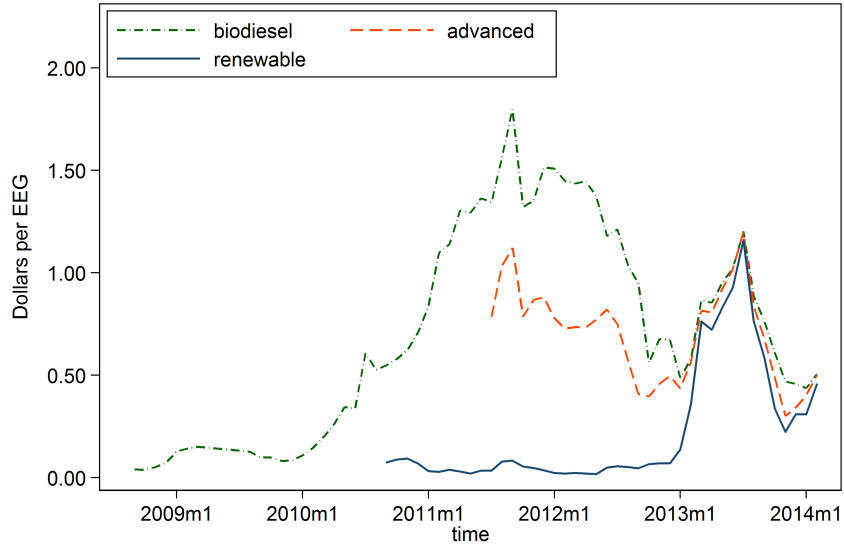
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<sup>20</sup>Lade, Lin, and Smith (2014) examine RIN prices in a dynamic context.

<sup>21</sup> $BC_{E10} = F_{E10}(P_{E100} - P_{R6}) + (1 - F_{E10})(P_{E0} + \rho P_{RIN}) + (.1 - F_{E10})(\nu_{OBA} P_{E0})$

<sup>22</sup>Babcock, Moreira, and Peng (2013) posit an ethanol demand curve which is elastic for low ethanol volumes at a price ratio relative to BOB of 1.2 ( $\nu_{OBA} = 0.20$ ). As the ethanol volume approaches the blendwall in their demand curve, the price ratio decreases, so I assume a lower price ratio ( $\nu_{OBA} = 0.15$ ).

Figure 2.2: Monthly RIN prices



Note: This figure shows the monthly RIN prices calculated from Bloomberg. RIN prices are reported in separate vintages depending on the year in which the RIN was generated. A monthly average within vintage is calculated as a simple average of available daily prices. Missing months, which occur mostly in the earlier years of the mandate when RIN prices were near zero, are linearly interpolated. The price is then taken as the maximum among all reported vintages.

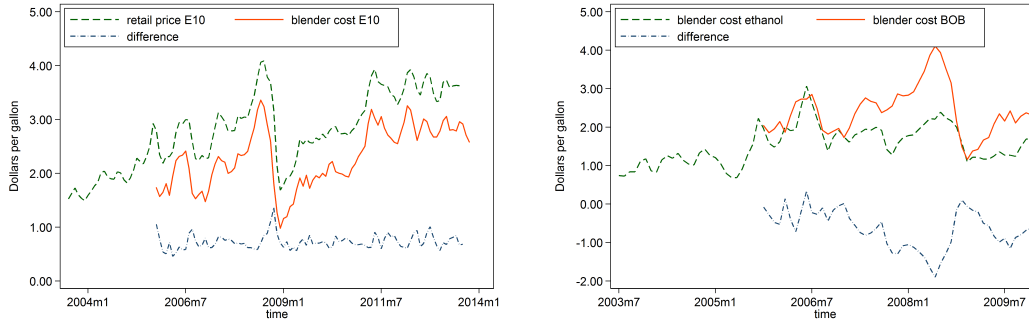
not in the model like transportation costs and taxes. When I simulate the model, I add a wedge between the retail price and the blender cost. I allow the wedge to include an ad valorem component  $\nu_{G1}$  and a per unit component  $\nu_{G2}$  because some gasoline taxes are ad valorem and others are expressed per unit volume. Equation 2.11 becomes:  $RP_{E10} = BC_{E10}\nu_{G1} + \nu_{G2}$ . I estimate both components empirically, and use the estimates for calibrating the model.

The parameter  $\nu_{G2}$  expresses a constant markup per gallon. To estimate the constant markup per gallon  $\nu_{G2}$ , I regress the retail price of E10 on the blender cost of components.<sup>23</sup> Table 2.2 shows that the retail price exceeds the blender cost of components by about 72 cents.<sup>24</sup> I use this estimate for the parameter  $\nu_{G2}$  in

<sup>23</sup>The equation is:  $RP_{E10,t} = \nu_{G2} + \beta_1 BC_{E10,t} + u$ .

<sup>24</sup>This is very close in concept and magnitude to the “wholesale-to-retail price markup” of 75 cents reported by Pouliot and Babcock (2014).

Figure 2.3: E10 retail price and blender cost



Note: The left panel compares the retail price of E10 with the blender cost of E10. The right panel compares the blender cost of ethanol to the blender cost of BOB. Retail price is the U.S. city average retail price of unleaded regular gasoline, from EIA. Blender cost (BC) is calculated according to the following equation:  $BC_{E10} = F_{E10}(P_{E100} - P_{R6}) + (1 - F_{E10})(P_{E0} + \rho P_{RIN}) + (.1 - F_{E10})(\nu_{OBA} P_{E0})$ . Ethanol fraction  $F_{E10}$  is ethanol share of finished gasoline consumption, from EIA. Ethanol price  $P_{E100}$  is blender cost of ethanol with credit, from U.S. Bioenergy Statistics. The vector of RIN prices  $P_{RIN}$  includes renewable  $P_{R6}$ , advanced  $P_{R5}$ , and biodiesel  $P_{R4}$  RIN prices, from Bloomberg. BOB price  $P_{E0}$  is generic RBOB gasoline (XB1), from Bloomberg. The vector of RFS fractions  $\rho$  is from past EPA rules. The cost of octane-boosting additives is assumed to be proportional to the price of BOB,  $\nu_{OBA} = 0.15$ .

Table 2.2: Regression of retail price of E10 on blender cost of E10

$BC_{E10,t}$	1.006*** (0.0252)
Constant	0.717*** (0.0595)
Observations	95
R-squared	0.945
Standard errors in parentheses	
*** $p < 0.01$ , ** $p < 0.05$ , * $p < 0.1$	

Note: This table reports regression results of retail price on blender cost of E10 using monthly data. See note on Figure 2.3.

simulations.

The parameter  $\nu_{G1}$  expresses the passthrough of blender costs to the retail price of E10. In the model, arbitrage is instantaneous, but in data cost changes may not be passed through right away or at all. As a simple exercise, I regress retail price on a distributed lag of the blender cost. The regression will be endogenous if there is reverse causality from retail prices to blender costs. Table 2.3 shows the results

Table 2.3: Regression of change in retail price of E10 on lagged changes in blender cost of E10

$\Delta\Delta BC_{E10,t}$	0.597*** (0.0463)
$\Delta\Delta BC_{E10,t-1}$	1.079*** (0.0530)
$\Delta\Delta BC_{E10,t-2}$	1.129*** (0.0591)
$\Delta BC_{E10,t-3}$	1.093*** (0.0656)
Constant	-0.000346 (0.00873)
Observations	91
R-squared	0.851
Standard errors in parentheses	
*** $p < 0.01$ , ** $p < 0.05$ , * $p < 0.1$	

Note: This table reports regression results of a change in retail price on a distributed lag of blender cost of E10 using monthly data. See note on Figure 2.3.

of the regression.<sup>25</sup> A price change in the blender cost of components is followed by a price change in the retail price of E10. I use the three-month estimate that 109% of a change to the blender cost of components is reflected in the retail price for the parameter  $\nu_{G1}$  in simulations. An effect larger than 100% is consistent with passing through ad valorem taxes.

**Blending components of E10**—The model predicts that the blender cost of ethanol will equal the blender cost of BOB whenever the blend fraction is interior, i.e. not at the 0% or 10% boundaries.<sup>26</sup> This relationship is expressed by equation 2.12. Figure 2.3 shows that this prediction fails—the blender cost of ethanol is in general not equal to the blender cost of BOB. I attribute this to regional variation that is not captured by the model. Individual blenders in Minnesota face a blender cost of ethanol below the national average because of local subsidies and proximity to ethanol distilleries. Minnesota blenders are therefore more likely to be at the corner

<sup>25</sup>The regression equation is  $\Delta RP_{E10,t} = \beta_0 + \sum_{i=0}^2 \beta_{i-1} \Delta\Delta BC_{E10,t-i} + \nu_{G1} \Delta BC_{E10,t-3} + u$ . See Knittel, Meiselman, and Stock (2015) for a more thorough treatment of passthrough under the RFS.

<sup>26</sup>Salvo and Huse (2011) observe this link between the price of ethanol and the price of BOB in Brazil.

solution, blending in the maximum 10% ethanol into E10 gasoline, when blenders in other states like Mississippi still observe a cost of ethanol above the cost of BOB.<sup>27</sup> Even though the blender cost of ethanol is not equal to the blender cost of BOB nationally, the model can still be a good description of local choices.

**Retail price and blender cost of diesel and E85**—The model’s predictions for diesel prices are supported by the data.<sup>28</sup> The predictions for diesel are parallel to the predictions for E10: retail price is equal to blender cost of components (with a stable wedge), and the blender cost of one component is equal to the blender cost of the other component at interior blends. For diesel, an “interior blend” corresponds to the situation in which both unblended petroleum-based diesel and a diesel blend with 5% biodiesel are being consumed.

The model’s predictions for E85 prices are not supported by the data. This is not surprising because E85 volumes are low and E85 price data are less reliable than E10 and diesel price data. National prices for E85 are biased downward relative to the blender cost of components because they are weighted by sales volume, which is highest in regions of the country where the price is lowest. Furthermore, demand for E85 is not large enough to impose a relationship between the blender cost of ethanol and the blender cost of BOB. In simulations, I use the estimated E10 price wedges for all blends of gasoline.

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<sup>27</sup>Appendix Figure 2.20 illustrates regional variation in ethanol blending. States are shaded according to the fraction of ethanol in blended gasoline from 2003 to 2011. Minnesota, Illinois, and California stand out as having relatively high fractions, while Texas and the Southeast have relatively low fractions.

<sup>28</sup>Appendix Section 2.8.3 illustrates the price relationships for diesel and E85 and estimates a price wedge between the retail price and blender cost of diesel.

Table 2.4: Calibrated parameters

Parameter	Symbol	Value	Source/Target
nonfuel corn demand elasticity	$\epsilon_C$	-0.25	Babcock, Barr, and Carriquiry (2010)
gasoline demand elasticity	$\epsilon_G$	-0.20	Hughes, Knittel, and Sperling (2008) and Coglianesi et al. (2016)
diesel demand elasticity	$\epsilon_B$	-0.07	Dahl (2012)
corn supply elasticity	$\eta_C$	0.05	Roberts and Schlenker (2013)
bushels of corn per gallon of ethanol	$\mu$	0.361	Westhoff (2006)
ethanol wedge over nonfuel corn	$\nu_C$	0.76	average wedge 1982 to 2013
petrogas supply elasticity	$\eta_G$	10	assumption
petrodiesel supply elasticity	$\eta_D$	10	assumption
energy-equivalent e10 gallons per e85	$\gamma$	0.86	EPA BTU/barrel: 3.6 E100, 5.3 E0
gasoline price wedge per unit value	$\nu_{G1}$	1.09	Section 2.4
gasoline price wedge per unit volume	$\nu_{G2}$	0.72	Section 2.4
diesel price wedge per unit value	$\nu_{B1}$	1.07	Section 2.4
diesel price wedge per unit volume	$\nu_{B2}$	0.81	Section 2.4
gasoline demand elasticity of substitution	$\frac{\sigma}{1-\sigma}$	-7.6	Salvo and Huse (2013)
gasoline demand share	$\alpha$	0.65	0.3 bgals E85
sugarcane ethanol supply intercept	$\log(\theta_S)$	1.23	280 mgals net imports
sugarcane ethanol supply elasticity	$\eta_S$	35.1	Babcock, Moreira, and Peng (2013)
biodiesel refining supply intercept	$\log(\theta_B)$	0.43	1.28 bgals B100
biodiesel refining supply elasticity	$\eta_B$	1.37	Babcock, Moreira, and Peng (2013)
soy input cost per biodiesel gallon	$\psi_B$	3.6	price of soy oil

Note: This table omits some parameters. Mandate fractions ( $\rho$ ) are listed in Table 2.1. The demand and supply intercepts at the calibrated point are in Appendix Table 2.7.

## 2.5 Calibration

The calibration is designed to permit policy experiments for 2014. Table 2.4 shows the values used for model parameters, and I discuss the parameters using the table as a guide.

**RFS fractions**—The RFS renewable fraction is calibrated to the blendwall and the other RFS fractions to the 2014 Notice of Proposed Rulemaking (Environmental Protection Agency 2013). This is appropriate because the goal of the calibration is to perform policy experiments for 2014. In the policy experiment, I will increase the renewable RFS fraction and observe the equilibrium response as the RFS obligation exceeds the blendwall.

**Demand elasticities and income**—Values for demand elasticity parameters are based on estimates in the literature. Babcock, Barr, and Carriquiry (2010)



construct several demand curves for nonfuel corn products. I use their estimated elasticity for corn feed -0.25. Hughes, Knittel, and Sperling (2008) estimate a range for gasoline demand elasticity in the 2000s of -0.034 to -0.077. However, Coglianesse et al. (2016) argue that gasoline demand elasticity estimates that use contemporary tax changes as an instrument are too low, and they offer a much higher point estimate of -0.368. In my base case I use a gasoline demand elasticity between these two estimates (-0.20), and the results are robust to alternative simulations with a lower elasticity (-0.03) and a higher elasticity (-0.37). I use a diesel demand elasticity of -0.07 from Dahl (2012).

**Corn supply**—Values for three corn supply parameters are from various sources. For corn supply elasticity ( $\eta_C = 0.05$ ), I rely on Roberts and Schlenker (2013), who identify supply elasticities of storable commodities with the express purpose of evaluating the RFS. For the bushels of corn input into one gallon of ethanol ( $\mu = 0.361$ ), I use the ratio in a briefing from the Food and Agricultural Policy Research Institute (Westhoff 2006). For the difference between the price of ethanol and the price of corn inputs into ethanol ( $\nu_C = 0.76$ ), I use the average of the observed difference from 1982 through 2013.<sup>29</sup>

**Petroleum-based blending components**—I assume a supply elasticity for BOB and diesel. The market for these products is sufficiently global that small changes in the United States are unlikely to have a large impact on the global price. If a refiner can sell BOB outside the United States at some global price without paying the cost of RFS compliance, then the price the refiner receives in the United States must exceed the global price by the cost of RFS compliance. So  $P_{US} = P_{WORLD} + \text{RFS COST}$ . In my base case I use an elasticity of 10, and the results are

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<sup>29</sup>The price of ethanol reflects the cost of the corn input, the cost of the refining process, and the revenue from distillers grains, a valuable byproduct of ethanol production.

robust to alternative choices of 5 or 20.

**Energy-equivalence factor**—The E10-E85 energy-equivalence factor is computed using EPA assumptions about the energy content of ethanol and BOB. In the 2014 proposal, the EPA assumes 3.561 million British thermal units (BTU) per barrel for ethanol and 5.253 million BTU per barrel for BOB. I assume the fraction of ethanol in E10 is 10% and the ethanol fraction in E85 is 51%, and I use an energy-equivalence factor of 0.86 in my base case. The results are robust to assuming the ethanol fraction in E85 is 85%, which implies an energy-equivalence factor of 0.75.

**Blended fuel price wedge and regional variation**—Section 2.4 describes estimation of price wedges for gasoline and diesel. The gasoline markup per gallon is 72 cents, and the gasoline passthrough of blender costs is 1.09. The diesel markup per gallon is 81 cents, and the diesel passthrough of blender costs is 1.07.

The model does not make regional distinctions even though there is substantial regional variation.<sup>30</sup> There are state-specific taxes and subsidies on biofuel, gasoline and diesel. The cost of transporting ethanol distilled in Minnesota to Wisconsin is considerably different than the cost of transporting it to Alabama. The aggregate price relationship between blender cost and retail price is likely to be noisier than the model predicts due to regional variation. The main regional-related shortcoming of the model is the need to choose a single national blender cost of ethanol. Ethanol transportation costs vary widely by region. Variation in the price of BOB is likely to be less severe because it is often transported through low-cost pipelines.

**E85 demand**—The elasticity of substitution between E10 and E85 is inferred from the behavior of drivers switching between ethanol and gasoline. For tractability, I assume a constant elasticity of substitution. Salvo and Huse (2013) find that 20%

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<sup>30</sup>Pouliot and Babcock (2014) also do not distinguish among regions, and their wholesale-retail price wedge is 75 cents. That is similar to my estimate of 72 cents. Liu and Greene (2013) compute region-specific E85 demand intercepts to account for such differences.

of Brazilian FFV drivers choose ethanol even when it is 20% more expensive per mile, and 20% of FFV drivers choose gasoline even when ethanol is 20% less expensive per mile. From these points, I calculate an elasticity of -7.6. I also solve the model with a higher elasticity and a lower elasticity. For each elasticity, the E10 demand share  $\alpha$  is calculated such that the E85 demand curve passes through 300 million gallons at a price of \$3.50.<sup>31</sup>

There are two significant differences between what Salvo and Huse measure and what I model. First, they measure the elasticity of substitution between 100% ethanol and 100% petroleum gasoline, whereas the relevant elasticity in my model is between E85 and E10. This difference in fuel blends should lead their estimate to understate the elasticity in my model because whatever non-performance factors consumers take into account are reduced for less extreme blends. Second, they measure the elasticity for FFV drivers only, whereas my model has a representative consumer, and FFVs are only about 5% of the fleet. This difference in fleet composition should lead their estimate to overstate the elasticity in my model, although drivers may convert their non-flex fuel vehicles to become FFVs.

**Biofuel supply**—I assume biofuel supply elasticities based on discussion by Babcock, Moreira, and Peng (2013). They argue that the supply of sugarcane ethanol from Brazil should be very elastic because Brazil’s flexible infrastructure—FFVs and fueling stations—facilitates substitution between ethanol and gasoline.<sup>32</sup> I use a sugarcane ethanol supply elasticity of 35 in the baseline calibration. I choose the sugarcane ethanol supply intercept such that consumption will be equal to 280 million gallons at the calibrated point. I use a biodiesel supply elasticity of 1.37 in the

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<sup>31</sup>See Appendix Section 2.8.4 for a comparison to E85 demand estimated by Pouliot and Babcock (2014)

<sup>32</sup>Figure 15 in Babcock, Moreira, and Peng (2013) illustrates a supply curve that passes through 0 volume at a price of \$2.70 and 1.8 billion gallons at a price of \$3.10. In my model, this corresponds to a supply elasticity of about 35.

baseline calibration.<sup>33</sup> I choose the supply intercept such that biodiesel production will be equal to 1.28 billion gallons at the calibrated point. The results are robust to alternate sugarcane ethanol supply elasticities and to alternate biodiesel supply elasticities.

**Supply and demand intercepts**—The model has 26 equations and 26 endogenous variables. All but six of the parameters are discussed above. The remaining six parameters are the demand intercepts for nonfuel corn, gasoline, and diesel, and the supply intercepts for corn, BOB, and petrodiesel. Six endogenous variables are chosen based on projections or recent history, and the model is solved as if the six unknown parameters were endogenous variables.

I set the quantity of BOB and petrodiesel to the quantities assumed in the 2014 proposal, 119.5 bgals and 45.7 bgals. I set the quantity of nonfuel corn to 6 billion bushels and the price of petrodiesel to \$3.00, in line with their recent observed values. At the blendwall, the model requires the blender cost of ethanol to equal the blender cost of BOB. In order to calibrate the model at the blendwall, price of BOB must be below the price of ethanol, so I set the price of BOB to \$2.50 and the price of ethanol to \$3.00.

Because six “endogenous variables” are chosen and six “parameters” are permitted to take on any value, the model still describes a system with 26 equations and 26 unknowns. I solve the system and retain the parameter values for the demand and supply intercepts for use in simulation. For robustness checks using alternative elasticities, I recalibrate these six intercepts.

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<sup>33</sup>This elasticity is based on Babcock, Moreira, and Peng (2013), who estimate that the quantity supplied of biodiesel is 1.28 billion gallons when price exceeds variable cost by 43 cents per gallon and 1.85 billion gallons when price exceeds variable cost by one dollar.

Table 2.5: Empirical verification of endogenous variables

Variable	Actual		Calibration	Unit	Description
	2012	2013			
$F_{BX}$	1.7%	2.4%	2.7%	%	fraction of biodiesel in diesel
$F_{E10}$	9.7%	9.9%	9.9%	%	fraction of ethanol in E10 gasoline
$F_{E85}$	71%	71%	51%	%	fraction of ethanol in E85 gasoline
$P_{BX}$	3.95	3.94	4.04	usd/gal	price of diesel
$P_{E10}$	3.69	3.62	3.51	usd/gal	price of E10 gasoline
$P_{E85}$	3.33	3.23	3.67	usd/gal	price of E85 gasoline
$Q_{BX}$	53.0	54.5	47.0	bgal	quantity of diesel
$Q_{E10}$	133.7	133.2	132.5	bgal	quantity of E10 gasoline
$Q_{E85}$	0.2	0.2	0.3	bgal	quantity of E85 gasoline
$P_{B0}$	3.11	3.02	3.00	usd/gal	price of petroleum-based diesel
$P_{B100}$	4.51	4.76	4.44	usd/gal	price of biodiesel
$P_{E0}$	3.03	2.97	2.50	usd/gal	price of BOB
$P_{E100}$	2.58	2.40	3.00	usd/gal	price of corn ethanol
$Q_{B0}$	52.1	53.2	45.7	bgal	quantity of petroleum-based diesel
$Q_{B100}$	0.9	1.3	1.3	bgal	quantity of biodiesel
$Q_{E0}$	121.2	120.7	119.5	bgal	quantity of BOB
$Q_{E100}$	12.7	12.7	13.0	bgal	quantity of ethanol
$Q_{E100}^S$	0.32	0.20	0.28	bgal	quantity of sugarcane ethanol
$P_C$	6.67	6.47	6.21	usd/bsh	price of nonfuel corn
$Q_C$	7.6	6.9	7.0	bbsh	quantity of nonfuel corn
$P_{R3}$	0.89	0.95	1.05	usd/gal	price of cellulosic RINs
$P_{R4}$	1.12	0.76	0.95	usd/gal	price of biodiesel RINs
$P_{R5}$	0.64	0.70	0.41	usd/gal	price of advanced RINs
$P_{R6}$	0.04	0.59	0.10	usd/gal	price of renewable RINs

Note: Quantities in the model are expressed in billions of dollars, gallons, or bushels. Prices are expressed in dollars per gallon or bushel. Calibrated values for six variables ( $P_{B0}$ ,  $P_{E0}$ ,  $P_{E100}$ ,  $Q_{B0}$ ,  $Q_{E0}$ ,  $Q_C$ ) are chosen; the remaining values and six demand and supply intercepts are solved using the model system of equations.

## 2.5.1 Empirical verification

The model is a good description of the market for renewable fuels because, at the calibrated point, endogenous variables are near their observed values in 2012 and 2013. Table 2.5 lists the endogenous variables in the model, their observed values in 2012 and 2013, and their calibrated values. For calibrating price of renewable RINs at the blendwall, 2012 is more informative. For most other variables, 2013 is more informative.

The discrepancy between calibrated and actual diesel volume comes from the EPA's 2014 proposal, which reports a projected diesel volume of 47 billion gallons. I do not know why this projection is so low. However, I defer to the EPA on this

point. The effect of this deference is that the blended diesel demand intercept is lower than it would otherwise be. The results are robust to alternative assumptions about the blended diesel demand intercept.

I attribute deviations in the fraction of ethanol in E85 gasoline and the price of E85 to regional variation. Real gasoline blenders have costs that differ by region. In the model, there is just an average national cost, so the calibrated fraction of ethanol in E85 is more likely to be exactly 51% or exactly 85%. E85 prices are more likely to be reported in regions with lower E85 prices.

## 2.6 Results

I simulate policy alternatives by solving the system of equations numerically for a range of possible values for the renewable fuel mandate. This is represented by the parameter  $\rho_6$  in the model, which I vary exogenously. A key parameter in the model is the elasticity of substitution between E10 and E85, so I report results for the base case, a higher alternative and a lower alternative. Figure 2.4 shows simulation results for many endogenous variables. In each graph, the horizontal axis is the total RFS volume obligation for all four RIN categories combined, expressed in ethanol-equivalent gallons. The RFS fractions for cellulosic, biodiesel, and advanced are held constant, so the only change is in the renewable fraction. The dashed vertical line in each graph is the blendwall.

These results tell a story of how the market responds to increasing the RFS in light of the blendwall and the linkage among RIN prices. When the RFS is at the blendwall, the fraction of ethanol in E10 is below 10% and the fraction in E85 is above 10%. The first response of the market is to increase the fraction of ethanol in E10 to the 10% limit. When this is no longer possible, the price of renewable RINs

increases rapidly until the blender cost of ethanol reaches the blender cost of BOB. At that point blenders are indifferent between adding BOB and ethanol to E85, and the blend fraction in E85 increases from 51% to 85%. When the maximum E85 blend is reached, the price of renewable RINs continues increasing, which is passed through to consumers in the form of a lower price of E85. Consumers shift from E10 toward E85 until the price of renewable RINs reaches the price of biodiesel RINs. From then on, both biodiesel production and E85 consumption rise.

The price of blended diesel responds to the mandate even though the price of E10 does not. This is because the blended fuels respond differently to a change in the price of renewable RINs. As the price of renewable RINs rises, the blender cost of petrodiesel and the blender cost of BOB rise by the same amount. The cost of BOB is offset by a decline in the blender cost of ethanol, but the blender cost of biodiesel is unchanged.

### **2.6.1 Welfare analysis**

I estimate the welfare effects of an increase in the RFS volume by calculating the change in emissions, the change in producer and consumer surplus, and cost per ton of emissions reduction. I compare the cost per ton of emissions reduction to the social cost of carbon.

I choose measures of life cycle emissions that are likely to be seen as most relevant by the EPA.<sup>34</sup> I assume CO<sub>2</sub> emissions for petroleum-based gasoline and diesel are 16.8 and 15.8 kilograms per million British thermal units of energy.<sup>35</sup> I assume

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<sup>34</sup>There is not a consensus on these life cycle emissions measures. Some analysts have claimed that the life cycle emissions from corn ethanol actually exceed life cycle emissions from petroleum-based gasoline. I use estimates from the Department of Energy and the EPA because they are most likely to be used in evaluating policy alternatives.

<sup>35</sup>Regulatory Impact Analysis, Environmental Protection Agency, EPA-420-R-10-006, February 2010, page 467.

blending components have the following energy content: 0.124 million British thermal units per gallon of petroleum gasoline, 0.137 mmbtu/gal of petroleum diesel, 0.128 mmbtu/gal of biodiesel, and 0.085 mmbtu/gal of ethanol.<sup>36</sup> I assume the following emissions reductions per unit energy relative to the petroleum baseline: a 52% reduction for biodiesel, 19% for corn ethanol, and 78% for sugarcane ethanol.<sup>37</sup> These assumptions imply life cycle carbon emissions are 2.09, 2.17, 0.97, 0.31, and 1.15 kg/gal for BOB, petrodiesel, biodiesel, sugarcane ethanol, and corn ethanol. To calculate total emissions, I multiply the consumption volume of each blending component by its life cycle emissions.

Figure 2.5 shows that increasing the mandate from 15 to 16 billion EEGs reduces emissions by about 1 million metric ton. Around the blendwall, the marginal renewable volume is corn ethanol, which is only a small reduction in emissions relative to BOB. Emissions decline mostly through the channel of substituting ethanol for BOB until the price of renewable RINs rises enough to meet the price of biodiesel RINs. Biodiesel is a larger reduction in emissions relative to petroleum diesel, but the RFS generates 1.5 ethanol-equivalent RINs for each gallon of biodiesel. When marginal increases in the mandate are also met by biodiesel, the pace of emissions changes but not by much.

Increasing the mandate from 15 to 16 billion EEGs reduces total surplus by about \$800 million. Consumer surplus declines are offset by an increase in producer surplus. Producer surplus increases because the price of corn and the price of biodiesel rise, so there is a larger return to inframarginal production. The change in consumer surplus and producer surplus does not include private valuation of environmental

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<sup>36</sup>The energy content is the higher heating value reported in Alternative Fuels Data Center (2013a), which is consistent with values reported in the 2014 RFS proposal.

<sup>37</sup>Biodiesel reduction is from Alternative Fuels Data Center (2014a) and ethanol reductions are from Alternative Fuels Data Center (2014b).



quality. Total surplus declines at a slower pace once adjustment to the mandate is achieved through both biodiesel and ethanol. Marginal cost of reducing carbon emissions rises as the RFS volume increases. I find that the average cost of reducing carbon emissions by increasing the mandate from 15 to 16 billion gallons is about \$800 per metric ton. This is much larger than the social cost of carbon used by policymakers.<sup>38</sup>

## 2.7 Conclusion

This paper shows that the cost of reducing carbon emissions using the RFS is high in the short run. The cost of shifting behavior is relatively high because the blendwall limits the extent to which the mandate can be met through regular gasoline. The cost of shifting behavior is mitigated by the linkage among the different categories of renewable fuel; the renewable mandate can be met by shifting consumption from E10 to E85 and also shifting the blend composition of diesel towards biodiesel. The benefit of shifting consumption from E10 to E85 is relatively low because the life cycle carbon emissions of conventional ethanol are nearly as high as the life cycle carbon emissions of petroleum-based gasoline. The benefit of shifting the blend composition of diesel towards biodiesel is more substantial, but biodiesel is expensive to produce.

In the long run, the RFS could still be beneficial. The Renewable Fuel Standard was built to support investment in production technology for cellulosic fuel, which emits around one fifth as much greenhouse gas as petroleum-based gasoline for the same energy output. The RFS pushes refiners to develop technology, blenders to invest in infrastructure, and consumers to drive FFVs. Whether those investments are worthwhile is beyond the scope of this analysis, as are the long term costs of

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<sup>38</sup>The social cost of carbon for 2014 is estimated to be \$36. See Interagency Working Group on Social Cost of Carbon (2013).

devoting more agricultural land to corn production and integrating the supply of food with the supply of fuel. Policymakers should consider both the short run and the long run tradeoffs.

## 2.8 Appendix

### 2.8.1 Institutions

Table 2.6: Transportation fuel volume, billions of gallons

Year	Gasoline bgals	Ethanol bgals	Ethanol/ Gasoline	Diesel bgals	Biodiesel bgals	Biodiesel/ Diesel
2005	140.4	4.1	2.9%	54.6	0.1	0.2%
2006	141.8	5.5	3.9%	56.7	0.2	0.4%
2007	142.4	6.9	4.8%	56.7	0.5	0.9%
2008	138.2	9.7	7.0%	53.8	0.7	1.3%
2009	138.0	11.0	8.0%	49.4	0.5	1.1%
2010	137.8	12.9	9.3%	52.6	0.3	0.6%
2011	134.1	12.9	9.6%	54.3	0.9	1.6%
2012	133.4	12.9	9.7%	53.2	0.9	1.7%
2013	133.8	13.2	9.9%	54.0	1.3	2.4%

Note: By 2013, the ethanol fraction rose to the 10% limit in E10 gasoline. The biodiesel fraction was substantially below the 5% limit in B5 diesel. Short Term Energy Outlook.

### 2.8.2 Model

This appendix includes the full set of equations in the single-period model described in Section 2.3. For the list of variables see Table 2.5. For the list of parameters see Table 2.7.

Table 2.7: Calibrated parameters

Parameter	Symbol	Value	Source/Target
mandate fraction for D3 RINs	$\rho_3$	0.0001	NPRM 2014
mandate fraction for D4 RINs	$\rho_4$	0.0116	NPRM 2014
mandate fraction for D5 RINs	$\rho_5$	0.0016	NPRM 2014
mandate fraction for D6 RINs	$\rho_6$	0.0787	blendwall
nonfuel corn demand elasticity	$\epsilon_C$	-0.25	Babcock, Barr, and Carriquiry (2010)
gasoline demand elasticity	$\epsilon_G$	-0.20	Hughes, Knittel, and Sperling (2008) and Coglianesi et al. (2016)
diesel demand elasticity	$\epsilon_B$	-0.07	Dahl (2012)
corn supply elasticity	$\eta_C$	0.05	Roberts and Schlenker (2013)
bushels of corn per gallon of ethanol	$\mu$	0.361	Westhoff (2006)
ethanol wedge over nonfuel corn	$\nu_C$	0.76	average wedge 1982 to 2013
petrogas supply elasticity	$\eta_G$	10	assumption
petrodiesel supply elasticity	$\eta_D$	10	assumption
energy-equivalent e10 gallons per e85 income	$\gamma$ $Y$	0.86 17000	EPA BTU/barrel: 3.6 E100, 5.3 E0 GDP
gasoline price wedge per unit value	$\nu_{G1}$	1.09	Section 2.4
gasoline price wedge per unit volume	$\nu_{G2}$	0.72	Section 2.4
diesel price wedge per unit value	$\nu_{B1}$	1.07	Section 2.4
diesel price wedge per unit volume	$\nu_{B2}$	0.81	Section 2.4
gasoline demand elasticity of substitution	$\frac{\sigma}{1-\sigma}$	-7.6	Salvo and Huse (2013)
gasoline demand share	$\alpha$	0.65	0.3 bgals E85
sugarcane ethanol supply intercept	$\log(\theta_S)$	1.23	280 mgals net imports
sugarcane ethanol supply elasticity	$\eta_S$	35.1	Babcock, Moreira, and Peng (2013)
biodiesel refining supply intercept	$\log(\theta_B)$	0.43	1.28 bgals B100
biodiesel refining supply elasticity	$\eta_B$	1.37	Babcock, Moreira, and Peng (2013)
soy input cost per biodiesel gallon	$\psi_B$	3.6	price of soy oil
nonfuel corn demand intercept	$\log(\phi_C)$	37.8	calibration
gasoline demand intercept	$\log(\phi_G)$	224.5	calibration
diesel demand intercept	$\log(\phi_B)$	193.9	calibration
corn supply intercept	$\log(\theta_C)$	-45.4	calibration
BOB supply intercept	$\log(\theta_G)$	0.21	calibration
petrodiesel supply intercept	$\log(\theta_D)$	0.72	calibration

Note: This table reports the full list of calibrated parameters.

### 2.8.2.1 Consumers

The consumer's maximization problem:

$$\begin{aligned}
 \max_{Q_{E10}, Q_{E85}, Q_{BX}, Q_C, Q_Z} & \phi_G \frac{\left[ (\alpha)(Q_{E10})^{\frac{1}{\sigma}} + (1-\alpha)(\gamma Q_{E85})^{\frac{1}{\sigma}} \right]^{(\sigma)(1-\frac{1}{\epsilon_G})}}{1 - \frac{1}{\epsilon_G}} \\
 & + \phi_B \frac{Q_{BX}^{1-\frac{1}{\epsilon_B}}}{1 - \frac{1}{\epsilon_B}} + \phi_C \frac{Q_C^{1-\frac{1}{\epsilon_C}}}{1 - \frac{1}{\epsilon_C}} + Q_Z
 \end{aligned}$$

The consumer's budget constraint:

$$P_{E10}Q_{E10} + P_{E85}Q_{E85} + P_{BX}Q_{BX} + P_CQ_C + Q_Z = Y \quad (2.21)$$

The first order conditions yield the following equations:

$$P_{E10} = \phi_G[(\alpha)(Q_{E10})^{\frac{1}{\sigma}} + (1 - \alpha)(\gamma Q_{E85})^{\frac{1}{\sigma}}]^{\sigma - \frac{\sigma}{\epsilon_G} - 1} Q_{E10}^{\left(\frac{1-\sigma}{\sigma}\right)}(\alpha) \quad (2.22)$$

$$P_{E85} = \phi_G[(\alpha)(Q_{E10})^{\frac{1}{\sigma}} + (1 - \alpha)(\gamma Q_{E85})^{\frac{1}{\sigma}}]^{\sigma - \frac{\sigma}{\epsilon_G} - 1} Q_{E85}^{\left(\frac{1-\sigma}{\sigma}\right)}(1 - \alpha)\gamma \quad (2.23)$$

$$P_{BX} = \phi_B Q_{BX}^{-\frac{1}{\epsilon_B}} \quad (2.24)$$

$$P_C = \phi_C Q_C^{-\frac{1}{\epsilon_C}} \quad (2.25)$$

Combining equations (2.22) and (2.23) yields a more convenient equation relating E10 and E85 demand.

$$\frac{P_{E85}}{\gamma P_{E10}} = \left(\frac{Q_{E10}}{\gamma Q_{E85}}\right)^{1 - \frac{1}{\sigma}} \left(\frac{1}{\alpha} - 1\right) \quad (A.3^*)$$

I assume the fraction of ethanol in E10 is 10% for the purpose of calculating its energy content. The energy-equivalence factor  $\gamma$  expresses the number of gallons of E10 that have the same amount of energy as one gallon of E85.  $\gamma$  is a function of

the fraction of ethanol in E85  $F_{E85}$ .

$$\begin{aligned}
 \gamma &= \frac{\text{gallons of E10}}{\text{gallon of E85}} \\
 &= \frac{\text{BTU per gallon of E85}}{\text{BTU per gallon of E10}} \\
 &= \frac{BTU_{E0} + F_{E85}(BTU_{E100} - BTU_{E0})}{BTU_{E0} + F_{E10}(BTU_{E100} - BTU_{E0})} \\
 &= \frac{5.253 + F_{E85}(3.561 - 5.253)}{5.253 + 0.1(3.561 - 5.253)} \\
 &= 1.03 - .33F_{E85}
 \end{aligned}$$

The fraction of ethanol in E85 ranges from 51% to 85%, and the energy-equivalence factor ranges from 0.86 to 0.75.

### 2.8.2.2 Blenders

Define the vectors  $\rho$  and  $P_{RIN}$  such that they succinctly express the RFS compliance cost for one gallon of nonrenewable fuel:

$$\rho P_{RIN} = \rho_3 P_{R3} + \rho_4 P_{R4} + \rho_5 P_{R5} + \rho_6 P_{R6}$$

**Gasoline Blenders** For simplicity, the role of sugarcane ethanol was omitted from the main text. The relationship among blender costs follows the same logic as for ethanol and BOB; the blender cost of corn ethanol must equal the blender cost of

sugarcane ethanol. The E10 blender's maximization problem:

$$\begin{aligned} \max_{Q_{E10}, F_{E10}, F_{E10}^S} \quad & Q_{E10} \left( \left[ P_{E10} - F_{E10} \left[ (1 - F_{E10}^S)(P_{E100} - P_{R6}) + F_{E10}^S(P_{E100}^S - P_{R5}) \right] \right. \right. \\ & \left. \left. - (1 - F_{E10})(P_{E0} + \rho P_{RIN}) - (.1 - F_{E10})(\nu_{OBA} P_{E0}) \right] \nu_{G1} + \nu_{G2} \right) \\ \text{s.t.} \quad & 0 \leq F_{E10} \leq 0.1 \end{aligned}$$

The E10 blender's first order conditions:

$$\begin{aligned} P_{E10} = & \left[ F_{E10}(P_{E100} - P_{R6}) + (1 - F_{E10})(P_{E0} + \rho P_{RIN}) \right. \\ & \left. + (.1 - F_{E10})(\nu_{OBA} P_{E0}) \right] \nu_{G1} + \nu_{G2} \end{aligned} \quad (2.26)$$

$$P_{E100} - P_{R6} = (1 + \nu_{OBA})P_{E0} + \rho P_{RIN} \quad \text{or} \quad F_{E10} = 0 \quad \text{or} \quad F_{E10} = .1 \quad (2.27)$$

$$P_{E100}^S - P_{R5} = P_{E100} - P_{R6} \quad \text{or} \quad F_{E10}^S = 0 \quad \text{or} \quad F_{E10}^S = 1 \quad (2.28)$$

The E85 blender's maximization problem:

$$\begin{aligned} \max_{Q_{E85}, F_{E85}} \quad & Q_{E85} \left( \left[ P_{E85} - F_{E85}(P_{E100} - P_{R6}) \right. \right. \\ & \left. \left. - (1 - F_{E85})(P_{E0} + \rho P_{RIN}) \right] \nu_{G1} + \nu_{G2} \right) \\ \text{s.t.} \quad & .51 \leq F_{E85} \leq .85 \end{aligned}$$

The E85 blender's first order conditions:

$$P_{E85} = \left[ F_{E85}(P_{E100} - P_{R6}) + (1 - F_{E85})(P_{E0} + \rho P_{RIN}) \right] \nu_{G1} + \nu_{G2} \quad (2.29)$$

$$P_{E100} - P_{R6} = P_{E0} + \rho P_{RIN} \quad \text{or} \quad F_{E85} = .51 \quad \text{or} \quad F_{E85} = .85 \quad (2.30)$$

**Diesel Blenders** The diesel blender's maximization problem:

$$\max_{Q_{BX}, F_{BX}} Q_{BX} \left( \left[ P_{BX} - F_{BX}(P_{B100} - P_{R4}) - (1 - F_{BX})(P_{B0} + \rho P_{RIN}) \right] \nu_{B1} + \nu_{B2} \right)$$

The diesel blender's first order conditions:

$$P_{BX} = \left[ F_{BX}(P_{B100} - P_{R4}) + (1 - F_{BX})(P_{B0} + \rho P_{RIN}) \right] \nu_{B1} + \nu_{B2} \quad (2.31)$$

$$P_{B100} - P_{R4} = P_{B0} + \rho P_{RIN} \quad (2.32)$$

### 2.8.2.3 Producers

**Ethanol and nonfuel corn** The corn producer's maximization problem:

$$\max_{Q_C, Q_{E100}} P_C Q_C + (P_{E100} - \nu_C) Q_{E100} - \theta_C \frac{(Q_C + \mu Q_{E100})^{1 + \frac{1}{\eta_C}}}{1 + \frac{1}{\eta_C}}$$

The corn producer's first order conditions:

$$P_C = \theta_C (Q_C + \mu Q_{E100})^{\frac{1}{\eta_C}} \quad (2.33)$$

$$P_{E100} - \nu_C = \theta_C \mu (Q_C + \mu Q_{E100})^{\frac{1}{\eta_C}} \quad (2.34)$$

Combining equations (2.33) and (2.35) yields a more convenient equation relating the price of ethanol and nonfuel corn.

$$P_{E100} = \mu P_C + \nu_C \quad (13a)$$

**Sugarcane ethanol** The sugarcane ethanol importer's maximization problem:

$$\max_{Q_{E100}^S} P_{E100}^S Q_{E100}^S - \nu_S Q_{E100}^S - \theta_S \frac{(Q_{E100}^S)^{1+\frac{1}{\eta_S}}}{1 + \frac{1}{\eta_S}}$$

The interpretation of  $Q_{E100}^S$  is the *net imports* of Brazilian sugarcane ethanol. If the price of advanced RINs exceeds the price of renewable RINs by more than the cost of transporting ethanol to and from Brazil, then an arbitrageur could export corn ethanol and import sugarcane ethanol. The model permits such trade but does not keep track of gross flows. Knowing domestic corn ethanol production and net sugarcane imports is sufficient for determining the effect on the market for blended fuels. The sugarcane ethanol importer's first order condition:

$$P_{E100}^S = \nu_S + \theta_S (Q_{E100}^S)^{\frac{1}{\eta_S}} \quad (2.35)$$

**Biodiesel** The biodiesel refiner's maximization problem:

$$\max_{Q_{B0}} P_{B100} Q_{B100} - \nu_B Q_{B100} - \theta_B \frac{Q_{B100}^{1+\frac{1}{\eta_B}}}{1 + \frac{1}{\eta_B}}$$

The biodiesel refiner's first order condition:

$$P_{B100} = \nu_B + \theta_B Q_{B100}^{\frac{1}{\eta_B}} \quad (2.36)$$

**Petroleum gasoline** The petroleum gasoline refiner's maximization problem:

$$\max_{Q_{E0}} P_{E0} Q_{E0} - \theta_G \frac{Q_{E0}^{1+\frac{1}{\eta_G}}}{1 + \frac{1}{\eta_G}}$$



The petroleum gasoline refiner's first order condition:

$$P_{E0} = \theta_G Q_{E0}^{\frac{1}{\eta_G}} \quad (2.37)$$

**Petroleum diesel** The petroleum diesel refiner's maximization problem:

$$\max_{Q_{B0}} P_{B0} Q_{B0} - \theta_D \frac{Q_{B0}^{1+\frac{1}{\eta_D}}}{1+\frac{1}{\eta_D}}$$

The petroleum diesel refiner's first order condition:

$$P_{B0} = \theta_D Q_{B0}^{\frac{1}{\eta_D}} \quad (2.38)$$

#### 2.8.2.4 Market clearing conditions

The market clearing condition for ethanol:

$$F_{E10} Q_{E10} + F_{E85} Q_{E85} = Q_{E100} + Q_{E100}^S \quad (2.39)$$

The market clearing condition for BOB:

$$(1 - F_{E10}) Q_{E10} + (1 - F_{E85}) Q_{E85} = Q_{E0} \quad (2.40)$$

The market clearing condition for biodiesel:

$$F_{BX} Q_{BX} = Q_{B100} \quad (2.41)$$

The market clearing condition for petroleum diesel:

$$(1 - F_{BX})Q_{BX} = Q_{B0} \quad (2.42)$$

The market clearing condition for renewable RINs:

$$Q_{E100} + Q_{E100}^S + 1.5Q_{B100} = \Delta R4 + \Delta R5 + \Delta R6 + (Q_{E0} + Q_{B0})(\rho_3 + \rho_4 + \rho_5 + \rho_6) \quad (2.43)$$

Recall that  $Q_{E100}^S$  is net imports of sugarcane ethanol. The market clearing condition for advanced RINs:

$$Q_{E100}^S + 1.5Q_{B100} = \Delta R4 + \Delta R5 + (Q_{E0} + Q_{B0})(\rho_3 + \rho_4 + \rho_5) \quad (2.44)$$

The preceding condition is slack does not need to hold if the price of advanced RINs exceeds the price of renewable RINs by a sufficient margin. The market clearing condition for biodiesel RINs:

$$1.5Q_{B100} \geq \Delta R4 + (Q_{E0} + Q_{B0})(\rho_4) \quad (2.45)$$

### 2.8.3 Empirics

This appendix extends the E10 analysis in Section 2.4 to E85 and blended diesel. I use the convention  $\Delta X_t = X_t - X_{t-1}$ .

#### 2.8.3.1 Price and blender cost of diesel

The model predicts that the retail price of blended diesel will equal the blender cost (BC) of components.

Figure 2.9 plots diesel retail price and blender cost of components. Like E10, the two series track each other closely and the retail price exceeds blender cost by a substantial margin, which I attribute to transportation costs and taxes. When I simulate the model, I add a wedge between the retail price and the blender cost. I allow the wedge to include an ad valorem component  $\nu_{B1}$  and a per unit component  $\nu_{B2}$  because some taxes are ad valorem and others are expressed per unit volume. The equation is  $RP_{BX} = BC_{BX}\nu_{B1} + \nu_{B2}$ . I estimate both components empirically, and use the estimates for calibrating the model.

Table 2.8: Regression of retail price of diesel on blender cost of diesel

$BC_{BX}$	0.997*** (0.0247)
Constant	0.809*** (0.0666)
Observations	78
R-squared	0.956
Standard errors in parentheses	
*** $p < 0.01$ , ** $p < 0.05$ , * $p < 0.1$	

Note: This table reports regression results of retail price on blender cost of blended diesel using monthly data. See note on Figure 2.9.

Table 2.9: Effect of blender cost of diesel on retail price of diesel

$BC_{BX}$	0.997*** (0.0247)
Constant	0.809*** (0.0666)
Observations	78
R-squared	0.956
Standard errors in parentheses	
*** $p < 0.01$ , ** $p < 0.05$ , * $p < 0.1$	

Note: This table reports regression results of a change in retail price on a distributed lag of blender cost of blended diesel using monthly data. See note on Figure 2.9.

The parameter  $\nu_{B2}$  expresses a constant markup per gallon. To estimate the constant markup per gallon  $\nu_{B2}$ , I regress the retail price of blended diesel on the blender cost of components.<sup>39</sup> Table 2.8 shows that the retail price exceeds the

<sup>39</sup>The equation is:  $RP_{BX,t} = \nu_{B2} + \beta_1 BC_{BX,t} + u$ .

blender cost of components by about 81 cents. I use this estimate for the parameter  $\nu_{B2}$  in simulations.

The parameter  $\nu_{B1}$  expresses the passthrough of blender costs to the retail price of blended diesel. As with E10, I regress retail price on a distributed lag of the blender cost. Table 2.9 shows the results of the regression.<sup>40</sup> A price change in the blender cost of components is followed by a price change in the retail price of blended diesel. I use the five-month estimate that 107% of a change to the blender cost of components is reflected in the retail price for the parameter  $\nu_{B1}$  in simulations.

The model predicts that the blender cost of biodiesel will equal the blender cost of petroleum-based diesel whenever the blend fraction is interior, i.e. between 0% and 5%. Figure 2.9 shows that the prices of the two components track each other closely.

### 2.8.3.2 Price and blender cost of E85

The model predicts that the retail price of E85 will equal the blender cost (BC) of components:

$$BC_{E85} = F_{E85}(P_{E100} - P_{R6}) + (1 - F_{E85})(P_{E0} + \rho P_{RIN})$$

Whereas the model was augmented with octane-boosting additives for the empirical analysis of E10, there is no need to do that for E85 because E85 has high octane content without additives.

Figure 2.10 shows that the retail price of E85 exceeds the blender cost of components. As with E10, I regress the retail price of E85 on the blender cost of components.<sup>41</sup> Table 2.10 shows that the retail price exceeds the blender cost of components

<sup>40</sup>The regression equation is  $\Delta RP_{BX,t} = \beta_0 + \sum_{i=0}^2 \beta_{i-1} \Delta \Delta BC_{BX,t-i} + \nu_{B1} \Delta BC_{BX,t-3} + u$ .

<sup>41</sup>The equation is:  $RP_{E85,t} = \nu_{G2} + \beta_1 BC_{E85,t} + u$ .

by about \$1.75. However, the sample period is short, so in simulations I use the E10 estimate of markup per gallon ( $\nu_{G2} = 0.72$ ).

Table 2.10: Regression of retail price of E85 on blender cost of E85

$BC_{E85,t}$	0.601*** (0.151)
Constant	1.751*** (0.348)
Observations	15
R-squared	0.550
Standard errors in parentheses	
*** $p < 0.01$ , ** $p < 0.05$ , * $p < 0.1$	

Note: This table reports regression results of retail price on blender cost of E85 using monthly data. See note on Figure 2.10.

As with E10, I regress retail price on a distributed lag of the blender cost. Table 2.11 shows the results of the regression.<sup>42</sup> These estimates are not precise, so in simulations I use the E10 estimate of passthrough of blender costs ( $\nu_{G1} = 1.09$ ).

Table 2.11: Effect of blender cost of E85 on retail price of E85

$\Delta\Delta BC_{E85,t}$	0.247 (0.331)
$\Delta\Delta BC_{E85,t-1}$	0.519 (0.463)
$\Delta\Delta BC_{E85,t-2}$	0.497 (0.558)
$\Delta BC_{E85,t-3}$	0.413 (0.666)
Constant	-0.0289 (0.0376)
Observations	14
R-squared	0.196
Standard errors in parentheses	
*** $p < 0.01$ , ** $p < 0.05$ , * $p < 0.1$	

Note: This table reports regression results of a change in retail price on a distributed lag of blender cost of E85 using monthly data. See note on Figure 2.10.

## 2.8.4 Calibration

The two parameters that determine demand for E85 are the elasticity of substitution  $\frac{\sigma}{1-\sigma}$  and the E10 demand share  $\alpha$ . The main results are reported for an elasticity

<sup>42</sup>The regression equation is  $\Delta RP_{E85,t} = \beta_0 + \sum_{i=0}^2 \beta_{i-1} \Delta\Delta BC_{E85,t-i} + \nu_{G1} \Delta BC_{E85,t-3} + u$ .

of -7.6, and results are calculated for elasticities 50% higher and lower as well, -3.8 and -11.4. For each elasticity,  $\alpha$  is calculated such that the E85 demand curve passes through 300 million gallons at a price of \$3.50. For elasticities of -3.8, -7.6, and -11.4, the demand shares are .95, .80, and .59. Holding fixed the ethanol fraction in E85 and the quantity and price of E10, the implied demand curves for E85 at various elasticities of substitution are shown in Figure 2.11.

Pouliot and Babcock (2014) estimate E85 demand with various assumptions about the convenience cost of E85 and the strength of consumer preferences for regular gasoline. When the price of E85 is at the energy-equivalent parity price of E10, their estimates of E85 quantity demanded range from about 0.5 to 6.0 billion gallons, with the main cases near 2 billion gallons at parity.<sup>43</sup> Under nearly all preference assumptions, Pouliot and Babcock (2014) estimate that FFV drivers would be willing to consume as much as 8 billion gallons of E85 at a sufficiently large discount relative to E10. However, even though drivers might be willing to consume E85, Pouliot and Babcock find that the capacity constraints of existing E85 fueling stations could limit distribution to about 1.5 billion gallons. In other words, their estimates imply the binding constraint on consumption of E85 is the capacity of E85 fueling stations, not consumer demand or the number of FFVs.

My constant-elasticity-of-substitution specification of E85 demand is different from Pouliot and Babcock's, but the implications for E85 demand are largely consistent. In my base case with an elasticity of substitution equal to -7.6, the E85 quantity demanded at the energy-equivalent parity price of E10 is 1.3 billion gallons. This is a bit lower than most of Pouliot and Babcock's estimates of consumer demand but still within their estimates of fueling station capacity. In my high elasticity alternative case, the E85 quantity demanded at the energy-equivalent parity price of

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<sup>43</sup>Pouliot and Babcock (2014) figures 4 through 7.

E10 is 2.7 billion gallons. This would be appropriate to consider if willingness to pay for E85 is relatively high and investment in new fueling stations is very responsive to the mandate. In my low elasticity alternative case, the E85 quantity demanded at the energy-equivalent parity price of E10 is 0.6 billion gallons. This would be appropriate to consider if willingness to pay for E85 was very low.

One shortcoming of my specification is that it does not capture the upper limit on E85 consumption. Even for very large price discounts, there would be some limit on the ability of FFVs to consume E85. The CES specification implies that greater price discounts will always lead to more consumption. However, this shortcoming is not empirically relevant in my simulations because E85 consumption remains below 1.5 billion gallons in all of the scenarios considered.

Table 2.12: Net imports of ethanol from Brazil to the United States

Million gallons			
Year	Imports	Exports	Net imports
2010	0	23	-23
2011	101	396	-295
2012	404	86	318
2013	242	47	195

Source: Energy Information Administration  
<http://www.eia.gov/petroleum/data.cfm>.

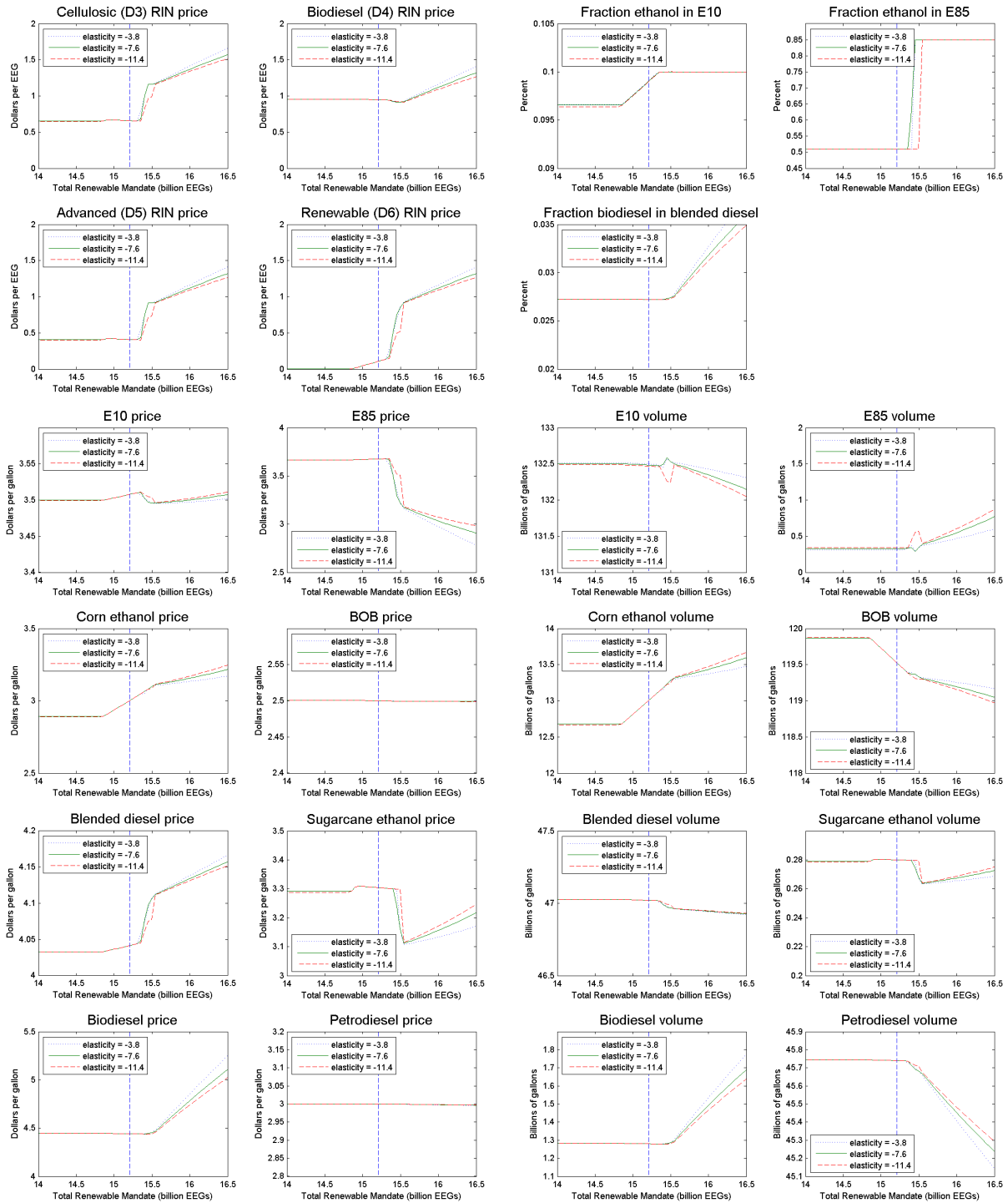
To estimate the response to a change in the RFS fraction, I must make some assumption about the supply of sugarcane ethanol and biodiesel. The supply of sugarcane ethanol probably has a smaller impact because its price is tied to the price of corn ethanol. Recall that the different treatment by the RFS of corn ethanol and sugarcane ethanol creates a potential arbitrage opportunity. If the price of an advanced RIN is high enough relative to the price of a renewable RIN, an arbitrageur will export corn ethanol from the United States to Brazil and import sugarcane

ethanol from Brazil to the United States. Table 11 shows net imports of ethanol from Brazil in 2012 and 2013 were 318 million gallons and 195 million gallons.

### **2.8.5 Sensitivity analysis**

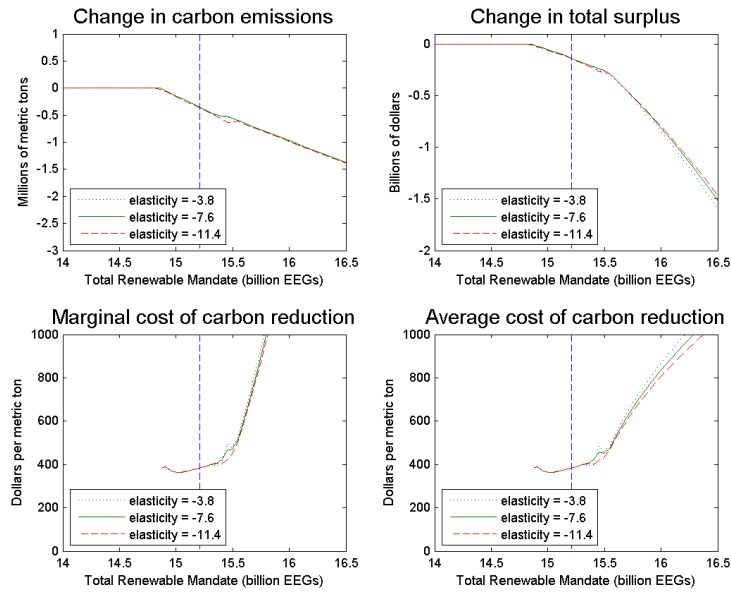


Figure 2.4: Simulation for three values of gasoline demand elasticity of substitution



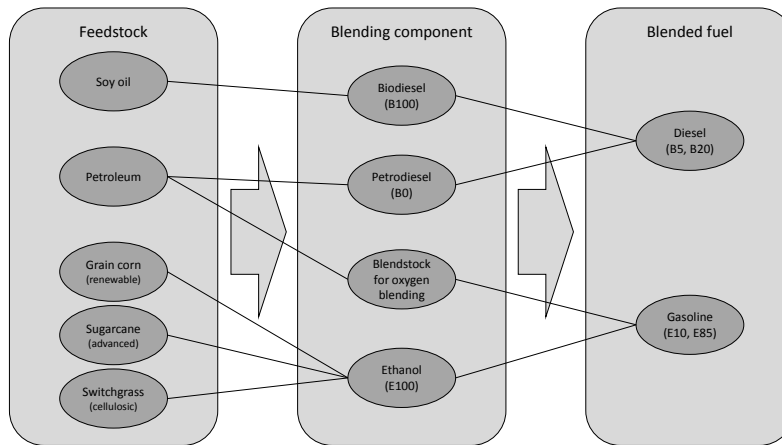
Note: These graphs depict the results of numerically solving the system of equations for many values for the renewable fuel mandate (14 to 16.5 billion ethanol equivalent gallons) and three values for the gasoline demand elasticity of substitution (-3.8, -7.6, -11.4).

Figure 2.5: Emissions and welfare



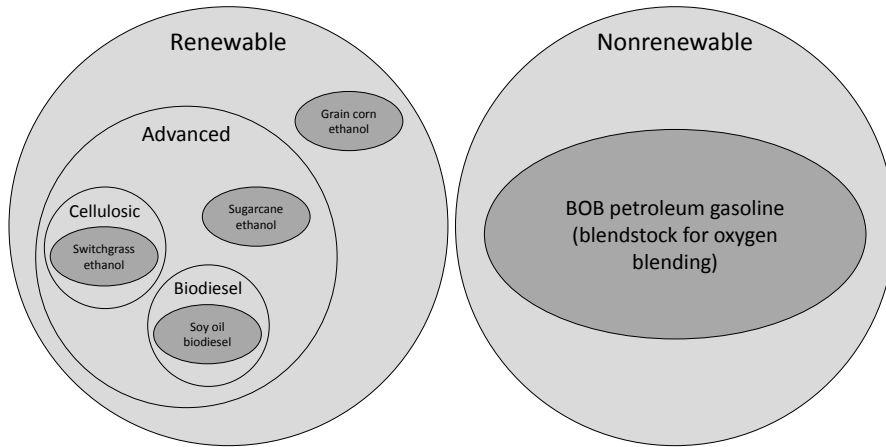
Note: Total emissions equal consumption volume times life cycle emissions, by blending component.

Figure 2.6: Flow of fuel and feedstocks



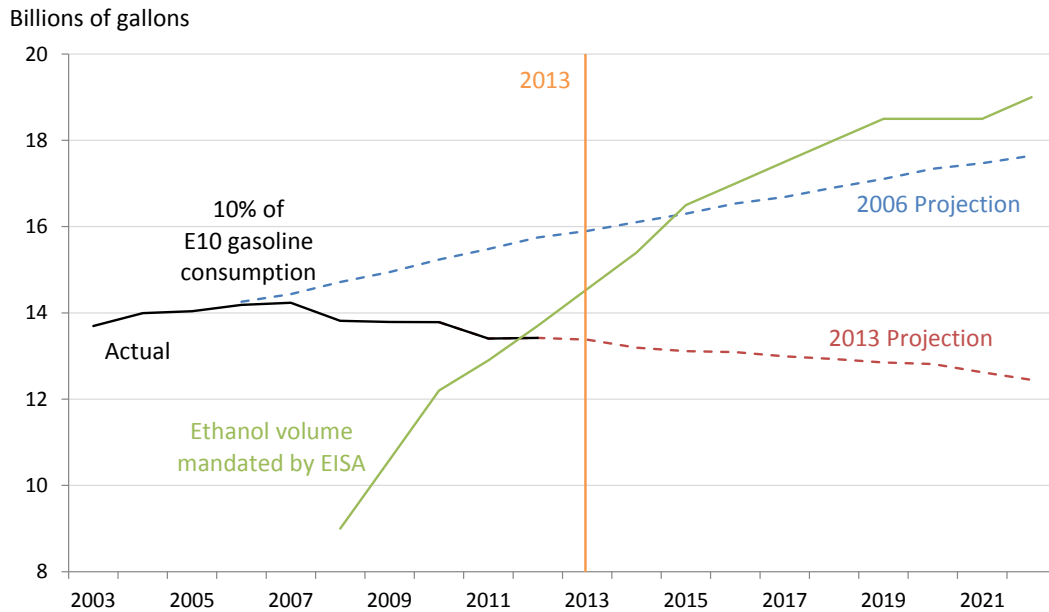
Note: The treatment of a gallon of ethanol under the RFS depends on the feedstock used to produce that gallon even though the performance of ethanol as a fuel does not depend on the feedstock.

Figure 2.7: Fuels for blending



Note: Light circles are sets. Dark ovals are the most common elements. The eligibility requirements for cellulosic fuel are more stringent than the eligibility requirements for advanced fuel; all fuel that qualifies as cellulosic also contributes to meeting the advanced requirement. Cellulosic and biodiesel are mutually exclusive subsets of advanced, and advanced is a subset of renewable.

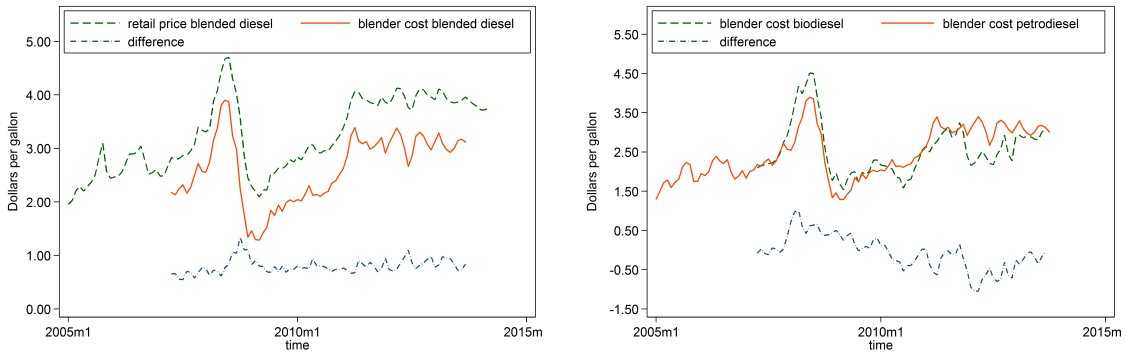
Figure 2.8: The blendwall



Source: AEO 2006, AEO 2013, Energy Independence and Security Act of 2007.  
 Note: Ethanol volume is calculated as total renewable minus biomass-based diesel and cellulosic.

Source: AEO 2006, AEO 2013, Energy Independence and Security Act of 2007.  
 Note: Ethanol volume is calculated as total renewable minus biomass-based diesel and cellulosic.

Figure 2.9: Diesel retail price and blender cost



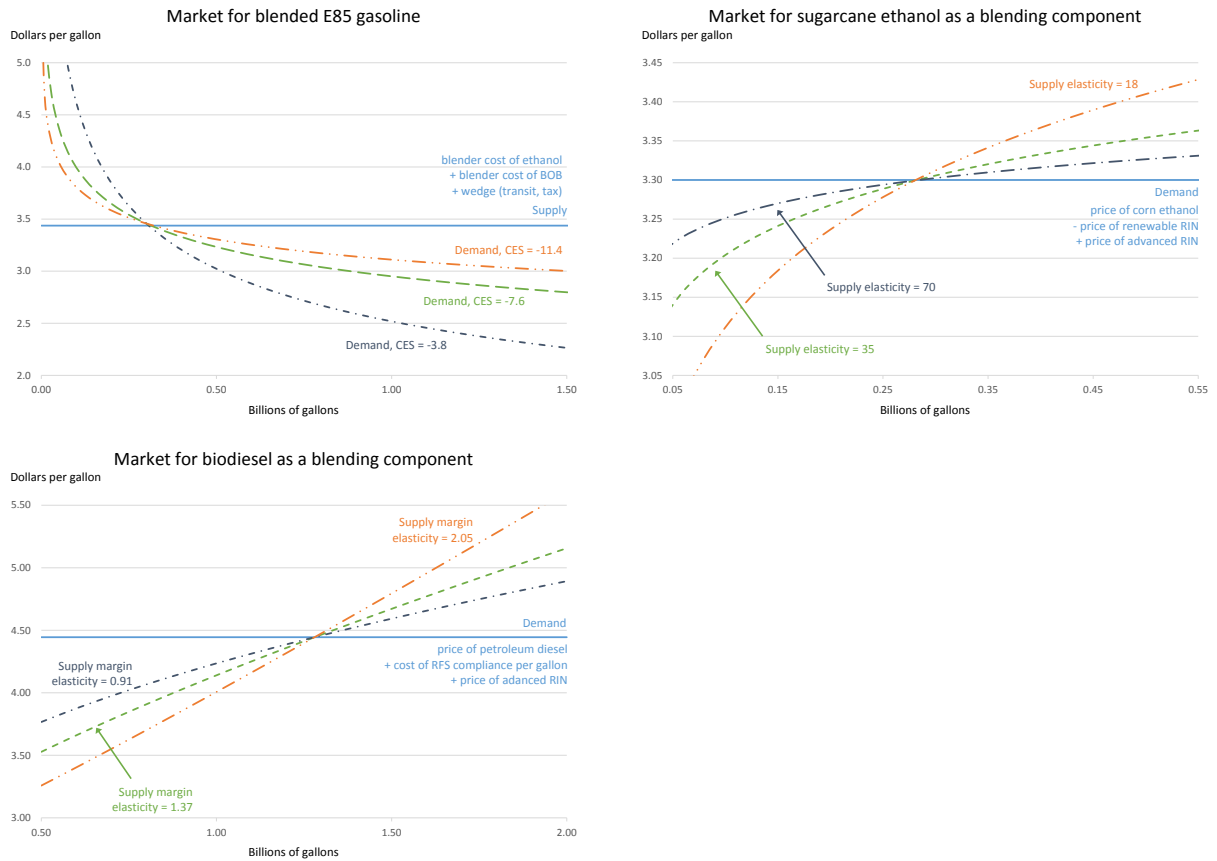
Note: The left graph compares the retail price of diesel with the blender cost of diesel. The right graph compares the blender cost of biodiesel with the blender cost of petroleum-based diesel. Retail price is diesel fuel retail price including taxes, U.S. average, from EIA's Short Term Energy Outlook. Blender cost (BC) is calculated according to the following equation:  $BC_{BX} = F_{BX}(P_{B100} - P_{R4}) + (1 - F_{BX})(P_{B0} + \rho P_{RIN})$ . Biodiesel fraction  $F_{BX}$  is computed from the biodiesel quantity and diesel quantity reported in EIA's Short Term Energy Outlook. Biodiesel price  $P_{B100}$  is B-100 freight on board at Illinois, Indiana and Ohio, from U.S. Bioenergy Statistics. The vector of RIN prices  $P_{RIN}$  includes renewable  $P_{R6}$ , advanced  $P_{R5}$ , and biodiesel  $P_{R4}$  RIN prices, from Bloomberg. Petroleum-based diesel price  $P_{B0}$  is Los Angeles ultra-low sulfur CARB diesel spot price, from EIA. The vector of RFS fractions  $\rho$  is from past EPA rules.

Figure 2.10: E85 retail price and blender cost



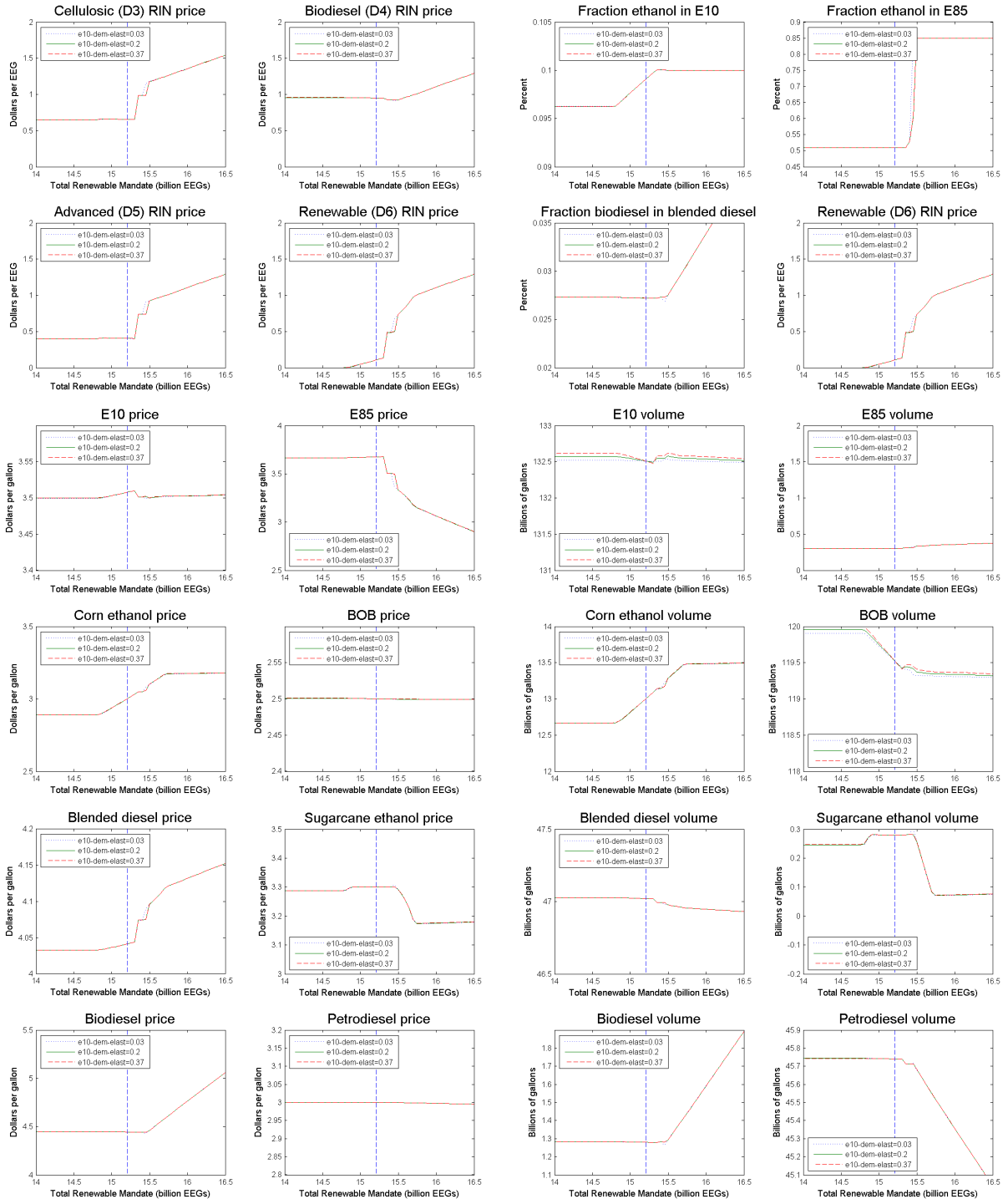
Note: The left graph compares the retail price of E85 with the blender cost of E85. The right graph compares the blender cost of ethanol with the blender cost of BOB. Retail price is the U.S. city average retail price of unleaded regular gasoline, from EIA. Blender cost (BC) is calculated according to the following equation:  $BC_{E85} = F_{E85}(P_{E100} - P_{R6}) + (1 - F_{E85})(P_{E0} + \rho P_{RIN})$ . I assume the ethanol fraction  $F_{E85}$  is 71%, the average blend reported by EIA. Ethanol price  $P_{E100}$  is blender cost of ethanol with credit, from U.S. Bioenergy Statistics. The vector of RIN prices  $P_{RIN}$  includes renewable  $P_{R6}$ , advanced  $P_{R5}$ , and biodiesel  $P_{R4}$  RIN prices, from Bloomberg. BOB price  $P_{E0}$  is generic RBOB gasoline (XB1), from Bloomberg. The vector of RFS fractions  $\rho$  is from past EPA rules.

Figure 2.11: Alternative biofuel supply and demand elasticities



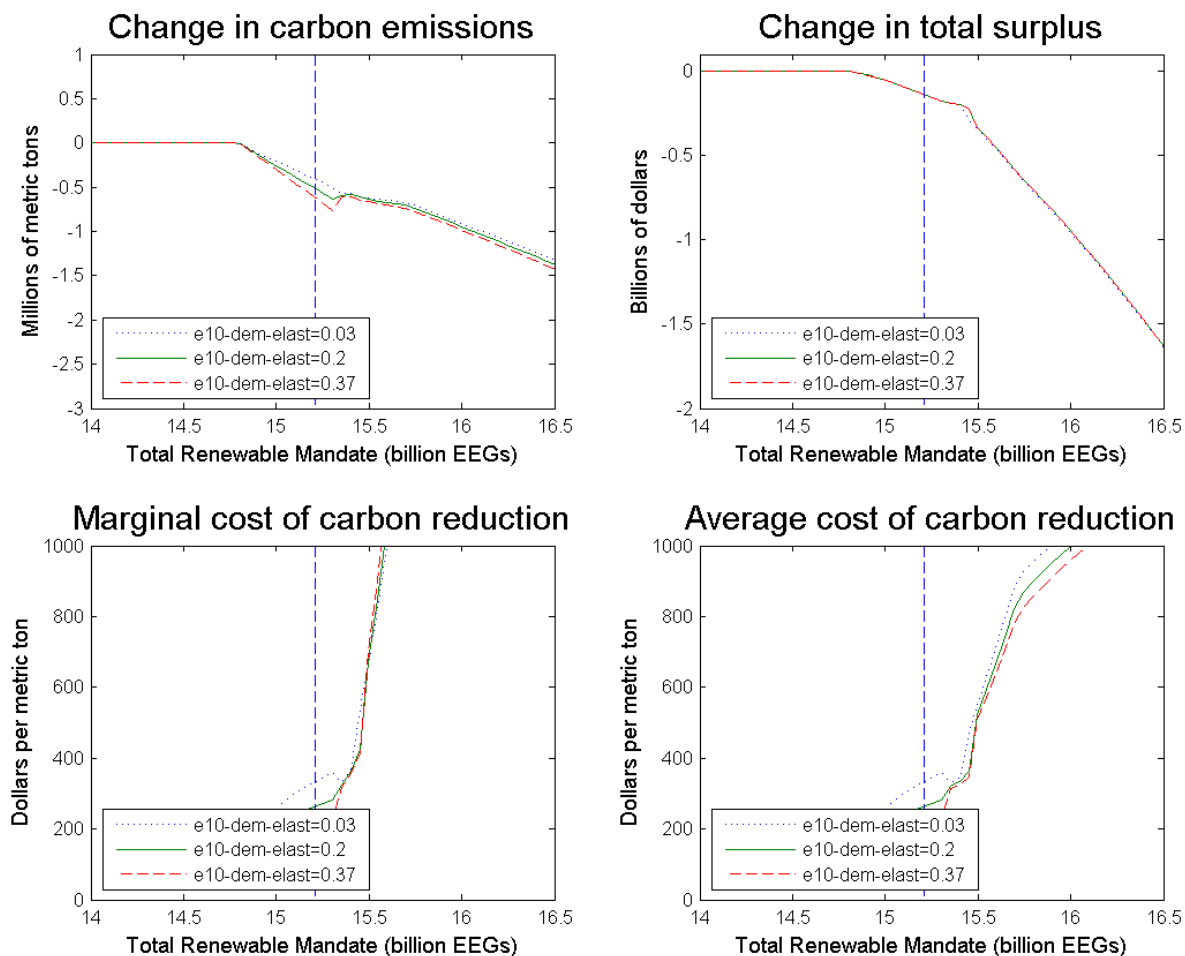
Note: These graphs depict alternative assumptions about biofuel supply and demand elasticities. For E85, the elasticity of substitution with E10 takes on the values -3.8, -7.6, and -11.4. In each case, the demand share is adjusted such that the demand for E85 is 300 million gallons at \$3.40 per gallon. For sugarcane ethanol, the elasticity of supply takes on the values 18, 35, and 70, and the supply intercept is adjusted such that the supply of sugarcane ethanol is 280 million gallons at \$3.30 per gallon. For biodiesel, the elasticity of supply takes on the values 0.91, 1.37, and 2.05, and the demand intercept is adjusted such that the supply of biodiesel is 1.28 billion gallons at \$4.44 per gallon.

Figure 2.12: Simulation for three values of gasoline elasticity of demand



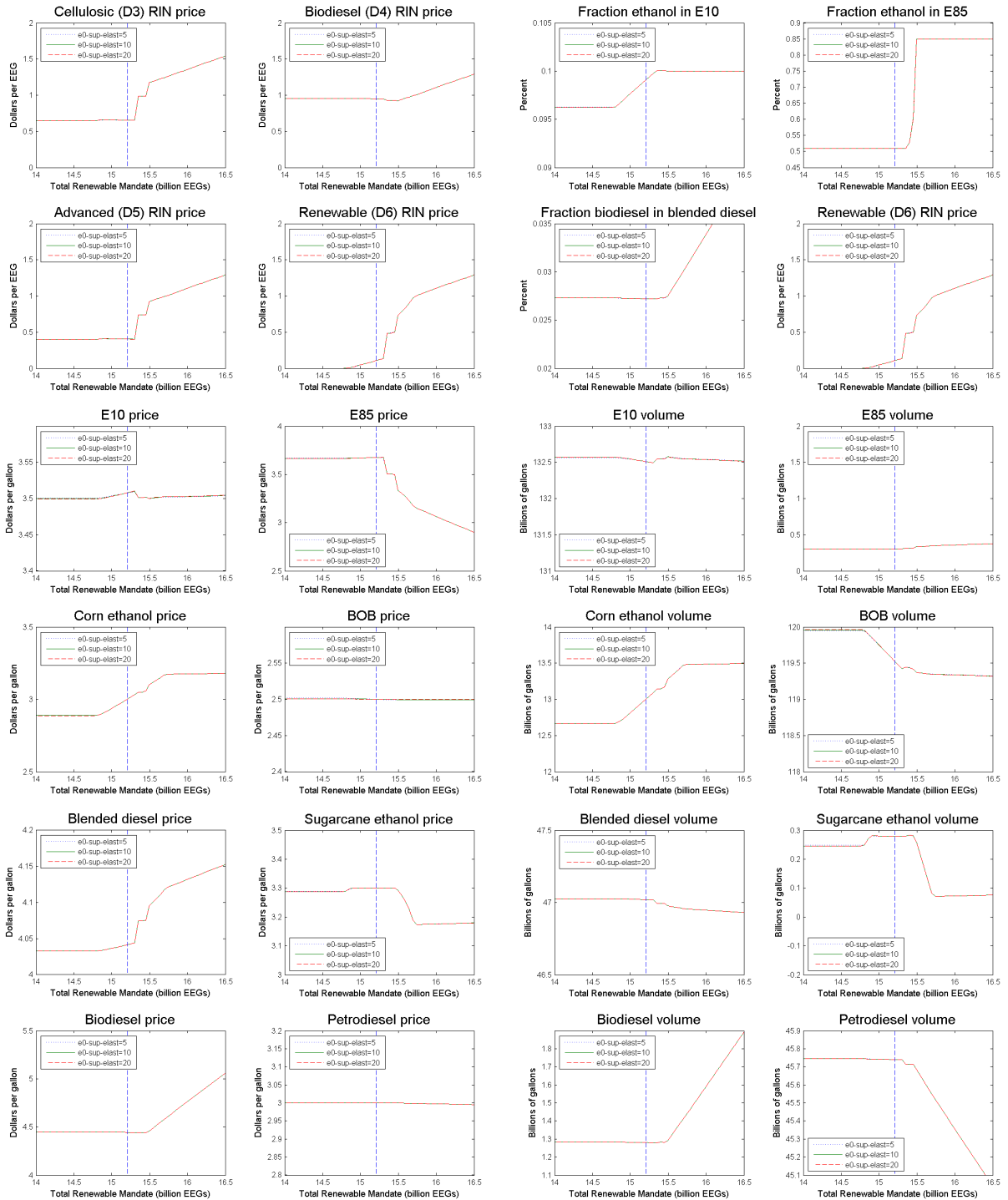
Note: These graphs depict the results of numerically solving the system of equations for many values for the renewable fuel mandate (14 to 16.5 billion ethanol equivalent gallons) and three values of gasoline elasticity of demand.

Figure 2.13: Emissions and welfare for three values of gasoline elasticity of demand



Note: To calculate total emissions, I multiply the consumption volume of the various blending components by their life cycle emissions. The change in total surplus is calculated using the model supply and demand curves.

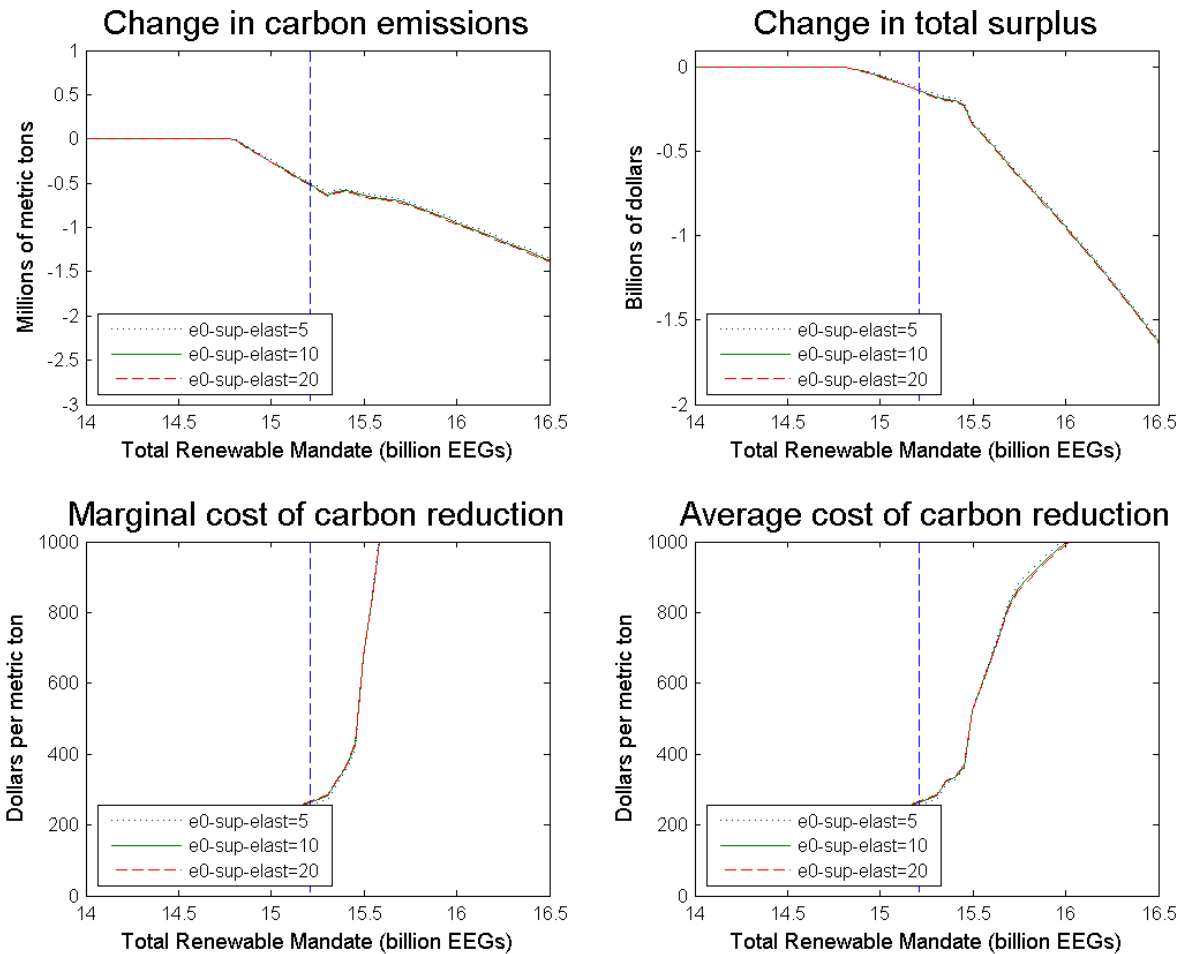
Figure 2.14: Simulation for three values of BOB elasticity of supply



Note: These graphs depict the results of numerically solving the system of equations for many values for the renewable fuel mandate (14 to 16.5 billion ethanol equivalent gallons) and three values of BOB elasticity of supply.

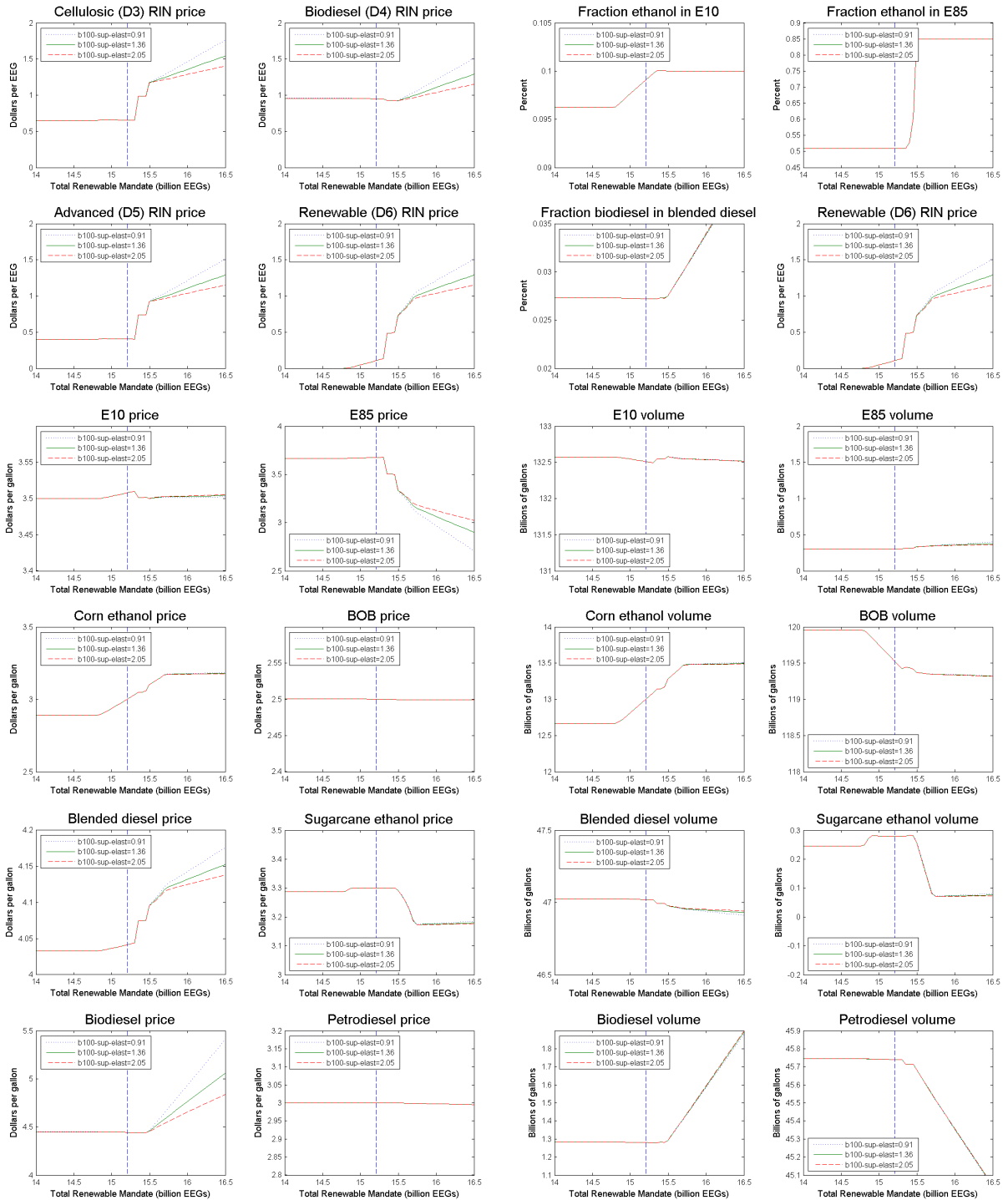


Figure 2.15: Emissions and welfare for three values of BOB elasticity of supply



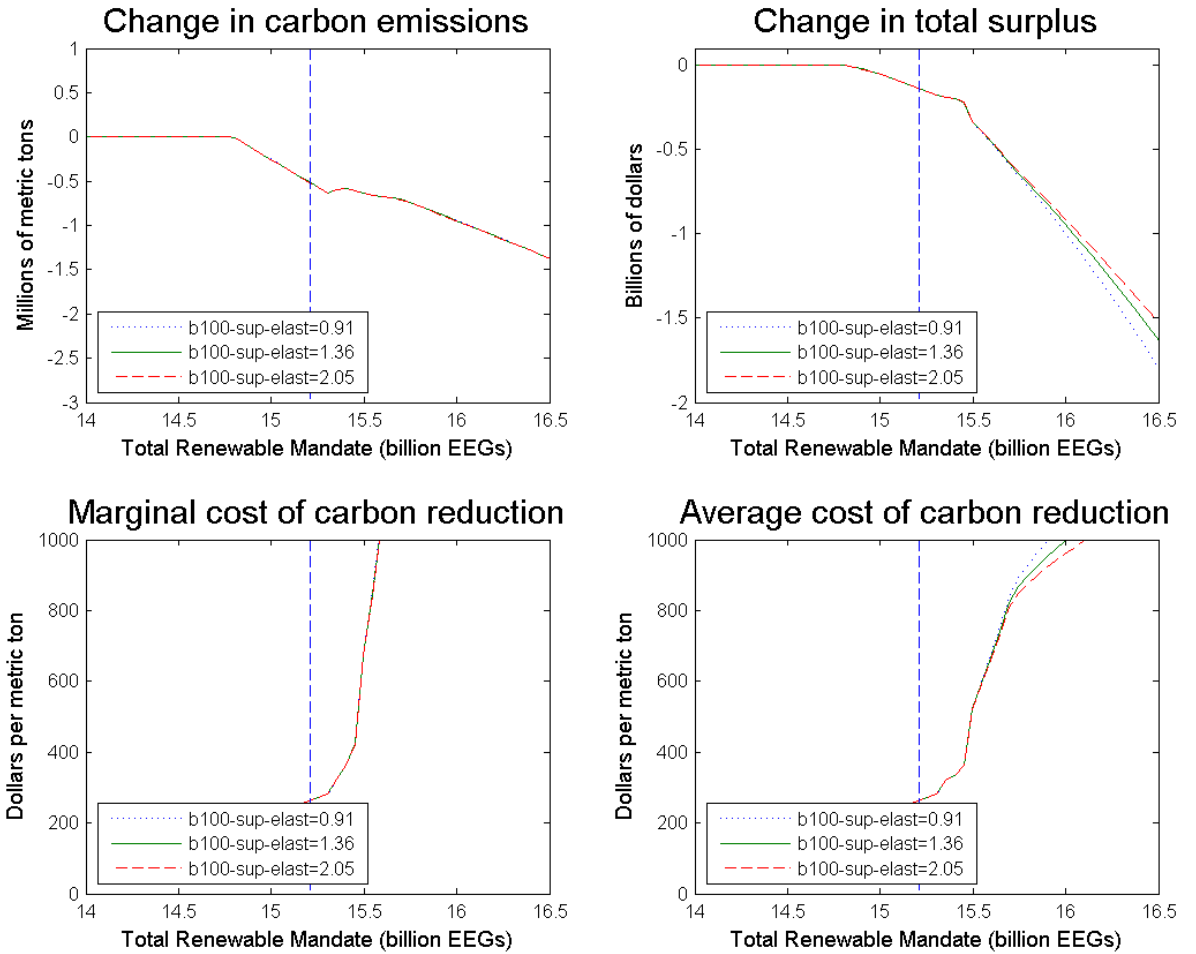
Note: To calculate total emissions, I multiply the consumption volume of the various blending components by their life cycle emissions. The change in total surplus is calculated using the model supply and demand curves.

Figure 2.16: Simulation for three values of biodiesel elasticity of supply



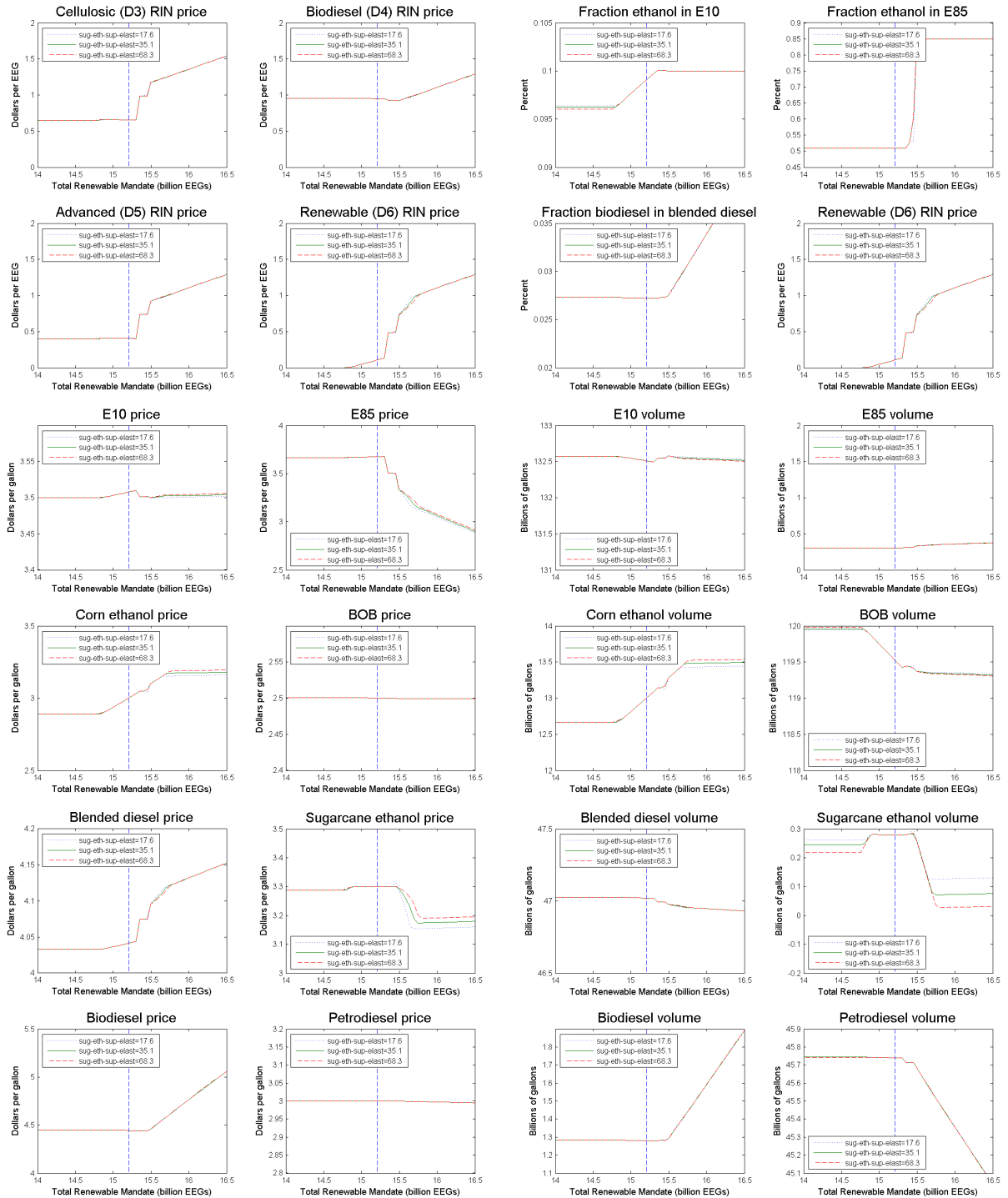
Note: These graphs depict the results of numerically solving the system of equations for many values for the renewable fuel mandate (14 to 16.5 billion ethanol equivalent gallons) and three values of biodiesel elasticity of supply.

Figure 2.17: Emissions and welfare for three values of biodiesel elasticity of supply



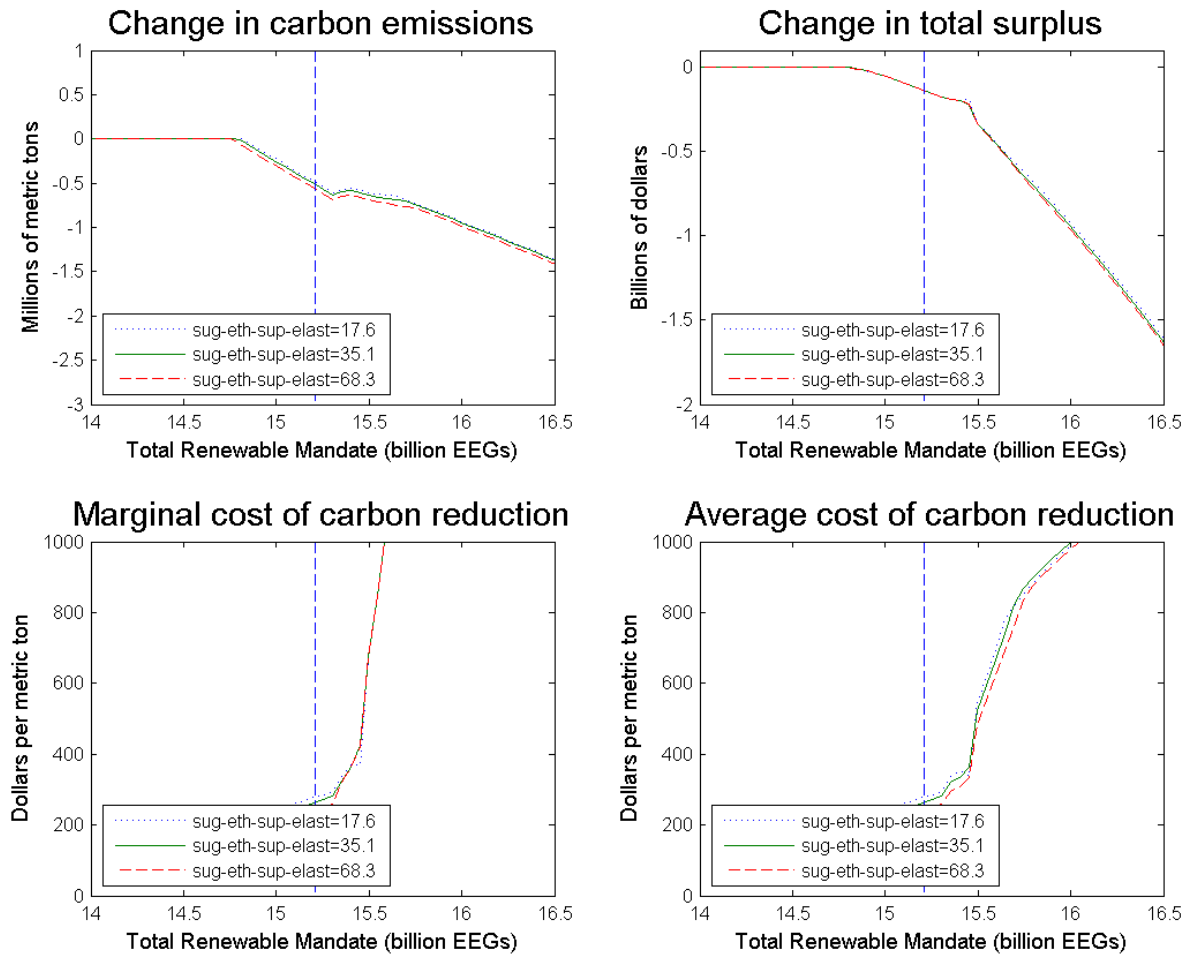
Note: To calculate total emissions, I multiply the consumption volume of the various blending components by their life cycle emissions. The change in total surplus is calculated using the model supply and demand curves.

Figure 2.18: Simulation for three values of sugarcane ethanol elasticity of supply



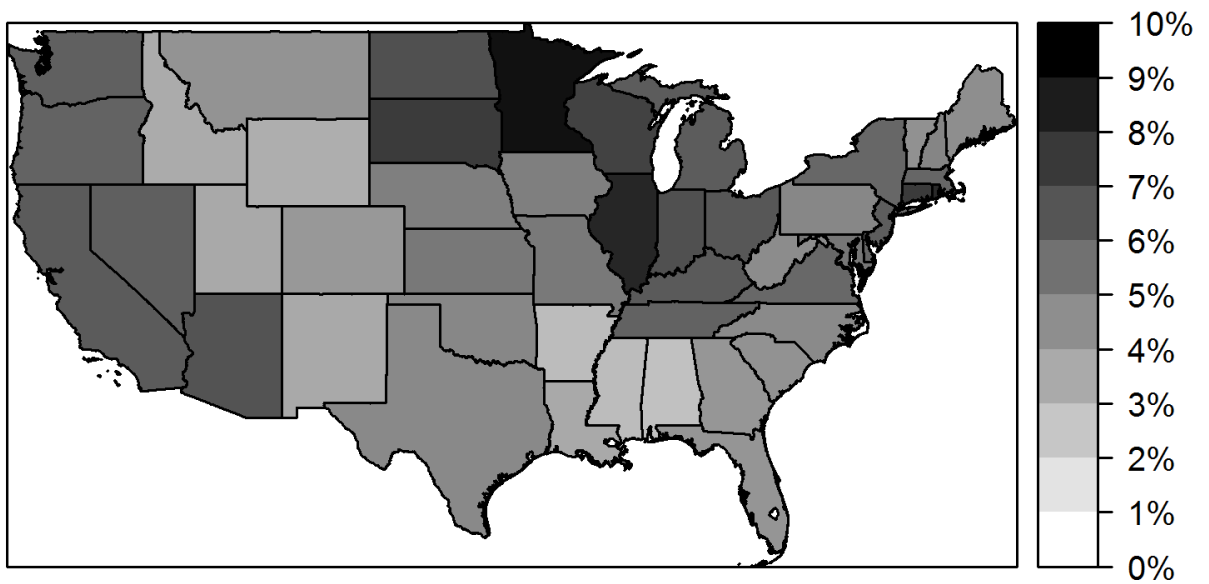
Note: These graphs depict the results of numerically solving the system of equations for many values for the renewable fuel mandate (14 to 16.5 billion ethanol equivalent gallons) and three values of sugarcane ethanol elasticity of supply.

Figure 2.19: Emissions and welfare for three values of sugarcane ethanol elasticity of supply



Note: To calculate total emissions, I multiply the consumption volume of the various blending components by their life cycle emissions. The change in total surplus is calculated using the model supply and demand curves.

Figure 2.20: Ethanol as a fraction of gasoline, 2003-2011



Note: States are shaded in proportion to the fraction of ethanol in blended gasoline from 2003 to 2011. Source data from Energy Information Agency State Energy Data System.

## CHAPTER III

# How does systematic risk affect optimal bank capital?

### 3.1 Introduction

There is a consensus among bank regulators that leverage (the ratio of debt to equity) contributes to systematic risk—the risk that the financial system will fail. Leverage requirements are an important tool for managing systematic risk. However, existing models of leverage requirements do not consider the contribution of leverage to the probability of a crisis. So, how does bank leverage contribute to systematic risk?

This paper argues that optimal bank leverage trades off between two forces. On one hand, bank leverage exacerbates systematic risk by lowering the threshold at which a shock to risky bank assets becomes a financial crisis. On the other hand, bank leverage creates liquidity. I characterize socially optimal capital requirements in a model that compares the benefit of liquidity provision with the cost of more frequent crises. I calibrate the model and show how sensitive the optimal capital ratio is to alternative parameterizations. I show that other policy tools—taxes and government bonds—can attain better outcomes than a capital ratio.

The intuition in my model is simple: a regulator (social planner) chooses a le-

verage requirement to balance the tradeoff between liquidity creation and systematic risk. Bank debt is liquid because a household that owns bank debt is able to avoid transaction costs. However, bank debt also raises systematic risk. Risky bank assets are subject to an aggregate shock, and when that aggregate shock exceeds some threshold there is a financial crisis.

I define systematic risk as the probability of a crisis triggered by the insolvency of the banking sector. This is distinct from other analyses of bank failure in two ways. First, failure is the consequence of being *insolvent*; this is not an analysis of bank runs triggered by sunspots. Bank runs arise in models with demandable debt—specifically fixed-value, first-come first-served, short-term debt—and sunspot equilibria. However, a sunspot equilibrium does not have a well defined probability. In contrast, the probability of a crisis in my model is well-defined because a crisis is based on fundamentals. Second, failure occurs on the level of the banking sector, not an individual bank. An environment that features the failure of the banking sector is more appropriate for examining financial crises.

This paper avoids common pitfalls in the debate about leverage requirements by articulating that the social value of bank debt is liquidity, which raises real consumption. Chief among the pitfalls, which are skillfully elucidated by Admati et al. (2011), are misunderstanding what constitutes “capital” and confusion between private cost and social cost. The liquidity of bank debt is supported by Gorton and Pennacchi (1990), who articulate the argument that bank debt is valuable because it is informationally insensitive. That bank debt raises real output is supported by Jayaratne and Strahan (1996). In my model, the social value of bank debt is clear: bank debt raises real output by creating liquidity, which permits households to avoid transaction costs.

I focus on aggregate shocks to risky bank assets because this paper is about finan-



cial crises not individual bank failures. Many discussions of leverage requirements are concerned with the failure of an individual bank, but the cost of a financial crisis is more than the sum of its parts. The probability of a financial crisis is determined by an interaction between *aggregate* bank leverage and an *aggregate* shock to risky bank assets. The aggregate shock in my model is the depreciation rate of capital assets. It would be reasonable to add other shocks as well but not meaningful for examining the probability of a crisis. A productivity shock, for instance, would have no bearing on the the probability of a crisis in this model.

My model suggests that current international capital standards are too low. Capital standards are a single tool that serves multiple purposes, so there are other factors to consider in setting them, but I argue that the tradeoff between liquidity and systematic risk is more important than the others.

The rest of the paper has the following structure: Section 3.2 explains how the key tradeoff in the model corresponds to banking institutions and how the model fits into the literature, Section 3.3 describes the model and presents the criterion for the optimal capital ratio, Section 3.4 derives properties of the optimal capital ratio analytically, Section 3.5 analyzes the sensitivity of the optimal capital ratio to model parameters numerically, and Section 3.6 concludes.

## **3.2 Background**

This section describes institutions and prior literature that motivate the key tradeoff in my model: bank debt has social value because it is liquid, and financial crises are costly. Then I compare my approach to finding the optimal mix of debt and equity with the standard approach for industrial firms, with prior approaches to capital requirements for banks specifically, and to alternative macroprudential policies that

address the cost of crises.

To highlight the tradeoff between liquidity and the cost of crises, the model in this paper expresses financial crises very simply, but it is reasonable to think of the simple, “reduced form” expression of financial crises in this model as corresponding to more complex, “micro founded” mechanisms. For example, an aggregate shock leads to a crisis in this model if the shock leads to an insolvent banking sector. In a more complex model, an aggregate shock could instead trigger a crisis by crossing a global games threshold for a bank run on an illiquid banking sector, along the lines of Morris and Shin (2001). Indeed, what is called bank debt in the model is meant to represent demandable liabilities with guaranteed value of any financial institutions, including bank deposits and money market mutual funds. Instruments with these properties are subject to runs, so an extension of the model featuring runs would be natural.

The literature supports this paper’s assumption that bank debt has social value because it is liquid. The value of debt to households is expressed in a simple form—similar to a cash-in-advance constraint—which is intended to be a reduced form of the informational insensitivity of debt (Gorton and Pennacchi 1990). In my model, liquidity is provided exclusively on the liability side of a bank’s balance sheet—banks hold assets simply because they need to do something with the financing they’ve raised through liquidity provision. Previous work has stressed that liquidity creation occurs on both sides of the balance sheet (Kashyap, Rajan, and Stein 2002). The liquidity of bank debt enhances welfare by raising output and consumption. The connection between financial intermediation and output is supported empirically by Jayaratne and Strahan (1996).

Just as the model’s trigger for a crisis is a simplification, the model also expresses the cost of crises simply. A crisis in this model is assumed to impose a negative

externality with a direct utility cost. In a more elaborate model, a financial crisis could disrupt other explicitly-modeled financial intermediation by the same banking institutions. Indeed, the literature explores many mechanisms for motivating the cost of financial crises. The externality imposed by a financial crisis in the model is thus intended to reflect the direct cost of individual bank failure (James 1991), as well as costs of fire sales (Diamond and Rajan (2011), Shleifer and Vishny (2011)) and non-relationship-specific disruption to financial intermediation (Campello, Graham, and Harvey (2010), Ivashina and Scharfstein (2010), Duchin, Ozbas, and Sensoy (2010)).

The tradeoff I consider between liquidity and the cost of crises is different from the standard tradeoff between debt and equity in the finance literature. The benchmark result for industrial firms is that any mix of debt and equity is equally good because investors can obtain any risk profile by borrowing or lending at a risk-free rate (Modigliani and Miller 1958). The benchmark of debt-equity neutrality is often broken by principal-agent problems that arise if inside equity provided by the firm's manager is insufficient to fund all positive net present value projects (Shleifer and Vishny 1997). Outside equity encourages a manager to direct firm resources for her private benefit at the expense of maximizing firm value, and debt encourages a manager to invest in excessively risky projects (Jensen and Meckling 1976). This paper considers the optimal mix of debt and equity for banks without principal-agent problems; banks are assumed to act in the interest of shareholders, and debtholders know in advance the riskiness of banks' asset portfolios. The neutrality of the debt-equity mix is instead broken by the social value of bank debt as a source of liquidity and by the externality of bank debt contributing to the probability of a crisis.

Some prior literature uses the equity capital ratio to address other tradeoffs. The standard approach regards bank failure as the consequence of a multiple-equilibrium bank run. Demandable debt fulfills a need for liquidity insurance but also makes

possible equilibrium bank runs, which can be eliminated by deposit insurance (Diamond and Dybvig 1983). Although deposit insurance solves the problem of bank runs, it also creates the problem of risk-shifting. This is the starting point for many explorations of optimal capital: bank runs are solved, so capital is a tool for dealing with risk shifting. This risk shifting is analyzed by Nguyen (2013) and Begenau (2015). This is also the welfare cost setup adopted by Van den Heuvel (2008).

Other prior literature uses other policy tools to address the tension between liquidity and the cost of crises. Section 3.3.7 considers one of the suggestions in Cochrane (2014) that government bonds could obviate the need for a tradeoff. Hanson, Kashyap, and Stein (2011) suggest remedies including time varying capital requirements, quality capital, corrective action, and contingent capital. Acharya et al. (2017) present a model of risky banking in which they obtain an efficient outcome by imposing a tax on a bank's contribution to systemic risk. Section 3.3.6 considers taxes.

### 3.3 Model

This section presents a two-period model in which bank debt makes crises more frequent and raises real output. The model will be used to characterize the optimal capital ratio (equity/assets). There are two agents in the model: households and banks.<sup>1</sup>

The key features of the model are the aggregate depreciation rate of capital assets, the use of debt to avoid transaction costs, and the cost of a crisis. Banks own risky capital assets, and the aggregate depreciation rate on capital assets  $\delta$  is a random

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<sup>1</sup>The word “capital” is used widely both for productive durable assets and for equity-like bank liabilities. I have found that both uses are indispensable, but wherever possible I will use “capital assets” for the productive durables and “equity capital” for the bank liabilities.

variable. Households pay transaction costs on transactions in excess of their holdings of bank debt. If banks are levered, then a high draw of the aggregate depreciation rate  $\delta$  leaves banks with insufficient funds to pay their debt to households, which triggers a crisis.

### 3.3.1 Households

This section describes how households purchase capital assets for use in production and avoid transaction costs by holding bank debt.

Households use capital assets to produce output. Households purchase capital assets from banks at the beginning of the first period and sell it back to banks at the end of the first period. Before production, capital assets are freely convertible with the consumption good at parity, so the pre-production price of capital assets is 1. After production, households sell capital assets to banks, which bear the risk of an uncertain depreciation rate from the first period to the second period. The post-production price of capital  $P$  may be less than one.

Households face transaction costs for capital asset purchases. Transaction costs are quadratic in the volume of capital assets used by households. However, households also hold bank debt. Bank debt is liquid, so households do not need to pay transaction costs on capital that can be covered using holdings of bank debt. Transaction costs are only incurred on capital assets in excess of bank debt.

Events within the first period occur in the following sequence: (1) Households purchase debt and equity from banks, (2) Households purchase capital assets from banks, (3) Households use capital assets to produce output, (4) Households sell capital assets to banks, (5) Households consume. Households have the ability to hold capital assets from the first period to the second period rather than selling them to a bank, but in equilibrium they choose not to do so because the expected

return on bank equity exceeds the expected return on capital assets.

Households maximize expected utility subject to a budget constraint:

$$\max_{C_1, C_2, E, D, K} U(C_1) + \beta \mathbb{E}[U(C_2)] - \beta \xi \mathbb{P}[\text{crisis}] \quad (3.1)$$

$$s.t. \quad C_1 + E + D + K + H(K, D) \leq F(K) + PK + W \quad (3.2)$$

$$\mathbb{E}[C_2] \leq \mathbb{E}[\pi]E + \mathbb{E}[r]D \quad (3.3)$$

$$U(C_t) = C_t, \quad H(K, D) = \frac{\gamma}{2}(K - D)^2, \quad F(K) = K^\alpha$$

where  $C_t$  is consumption in period  $t$ ,  $\xi$  is the utility cost of a crisis,  $E$  is bank equity,  $D$  is bank debt,  $K$  is capital assets,  $P$  is the end-of-period price of capital assets,  $W$  is the initial stock of wealth,  $\pi$  is the return on equity,  $r$  is the return on bank debt,  $U(\cdot)$  is a utility function,  $H(\cdot)$  is a transaction cost function,  $F(\cdot)$  is a production function,  $\mathbb{E}[\cdot]$  is the expectation operator, and  $\mathbb{P}[\text{crisis}]$  is the probability of a crisis. From now on I use the convention  $\bar{X} \equiv \mathbb{E}[X]$ .

The household first order conditions<sup>2</sup> imply:

$$\beta \bar{\pi} = 1 \quad (3.4)$$

$$\beta \bar{r} = 1 - \gamma(K - D) \quad (3.5)$$

$$F'(K) = (1 - P) + \gamma(K - D) \quad (3.6)$$

A household pays a cost  $\xi$  in a financial crisis. The cost of a crisis and the probability of a crisis are outside the control of an individual household, so they have no impact on any household decisions. I will discuss crises in more detail in a later section.

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<sup>2</sup>See appendix for first order conditions.

### 3.3.2 Banks

This section describes how banks choose whether to borrow in order to finance risky assets. If debt is cheap, banks borrow as much as they are permitted by the capital ratio.

Banks receive income from owning capital assets. Banks purchase capital assets at the end of the first period for the post-production price  $P$ . Banks earn a risky rate of return on capital assets because capital assets depreciate stochastically. The aggregate depreciation rate on the stock of capital assets  $K$  becomes known at the beginning of the second period:  $\delta$ . The surviving capital assets owned by the bank,  $(1-\delta)K$ , are available for banks to distribute to debtholders and shareholders. Recall that, before production, capital assets are freely convertible with the consumption good at parity, so the pre-production price of capital assets is 1.

Banks issue debt and equity, and debt receives payment priority over equity. The cash balance constraint requires that the value of capital assets equal liabilities,  $PK = D + E$ . Bank debt claims  $D$  are issued with a promised interest rate  $r^*$ . Whenever banks are able to pay the promised interest rate, they do so and remit whatever remains as returns to shareholders:  $\pi E = \max \{0, (1-\delta)K - r^*D\}$ . Whenever banks are unable to pay the promised interest rate, returns to shareholders are zero and banks remit whatever cash they do hold to debtholders:  $rD = \min \{r^*D, (1-\delta)K\}$ .

The bank's problem is to maximize the expected second-period return on equity subject to budget constraints and a capital requirement. The capital requirement is

a minimum capital ratio (equity/assets). Formally,

$$\begin{aligned}
 & \max_{\{K,D\}} \bar{\pi}E \\
 \text{s.t.} \quad & \underbrace{PK}_{\text{end-of-period capital}} = \underbrace{D}_{\text{bank debt}} + \underbrace{E}_{\text{bank equity}} \tag{3.7}
 \end{aligned}$$

$$\underbrace{(1 - \bar{\delta})K}_{\text{income from capital}} = \underbrace{\bar{r}D}_{\text{debt payments}} + \underbrace{\bar{\pi}E}_{\text{expected return on equity}} \tag{3.8}$$

$$\phi PK \leq E \tag{3.9}$$

where  $\bar{\delta}$  is the expected depreciation rate of capital,  $\bar{r}$  is the expected return on bank debt,  $\bar{\pi}$  is the expected return on bank equity, and  $\phi$  is the required capital ratio.<sup>3</sup>

The capital ratio can also be understood as a limit on debt. Combining equations 3.7 and 3.9 yields an equivalent expression of the capital ratio in terms of debt:

$$(1 - \phi)PK \geq D \tag{3.10}$$

The bank problem is essentially a question of whether to expand the balance sheet by borrowing. If debt is cheaper than the return on assets,  $\bar{r} < \frac{(1-\bar{\delta})}{P}$ , then banks borrow as much as they are permitted to finance assets, and the capital ratio in equation 3.9 is binding. If debt is more expensive than the return on assets,  $\bar{r} > \frac{(1-\bar{\delta})}{P}$ , then banks do not borrow to finance assets and bank debt is zero. If the return on debt is equal to the return on assets, then any level of debt is consistent with bank optimization. Figure 3.1 shows that equilibrium in the market for bank

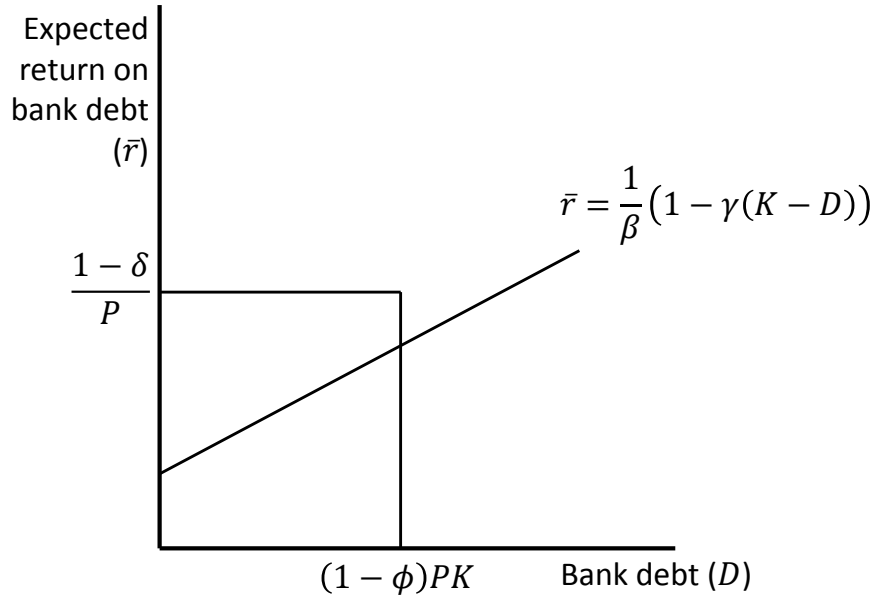
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<sup>3</sup>Using  $\lambda$ ,  $\mu$ , and  $\psi$  as the Lagrange multipliers, a bank has the following first order conditions:

$$\begin{aligned}
 \lambda P &= \mu(1 - \bar{\delta}) + \psi \phi P \\
 \lambda &= \mu \bar{r}
 \end{aligned}$$



Figure 3.1: Market for bank debt



Note: This figure shows that in the competitive equilibrium the expected interest rate  $\bar{r}$  and the quantity of debt  $D$  satisfy the household first order conditions and the bank capital ratio.

debt requires that either the expected return on debt equal the expected return on assets or the capital ratio binds.

### 3.3.3 Competitive equilibrium

This section defines a competitive equilibrium and characterizes the competitive equilibrium for an exogenous capital ratio  $\phi \in [0, 1]$ . Later, I will consider the Ramsey problem for  $\phi$ : how the capital ratio would be chosen by a social planner to maximize household utility.

**Definition III.1.** A **competitive equilibrium** is a set of prices  $\{P, \bar{\pi}, \bar{r}\}$  and quantities  $\{C_1, \bar{C}_2, E, D, K\}$  that satisfy the household and bank resource constraints and first order conditions in equations 3.2 through 3.9.

We obtain an intuitive relationship between the weighted average cost of bank finance and the expected return on assets by combining equations 3.4, 3.5, 3.7, 3.8,

and 3.9:

$$\underbrace{\frac{1}{\beta}[\phi + (1 - \phi)(1 - \gamma(K - D))]}_{\text{weighted average cost of bank finance}} = \underbrace{\frac{1 - \bar{\delta}}{P}}_{\text{expected return on assets}} \quad (3.11)$$

**Proposition 1.** *If transaction costs are positive,  $\gamma > 0$ , then there is a unique competitive equilibrium for each capital ratio  $\phi \in [0, 1]$ . The competitive equilibrium can be expressed as a system of three equations (3.6, 3.10, and 3.11) with three endogenous variables (debt, capital assets, and post-production price), or as one equation in capital assets, with  $D(K) = \frac{(1-\phi)K(1+\gamma K - F'(K))}{1+(1-\phi)\gamma K}$ .*

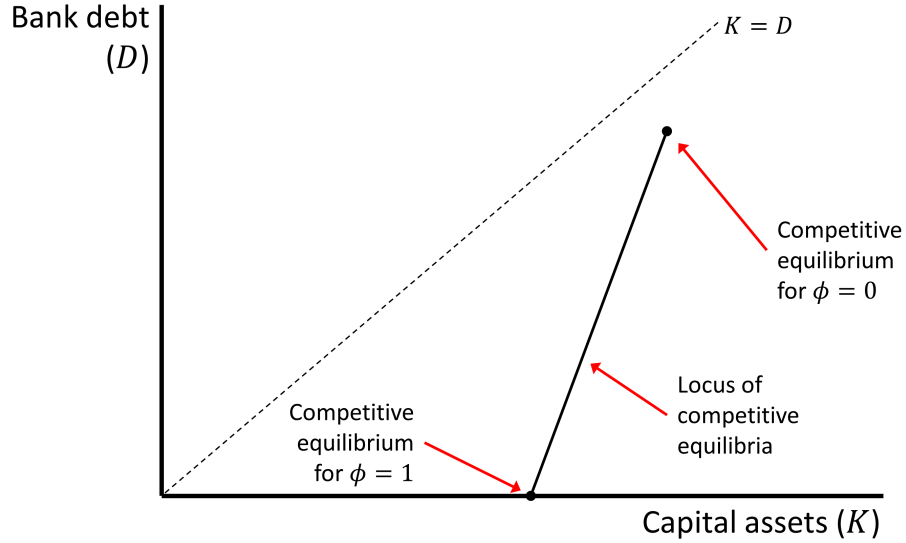
$$\underbrace{1}_{\text{initial price}} + \underbrace{\gamma(K - D(K))}_{\text{transaction cost}} = \underbrace{F'(K)}_{\text{marginal product}} + \underbrace{\frac{\beta(1 - \bar{\delta})}{\phi + (1 - \phi)(1 - \gamma(K - D(K)))}}_{\text{end-of-period price}} \quad (3.12)$$

We are interested in how the capital ratio affects the competitive equilibrium. When the capital ratio requires total equity finance,  $\phi = 1$ , debt is zero, so transaction costs are high, so households choose less capital. When the capital ratio permits total debt finance,  $\phi = 0$ , debt is high, so transaction costs are low, so households choose more capital. Figure 3.2 shows conceptually that capital assets and debt are both decreasing as a function of  $\phi$ .

### 3.3.4 Crisis

This section explains the cause, consequence, and probability of a crisis. A crisis occurs endogenously when the depreciation rate is so high that the banking sector cannot pay its debt. The consequence is that households suffer a utility penalty. Households and banks do not consider the impact their choices have on the proba-

Figure 3.2: Competitive equilibria



Note: This figure shows that among competitive equilibria, both capital assets and debt decrease as a function of the capital ratio  $\phi$ .

bility of a crisis, but the social planner does consider the probability of a crisis when choosing policies.

A crisis occurs when the banking sector is insolvent. The solvency of the banking sector is determined at the beginning of the second period when the aggregate depreciation rate of capital is realized. The aggregate depreciation rate is between zero and one, distributed according to the cumulative distribution function  $G(\delta)$ , with mean  $\bar{\delta}$  and variance  $\sigma^2$ . Banks' only assets are capital assets, and the beginning-of-period price of capital assets is one, so the resources available for banks to distribute as returns on equity and debt are the surviving stock of capital assets:  $(1 - \delta)K$ . A crisis occurs when banks cannot pay the interest rate that was promised in the first period:  $(1 - \delta)K < r^*D$ .

**Definition III.2.** The **crisis threshold**  $\delta^*$  is the depreciation rate at which banks can pay the promised interest rate but the return on equity is zero:  $r = r^*$  and

$\pi = 0$ .

In a crisis, households suffer a utility penalty  $\xi$ .<sup>4</sup> Households are small in the sense that their individual choices of debt do not influence the probability of a crisis. However, in the aggregate, household choices do determine the probability of a crisis, so the expected cost of a crisis  $\xi\mathbb{P}[\text{crisis}]$  is endogenous.

**Definition III.3.** The **probability of a crisis** is the probability that the depreciation rate  $\delta$  exceeds the crisis threshold  $\delta^*$ . The probability of a crisis can be expressed as  $1 - G(\delta^*)$ . The probability of a crisis can also be expressed as an implicit function of capital assets and equity, denoted  $J\left(\frac{\bar{\pi}E}{K}\right) \equiv 1 - G(\delta^*\left(\frac{\bar{\pi}E}{K}\right))$ .

Recall the expression for the return on equity:  $\pi E = \max\{0, (1 - \delta)K - r^*D\}$ . The expression for the probability of a crisis as an implicit function of capital assets is derived by taking expectations of the return on equity and substituting for bank debt obligations,  $r^*D = (1 - \delta^*)K$ :

$$\bar{\pi}E = G(\delta^*)\mathbb{E}[\delta^* - \delta | \delta < \delta^*]K \quad (3.13)$$

The probability of a crisis relates naturally to the return on equity. When the expected return on equity equals zero,  $\bar{\pi}E = 0$ , the crisis threshold must be zero, so the probability of a crisis is one,  $J(0) = 1$ . When the expected return on equity equals the expected survival of capital,  $\bar{\pi}E = (1 - \bar{\delta})K$ , the crisis threshold must be one, so the probability of a crisis is zero,  $J(1 - \bar{\delta}) = 0$ .

In the following sections I will consider a social planner with a variety of policy instruments, including a capital ratio ( $\phi$ ), taxes on capital, debt, and equity ( $\tau_K, \tau_D, \tau_E$ ), lump sum taxes ( $T$ ), government bonds ( $B$ ), and direct choices of prices

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<sup>4</sup>As noted earlier, the externality imposed by a crisis could be modeled in a more elaborate model as a disruption to other financial services performed by banks such as making loans.

$(P, \bar{\pi}, \bar{r})$  and quantities  $(C_1, E, D, K)$ . In all cases, the social planner will maximize expected consumption with consideration given to the probability of a crisis. The social planner's objective function is the same as for households in Equation 3.1, except that the social planner behaves in a way to control the cost of a crisis and households do not:

$$\max C_1 + \beta \mathbb{E}[C_2] - J\left(\frac{\bar{\pi}E}{K}\right)\xi \quad (3.14)$$

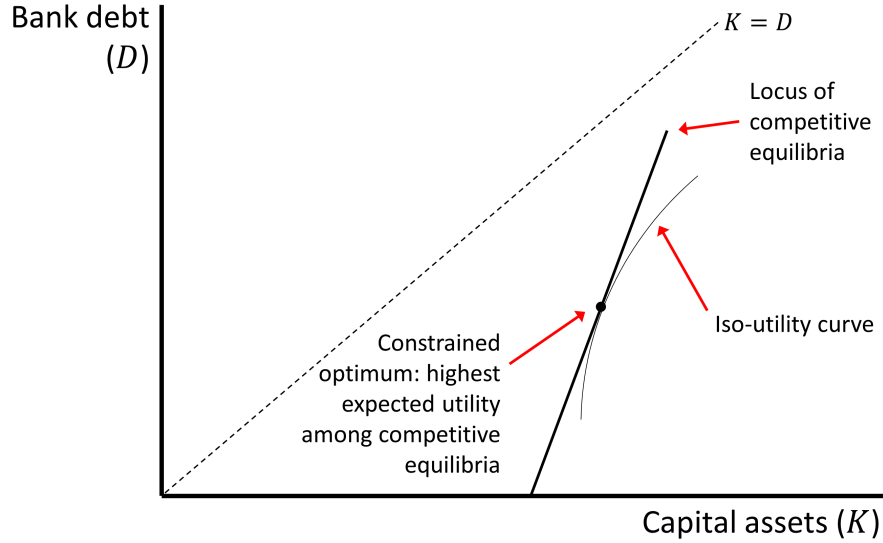
### 3.3.5 Social planner with capital ratio

This section describes the Ramsey problem when the social planner's policy instrument is the equity capital ratio  $\phi$ . Banks and households behave competitively, so the social planner uses  $\phi$  to choose from the set of competitive equilibria.

When the social planner's policy instrument is the capital ratio, the social planner must choose from the set of competitive equilibria. The social planner chooses the capital ratio to maximize household expected utility, subject to the household and bank resource constraints and first order conditions. In other words, the social planner chooses the competitive equilibrium that maximizes expected utility from the set of competitive equilibria. Figure 3.3 shows the intuition for the social planner's solution. Relative to the constrained optimum, the social planner would prefer to have more capital assets and less debt, but competitive behavior by banks and households makes that infeasible.

The social planner's problem can be restated in a simple form. Define the function  $K(\phi)$  as the capital assets  $K$  chosen in the competitive equilibrium, conditional on the capital ratio  $\phi$ . Define  $E(\phi)$ ,  $D(\phi)$ , and  $P(\phi)$  similarly as equity, debt, and the post-production price of capital assets in the competitive equilibrium. Define  $J(\phi) = J\left(\frac{\bar{\pi}E(\phi)}{K(\phi)}\right)$  as the probability of a crisis. Then the social planner's problem can

Figure 3.3: Social planner with capital ratio



Note: Relative to the constrained optimum, the social planner would prefer to have more capital assets and less debt, but competitive behavior by banks and households makes that infeasible.

be restated as

$$\max_{\phi} F(K(\phi)) - K(\phi) - \frac{\gamma}{2} (K(\phi) - D(\phi))^2 + \beta(1 - \delta)K(\phi) - \beta\xi J(\phi) \quad (3.15)$$

**Proposition 2.** *When the social planner's policy instrument is a capital ratio, the solution is to equate the marginal benefit of liquidity with the marginal cost of crisis and the marginal external cost of capital assets:*

$$\underbrace{\gamma(K(\phi) - D(\phi))}_{\text{transaction cost}} \underbrace{D'(\phi)}_{(-)} = \underbrace{\beta\xi}_{\text{cost of crisis}} \underbrace{J'(\phi)}_{(-)} + \underbrace{\left( P(\phi) - \beta(1 - \bar{\delta}) \right)}_{\text{external cost of assets}} \underbrace{K'(\phi)}_{(-)} \quad (3.16)$$

The quantities  $\{C_1, \bar{C}_2, E, D, K\}$  that result from the optimal capital ratio are the **constrained optimum**.

The benefit of leverage is expressed on the left side of equation 3.16. As the equity

capital ratio  $\phi$  increases, debt decreases, which reduces the benefit of liquidity. The cost of leverage is expressed on the right side of equation 3.16. As the equity capital ratio  $\phi$  increases, the probability of a crisis decreases, which reduces the cost of a crisis. The second expression on the righthand side, which uses a substitution from equation 3.6, expresses the external cost of assets—a household values a capital asset more than the social planner to the extent that the end-of-period price exceeds the social value of the capital asset.

### 3.3.6 Social planner with taxes

This section describes the Ramsey problem when the social planner chooses a vector of tax instruments. The social planner is constrained to a competitive equilibrium, but the household and bank resource constraints and first order conditions are different from equations 3.2 through 3.9. The solution for a social planner with taxes is an intuitive criterion for the tradeoff between liquidity and crises.

The social planner's vector of tax instruments affects the first period household budget constraint. The social planner can choose four taxes: lump sum taxes, and taxes on household choices of capital assets, debt, and equity,  $\tau \equiv \{T, \tau_E, \tau_D, \tau_K\}$ . Any of these taxes may be negative, in which case we would call them transfers or subsidies. Thus, the social planner with taxes operates in a slightly different environment from the social planner with a capital ratio. The objective functions of households and banks remain the same as described previously, as do most resource constraints. The exception is the household first-period budget constraint becomes:

$$C_1 + E(1 + \tau_E) + D(1 + \tau_D) + K(1 + \tau_K) + H(K, D) + T \leq F(K) + PK \quad (3.2b)$$

The social planner with taxes faces two noteworthy constraints that were ignored

in the preceding discussion of the capital ratio. The first constraint is that the post-production price of capital must be less than one,  $P \leq 1$ , because capital is freely convertible at parity with the consumption good before production. This constraint will bind because a higher price permits both more debt (to defray transaction costs) and more equity (to reduce the probability of a crisis) for a given level of capital. The second constraint is the condition under which banks have a perfectly elastic supply of bank debt,  $\bar{r}P = 1 - \bar{\delta}$ , which must be met if both debt and equity are positive. Together, these constraints imply  $\bar{r} = 1 - \bar{\delta}$ .

Before stating the main result, we need to introduce some notation. For examining the social planner with taxes, it will be convenient to express the probability of a crisis as a function of debt and capital:

$$J\left(\frac{\bar{\pi}E_t}{K_t}\right) = J\left(\frac{(1 - \bar{\delta})K - \bar{r}D}{K_t}\right) = J\left((1 - \bar{\delta})\left(1 - \frac{D}{K}\right)\right) = J(K, D) \quad (3.17)$$

where the first equality holds by equation 3.8 and the second equality holds because  $\bar{r} = 1 - \bar{\delta}$ . The social planner can independently control  $K$  and  $D$  as implicit functions of  $\tau$ , and I write  $J_i(K(\tau), D(\tau))$  to indicate the partial derivative of  $J$  with respect to argument  $i$ .

**Proposition 3.** *When the social planner's policy instrument is a vector of taxes and subsidies  $\tau$ , the optimal regime equates the marginal benefit of liquid debt with the marginal contribution of debt to the expected cost of a crisis. The optimal tax regime also equates the marginal benefit of capital assets with their marginal cost. The quantities  $\{C_1, \bar{C}_2, E, D, K\}$  that result from the optimal tax regime are the **partially***



*constrained optimum.*

$$\underbrace{\beta\xi}_{\text{cost of crisis}} \underbrace{J_2(K(\tau), D(\tau))}_{\Delta \text{ crisis probability}} = \underbrace{\gamma(K(\tau) - D(\tau))}_{\text{value of liquidity}} \quad (3.18)$$

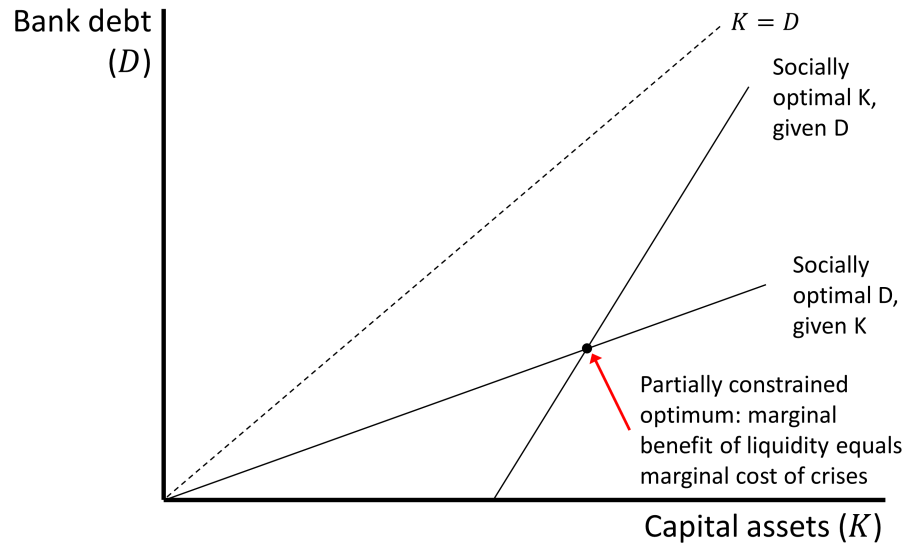
$$\underbrace{1}_{\text{price}} + \underbrace{\gamma(K(\tau) - D(\tau))}_{\text{transaction cost}} = \underbrace{F'(K(\tau))}_{\text{marginal product}} + \underbrace{\beta(1 - \bar{\delta})}_{\text{discounted value}} + \underbrace{\beta\xi}_{\text{cost of crisis}} \underbrace{J_1(K(\tau), D(\tau))}_{\Delta \text{ crisis probability}} \quad (3.19)$$

Figure 3.4 shows that the partially constrained optimum can be interpreted as the intersection of equation 3.18, which describes the optimal choice of debt conditional on capital assets, and equation 3.19, which describes the optimal choice of capital assets conditional on debt.

As expected, the social planner can achieve a better equilibrium when she has more policy levers. The intuition is that the social planner uses a tax on debt to control the choice of debt, a subsidy for capital assets to control the choice of capital assets, a subsidy for equity to ensure that banks are willing to issue debt, and lump sum taxes to achieve budget balance. Compare the social planner's optimal debt condition in equation 3.18 to the household's first order condition for debt in equation 3.5. Both the social planner and the household care about the marginal benefit of liquidity in the expression on the right. The social planner weighs the benefit of liquidity against the marginal effect of debt on the cost of a crisis. The household weighs the benefit of liquidity against the price of debt and the return on debt.

There are two differences between the condition for optimal capital assets in equation 3.19 and the household's first order condition for capital assets in equation 3.6. First, the optimal choice of assets consider the discounted value of surviving

Figure 3.4: Social planner with taxes



Note: The partially constrained optimum can be interpreted as the intersection of Equation 3.18, which describes the optimal choice of debt conditional on capital assets, and Equation 3.19, which describes the optimal choice of capital assets conditional on debt.

capital  $\beta(1 - \delta)$  rather than the price  $P$ . Second, the optimal choice of assets includes a term for the positive externality of capital assets on the probability of a crisis; holding debt fixed, raising the level of capital assets reduces the probability of a crisis.

### 3.3.7 Social planner with government bonds

This section describes the Ramsey problem when the social planner issues government bonds. As was the case with taxes, the social planner with government bonds is constrained to a competitive equilibrium with modified household resource constraints and first order conditions. The solution for a social planner with government bonds entirely avoids transaction costs with zero probability of a crisis.

Government bonds are liquid, which enables households to avoid transaction costs. Specifically, government bonds are perfectly substitutable with bank debt

from the perspective of households. Government bonds have the same liquidity properties as bank debt.

The availability of government bonds affects the household budget constraint in both periods. The social planner chooses to issue some quantity of government bonds  $B$ , on which interest is paid in the second period. Government budget balance is achieved by lump sum transfers in the first period and lump sum taxes in the second period. The objective functions of households and banks remain the same as described previously, as do most resource constraints. The exceptions are the household budget constraints in the first and second period:

$$C_1 + E + D + B + K + H(K, D + B) + T_1 \leq F(K) + PK \quad (3.2c)$$

$$\bar{C}_2 + T_2 \leq \bar{\pi}E + \bar{r}D + r^B B \quad (3.3c)$$

**Proposition 4.** *When the social planner's policy instrument is government bonds  $B$ , the optimal policy is to equate the quantity of government bonds with the quantity of capital assets. The quantities  $\{C_1, \bar{C}_2, E, D, K\}$  that result from the optimal tax regime are the **unconstrained optimum**. In the unconstrained optimum, transaction costs are zero and the probability of a crisis is zero.*

$$\underbrace{1}_{\text{price}} = \underbrace{F'(K)}_{\text{marginal product}} + \underbrace{\beta(1 - \bar{\delta})}_{\text{discounted value}} \quad (3.20)$$

Equation 3.20 describes the choice of capital assets in the unconstrained optimum. Compare equation 3.20 to equations 3.6 and 3.19. The transaction cost term drops out because government bonds are abundant. The post-production price of capital assets in the unconstrained optimum is equal to the social value, the discounted value of expected surviving capital assets,  $P = \beta(1 - \bar{\delta})$ . Figure 3.5 illustrates the

unconstrained optimum relative to the constrained optimum and the the partially constrained optimum.

### 3.4 Analytical Results

The optimal capital ratio is an implicit function of the model parameters. This section explains how the optimal capital ratio reacts to parameter changes. I examine special cases for transaction costs  $\gamma$ , the utility cost of a crisis  $\xi$ , and the distribution of the aggregate depreciation rate  $G(\delta)$ .<sup>5</sup> The standard assumptions will be positive transaction costs, positive utility cost, and positive variance, and these will be relaxed individually.

#### 3.4.1 No transaction costs, $\gamma = 0$

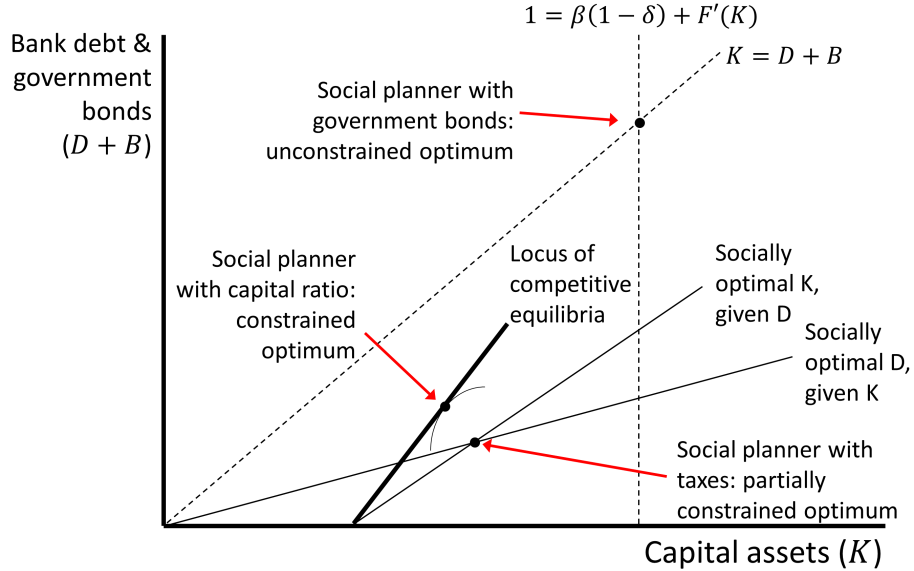
Suppose that capital assets can be purchased by households for use in production without incurring transaction costs. In this case, households are indifferent between equity and debt at a rate of return equal to  $\frac{1}{\beta}$ . The post-production price of capital assets is  $\beta(1 - \bar{\delta})$ , so banks are also willing to borrow. Any mix of equity and debt is an equilibrium in this case, even though equilibria with debt will expose households to the cost of a crisis. The optimal capital ratio with zero transaction costs is one, because there is no benefit to liquid debt.

For  $\gamma$  near zero, the optimal capital ratio may still be one. This could be true if the utility cost of a crisis is high and the distribution of the aggregate default rate is concentrated around  $\delta = 1$ . Define  $\underline{\gamma}$  as the lowest value of gamma at which a capital ratio of one is optimal. Now we see what happens to the optimal capital ratio as  $\gamma$

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<sup>5</sup>In the following analysis, I will denote the optimal capital ratio as  $\phi^*$ . The optimal ratio is an implicit function of all of the model parameters,  $\phi^* = \phi^*(\alpha, \beta, \gamma, \bar{\delta}, \delta_\sigma, \xi)$ . When considering a particular parameter like  $\gamma$ , I will suppress the full notation and write simply  $\phi^*(\gamma)$ .

Figure 3.5: Social planner with government bonds



Note: Households avoid transaction costs in the unconstrained optimum by holding government debt rather than bank debt.

increases past  $\underline{\gamma}$  by linearizing the system around  $\gamma = \underline{\gamma}$ . All endogenous variables  $\{E, D, K, P, \bar{r}, \bar{\pi}\}$  are treated as functions of  $\phi^*(\gamma)$  and  $\gamma$ . So  $K = K(\phi^*(\gamma), \gamma)$ .

**Proposition 5.** *The optimal capital ratio is a monotonically decreasing function of transaction costs  $\gamma$ . Near  $\gamma = \underline{\gamma}$ , a small increase in transaction costs  $\gamma$  reduces the optimal capital ratio as follows:*

$$\frac{\partial \phi^*(\gamma = \underline{\gamma})}{\partial \gamma} = \frac{-K \frac{\partial D}{\partial \phi} - \gamma \frac{\partial D}{\partial \phi} \frac{\partial K}{\partial \gamma}}{\gamma K \left(-\frac{\partial E}{\partial \phi}\right) + \gamma \frac{\partial D}{\partial \phi} \frac{\partial K}{\partial \phi} - \beta \xi \frac{\partial^2 J}{\partial \phi^2}} \quad (3.21)$$

### 3.4.2 No utility cost of crisis, $\xi = 0$

Suppose that there is no consequence of an insolvent banking sector. For a depreciation rate that exceeds the crisis threshold such that the realized interest rate on bank debt is below the promised interest rate, there is still no utility cost. Assuming transaction costs are positive, the optimal capital ratio with zero utility cost of a

crisis is zero, because there is no benefit to avoiding an insolvent banking sector.

**Proposition 6.** *The optimal capital ratio is a monotonically increasing function of the utility cost of a crisis  $\xi$ . Near  $\xi = 0$ , a small increase in the utility cost of a crisis  $\xi$  increases the optimal capital ratio as follows:*

$$\frac{\partial \phi^*(\xi = 0)}{\partial \xi} = \frac{-K \frac{\partial D}{\partial \phi} - \gamma \frac{\partial D}{\partial \phi} \frac{\partial K}{\partial \gamma}}{\gamma K \left(-\frac{\partial E}{\partial \phi}\right) + \gamma \frac{\partial D}{\partial \phi} \frac{\partial K}{\partial \phi} - \beta \xi \frac{\partial^2 J}{\partial \phi^2}} \quad (3.22)$$

### 3.4.3 The distribution of depreciation draws, $G(\delta)$

If depreciation is known in advance, then the expected interest rate on debt will equal the promised interest rate on debt and the realized interest rate, so there will be no crisis. In this context a capital ratio of zero is optimal.

If depreciation can take on one of two possible values, for example  $\delta \in \{\delta^L, \delta^H\}$ , then there are two candidates for the optimal capital ratio. At a capital ratio of zero, there is a crisis for a high draw of the depreciation rate but not for the low draw. There is some other capital ratio that depends on  $\delta^H$  and  $\delta^L$  at which there is no crisis for either draw of the depreciation rate. Either of these two candidate depreciation rates could be optimal, depending on the probability of  $\delta^L$  and the cost of a crisis  $\xi$ .

## 3.5 Empirical illustration

This section calibrates the model, calculates the optimal capital ratio numerically, and examines the sensitivity of the optimal ratio to alternative parameterizations. In this stylized model of liquidity and crises, the goal of a calibration exercise is to explore how sensitive the optimal capital ratio is to the model parameters. Table 3.1 summarizes the parameters calibrated for the United States at an annual frequency.

Table 3.1: Calibrated parameters

Parameter	Symbol	Value	Source/Target
Capital scale	$\alpha$	0.54	bank risk-weighted assets \$9.3 trillion
Discount factor	$\beta$	0.93	return on bank equity 8%
Transaction cost	$\gamma$	0.02	return on bank debt 3%
Depreciation mean	$\bar{\delta}$	0.10	
Depreciation stdev	$\delta_\sigma$	0.10	
Capital ratio	$\phi$	0.13	aggr. risk-weighted capital ratio 13%
Utility cost of crisis	$\xi$	0.30	one third of average consumption

This table shows the model parameters and their values at the calibrated point.

The policy tool of interest is the capital ratio  $\phi$ , which I calibrate using the observed aggregate ratio of equity to assets in the U.S. commercial banking sector. This is similar to several policy tools in the Basel III regulatory framework: the leverage ratio and the risk-weighted capital ratio. Precisely matching a real-world policy tool is not essential; commercial banks are rarely at the exact minimum in any case because banks maintain a buffer above the regulatory minimum. The purpose of the exercise is to identify a real-world aggregate moment which regulators have the capability of targeting with existing policy tools, and that moment is the aggregate ratio of equity to assets. For U.S. commercial banks the actual ratio of equity to assets is 13%, which I use for  $\phi$  in the baseline calibration.<sup>6</sup>

For the purpose of targeting the capital scale parameter  $\alpha$ , I use aggregate assets in the U.S. commercial banking sector. This is important because the size of the banking sector determines how much liquid debt is being provided by banks. Using only commercial banks may be too small if other financial intermediaries perform

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<sup>6</sup>The aggregate capital ratio and other moments from the commercial banking sector are constructed from Call Reports—regulatory filings with the Federal Deposit Insurance Corporation. The process of constructing data from Call Reports is discussed by Kashyap and Stein (2000) and Den Haan, Sumner, and Yamashiro (2002). I obtain commercial bank data from [www.chicagofed.org](http://www.chicagofed.org) and documentation from [www.federalreserve.gov/apps/mdrm](http://www.federalreserve.gov/apps/mdrm). I use item numbers 3210 for equity and 2170 for assets to construct the aggregate capital ratio.

the same functions—selling liquid debt and buying risky assets. If the crisis-relevant financial sector is larger than the commercial banking sector, then the capital scale parameter should be larger than in the baseline calibration. The volume of commercial bank assets used in calibration is aggregated from Call Reports.

The discount factor  $\beta$  and the transaction cost parameter  $\gamma$  are closely related to two prices in the model: the expected return on equity and the expected return on debt. The discount factor is simply the inverse of the expected return on equity, which I take to be 8%. The wedge between the expected return on equity and the expected return on debt is a liquidity premium. The liquidity premium depends on the transaction cost parameter.

Recalling that this is an empirical illustration of how to implement this model empirically, the optimal capital ratio at the calibrated point is 19%. Table 3.2 summarizes how the optimal capital ratio changes for alternative parameter values.

### **3.6 Conclusion**

Macroprudential bank regulation should depend on the tradeoff between liquidity creation and the contribution of bank debt to systematic risk. This paper presents a simple model featuring that tradeoff. It articulates a criterion for optimal leverage requirements and considers alternative policy tools and what they could achieve. The empirical illustration demonstrates how this tradeoff could be applied in a more elaborate model. Natural extensions to this paper would be to embed explicit micro foundations for the cost of a crisis and to alter the definition of a crisis from bank sector insolvency to illiquidity through a global games mechanism.



Table 3.2: Optimal capital ratios for alternative parameter values

Alpha ( $\alpha$ )		Beta ( $\beta$ )		Gamma ( $\gamma$ )		Xi ( $\xi$ )		Deltabar ( $\bar{\delta}$ )		Deltasig ( $\delta_\sigma$ )	
Value	Optimal capital ratio	Value	Optimal capital ratio	Value	Optimal capital ratio	Value	Optimal capital ratio	Value	Optimal capital ratio	Value	Optimal capital ratio
0.29	0.39	0.79	0.31	$2 \times 10^{-9}$	0.90	$3.0 \times 10^{-2}$	0.16	0.04	0.06	0.02	0.06
0.34	0.35	0.81	0.29	$2 \times 10^{-8}$	0.86	$9.5 \times 10^{-2}$	0.17	0.06	0.13	0.04	0.11
0.39	0.31	0.83	0.28	$2 \times 10^{-7}$	0.80	<b><math>3.0 \times 10^{-1}</math></b>	<b>0.19</b>	0.08	0.17	0.06	0.15
0.44	0.27	0.85	0.26	$2 \times 10^{-6}$	0.72	$9.5 \times 10^{-1}$	0.24	<b>0.10</b>	<b>0.19</b>	0.08	0.17
0.49	0.23	0.87	0.24	$2 \times 10^{-5}$	0.60	$3.0 \times 10^0$	0.33	0.12	0.21	<b>0.10</b>	<b>0.19</b>
<b>0.54</b>	<b>0.19</b>	0.89	0.23	$2 \times 10^{-4}$	0.45	$9.5 \times 10^0$	0.42	0.14	0.23	0.12	0.20
0.59	0.16	0.91	0.21	$2 \times 10^{-3}$	0.30	$3.0 \times 10^1$	0.51	0.16	0.25	0.14	0.20
0.64	0.13	<b>0.93</b>	<b>0.19</b>	<b><math>2 \times 10^{-2}</math></b>	<b>0.19</b>	$9.5 \times 10^1$	0.59	0.18	0.27	0.16	0.20
0.69	0.09	0.95	0.18	$2 \times 10^{-1}$	0.12	$3.0 \times 10^2$	0.66	0.20	0.29	0.18	0.18
0.74	0.07	0.97	0.16	$2 \times 10^0$	0.00	$9.5 \times 10^2$	0.71	0.22	0.31	0.20	0.15
0.79	0.06	0.99	0.15	$2 \times 10^1$	0.00	$3.0 \times 10^3$	0.76	0.24	0.32	0.22	0.13

This table reports optimal capital ratios for alternative parameter values. The first column reports the values of the production scale parameter  $\alpha$  that were considered, from 0.29 to 0.79. For each value of  $\alpha$ , the second column reports the optimal capital ratio, holding all other parameters at their calibrated values as reported in Table 3.1. The value of the production scale parameter  $\alpha$  at the calibrated point, 0.54, and the corresponding optimal capital ratio, 0.19, are highlighted. Similarly, columns 3 and 4 report the value of the discount parameter  $\beta$  and the corresponding optimal capital ratios. Columns 5 and 6 report optimal ratios for alternative values of the transaction cost parameter  $\gamma$ , columns 7 and 8 report for the utility cost of crises  $\xi$ , columns 9 and 10 report for the mean depreciation rate  $\bar{\delta}$ , and columns 11 and 12 report for the variance of the depreciation rate  $\delta_\sigma$ .

## 3.7 Appendix

### 3.7.1 Household first order conditions

Section 3.3.1 describes the household problem, to which sections 3.3.6 and 3.3.7 add taxes and government bonds. Using  $\lambda$  and  $\mu$  as the Lagrange multipliers on equations 3.2 and 3.2—modified to include taxes and bonds as in equations 3.2b, 3.2c, and 3.3c—households have the following first order conditions:

$$1 - \lambda = 0$$

$$\beta - \mu = 0$$

$$\mu\bar{\pi} - \lambda = 0$$

$$\mu\bar{r} - \lambda + \gamma(K - D - B) = 0$$

$$\mu\bar{r}^B - \lambda + \gamma(K - D - B) = 0$$

$$\lambda F'(K) + P - 1 - \gamma(K - D - B) = 0$$

Equations 3.4, 3.5, and 3.6 assume taxes and government bonds equal zero.

### 3.7.2 Proof of proposition 1

The competitive equilibrium, if it exists, is described by a system of two equations in debt and capital assets:

$$D = [1 + H_1(K, D) - F'(K)](1 - \phi)K \quad (3.23)$$

$$\frac{\beta(1 - \bar{\delta})}{1 + (1 - \phi)H_2(K, D)} = [1 + H_1(K, D) - F'(K)] \quad (3.24)$$

Where 3.23 follows from equations 3.10 and 3.11 and 3.24 follows from equations 3.6 and 3.11. The expression  $[1 + H_1(K, D) - F'(K)]$  appears in both equations. For any

$D \geq 0$ , this expression goes from  $-\infty$  to  $\infty$  as  $K$  goes from 0 to  $\infty$ . Consider  $K$  as an implicit function of  $D$  in both equations. In equation 3.23,  $K(0) = 0$ ,  $K(\infty) = \infty$  and  $K$  is strictly increasing in  $D$  because  $H_{11} > 0$ ,  $H_{12} < 0$  and  $F''(K) < 0$ . In equation 3.23,  $K(0) > 0$  and  $K$  is strictly decreasing in  $D$  because  $H_{12} < 0$ ,  $H_{22} > 0$ ,  $H_{11} > 0$ , and  $F''(K) < 0$ . Therefore there is a unique  $(K, D)$  that satisfies both equations.

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