CLIMATE RISK IN AMERICAN FINANCIAL INSTITUTIONS

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ABSTRACT

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Climate Risk in American Financial Institutions.

(Under the direction of Dr. Yasser Boualam)

Climate change will inevitably lead some companies to default on their debt, putting stress on banks and financial institutions. To ensure financial stability, financial institutions must prepare for climate risk appropriately. Although the first step to mitigating climate risk is quantifying that risk, researchers have not come to a consensus on the magnitude of climate-related credit risk. This thesis builds on prior research by taking a bottom-up approach to modeling climate risk in the American financial system. I find that risk is concentrated in certain companies, industries, regions, and financial institutions. Although these findings do not provide evidence that there is systematic climate risk in the American financial system, they do indicate that certain parts of the financial system are vulnerable and warrant regulation.

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LIST OF ABBREVIATIONS AND SYMBOLS

Abbreviations

BCBS: Basel Committee on Banking Supervision

CET1: Common equity tier 1

CFTC: Commodity Futures Trading Commission

CO_2e: Carbon dioxide equivalent

DSIB: Domestic systematically important bank

EAD: Exposure at default

EPA: Environmental Protection Agency

GDP: Gross domestic product

GHG: Greenhouse gas

GSIB: Global systematically important bank

LGD: Loss given default

MPD: Marginal probability of default

NiGEM: National Institute Global Econometric Model

NGFS: Network of Central Banks and Supervisors for Greening the Financial System

PD: Probability of default

SIC Code: Standard industrial classification code

SLR: Supplementary leverage ratio

TCFD: Task Force on Climate-Related Financial Disclosures

TVF: Transition vulnerability factor

U.S.: United States

Symbols

$\boldsymbol{A}$ **=** Asser value

$\boldsymbol{L}$ = Company liabilities

$\boldsymbol{r}$ = Risk-free rate

$\boldsymbol{t}$ **=** Time period

$\boldsymbol{\sigma_A}$ **=** Asset Volatility

1. INTRODUCTION

Climate change poses a severe threat to ecosystems, cities, and economies. In certain areas, extreme weather events like tropical cyclones, droughts, and heatwaves have already become stronger and more prevalent than they were previously due to climate change (Bouwer, 2018). Between 1988 and 2017, the average number of natural catastrophes per year rose 26%, and the cost of those catastrophes rose by 35.7% (Munich Re, 2019). Scientists expect the effects of climate change to worsen in the future. Jevrejeva et al.et al. (2018) found that the damage caused by climate change-induced flooding could slow global Gross Domestic Product (GDP) growth by 2.8% per year by 2100. The United States (U.S.) is not immune from economic climate risk: for each 1°C increase in global temperature, Hsiang et al. (2017) predicts the U.S.' GDP growth will shrink by 1.2%. Therefore, climate change is a serious risk to economic productivity in the U.S.

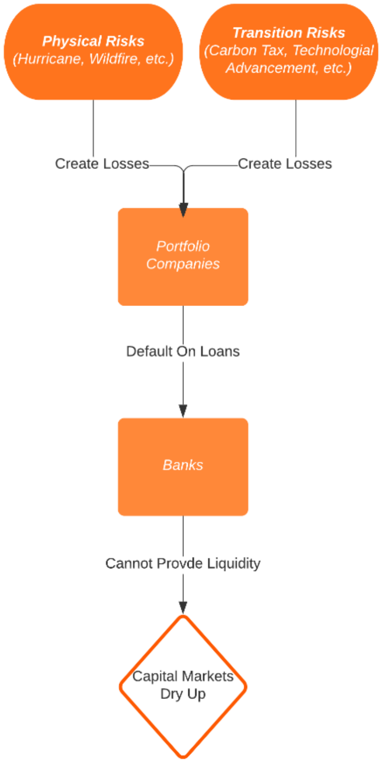
Climate-based economic risk could lead to financial instability. The Governor of the Bank of England, Mark Carney, noted in his seminal 2015 address that "Climate change will threaten financial resilience and longer-term prosperity" (Carney, 2015, p. 16), creating risk for financial institutions. Most of this risk will either stem from climate change's physical threats to operations or from phasing out greenhouse gas (GHG) emissions. Because financial institutions typically do not have expansive physical operations and do not emit large quantities of GHGs, their exposure to climate risk stems from their investment portfolios. Financial institutions invest in portfolio companies with varying degrees of climate exposure, primarily through debt products. If enough of those debt investments were to go into default, financial institutions would be unable to provide capital to those who need it, creating financial instability. Therefore, widespread default on bank loans is the most likely way that climate change will threaten financial stability, as shown in Figure 1.

For climate risk to threaten financial institutions, climate risk must materially threaten portfolio companies, and portfolio companies must fail to mitigate this risk themselves. Even if portfolio companies fail to mitigate climate risk, lending to companies with high exposure to climate risk is only problematic if financial institutions do not appropriately account for the riskiness of their investments. Financial institutions lend to companies with very high levels of existing debt (highly leveraged companies), which are more likely to go into default than companies with lower levels of debt. However, financial institutions understand that lending to highly levered companies is risky and account for that risk by making fewer loans and holding more capital in reserve against those loans, so there is no systematic issue. Climate risk may pose a threat to financial stability if regulators fail to impose restrictions on financial institutions' climate risk exposures and financial institutions fail to address this risk independently.

In this introduction, I describe how the current financial system is vulnerable to climate-induced financial instability or fragility. I outline the climate risks facing portfolio companies, those companies' failure to mitigate climate risks, the lack of federal regulatory oversight on financial climate risk, and financial institutions' failure to voluntarily address climate risk.

Figure 1

Pathway from Climate Change to Financial Risk



Note. Risk for financial institutions comes from their portfolio companies. If portfolio companies default on their debt, financial institutions will suffer losses and will not be able to provide capital markets with liquidity. This failure could result in financial instability.

1.1 Generic Climate Risks

The first step in determining whether climate change creates the potential for financial instability is determining whether it poses material financial risks to financial institutions' portfolio companies. Climate change poses two types of generic risk to corporations and the broader economy: physical risks and transition risks. Physical risk includes the direct impact of climate change on ecosystems and environments, whereas transition risk is risk to corporations or the broader economy that is created by humans' attempts to mitigate physical risks.

1.1.1 Physical Risk

Although the physical impacts of climate change on ecosystems and environments will be wide-reaching and varied (Carleton & Hsiang, 2016), the impact of natural disasters, lowered labor productivity, and lowered agricultural productivity on overall economic productivity are the most well researched (e.g., TCFD, 2017; U.S. Commodity Futures Trading Commission, 2020).

As the climate changes, natural disasters such as hurricanes, wildfires, and heatwaves become more severe. In their wake, these events create economic destruction that poses a risk to corporations. In 2017, Hurricane Harvey caused roughly $90Bn of damage, $67Bn of which Frame et al. (2020) attribute to climate change. Abatzoglou and Williams (2016) found that climate change is increasing aridity in the Western U.S., doubling the area susceptible to wildfires, a trend that will continue. Fifteen of the 20 worst wildfires in California's history have occurred since the year 2000, and 10 of those have been since 2015 (Governor Newsom's Strike Force, 2019). Dinan (2017) projects that the average yearly damage from hurricanes will increase from $28Bn in 2015 to $63Bn by 2075.

Lower labor productivity is another type of material physical risk. Zhang et al. (2018) found that higher temperatures lead to lower labor productivity in both physically and mentally intensive work and predict that unabetted temperature rise could shrink China's GDP by 12.8% by 2100. Given that temperatures have risen more quickly in the U.S. than in the rest of the world since 1970 (EPA, 2016), labor productivity is also likely to decrease domestically.

Therefore, portfolio companies are exposed to physical risk through lower workforce productivity.

The final well-research physical risk to portfolio companies is lowered agricultural productivity. As climates change, places where crops currently grow will degrade until they are no longer arable. Hsiang et al. (2017) forecast a 9.1% decrease in crop yields for each degree Celsius of global temperature rise in the U.S. Because basic agricultural commodities are inputs for many other sectors, decreased agricultural productivity will have widespread ramifications outside of the agricultural sector. Increases in agricultural commodity prices will likely hurt all sectors that rely on agricultural products.

In sum, the costs of increasingly severe and frequent natural disasters, lowered labor productivity, and lowered agricultural productivity caused by climate change create physical risk for corporations. These risks could result in lower operating profit margins and large one-time losses, which might cause portfolio companies to go into default. However, not only do portfolio companies face physical risks from climate change but also transition risks stemming from actions taken with the goal of decreasing the physical effects of climate change.

1.1.2 Transition Risk

Transition risks stem from attempts to mitigate physical risk. The first and most significant type of transition risk comes from government regulation of GHG emissions. Regulations can include carbon taxes, clean energy subsidies, or a combination of the two (Chen & Hu, 2018). The two most popular types of carbon tax are cap and trade, in which companies receive a carbon allocation they can sell on the open market, and a simple tax on emissions. Sixty-two different jurisdictions, including California, British Columbia, and the European Union have instituted some form of regulation on carbon emissions, but generally, these regulations only apply to certain industries and under-tax carbon relative to its true cost (Skovgaard et al., 2019). However, even with underpriced carbon regulation systems, emission regulation can be costly for portfolio companies. For example, although California's cap-and-trade system only applies to 450 large electric power plants, industrial plants, and fuel distributors, it has charged companies $12.5Bn in taxes since 2013, which equates to roughly $28.8MM per firm (Center for Climate and Energy Solutions, 2021).

Another prominent form of transition risk comes from technology stranding assets. Assets become stranded when decreases in demand for a product render the assets used to produce that product worthless. In the case of climate change, a large shift in the relative prices of fossil fuels and renewable energy could make fossil fuel production economically non-viable and strand associated assets. For example, if there were a drastic decrease in the cost of storing energy that caused renewable energy to become cheaper than fossil fuels, oil extraction assets would become worthless. Lithium-ion batteries are used to store renewable energy, and their cost is a large preventative factor from more widespread adoption of renewable energy. The price of lithium-ion batteries fell by 80% between 2010 and 2017, and prices will likely continue to fall, creating a serious risk for fossil fuel producers (Deloitte Center for Energy Solutions, 2019). In fact, Linquiti and Cogswell (2016) find that if fossil fuels were to become significantly more expensive relative to renewables, the value of fossil fuel reserves would drop 63%, or $185 trillion. Therefore, stranded assets due to technological advancements create an important form of transition risk.

One other less prominent but noteworthy form of transition risk is legal risk. As environmental groups work to control industrial contributions to emissions, they will seek to hold companies liable for environmental harm through legal actions. For example, the city of

Baltimore is currently suing fossil fuel companies, including BP, ExxonMobil, and Shell, because the companies knew their products would lead to climate change and continued to sell them (Hersher et al., 2021). According to the Sabin Center at Columbia University Law School (2020), at least 1,561 climate related lawsuits have been filed in the U.S., demonstrating the scale of future liabilities companies may face from high emissions. Government organizations have been slow to define the limits of companies' liability for climate-related harms that they cause, which increases the risk of facing litigation.

Regardless of whether the global community takes action to mitigate the physical risks described above (and in the process creates transition risk), corporations will face losses due to climate change. Additionally, since physical risk affects real capital, those with large physical operations are likely to face more physical risk than those with less expansive operations. Similarly, since transition risk results from attempts to mitigate physical risk (accomplished by decreasing GHG emissions), those that emit high levels of GHGs are more likely to face transition risk than other companies. Therefore, the companies to which financial institutions lend face material climate risk. It will only be by effectively mitigating these risks that financial institutions will avoid instability.

1.2 Portfolio Companies' Responses to Risk

If portfolio companies mitigate risk appropriately and financial markets price risk efficiently, financial institutions' exposure to climate risk should not lead to financial instability. If portfolio companies are able to protect themselves against climate risk, climate change will not cause them to default on their debt. Similarly, if financial markets price loans fairly, financial institutions' existing risk mitigation strategies should also control climate risk. However, poor planning at the portfolio company level and the market's mispricing of assets creates potential climate risk for financial institutions.

Portfolio companies do not appear to be preparing adequately for climate change, meaning that climate change could cause those companies to default on their debt. Of the corporations that disclosed their climate risk mitigation practices to the Carbon Disclosure Project in 2016, only 46% reported dedicating any additional funds to addressing risks associated with climate change (Goldstein et al., 2018). Only 3.3% of companies in industries that rely on natural resources such as rivers or farmland had taken action to preserve those assets. Furthermore, whereas the scientific consensus projects losses to be on the scale of trillions of dollars, companies have only been planning for stranded assets on the scale of billions of dollars (Goldstein et al., 2018). Taken together, it appears that corporations are not taking sufficient action to address risks associated with climate change, and climate change could devalue the investment vehicles that rely on those companies. However, if the government regulates financial institutions' exposure to investment vehicles with high climate risk, it will eliminate systemic financial risk.

1.3 Regulation of Financial Risk

Stress testing in the U.S. has largely been defined by standards set by the Basel Committee on Banking Supervision (BCBS) and enhanced by the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 (Basel Committee on Banking Supervision, 2019; H.R.4173 - Dodd-Frank Wall Street Reform and Consumer Protection Act, 2010). Founded in 1974 to standardize global financial institution regulation, the BCBS is best known for its capital adequacy regulation guidelines, the Basel I, II, and III. The first iteration of those guidelines was issued in response to the Latin American debt crisis of the 1980's. Although the Basel guidelines are not binding (each nation's central bank or appropriate authority must issue their own directives), all 45 member institutions agree to implement them (The Bank of International Settlements, n.d.).

The Comprehensive Capital Analysis and Review is currently a scenario-based exercise, or "stress test," that tests the ability of American bank holding companies with consolidated assets of over $100MM to withstand adverse economic conditions. Financial institutions with between $100MM and $250MM in assets must complete the exercise biannually, and financial institutions with over $250MM in assets must complete the exercise annually. The stress test includes both a quantitative and a qualitative exercise. If a financial institution fails either exercise, it cannot distribute capital to its shareholders via stock buybacks or dividends. The Federal Reserve can also issue a "conditional non-objection," in which case the financial institution must make some changes to its capital planning before being able to distribute capital.

In the quantitative exercise of the stress test, the Federal Reserve provides financial institutions a realistic baseline and hypothetical distressed economic scenario defined by 28 variables, including six measures of economic activity, four measures of asset prices, six measures of interest rates, and three macroeconomic variables by country bloc for four different blocs (Board of Governors of the Federal Reserve System, 2021a). The financial institutions must model how these variables will impact certain capital reserve ratios (i.e., what percentage of its assets are liquid and could be used to pay off depositors), as defined by the Basel III guidelines. To pass, a financial institution must project maintaining minimum capital reserve ratios both in the baseline and severely distressed scenarios. To project these ratios in the distressed scenario, financial institutions model changes in portfolio probabilities of default (PD), exposures at default (EAD), and loss given default (LGD) which yield projected losses.

With the losses, the institutions can model their new balance sheet, and therefore their reserve ratios.

The capital reserve ratios are defined by a measure of liquid capital (e.g., Common Equity Tier 1, Tier 1 Capital, etc.) divided by a measure of total assets (either risk weighted or unweighted). Essentially, these ratios measure what percentage of an institution's loans could go into default without putting that institution into insolvency. The current CCAR relies on five capital reserve ratios: Common Equity Tier 1 (CET1), tier 1 risk-based capital, total risk-based capital, tier 1 leverage, and Supplementary Leverage Ratio (SLR) (Board of Governors of the Federal Reserve System, 2020). CET1, tier 1 risk-based capital, and total capital are classified as "Capital Ratios" and are different from the "Leverage Ratios" (i.e., SLR and tier 1 leverage ratio) in that they weigh riskier assets more heavily than leverage ratios. For example, a mortgage may be weighted 100%, whereas a Treasury Bond may not count at all. However, even for the Capital Ratios, risk weightings are solely based on measures of financial risk and no other forms of risk such as climate risk.

The qualitative exercise assesses the adequacy of the underlying analyses and processes that are used in the quantitative portion of the stress test. It measures the adequacy of six areas of capital planning: governance, risk management, internal controls, capital policy, scenario design, and projection methodology. Typically, the Federal Reserve will not issue an objection unless an institution's capital planning is inadequate in multiple categories. However, after an institution has been subject to the qualitative assessment for four years and passes in the fourth year, it is no longer required to complete the qualitative portion of the assessment. Because of this rule, the exercise for 2020 was the last for which any financial institution could receive objections on qualitative grounds. Therefore, no part of the existing framework for regulating financial institutions' exposures to financial risk includes monitoring their exposure to climate risk. Although it is possible that capital reserve ratios set under the current system are large enough to also account for climate risk, this is not clear and warrants further investigation. If it turns out that these existing reserve ratios do not account for climate risk, climate change would create the potential for financial instability unless financial institutions moderate their own risk.

1.4 Financial Institutions' Responses to Risk

If financial institutions were adequately moderating their exposure to climate risk, one would expect an inverse correlation between asset prices and climate risk. Because investors demand compensation for taking on risk, this inverse correlation would mean that financial institutions accurately view assets that are more vulnerable to climate change as riskier than average assets. Unfortunately, although asset prices are somewhat inversely correlated with climate risk (Bolton & Kacperczyk, 2020), they are not correlated to the degree one would expect given the severity of climate risk, meaning that the full risks of climate change are not priced in (Griffin et al., 2019; Hong et al., 2020). The market's failure to efficiently price in climate risk may mean that financial institutions are inefficiently pricing climate risk, which would introduce systemic risk in the financial system.

1.5 Summary

Climate change poses material physical and transition risks to companies and the broader economy. Because companies are not fully mitigating climate risk, their securities also pose a climate risk to those who hold them. The government is not regulating the investments that financial institutions make in securities that pass climate risk on to their owners, and the financial institutions themselves may not be efficiently accounting for climate risk. This lack of risk mitigation increases the possibility of financial instability.

To successfully address this potential for financial instability, governments and researchers must accurately calculate the magnitude of climate risk to which financial institutions are exposed. This thesis presents a model by which this could be accomplished. The paper proceeds as follows. Section 2 outlines the approaches that exist in the literature for measuring financial climate risk. Section 3 provides an overview of the datasets that I use and their manipulations for use in this thesis. It also covers the theoretical model that I use to calculate risk. Section 4 reports results, Section 5 discusses the results, and I conclude my paper in Section 6.

2. LITERATURE REVIEW

Given the possibility of significant climate risk in the financial system, regulators, multinational organizations, and academics have proposed principles for measuring the seriousness of this risk. Most existing literature focuses on a three-tiered, top-down approach to modeling risk with a climate scenario, macroeconomic model, and microeconomic model (e.g., Allen et al., 2020; Bingler & Senni, 2020; NGFS, 2020; Vermeulen et al., 2018), that is shown in Figure 2. In the top-down approach, the macroeconomic model takes inputs from the climate scenario to predict economic performance, and the microeconomic model translates the macroeconomic performance into implications for companies. Bottom-up approaches are also based on climate scenarios. However, they measure financial institution exposure on a loan-by-loan basis and are becoming increasingly popular for their applications. If a regulator wants to model the direct impact of a policy on companies and not the general macroeconomic impact, a bottom-up approach is preferable to a top-down approach. To understand either approach, it is important to understand the climate scenarios on which the assessments are based.

2.1 Climate Scenarios

Climate scenarios define the real-world situations on which the financial climate risk assessment is based. Climate scenarios are typically based around a set of climate change mitigation goals and governments' regulatory actions to reach those goals. The policies enacted to reach these goals define the transition risk that companies will face and influence the rate and timing of climate change, indirectly determining levels of physical risk.

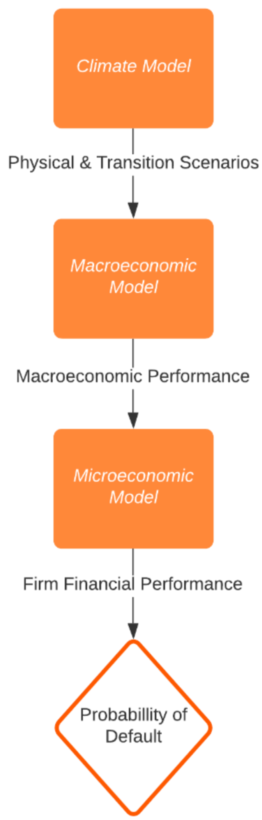
Common policy action scenarios are designed to avoid the most severe physical effects of climate change by limiting global temperature rise to 2°C (e.g., Allen et al., 2020; Eis & Schafer, 2019; NGFS, 2020; Vermeulen et al., 2018), meeting the nationally determined contributions defined in the Paris Climate Agreement (e.g., TCFD, 2017), or doing nothing (e.g., NGFS, 2020; Vermeulen et al. 2018). Most models (e.g., Allen et al., 2020; NGFS, 2020; TCFD, 2017; Vermeulen et al., 2018) include scenarios in which the government implements policies to achieve these goals immediately (a shock) or by 2030 (a smooth transition). Most transition risk models focus primarily on regulatory action, but some focus on other transition risks such as technological obsolescence (e.g., Vermeulen et al., 2018). Although some scenario models are country specific (e.g., Allen et al., 2020; Vermeulen et al., 2018), others are international (e.g., Eis & Schafer, 2019; NGFS, 2020; TCFD, 2017). Different choices for goals, implementation timeline and scope can be useful in different scenarios, depending on the purpose of the research. Once these decisions are made, researchers can either apply those scenarios to the macroeconomy in a top-down approach or to individual companies in a bottom-up approach.

2.2 Top-Down Approach

The most popular approach to measuring financial climate risk has been top-down modeling. In the top-down approach, researchers model the impacts of climate change on the broader economy, then allocate that risk to individual firms, and finally measure how that risk will influence the probabilities that firms will default on their loans. Figure 2 illustrates this process. This approach, however, is not as accurate in modeling risks as a bottom-up approach because it must rely on a larger number of approximations than would a bottom-up approach. Instead of making one approximation to model risk at the firm level, it must first make an approximation to model macroeconomic risk and then another approximation to allocate that risk to firms. An example of a transition risk that can be cleanly modeled at the firm level is a carbon tax since the carbon tax impacts firms directly and individually, so if a government wanted to assess the impacts of a carbon tax, a bottom-up approach would be preferable.

Figure 2

Typical Financial Climate Risk Assessment Model: Top-Down Approach



Note. Most financial climate risk assessment models follow this pattern. They begin with a climate model that produces climate scenarios. A macroeconomic model then uses the climate scenarios to determine the impact of climate change on the economy. A microeconomic operational model then maps the economy's performance to predicted company performance and probability of default.

2.2.1 Macroeconomic Model

After forming a climate scenario, the first step in a top-down approach is using climate scenarios as inputs for a macroeconomic model. However, typically, macroeconomic models only account for the physical (e.g., Woetzel et al., 2020) or transition risk (e.g., Allen et al., 2020; Nguyen, 2021; Vermeulen et al., 2018) proposed by the climate scenario, but not both. This is because physical risk and transition risk are inversely correlated, but researchers have not definitively determined the nature of this relationship (Jones & Friedlinstein, 2020). Based on the conditions described by the climate scenario, researchers predict changes to certain macroeconomic variables such as labor productivity, commodity prices, or interest rates (e.g., Allen et al., 2020; Vermeulen et al., 2018). Researchers then use these variables as inputs for a macroeconomic model (typically an integrated assessment model or a dynamic stochastic general equilibrium model) to project the scenario's impact on the economy. This macroeconomic model then outputs how the scenario will impact economic growth and productivity, but not how the scenario will impact individual companies.

One popular model that Allen et al. (2020) and Vermeulen et al. (2018) use is the National Institute Global Econometric Model (NiGEM). NiGEM is a dynamic stochastic general equilibrium model that includes between 80 and 200 economic variables (depending on the country the researcher is modeling) to predict global macroeconomic indicators such as GDP. Although NiGEM was not specifically designed for modeling climate change scenarios, manipulating inputs can project the economic impacts of climate change on gross domestic product.

After a macroeconomic model determines the large-scale impacts of climate change on the economy, an accompanying microeconomic model allocates those impacts to portfolio companies.

2.2.2 Microeconomic Model

To distribute macroeconomic risks to individual companies in the microeconomic model, researchers typically relate climate risk to company attributes (e.g., Allen et al., 2020; Vermeulen et al., 2018). Because increases in the price of GHG emissions typically drive transition risk, many researchers assume that the impact that transition risks will have on companies is associated with their emissions. If companies that emit more GHG account for a greater portion of the macroeconomic cost of climate change, the microeconomic model assigns to them more risk than those with less GHG emissions. Because there is no reliable data for GHG emissions at the firm level, researchers typically aggregate firms and distribute risk by industry.

One popular form of distributing transition risk to companies in a microeconomic model, described by Vermeulen et al. (2018), is using a Transition Vulnerability Factor (TVF). A TVF measures the number of standard deviations separating an industry's GHG emissions from the mean GHG emissions. A company's TVF is essentially the z-score for the industry's emissions and yields a proxy for the microeconomic impact of climate change when multiplied by the average economic impact of climate change across the wider economy.

Researchers typically follow a similar pattern for estimating physical risk. A firm's exposure to physical risk depends on its location, so the physical risk is generally determined locally. For example, a firm that has most of its operations in the Gulf of Mexico would face physical threats from hurricanes, but a firm operating in California would face threats from drought and wildfire. To account for geographic variations in the effects of climate change, researchers focus on operational geography as opposed to industry to assess physical risk (e.g., Woetzel et al., 2020).

After determining the operational economic impact of climate change on companies, the models translate the microeconomic operational risk to financial risk and predict probability of default at a company level. In summary, the bottom down approach arrives at financial institutions' exposure level by creating climate scenarios, modeling the economic impacts of those scenarios, distributing those impacts to individual firms, and modeling the probability of default. These results provide insight into systematic financial exposure. However, the mapping of climate scenarios onto inputs to macroeconomic models (e.g., interest rates, labor force participation rates, etc.) requires approximations which can add error to models.

2.3 Bottom-Up Approach

Recently, researchers have begun to map the climate scenarios directly onto firms to avoid the error associated with mapping to macroeconomic variables and then firms. This approach is especially helpful for addressing the impact of targeted policies like carbon taxes.

Reinders et al. (2020) apply a bottom-up approach to measure the market shock that implementing a carbon tax would cause. Specifically, they measure the Dutch financial system's exposure to climate risk by using a discounted cash flow analysis to model financial institutions' exposure to equity products with climate risk. They then employ Merton's Model (1974) to measure financial institutions' exposures to climate risk through debt products.

2.3.1 Equity Exposure

To measure the loss that financial institutions could suffer due a carbon tax decreasing equity market values, Reinders et al. (2020) used a discounted cash flow analysis. They equated the carbon tax to a decrease in cash flows for each year the carbon tax was assessed. Then, based on the assumption that equity value is the sum of the discounted cash flows that a company will generate, they calculated the loss that financial institutions would face in the equity market as the sum of the discounted carbon taxes.

Although this approach is elegant in its simplicity, it fails to account for the firms' responses to climate risk and priced-in investor expectations. If a carbon tax increases the cost of a firm's production process, the firm might change the process to one that would have been more expensive than the current process without the carbon tax but is cheaper than the current process with the carbon tax. Switching processes would mean that the firm would only lose a percentage of the carbon tax in cash flows. Additionally, equity investors have already begun to price transition risk into equity prices as the probability of those adverse events occurring multiplied by the magnitude of those expected risks (Ilhan et al., 2020; Kolbel et al., 2020). Therefore, equity prices may increase by only a portion of a carbon tax equal to the difference between the expected liability and actual liability, times one minus the probability of a carbon tax occurring.

2.3.2 Debt Exposure

The most common method of analyzing financial institutions' exposure to climate risk through debt products is treating the amount that a company will pay as a liability and evaluating how that liability will impact probability of default. Reinders et al. take this approach to measure risk in the Netherlands. A popular way to measure probability of default is using Merton's (1974) model for default, which is the model I use in this thesis and will describe in further detail in my methodology. Although Merton's model is an effective method for measuring probability of default, it makes various assumptions (including that borrowers do not pay dividends, a borrower enters default as soon as the value of its assets exceed the value of its liabilities, etc.)

that are not always true. Despite its drawbacks, treating a carbon tax as a liability is an effective way of measuring climate risk.

In summary, the bottom-up approach can be used to model financial institutions' exposures to both debt and equity products. Bottom-up approaches are preferable to top-down approaches for cases in which climate scenarios can easily be applied to individual firms because they avoid unnecessary approximations.

2.4 Climate Risk Assessment Results

Researchers have found evidence using both top-down and bottom-up financial climate risk assessments that European financial institutions have significant but manageable exposure to climate risk. Using a top-down approach, Allen et al. (2020) found that probabilities of default could increase by over 400% by 2040 in French industries such as petroleum production but by as little as 1.6% in the food service industry. Also using a top-down approach Vermeulen et al. (2018) found that regulatory ratios, a measure of how solvent financial institutions are, could decrease by 16% in Dutch financial institutions. Reinders et al. (2020) used a bottom-up approach and found that the available CET1 capital in the Netherlands could fall by 30%. However, reports that looked at the U.S., such as the U.S. Commodity Futures Trading Commission report (2020) assessed risk systematically and not at the financial institution level.

Researchers have largely shied away from assessing climate risk at the financial institution level in the U.S. because climate-related disclosures are incomplete. Nonetheless, such assessments would allow us to measure climate risk more accurately. Since the systemic risk could be distributed unevenly between financial institutions, researchers should examine financial institutions' portfolios to ensure that no individual financial institutions are materially exposed to climate risk. Although the first step to mitigating climate risk is quantifying that risk, researchers have not come to a consensus on the magnitude of climate-related credit risk. This thesis builds on prior research by taking a bottom-up approach to modeling climate risk in the American financial system.

3. EMPIRICAL METHODOLOGY

In this methodology, I first discuss the datasets that I used and the construction of the merged database that I used in my analysis. I then describe the theoretical steps that I take to measure exposure to climate risk among American Financial institutions.

3.1 Data and Database Construction

In this section, I describe the three datasets that I used and how I prepared those datasets for use in my methodology.

3.1.1 Sources and Limitations

The model in this thesis relies upon three types of data: greenhouse gas emissions data, financial institution loan data, and corporate financial data. The greenhouse gas emissions data came from the Carbon Disclosure Project's 2019 Supply Chain report. The financial institution loan data comes from Thomson Reuters' DealScan and the corporate financial data comes from CapitalIQ. Each data set makes unique contributions to the model and has specific limitations.

Greenhouse Gas Emissions Data

All emissions-related data comes from Carbon Disclosure Project (CDP) reports between 2017 and 2019. The three reports together contain data on 5,950 companies' sustainability goals and performance from 2015 to 2018. From the larger CDP dataset, I used self-reported data from 4,535 companies on Scope I greenhouse gas emissions in tons of CO_2 equivalent (CO_2e). Scope I emissions account only for emissions that come from sources that a company owns or operates (e.g., the fossil fuels burned while making steel), whereas Scope II emissions include the emissions required to generate the energy that a company purchases from a third party (e.g., the emissions from generating the electricity to power lights at a factory), and Scope III emissions include all other indirect emissions from a company's supply chain (i.e., the emissions required to ship a part). By only including Scope I emissions, I bias emissions towards companies that engage in transportation or energy generation services. Complete summary statistics for CDP data can be found in Table 1. CDP data allowed me to model borrowers' yearly greenhouse gas emissions and potential liabilities to a carbon tax.

Table 1

Summary of CDP Data

Variable	Full Dataset	2018	2017	2016	2015
Number of Companies	4,535	3,348	2,477	3,340	185
Average Emissions (tons of CO2e)	5,747,042	12,372,260	1,666,644	8,077,356	3,728,164
Average Revenue ($k)	932,862	966,954	979,621	950,008	748,277
Market Capitalization ($k)	1,136,709	1,173,443	1,182,798	1,152,330	506,302
Number of Industries Represented (4 digit SIC Code)	350	339	328	346	88
Number of Industries Represented (3 digit SIC Code)	240	231	225	238	79
Number of Industries Represented (2 digit SIC Code)	72	71	68	72	36

Note. There were 64 datapoints from 2008-2014 and 2019. The number of datapoints in each year was not high enough warrant inclusion in the table above.

Limitations of CDP data include its lack of auditing and industry coverage. Because CDP data is voluntarily self-reported and not audited, it may be unreliable (Stanny, 2018). Self-reporting also creates a response bias, meaning that companies who respond to the survey may not be representative of the larger population. Companies with high emissions or low profit margins are underrepresented in the dataset (Giannarakis et al., 2017; Datt et al., 2019). Although the CDP dataset excluded the eight industries listed in Table 2, none of the industries that it excluded are known as high-emissions industries. The lack of data from these industries meant that I had to exclude companies in those industries from my dataset.

Table 2

Two-Digit SIC Codes Missing from CDP Data

Two Digit SIC Code	Industry
89	Miscellaneous
76	Miscellaneous Repair
72	Dry cleaners, laundromats, barber shops
57	Home Furnishing
55	Automotive Dealers
83	Social Services
82	Educational Services

Corporate Lending Data

DealScan is a database that contains information on corporate loan issuance, primarily in the U.S. I drew corporate lending data from DealScan. Carey and Nini (2007) found that DealScan contains roughly 90% of loans (excluding “very small loans”) that are syndicated in the U.S. DealScan draws its data from SEC filings, publicly traded debt, and confirmed sources.

I used the data from DealScan to model the composition of financial institutions' lending portfolios.

There are several important limitations in the DealScan data. Because DealScan data only covers syndicated loans, it does not include bilateral agreements between companies and financial institutions. If these data were included in my model, the predictions for total losses due to climate change would be more severe. Accordingly, this limitation is likely to mean that climate-related risks are even greater than those predicted by my model. Because some loans reported in DealScan were not associated with an equity ticker, I could not pull necessary company information. As a result, I excluded 3,451 out of 4,109 borrowers from my model due to partial data. Finally, because the DealScan database only contains new loan issuance, I assumed that financial institutions buy and sell loans in equal volume and do not sell loans to companies in specific industries at a higher frequency than those to companies in other industries.

Corporate Financial Data

I drew corporate financial data from CapitalIQ. CapitalIQ is a data aggregator that pulls information from SEC filings (primarily 10K and 10Q filings) to build out a company's financial profile. It contains data on companies worldwide. I used data from CapitalIQ as inputs for Merton's model (1974) for probability of default.

CapitalIQ's data limitations included poor international ticker-to-company conversion and infrequent mistakes. I excluded most international companies from my analysis because CapitalIQ misidentified them as American companies and returned incorrect data. Additionally, data from platforms like CapitalIQ does not match 10K data between 6.5 and 7.7% of the time

(Boritz & No, 2019). Many of these discrepancies cause significant changes in probability of default calculations (Boritz & No, 2019).

Table 3

Summary of DealScan Data

Variable	All Current American Facilities	Term Loans	American Non-Financial Borrowers	Bank Lenders
Facilities	26,337	14,156	11,049	8,387
Lenders	7,403	1,656	1,452	536
Borrowers	10,110	6,685	5,052	4,109
Average Facility Quantum	$381,832,545	$364,539,025	$360,332,300	$409,432,200

Note. Current American facilities are USD denominated facilities syndicated in the U.S. that have a facility start date after Jan. 1, 1989 and maturity date after January 29, 2021. American Non-Financial Borrowers are companies with Primary SIC codes outside the range 6000-6999 whose "Country" field on DealScan is "USA". Bank Lenders are those whose "InstitutionType" on DealScan is either "US Bank" or "Investment Bank"

3.1.2 Data Construction

To prepare the data for use in my model, I removed all incomplete data or data unrelated to American financial institutions. I began with all DealScan facilities with a maturity date after 1/29/2021 and a start date after 1/1/1990. I then filtered out all loans that were not classified as a "Term Loan …" or a "Delayed Draw Term Loan" because other loans may not be funded (i.e., the financial institution may have made a commitment to the company, but not actually paid it anything yet), and the financial institution may have the right to refuse funding if the company enters default. Once I had the term loans, I removed loans to other financial services firms (with

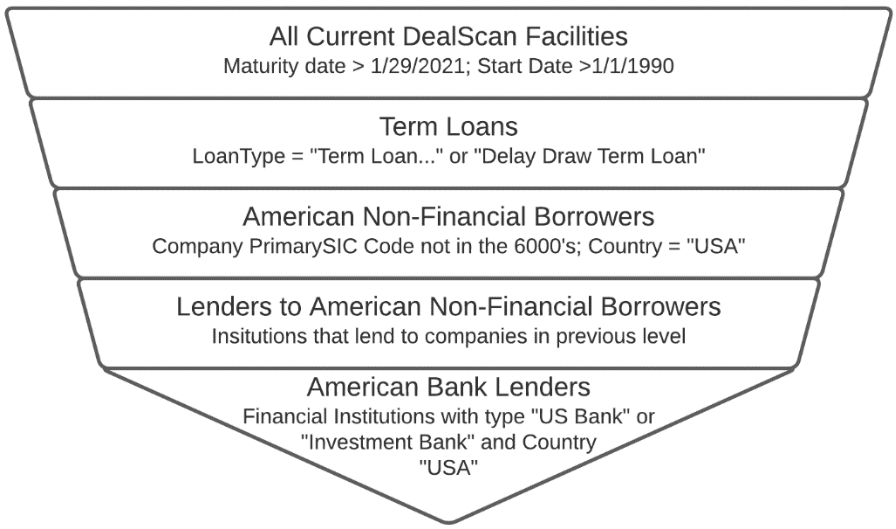
SIC Code in the 6000's) and non-American borrowers, because they are outside the scope of this project. Next, I eliminated any lenders that were not classified in the InstitutionType as "US Bank" or "Investment Bank," because they are outside the scope of this thesis.

After creating the list of American facilities, lenders, and borrowers that fell within the scope of this thesis, I drew financial data on those borrowers from CapitalIQ. I grouped the companies by their UltimateParentIDs in DealScan (which maps subsidiary companies to their parents), because larger companies are easier to match with their CapitalIQ entry than smaller companies. There were 4,109 parent companies. A ticker was available in DealScan for 1,473 parent companies which allowed matching with their CapitalIQ company profile.

For companies that did not have a ticker in DealScan I used the DealScan/Compustat match table created by Schwert (2018). This link table contains GV Keys, which can be used to identify companies, along with DealScan FacilityIDs and DealScan CompanyIDs. However, because 67 out the 1,182 borrowers that are in the link table have different GV keys across different facilities, I first attempted to match companies by facility. If the facility was not in the link table and the borrower only had one GV Key in the link table, I used the GV Key based on the borrower's DealScan Borrower ID to pull financial data from CapitalIQ. This data screening methodology is depicted graphically in Figure 3. In total, I was able to locate an identifier for 1,314 out of 4,109 companies. CapitalIQ only accepted 707 of these companies, and only 647 companies were associated with enough data to be usable. Nonetheless, these 647 companies account for 1,532 facilities worth $1.1 trillion.

Figure 3

Data Screening Methodology



Note. I followed this methodology to narrow data to match the scope of this thesis.

3.2 Theoretical Approach

My theoretical methodology consisted of three steps: predicting borrowers' exposures to transition risk in the form of a carbon tax, modeling a company's marginal probability of default due to that liability, and aggregating borrowers' probabilities of default at the industry and financial institution levels. I treated the assessed carbon tax as a liability on a company level in calculations of probability of default. I multiplied marginal probability of default (the increase in probability of default due to the carbon tax) by the loans quantum and a recovery rate to calculate financial institutions' loan losses and scale those numbers to match the size of capital markets.

3.2.1 Borrower Exposure to Transition Risk

Since carbon taxes depend directly on greenhouse gas (GHG) emissions, to calculate a borrower's exposure to transition risk from a carbon tax, I modelled the borrower's yearly GHG emissions. Because companies are not required to disclose their GHG emissions, I used incomplete self-reported data from the Carbon Disclosure Project (CDP) to project emissions. If the CDP dataset contained the borrower, I used the borrower's average reported emissions between 2008 and 2019 (for all years that there were data). Approximately 19.5% of borrowers were included in at least one CDP report. For the rest of the companies in the sample, I predicted carbon emissions using company characteristics such as their industry classifications.

According to the United States Environmental Protection Agency (2006) certain sectors, such as transportation or heavy industry, produce outsized amounts of carbon emissions. Therefore, If the CDP dataset did not contain information on a specific borrower, I used average carbon intensity per dollar of revenue (carbon intensity) for companies in the borrower's industry to model emissions. To determine a borrower's industry, I use its Standard Industrial Classification Code (SIC code). SIC codes have three tiers: Major Group (two-digit code), Industry Group (three-digit code), and Industry (four-digit code). I used the most specific SIC code (either two-, three-, or four-digit) for which there were data. Overall, the CDP dataset contained actual data for 19.5% of portfolio companies, Industry level data for 45.5% of portfolio companies, Industry Group Level data for 18.8% of portfolio companies, Major Group level for 11.4% of portfolio companies, and no data for 4.7% of portfolio companies. I then multiplied the portfolio company's implied carbon intensity (i.e., how much I predict the company will emit per dollar of revenue based on its industry) by its revenue from the year 2020 to establish its taxable emissions.

To calculate tax liabilities, I multiplied portfolio companies' taxable emissions by a hypothetical carbon tax. I chose to analyze the impact of a range of carbon taxes from $5/ton CO_2e to $150/ton CO_2e because the range of values that scientists and policy experts are predicting is large, and providing a range allows governments to assess the impact of different levels of taxation on financial stability or of a carbon tax in addition to other transition risks. I selected the specific range of carbon taxes to consider based on research on carbon pricing.

The literature on carbon price is broken up into two categories: the price of carbon necessary to offset emissions-based externalities (social cost of carbon) and the price of carbon necessary to meet a predetermined goal (e.g., keep global temperatures from rising 2 degrees Celsius above pre-industrial levels). Peer-reviewed assessments of the social cost of carbon range from -$13.36 to $2,386.91 per ton of carbon dioxide with a mean of $54.71 (Wang et al., 2019) The mean of $54.71 is also in line with the Biden administrations' most recent (Interagency Working Group, 2021) assessment of the social cost of carbon, which gave an estimate for the social cost of carbon between $14 and $152 per ton of CO_2e and a best guess of $51 per ton of CO_2e.

Common targets on which carbon taxes are based include reaching net-zero emissions and meeting goals set in the Paris Accords. Kaufman et al. (2020) found that for the U.S. to reach net zero emissions by 2050, the government would be required to implement a carbon tax between $34 and $64 by 2025. Similarly, Chen and Hafstead (2016) found that to reach its Paris Accord goal of reducing emissions by 26%-28% by 2020, the U.S. would be required to implement a carbon tax of $20.78 in 2013 dollars (or $23.46 in 2020 dollars). Given that most assessments of the cost of carbon center around $50 per ton of CO_2e, I chose $50/ton as my base case, but also included most of the Biden administration's range of estimates, from $5/ton to $150/ton in my analyses.

I assessed the impact of this range of carbon taxes on probabilities of default over one, two-, three-, four-, and five-year time horizons to see how the implications of the carbon tax will differ over different time horizons. My base case is a five-year time horizon because a carbon tax ideally will stay in effect into perpetuity, but eventually portfolio companies will change their operations to minimize tax burden.

3.2.2 Marginal Probability of Default and Loan Losses

To calculate borrowers' marginal probabilities of default from a carbon tax, I calculated the probability of default using Merton's model (1974), as described below, before and after a carbon tax. My Python implementation of this methodology can be found in Appendix F.

Merton's Default Model

Merton's model for probability of default treats a company's capital structure as a European call option (an option to buy an equity at a specified price on a specified date) and uses the Black-Scholes equation to find the probability that a company enters default. For a full explanation of European call options and a derivation of the Black-Scholes equation, see Appendix G.

At its core, Merton's model (1974) assumes that a company is in default when the value of its liabilities exceeds the value of its assets. This assumption, (along with the assumptions that the equity does not pay dividends, assets grow at the risk-free rate, and there is no coupon on the debt) allows one to value a company's equity as a European call option where the value of the borrower's assets is analogous to the price of the option's underlying equity. This relationship is shown graphically in Figure 4. Similarly, the value of the borrower's liabilities is analogous to the strike price. Just as the value of the option on the date it expires equals the difference between the value of the underlying equity and the strike price (or zero, if greater), the value of a company's equity equals the difference between the value of the company's assets and its liabilities (but no less than zero). Plugging liabilities into strike price, asset volatility into equity volatility, and equity value into option value in the Black-Scholes equations (found in Appendix G) yields Formulas 1 through 3 where *A* is the asset value, *L* represents company liabilities, *r* is the risk-free rate, *t* is the time period, σ_A=Asset Volatility, and *N(x)* is the cumulative normal distribution of *x*.

Assuming one knows correct values for all specified variables and knows that $N(d_2)$ in the Black Scholes formula is equal to the probability that the option is in the money, one can calculate the probability that an option is out of the money (which is analogous to a company being in default), by subtracting $N(d_2)$ from 1, yielding probability of default. However, it is difficult to know true asset values or asset volatility because companies only disclose their financials once per quarter.

$$d1 = \ln\left(\frac{A}{L}\right) + \frac{r + \frac{\sigma_A{}^2}{2} * t}{\sigma_A * \sqrt{t}} \tag{1}$$

$$d2 = d1 - \sigma_A * \sqrt{t} \tag{2}$$

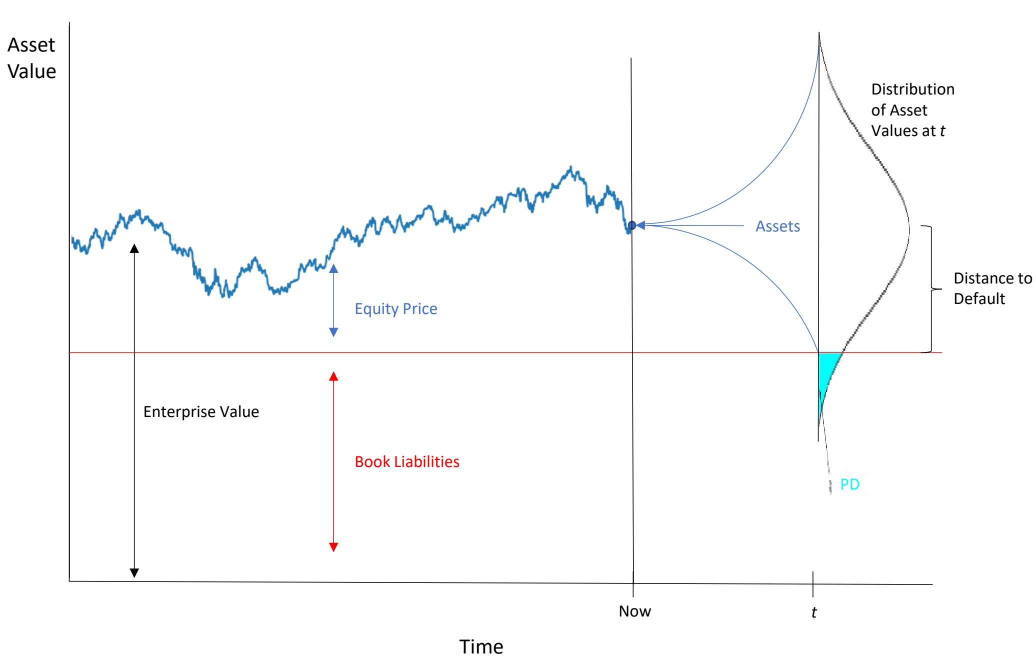
$$Equity\ Value = A * N(d1) - \mathrm{L} * e^{-r*t} * N(d2) \tag{3}$$

However, since public companies' asset values are only published quarterly, I implied portfolio companies' asset values and asset volatilities based on equity value and equity volatility. To arrive at asset value and volatility, I used equity volatility as asset volatility in

Merton's model to solve for asset values for all trading days in a year. To determine the asset volatility, I took the standard deviation of the natural log of day-on-day returns of the implied asset. I compared the implied asset values' volatility to the initial value for asset volatility. If the difference was greater than .001, I repeated this process using the new asset volatility that I calculated as my guess. Using the asset values and volatilities that I calculated from the converged model, I calculated the probability of default with the borrower's existing liabilities alone and added the carbon tax calculated in the first step to existing liabilities to calculate marginal probability of default.

Figure 4.

Graphical Depiction of Merton's Model for PD



Note. Merton's model for probability of default assumes returns on asset value are normally distributed. The probability that a company will be in default at time t is the probability that assets will be less than liabilities at that time.

For simplicity's sake, I assumed that borrowers would not change their behavior to decrease their GHG emissions and tax exposure over the one, two-, three-, four-, and five-year time horizons. I counted the carbon tax exposure in year one as short-term debt and the carbon tax exposures in years two through five (in scenarios that included those years) as long-term debt, because a carbon tax due in those years is similar to a debt instrument with a maturity date in those years. I only counted half of a company's long-term liabilities towards a company's liabilities in Merton's model to adjust for the possibility that long-term debt will be restructured or that assets might briefly exceed liabilities before the debt's maturity date. I then used Merton's model to calculate probability of default based on a risk-free rate of 2%, 252 trading days in a year, company's assets, a company's liabilities (with and without carbon tax liabilities), and a company's asset volatility to calculate marginal probability of default on a company-by-company basis due to the carbon tax.

To calculate expected loan losses, I multiplied the marginal probabilities of default by loan quantum and a recovery rate (the percentage of loan a lender will be able to recover if a borrower goes into default). According to Ou et al. (2021), the average recovery rate on a secured loan (which most term loans are) was 69% in 2020. However, if a portfolio company is going into default because of a carbon tax, its assets are likely intended for use in emissions-intensive processes. This fact is likely to reduce the assets' resale value in a world with a carbon tax. To consider this risk, I examined a scenario with a 0% recovery rate and a 69% recovery rate, with the 0% recovery rate being my base case.

Aggregation and Analysis of Probabilities of Default

Once I generated marginal probabilities of default at the borrower level, I aggregated the borrowers at the systematic, industry, and financial institution level. To understand the relation between emissions and probability of default and to determine if high emitters have different existing debt burdens than low emitters, I determined the distributions of emissions and tax burden at the company and industry level. I determined the total loan quantum included in my dataset and compared that quantum to the actual amount of Commercial, Industrial, and Commercial Real Estate Loans in the U.S., reported by the St. Louis Federal Reserve (Board of Governors of the Federal Reserve System, 2021b). To assess systematic risk, I multiplied the ratio of loan losses to loan base by the actual loan quantum in the U.S. and compared the result to losses under the 2020 CCAR stress test's severely adverse scenario. At the industry level, I grouped loan losses by two-, three-, and four-digit SIC code to find which industries were the greatest emitters. At the financial institution level, I distributed each facility's loan losses to each financial institution that lends to that facility evenly, then scaled those losses to match the financial institution's actual U.S. lending portfolio. Because financial institutions do not disclose the geographic breakdown of their lending portfolio, I scaled their total portfolio by the percentage of revenue that is derived from the Americas to arrive at their American loan portfolio (most financial institutions did not have country-level data and assumed that most American revenue is derived from the U.S.).

4. RESULTS

In this section, I explore the extent to which baseline probabilities of default (PDs) that my model calculated without any carbon tax are comparable to other researched values for PDs. Next, I investigate the extent to which the presence of a carbon tax would establish marginal probabilities of default (MPDs) and the drivers of those MPDs. I then determine the implied liabilities those MPDs create for U.S. financial markets, industries, and financial institutions.

4.1 Probabilities of Default Before Carbon Tax

I first analyzed the PDs for companies in my dataset without any carbon tax and compared those PDs to baseline values established in the literature. I found that that the average PD ranged from 8.46% over a time horizon of one year to 20.38% over a time horizon of five years, as Table 4 shows. Since these averages are higher than researched values for PDs, Merton’s model is likely overestimating values of PDs for companies in my dataset. This overestimation of PD in the case without a carbon tax means that average PDs in all other scenarios are also likely too high. However, the elevated PDs should not have a very large impact on MPDs, because both the baseline PDs and carbon tax PDs will be elevated. Additionally, percentage changes in PDs should not be impacted, again since both baseline and carbon tax PDs should be impacted by the same percentage factor. Table 4 contains average baseline PDs over all time horizons.

Table 4.

Baseline Probabilities of Default	Time Horizon				
	1 Year	2 Years	3 Years	4 Years	5 Years (Base Case)
Average PD	8.32%	11.82%	14.92%	17.72%	20.26%

Note. Across all time horizons, probabilities of default without a carbon tax are higher than would be expected based on the literature.

4.2 Marginal Probability of Default

After I determined base levels of PD, shown in Table 5, I analyzed how different levels of a carbon tax would change those baseline PDs. I found that average MPD arising from the carbon tax ranged from 0.03% over one year with a tax of \$5/ton of CO_2e to 1.6% over five years with a tax of \$150/ton of CO_2e, as Table 6 shows. For my base case of \$50/ton over five years, I found that the MPD averaged 0.60%. However, the distribution of MPD was skewed right, meaning that a few companies suffered a dramatic increase in PD while others suffered almost no increase in PD. This disparity is exemplified by the fact that the median MPD only ranged from 0.00001% in the one-year, \$5/ton scenario to 0.0491% in the five-year, \$150/ton scenario, as Table 7 shows and Figure 5 shows graphically. Even in the scenario with the most extreme carbon tax, the median company's PD remains practically unchanged. The fact that median MPD is so much lower than average MPD likely means that a few companies are accounting for most of the marginal probability of default. Since median MPD represents the "average" company, most companies' risks of default would not materially change. The PD and MPD values for all scenarios can be found in Appendices A and B, respectively. Generally, the MPDs increase linearly as carbon taxes increase. The skew in values of MPD can be explained by the distribution of emissions and carbon tax burden.

Table 5.

Summary of Average Probabilities of Default by Scenario

Carbon Tax ($)	Time Horizon 1 Year	2 Years	3 Years	4 Years	5 Years (Base Case)
0	8.32%	11.82%	14.92%	17.72%	20.26%
50 (Base Case)	8.46%	12.05%	15.29%	18.22%	20.87%
100	8.57%	12.30%	15.65%	18.67%	21.39%
150	8.69%	12.55%	16.00%	19.09%	21.87%

Note. These probabilities of default are the baseline values off which marginal probabilities of default are calculated.

Table 6.

Summary of Average Marginal Probabilities of Default by Scenario

Carbon Tax ($)	Time Horizon 1 Year	2 Years	3 Years	4 Years	5 Years (Base Case)
50 (Base Case)	0.14%	0.23%	0.37%	0.50%	0.61%
100	0.24%	0.48%	0.73%	0.95%	1.13%
150	0.37%	0.73%	1.08%	1.37%	1.61%

Note. Average marginal probabilities imply that a carbon tax would influence overall default rates.

Table 7.

Summary of Median Marginal Probabilities of Default by Scenario

Carbon Tax ($)	Time Horizon				
	1 Year	2 Years	3 Years	4 Years	5 Years (Base Case)
50 (Base Case)	0.00%	0.00%	0.01%	0.01%	0.02%
100	0.00%	0.00%	0.01%	0.02%	0.03%
150	0.00%	0.01%	0.02%	0.03%	0.05%

Note. Median marginal probabilities of default are much lower than average probabilities of default. This difference indicates that a few companies are accounting for most of the marginal probability of default and most companies' risks of default would not materially change.

Figure 5.

Probabilities and Marginal Probabilities of Default

Figure 5a.

Probabilities of Default

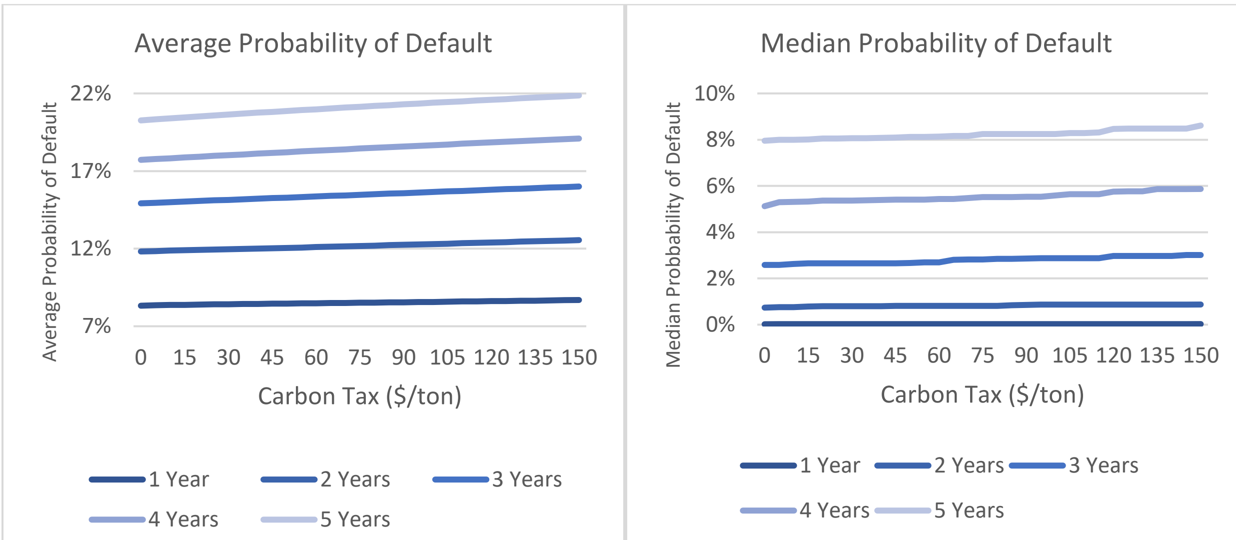
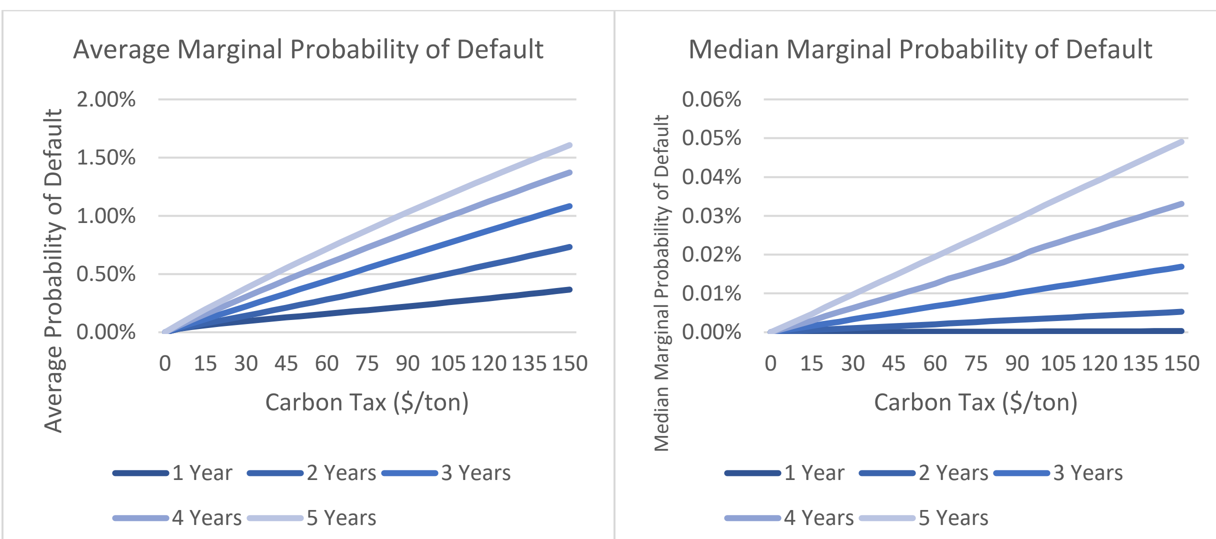


Figure 5b.

Marginal Probabilities of Default



Note. Economy-wide probabilities of default increase linearly as carbon taxes increase in one-, two-, three-, four-, and five-year scenarios. However, baseline PD numbers than previous research suggests they should be. It is critical to note that the median PD/MPD numbers better represent what would happen to the "average" company that is not in a high emissions industry, whereas the mean PD/MPD represent the effect across all companies. Although the trends in mean and median MPD are similar, the fact that in absolute terms, median PD is practically 0 while mean PD is much larger provides evidence that a few companies are being severely impacted by a carbon tax, while most companies are barely impacted at all.

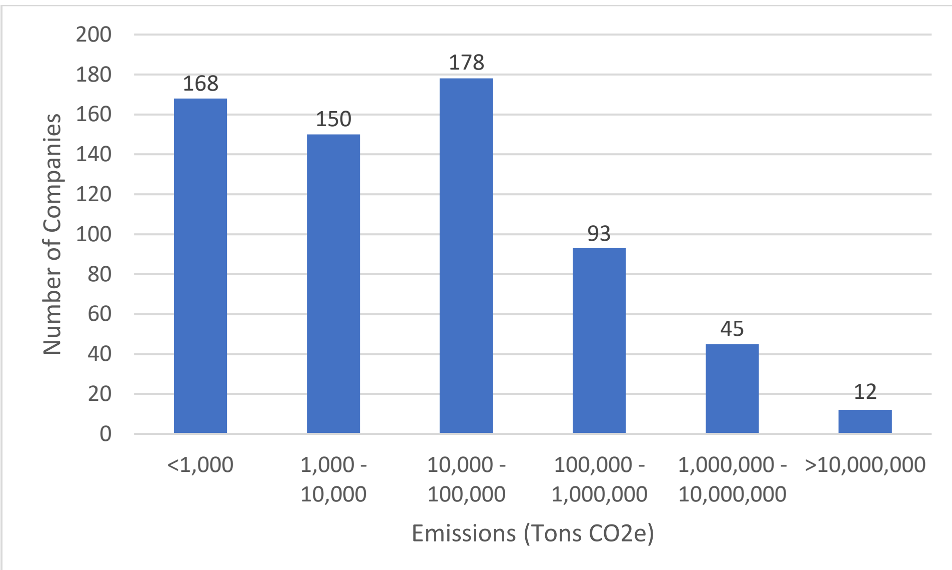
To determine what was causing the skew in the distribution of MPDs, I investigated the distribution of emissions and carbon tax burdens. I found that certain companies accounted for most emissions and most of the total carbon tax burden. I estimated that the average portfolio company emits 689,361 tons of CO_2e per year, which is materially lower than the average emissions in the CDP Database. This lower average emissions statistic does not mean that financial institutions are avoiding lending to high-emissions industries because the companies in the CDP database are not necessarily representative of the larger economy. However, As Figure 6 shows, the distribution of company emissions was skewed right, and the number of companies in each emissions bracket decreased exponentially. In fact, 387 companies emit less than 1,000 tons of CO_2e per year, but 12 companies emit more than 10,000,000 tons of CO_2e per year. As a result, the median quantity of CO_2e emissions is only 10,727 tons and the first and third quartile CO_2e emissions are 878 tons and 80,093 tons, respectively. Because carbon taxes are determined by emissions, the relative burden of the carbon tax is also focused heavily on a handful of companies.

In the base case ($50/ton carbon tax over five years), I found that portfolio companies were liable for a discounted total (liabilities after one year are counted as long term liabilities and divided by two) of $68.04Bn in carbon taxes. These liabilities translated to an average of only

1.51% of portfolio company revenue. However, the carbon tax liabilities ranged from practically 0% of revenue to over 71% of revenue. Because the distribution is skewed right, the median ratio of carbon tax to non-carbon tax liabilities was 0.06%, as Figure 7 shows. In fact, the top 1.5% of emitters in the dataset accounted for just over 60% of the total carbon tax liability. The skewed distribution of carbon taxes explains why the distribution of MPDs was also skewed. A full table of carbon taxes as percentage of liabilities can be found in Appendix C.

Figure 6.

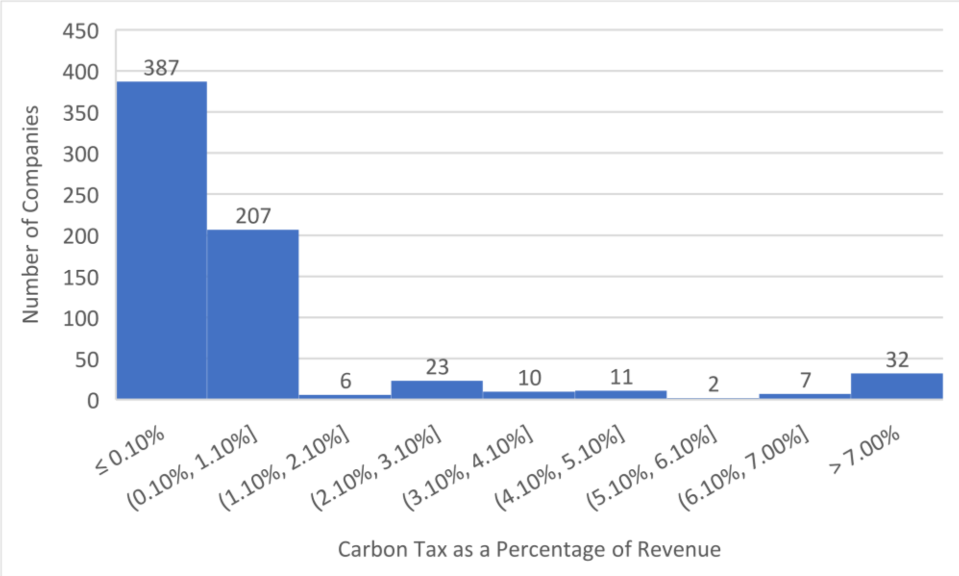
Distribution of Company Emissions



Note. Certain companies emit a far larger amount of greenhouse gasses than others do. Since the distribution is skewed right, a carbon tax will disproportionately affect certain companies.

Figure 7.

Distribution of Carbon Taxes as a Percentage of Company Revenue



Note. The distribution of emissions as a percentage of revenues is skewed right, just as the distribution of emissions. This skew also supports the fact that certain companies bear the brunt of the burden from a carbon tax.

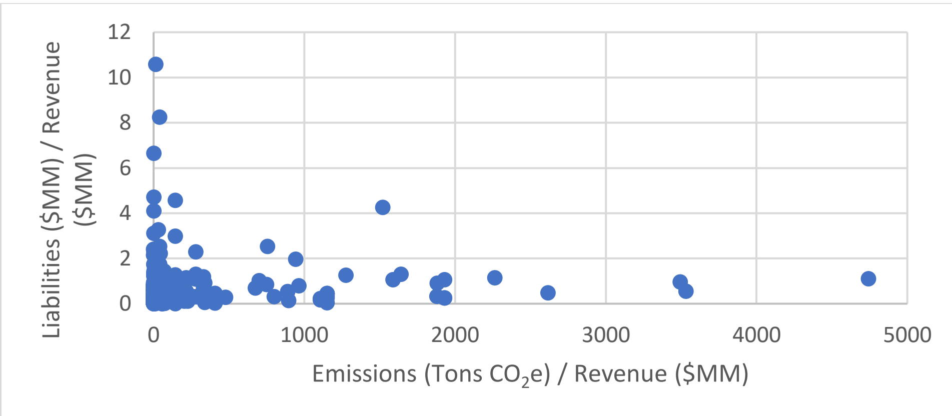
Additionally, Figure 8 shows that although the companies with the highest leverage have very low emissions, when excluding high leverage companies, there is a positive correlation between leverage and emissions. This means that companies with high emissions are likely to have more debt to begin with than companies with low emissions and amplifies the effect that the skewed distribution of carbon taxes has on MPDs.

Figure 8.

Distribution of Emissions and Leverage

Figure 8a.

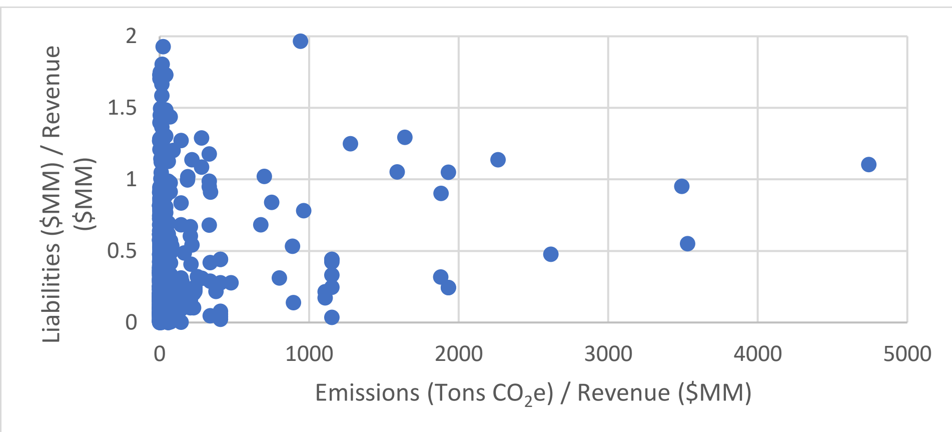
Full Distribution of Emissions and Leverage



Note. When looking at the distribution of all companies' leverage and emissions, there seems to be an inverse relationship between emissions and leverage.

Figure 8b.

Distribution of Emissions and Leverage, Excluding Highly Levered Companies



Note. However, when excluding companies with extremely high leverage (liabilities > 2*Revenue), there appears to be a positive correlation between emissions and leverage. This indicates that financial institutions do not hesitate to lend to companies with high emissions.

4.3 Cumulative Commercial, Industrial, and Commercial Real Estate Loan Losses

I multiplied MPDs by the value of loans and by a recovery rate, or the percentage of a loan that a lender will recover if the borrower defaults, to calculate projected loan losses. I then scaled projected loan losses to match market quantities of debt. Assuming a 0% recovery rate in my base case, I found that industry-wide losses would total $30.30Bn scaled to include commercial, industrial, and commercial real estate loans, and would fall to $9.39Bn scaled assuming the industry wide average recovery weight of 69%. However, I put more weight on the 0% recovery rate scenario, given that if a carbon tax is severe enough to force a company into bankruptcy, its assets are likely intended for use in emissions-intensive processes. Because a carbon tax would make those processes uneconomical, the value of assets that secured the loan would be impaired. Full tables of losses in each scenario, including unscaled losses and losses only scaled to match the commercial and industrial loan market can be found in Appendix D. Once again, I found that losses were skewed to the right, with a small number of firms accounting for most of the impact. After determining the cumulative losses in loan markets, I aggregated those losses by industry.

4.4 Loan Losses by Industry

To investigate whether companies in certain industries were more likely to go into default than companies in other industries I aggregated carbon tax liabilities and loan losses by SIC code. I found that a few industries at the two-, three-, and four-digit SIC code level accounted for most carbon emissions/carbon tax liabilities. As Table 8 shows, the top ten two-digit SIC codes accounted for 90.02% of carbon tax liability, and the top industry; Electric, Gas, and Sanitary

Services; independently accounted for 59.05% of the carbon tax burden. Although many of the industries in the top ten emitted large quantities of GHG per revenue dollar (i.e., Electric Gas, and Sanitary Services, Furniture and Fixtures, Transportation, and Heavy Construction), others had very low emissions, but were classified in the top ten because they earn large quantities of revenue (i.e., Apparel and Accessory Stores and Wholesale Trade), or made up a large percentage of the loans made by financial institutions. Just as the burden of the carbon tax was concentrated in certain companies and certain industries, MPDs due to the carbon tax were also concentrated among a few companies and industries.

Table 8.

Top Ten Industries by Carbon Tax Burden

SIC Code	Industry Description	Percentage of Carbon Tax Burden	Average Carbon Tax as Percentage of Revenue	Percentage of All Loans	Average Revenue ($Bn)
49	Electric, Gas, and Sanitary Services	59.05%	12.14%	5.37%	6.89
50	Wholesale Trade – Durable Goods	12.78%	0.05%	2.13%	454.27
45	Air Transportation	5.19%	5.54%	2.34%	4.26
28	Chemicals and Allied Products	2.33%	0.51%	8.25%	6.08
16	Heavy Construction	1.96%	5.63%	0.31%	3.49
25	Furniture and Fixtures	1.95%	11.14%	0.19%	3.06
51	Wholesale Trade – Nondurable Goods	1.86%	0.68%	2.80%	21.86
44	Water Transportation	1.77%	7.11%	1.03%	6.62
13	Oil and Gas Extraction	1.71%	1.48%	0.70%	8.77

56	Apparel and Accessory Stores	1.42%	0.01%	0.10%	879.43

Note. The ten industries that bear the highest carbon tax burdens do so because they emit large quantities of greenhouse gases for every dollar of revenue that they earn, they make up a large percentage of financial institutions' loan portfolios, or they generate large amounts of revenue.

4.5 Financial Institution Level Exposures

To determine whether individual financial institutions face serious climate risk, I aggregated loans by financial institution. I found that just as certain companies and industries would suffer disproportionately from a carbon tax, so too would certain financial institutions. Of the 19 American Domestic Systematically Important Banks (DSIB), Global Systematically Important Banks (GSIB) and companies with outsized carbon tax liabilities for which I had data, Comerica Bank was an outlier, with loan losses totaling 1.24% of its lending portfolio. The next closest financial institution only lost 0.69% of its portfolio, as Table 9 shows. This unequal distribution of climate risk by bank indicates that although the American financial system may not face fragility because of climate change, certain financial institutions may.

My results also indicate that some of these individual financial institutions may be taking on climate risk knowingly, while others may not be. One might expect that financial institutions that have higher risk tolerance in general would have higher risk tolerance to climate risk, indicating a conscious effort on the part of financial institutions to treat climate risk similarly to other risk, but that is not the case. I found that the coefficient of correlation between a financial institution's comparative rank for general loan losses and loan losses due to climate change is only 0.082. However, as Table 9 shows, certain financial institutions (Truist, Bank of America, Capital One, and Morgan Stanley) had low general loan losses and loan losses due to climate change, which indicates that although financial institutions as a group may not be meaningfully considering climate risk, certain institutions may be.

Additionally, my results indicate most of the exposure to climate risk in banks with the largest overall exposure comes from the same industry. Table 10 shows the top three industry exposures for each bank. For all six financial institutions with the largest carbon tax exposure, the two industries that accounted for most of their carbon tax burden were air transportation (SIC code 45) and electric, gas, and sanitary services (SIC code 49). This indicates that if financial institutions were to face instability due to climate risk it would be due to their exposures to the same companies and would happen at the same time.

Table 9.

Losses by Financial Institution

Financial Institution	Adjusted Losses ($MM)	Percentage Losses	Percentage Non-Performing Loans	Percentage Losses - Rank	Percentage Non-Performing Loans - Rank	Percentage Losses / Percentage Non-Performing Loans
JP Morgan	$2,058.46	0.42%	1.04%	9	3	39.90%
Bank of America	$1,729.86	0.39%	0.57%	11	12	68.35%
Citibank	$918.75	0.49%	1.00%	6	4	48.54%
Wells Fargo & Co	$896.30	0.26%	0.98%	14	5	26.26%
US Bancorp	$613.20	0.47%	0.41%	7	14	113.55%
Comerica Bank	$546.91	1.24%	0.67%	1	10	184.93%
PNC Bank NA	$482.92	0.29%	0.94%	12	6	30.57%
Truist	$464.03	0.27%	0.45%	13	13	61.22%
KeyBank	$428.99	0.61%	0.82%	4	8	74.36%
Compass Bank	$276.06	0.69%	0.20%	2	18	343.62%
Goldman Sachs & Co	$252.36	0.64%	1.46%	3	1	43.77%
Regions Bank	$228.16	0.43%	0.88%	8	7	48.27%
Huntington Bank	$164.80	0.40%	0.60%	10	11	66.13%
Fifth Third Bank	$144.79	0.23%	0.77%	16	9	29.68%
Capital One Bank	$81.85	0.11%	0.40%	17	15	27.31%
Northern Trust	$56.24	0.52%	0.39%	5	16	132.07%
Morgan Stanley Bank NA	$28.18	0.04%	0.24%	18	17	15.82%
Bank of New York Mellon	$27.31	0.23%	0.16%	15	19	146.59%
Ally Commercial Finance LLC	$1.33	0.01%	1.28%	19	2	0.43%

Table 10.

Financial Institution Exposure by Industry

Bank	SIC Code 1	Industry 1	Percentage of Liabilities 1	SIC Code 2	Industry 2	Percentage of Liabilities 2	SIC Code 3	Industry 3	Percentage of Liabilities 3
JP Morgan	45	Air Transportation	39.46%	49	Electric, Gas, and Sanitary	21.03%	25	Furniture Manufacturing	5.82%
Bank of America	45	Air Transportation	31.06%	49	Electric, Gas, and Sanitary	16.34%	36	Electronics Manufacturing	8.09%
Citibank	49	Electric, Gas, and Sanitary	43.80%	45	Air Transportation	32.91%	51	Wholesale Trade - Non-Durable	3.63%
Wells Fargo & Co	49	Electric, Gas, and Sanitary	24.67%	45	Air Transportation	16.80%	25	Furniture Manufacturing	14.65%
US Bancorp	45	Air Transportation	41.70%	49	Electric, Gas, and Sanitary	23.91%	51	Wholesale Trade - Non-Durable	7.44%
Comerica Bank	45	Air Transportation	33.50%	49	Electric, Gas, and Sanitary	31.80%	51	Wholesale Trade - Non-Durable	15.82%
PNC Bank NA	49	Electric, Gas, and Sanitary	43.56%	51	Wholesale Trade - Non-Durable	10.49%	12	Coal Mining	8.25%
Truist	51	Wholesale Trade - Non-Durable	23.64%	25	Furniture Manufacturing	17.89%	16	Heavy Construction	12.88%
KeyBank	49	Electric, Gas, and Sanitary	73.09%	16	Heavy Construction	11.99%	73	Business Services	7.91%
Compass Bank	36	Electronics Manufacturing	88.81%	49	Electric, Gas, and Sanitary	7.27%	70	Hotels	1.98%
Goldman Sachs & Co	49	Electric, Gas, and Sanitary	50.63%	45	Air Transportation	33.74%	16	Heavy Construction	2.41%
Regions Bank	49	Electric, Gas, and Sanitary	43.54%	16	Heavy Construction	18.24%	12	Coal Mining	10.80%

Bank	SIC Code 1	Industry 1	Percentage of Liabilities 1	SIC Code 2	Industry 2	Percentage of Liabilities 2	SIC Code 3	Industry 3	Percentage of Liabilities 3
Huntington Bank	12	Coal Mining	38.82%	49	Electric, Gas, and Sanitary	25.47%	32	Stone, Clay, Glass, and Concrete Manufacturing	20.59%
Fifth Third Bank	25	Furniture Manufacturing	33.60%	51	Wholesale Trade - Non-Durable	16.02%	26	Paper and Allied Products	12.06%
Capital One Bank	16	Heavy Construction	52.33%	73	Business Services	13.89%	13	Oil and Gas Extraction	5.10%
Northern Trust	25	Furniture Manufacturing	54.16%	28	Chemicals and Allied Products	20.59%	26	Paper and Allied Products	11.87%
Morgan Stanley Bank NA	46	Fossil Fuel Pipelines	31.97%	79	Amusement and Recreation Services	29.43%	48	Communications	22.04%
Bank of New York Mellon	49	Electric, Gas, and Sanitary	65.27%	26	Paper and Allied Products	32.39%	73	Business Services	0.82%
Ally Commercial Finance LLC	37	Transportation Equipment	98.13%	32	Stone, Clay, Glass, and Concrete Manufacturing	1.06%	59	Miscellaneous Retail	0.81%

5. DISCUSSION

Given that climate change is rapidly causing economic destruction in the U.S. and globally, this thesis measures American financial institutions' exposure to climate-induced transition risk in the form of a carbon tax and provides insight into the potential economic impacts of a carbon tax. I will discuss the implications of my analyses for systematic financial stability and the ways in which the implementation of a carbon tax would likely impact financial stability. I will also consider the implications of these results for financial regulators and consider limitations of my research that should be addressed in future work.

Overall, my findings support the proposition that a carbon tax would be minimally disruptive for most companies, industries, and financial institutions. However, outsized climate risk in regional banks means that there may be concentrated risk in certain regions or industries that could result in sub-systemic financial instability of those regions/industries. Additionally, concentration of climate risk in certain industries that are important to the American economy could have knock-on effects and cause financial instability. Taken together, my findings support increased oversight of financial climate risk in smaller financial institutions.

5.1 Implications for Financial Stability

Measures of institutions' financial risk at an aggregate level indicate if a carbon tax has the potential to create systemic financial instability. However, even if aggregate indicators of risk do not point to financial instability, financial instability at select financial institutions or economic instability in a particularly important industry can also create systematic instability.

Further, financial instability at regional financial institutions can create sub-systemic financial risk. Therefore, although my results for aggregate measures of exposure do not indicate that climate change will create financial instability, I find that risk at the industry level and at smaller, regional, financial institutions has the potential to create systemic financial risk. These findings are similar to those of Allen et al. (2020) in France and the CFTC in the United States.

5.1.1 Aggregate Measures of Climate Risk

The transition risk that a carbon tax poses to the American financial system in aggregate, although material, is not substantial enough to warrant regulation by itself. The cumulative size of loans that are unlikely to be paid back (non-performing loans) that financial institutions hold relative to the losses they are projected to suffer due to climate risk puts climate risk-induced losses into perspective. On average, loan losses due to climate risk are 79.02% of American financial institutions' current non-performing loans across all divisions (not only commercial, industrial, and commercial real estate lending). This means that financial institutions would suffer almost double the loan losses that they would in normal situations due to a carbon tax, which is material. However, Basel III stipulates that financial institutions must hold enough capital to be able to withstand losses in a severely adverse scenario, meaning that financial institutions may be able to withstand these abnormal losses due to climate change, just as they would withstand losses due to an economic downturn.

I found that in my base case scenario, loan losses would equal 6.62% of total losses in the 2020 CCAR severely adverse scenario, scaling for the difference in loan base (CCAR only tests a loan base of $2.4 trillion, compared to my scaled loan base of $5.0 trillion). Across all scenarios with a 0% recovery rate, average losses ranged from .32% ($5/ton tax over one year) to 17.54% ($150/ton over five years) of CCAR losses. This range means that even the most impactful carbon tax would only have a fraction of the impact that the severely adverse scenario would. The average percentage of CCAR losses across all scenarios are listed in Appendix H. Given the relative scale of average losses from a carbon tax and the fact that all financial institutions passed the CCAR stress test in 2020, the average financial institution could almost certainly withstand the loan losses resulting from a carbon tax in isolation. However, climate change will not happen in isolation, and the causes of financial instability and fragility that the CCAR assessment attempts to address in a world without climate risk will also exist in a world with climate risk.

Even if financial institutions' average losses due to a carbon tax are layered on top of their CCAR losses, the cumulative losses are not material enough to cause systematic financial fragility or instability. In the 2020 CCAR severely adverse scenario, CET1 capital ratios dropped from an average starting value of 12.2% to an average minimum value of 9.6%. When including both losses due to climate change and the original CCAR losses, average CET1 ratios only fall 0.17% further to 9.43%. Although minimum CET1 ratios vary by financial institution under Basel III, 9.43% is above the regulatory minimum in stressed scenarios for all financial institutions. Therefore, even losses from a carbon tax compounded with the losses in the 2020 CCAR severely adverse scenario would not be enough to create cause for concern at an aggregate level.

It is important to note that defaults due to transition risk would not be a one-time-event like the scenarios that the CCAR exercise emulate. Because these risks would continue until portfolio companies change their business processes to decrease their emissions, the impact of the risk could be larger than a short-term economic shock. In my model, I set the time horizon for transition risks at five years, but the impacts of a carbon tax could last longer. I am also only estimating Scope I emissions and excluding Scope II and III emissions, which could increase the scope of damages. Even with these additional losses, however, existing banking regulation requires that financial institutions maintain a sufficient capital buffer that climate risk is unlikely to cause financial instability or fragility. These results are similar to the findings of Vermeulen et al. (2018) and Allen et al. (2020), both of whom study financial institutions' exposure to climate risk in Europe and find that financial institutions are not at risk in aggregate. However, even if financial institutions in aggregate do not have exposure to climate risk that warrants concern, groups of financial institutions or industries may.

5.1.2 Industry Level Measures of Climate Risk

My results indicate that the concentration of climate risk in a few industries and financial institutions could create wider instability. Although the 2008 financial crisis was a unique case and was not caused entirely by the collapse of the housing market, it is evidence for how a bubble bursting in one industry can have wider implications. The same could be true for the transition risk from a carbon tax, and especially one focused on Scope I emissions like the one that I modeled. Because taxes on Scope I emissions penalize industries like transportation and electricity generation so heavily compared to other industries, there would more likely be a shock in one of those industries that would have knock-on effects throughout the economy. In the base case scenario, electricity generators' (SIC code 49) probabilities of default increase by 14.97%, from 19.16% to 22.03%. Although projecting the magnitude of increase in defaults necessary to shock the industry is difficult, any magnitude of disruption in such an essential industry could have knock-on effects.

Because so many other industries rely on electricity, a disturbance in the electricity generation industry could have wide-reaching implications, and potentially cause financial instability. The failure of Texas' power grid during a winter storm in February of 2021 could end up causing $155 Bn in economic damage, demonstrating the impact that a failure could have (Puelo, 2021). Given the concentration of carbon tax exposure in industries important to the American economy and the impact that high levels of default in those industries have, further research is warranted on the second-level impacts of implementing a carbon tax.

5.1.3 Financial Institution Level and Regional Measures of Climate Risk

My results indicate that financial institutions classified as GSIBs or DSIBs are not individually vulnerable to financial climate risk, meaning these financial institutions will not contribute to financial instability. However, my results also indicate that smaller and regional financial institutions bear outsized exposure to climate risk and may create sub-systemic financial instability or fragility.

Of the financial institutions classified as DSIBs or GSIBs, loan losses due to transition risk ranged from 0.05% (Ally) to 10.72% (Citi) of losses in the 2020 CCAR severely adverse scenario. Because climate-induced losses were such a small percentage of CCAR loan losses and all financial institutions passed the 2020 CCAR exercise, no GSIB or DSIB financial institutions individually face instability due to climate change. As Table 11 shows, even if DSIBs and GSIBs suffer losses from a carbon tax concurrently with losses similar to those they would suffer in the CCAR severely adverse scenario, each financial institutions' CET1 ratio would remain above its regulatory minimum. Therefore, a carbon tax would not because financial institutions classified as GSIBs or DSIBs to pose a threat to systematic financial stability.

However, certain non-DSIB and non-GSIB financial institutions, most notably Comerica and Compass, bear an outsized exposure to climate risk from a carbon tax and are not a part of the CCAR exercise. Even though these financial institutions are likely not large enough to create systemic risk, they could still create sub-systemic risk in the regions in which they operate. As Table 11 shows, I predict that 1.24% of Comerica's. Outside of Comerica, the highest loan loss percentage is Compass (0.69%), 44.4% lower than Comerica's. Coincidentally, although both financial institutions used to be classified as DSIBs and take part in the CCAR stress tests, neither is anymore. This means that the two financial institutions with the most relative exposure to climate risk are also the two financial institutions with the least oversight. However, even if underregulated financial institutions have the highest exposure to climate risk, these financial institutions would not create sub-systemic risk unless they are not appropriately accounting for this climate risk.

Although both Comerica and Compass both have CET1 ratios far above their regulatory minimums (as shown in Table 11), they could still face instability in poor economic conditions. Without knowing how Comerica and Compass would fare in the CCAR severely adverse scenario, one cannot say whether climate risk could push them into financial instability. For example, Goldman Sachs' CET1 ratio falls from 13.35% to 8.35% in the CCAR severely adverse scenario, and if either Comerica or Compass were to suffer similar losses, losses from climate risk could put them into financial instability.

More broadly, regional financial institutions (i.e., retail-focused financial institutions with operations in 20 or fewer states), have outsized exposure to climate risk. In my base case, national financial institutions' losses due to climate only averaged 65.7% of their non-performing loans, whereas regional financial institutions' losses averaged 88.7% of non-performing loans. Similarly, national financial institutions' losses averaged 0.37% of their total loan books, whereas regional financial institutions' losses totaled 0.43% of their total loan books. Therefore, because smaller, non-DSIB, financial institutions and regional institutions in my sample have higher exposure to climate risk, it is likely that less-regulated banks have the most exposure to climate risk.

Although these smaller, less regulated financial institutions are unlikely to cause systematic financial instability due to their size, they have the potential to create sub-systemic risk in the regions that they serve. Because they are not subject to the same levels of regulatory scrutiny as larger banks, adverse macroeconomic conditions combined with climate risk could make them unstable. Although instability among these smaller financial institutions would not be as pernicious as systematic financial instability, it could still jeopardize liquidity for regional companies that rely on regional financial institutions for capital. Therefore, the potential for financial instability among certain institutions and regional institutions more broadly means that sub-systemic risk may exist among American financial institutions and may warrant regulation.

5.2 Implications for Regulators

My results have implications for two types of regulators: those looking to implement a carbon tax and those looking to regulate financial risk. My findings indicate that regulators looking to implement a carbon tax should not worry about the tax's implications for systematic financial stability and that financial regulators should investigate implementing oversight for regional banks' exposures to climate risk.

I found a concentration of exposure to transition risk in a small number of industries, and within those industries, to a small number of companies. Allen et al. (2020) found the same industry and sub-industry concentration of climate risk with better data on company emissions (because their research focused on France). However, Allen et al. found a concentration of risk in different industries (petroleum extraction, agriculture, and mining) than I did, which is likely because I only considered Scope I emissions. Regardless, because my distribution of carbon tax burden is similar to a study that had better emissions data, my distribution of carbon tax burden is also likely reliable.

This concentration of burden means that a carbon tax will only disrupt the high-emitting industries that it likely intends to disrupt and will not cause widespread economic damage. Given that 59% of the tax burden is borne by one SIC code (code 49), most of the ten industries that bear the highest carbon tax burden are large emitters, and only 32% of companies would bear a burden of over 7% of 2020 revenues over 5 years, the carbon tax would likely target its intended audience closely. These findings mean that a carbon tax may be an effective tool for regulators to curb GHG emissions without inflicting unnecessary damage on the American economy.

Additionally, because my results indicate that the firms that are the most vulnerable to climate risk have the least oversight, regulators should consider regional banks' exposures to climate risk. An easy path to accomplishing this goal would be expanding the scope of the CCAR stress test. The two banks in my sample that have the highest exposure to climate risk both used to be subject to the CCAR stress test, but no longer are. Additionally, all banks that are subject to the CCAR stress seem adequately prepared to handle climate risk.

Table 11.

Financial Institutions' Relative Losses due to a Carbon Tax

Bank	Losses as Percentage of Loan Base	Losses as a Percentage of CET1 Capital	Losses as a Percentage of CCAR Scenarios[1]	Regulatory Minimum CET1 Capital Ratio[1]	Current CET1 Ratio[1]	CET1 Ratio Including Carbon Tax Losses	CET1 Ratio Including Carbon Tax + CCAR Losses
JP Morgan	0.42%	1.00%	8.72%	10.50%	13.82%	13.68%	9.79%
Bank of America	0.39%	0.98%	5.92%	9.50%	11.94%	11.82%	9.16%
Citibank	0.49%	5.95%	7.01%	10.00%	10.60%	9.96%	9.45%
Wells Fargo & Co	0.26%	0.65%	2.78%	9.00%	11.94%	11.86%	8.22%
US Bank NA	0.47%	1.61%	4.61%	6.50%	9.66%	9.51%	7.54%
Comerica Bank	1.24%	7.90%	N/A	6.50%	10.34%	9.52%	N/A
PNC Bank NA	0.29%	1.22%	4.20%	7.00%	12.16%	12.01%	9.53%
Truist	0.27%	1.23%	4.07%	6.50%	10.00%	9.88%	7.72%
KeyBank	0.61%	3.29%	10.72%	7.00%	11.10%	10.74%	7.55%
Compass Bank	0.69%	3.20%	N/A	6.50%	12.49%	12.09%	N/A
Goldman Sachs & Co	0.64%	0.31%	3.15%	9.50%	13.39%	13.35%	8.35%
Regions Bank	0.43%	2.17%	6.00%	6.50%	9.84%	9.63%	6.99%
Huntington Bank	0.40%	1.85%	5.32%	7.00%	10.00%	9.81%	7.90%
Fifth Third Bank	0.23%	0.99%	2.13%	6.50%	10.34%	10.24%	7.45%
Capital One Bank	0.11%	0.20%	1.20%	7.00%	13.67%	13.65%	7.04%
Northern Trust	0.52%	0.56%	8.03%	6.50%	12.83%	12.75%	12.54%
Morgan Stanley	0.04%	0.04%	0.81%	9.50%	17.36%	17.35%	12.37%
Bank of New York Mellon	0.23%	0.12%	5.46%	8.50%	13.14%	13.13%	11.86%
Ally Commercial Finance	0.01%	0.01%	0.05%	8.00%	10.64%	10.64%	7.40%

1. Citations for data included in reference list following format: "Bank Name (2020)…"

5.3 Limitations and Future Directions

The first major limitation in my research is the scope of risks that were included in my model. Because physical risks are inversely correlated with transition risks, a more accurate model would consider the interaction between physical and transition risk. My model currently outputs that as carbon taxes increase, so does overall economic destruction. This relationship does not account for the fact that as carbon taxes increase, the rate of climate change and impact of physical risks decrease. If I were to include physical risk in my model, there would be less of a positive correlation, and potentially even a negative correlation, between carbon tax and economic destruction.

Not only does my model fail to account for physical risk, but also some transition risks. Some forms of transition risk, such as legal risk, do not fit neatly into a carbon tax. In the example of legal risk, the costs are much less uniform, and therefore are not modeled as well by a carbon tax. Since a lawsuit is either won or lost and only filed in certain cases, it is not a definite cost like a carbon tax would be. Additionally, not all emissions are equally likely to result in a lawsuit, because many lawsuits are against companies that pollute locally (e.g., if a company were to pollute in a sparsely populated area, that company would be less likely to be sued) so there is a geographic factor in determining legal risk. If my model were to include transition risks that are not easily accounted for by a carbon tax, the impacts of climate change would be more severe.

The second major limitation of my research is the accuracy of my data. As I discussed in the Data section, most emissions data are self-reported. As such, the data can be incorrect due to poor data collection or to a desire to appear ecologically sustainable. Because I used self-reported data from available companies to estimate the likely emissions of similar companies', my emissions numbers include an additional layer that will add error. Another source of error in my data was created by excluding companies for which I was unable to draw financial data. The exclusion of companies that do not appear in the DealScan or CapitalIQ dataset, may have skewed my data. The relatively small size of my final sample required that I scale losses to fit markets, which is a further inaccuracy. The inaccuracy of financial data could skew results either way, depending on what the data inaccuracy is. The data limitations in my work are in contrast to work done by European researchers, as Europe has better emissions disclosure frameworks and bank loan data from central banks.

The third major limitation to my methodology was modelling simplifications that I made to be able to complete the project in the allotted timeframe. For example, assuming that only half of long-term debts should be counted towards liabilities in Merton's model is a simplification that is not necessarily accurate. Similarly, I model portfolio companies' attempts to mitigate their exposure to a climate task as having a binary effect in that there is no mitigation in my model's time horizon and a complete mitigation after my model's time horizon. To avoid having too many scenarios, I also fixed recovery rates at 0% and 69%, but the true recovery rate probably lies somewhere in between the two.

The final, and potentially most influential limitation of my research was that I only considered Scope I emissions. This simplification meant that electricity generation companies were heavily penalized, while those who consume the electricity were not. Had I included Scope II and III emissions the breakdown of carbon tax burden by industry would have been materially different, and my results likely also would have been materially different. The clumping of risk in certain industries that defines my results would also likely be less pronounced since Scope II and III emissions are more evenly distributed than Scope I emissions.

In future research it will be important to consider physical risk. My model currently gives results that indicate that lower carbon taxes will create less economic disruption. However, this may misrepresent the truth: although we do not know what the optimal level of carbon tax is, there is not a simple inverse relationship between carbon tax and economic disruption. Since including physical risks would materially impact the relationship between carbon taxes and financial stability, it would be the first change that I would make to my model.

6. CONCLUSION

Transition risk in the form of a carbon tax does not seem to pose a systematic threat to financial stability. A carbon tax would only cause a serious increase in probability of default for a select number of firms, concentrated in a select number of industries. On average, these select firms make up a small enough portion of financial institutions' portfolios that a carbon tax should not put them in a precarious situation.

However, as evidenced by the fact that certain financial institutions would fare better than others in a scenario with a carbon tax and the fact that certain financial institutions seem to be considering climate risk while others do not, transition risk could create sub-systemic shocks to certain financial institutions, regions, or industries. High levels of default in certain industries (i.e., electricity generation, air transportation, etc.) could also have knock-on effects throughout the larger economy and ultimately create financial risk. Therefore, moving forward, regulators should consider financial transition risk at a sub-systemic level.

APPENDIX A

Full Tables of Average Probabilities of Default by Scenario

Average Probability of Default by Year and Carbon Tax (Base Case Highlighted in Blue)

	Year 1	Year 2	Year 3	Year 4	Year 5
$0	8.32%	11.82%	14.92%	17.72%	20.26%
$5	8.35%	11.85%	14.96%	17.77%	20.33%
$10	8.37%	11.87%	15.00%	17.83%	20.39%
$15	8.39%	11.89%	15.03%	17.88%	20.46%
$20	8.40%	11.91%	15.07%	17.93%	20.52%
$25	8.41%	11.94%	15.11%	17.98%	20.58%
$30	8.42%	11.96%	15.14%	18.02%	20.64%
$35	8.43%	11.98%	15.18%	18.07%	20.70%
$40	8.44%	12.01%	15.22%	18.12%	20.76%
$45	8.45%	12.03%	15.25%	18.17%	20.81%
$50	8.46%	12.05%	15.29%	18.22%	20.87%
$55	8.47%	12.08%	15.33%	18.26%	20.92%
$60	8.48%	12.10%	15.36%	18.31%	20.98%
$65	8.49%	12.12%	15.40%	18.36%	21.03%
$70	8.50%	12.15%	15.43%	18.40%	21.09%
$75	8.51%	12.17%	15.47%	18.45%	21.14%
$80	8.52%	12.20%	15.51%	18.49%	21.19%
$85	8.54%	12.22%	15.54%	18.54%	21.24%
$90	8.55%	12.25%	15.58%	18.58%	21.29%
$95	8.56%	12.27%	15.62%	18.63%	21.34%
$100	8.57%	12.30%	15.65%	18.67%	21.39%
$105	8.58%	12.32%	15.69%	18.71%	21.44%
$110	8.59%	12.35%	15.72%	18.76%	21.49%
$115	8.60%	12.37%	15.76%	18.80%	21.54%
$120	8.62%	12.40%	15.79%	18.84%	21.59%
$125	8.63%	12.42%	15.83%	18.88%	21.64%
$130	8.64%	12.45%	15.86%	18.93%	21.68%
$135	8.65%	12.47%	15.90%	18.97%	21.73%
$140	8.66%	12.50%	15.93%	19.01%	21.78%
$145	8.68%	12.52%	15.97%	19.05%	21.82%
$150	8.69%	12.55%	16.00%	19.09%	21.87%

Median Probability of Default by Year and Carbon Tax (Base Case Highlighted in Blue)

	Year 1	**Year 2**	**Year 3**	**Year 4**	**Year 5**
$0	0.0195%	0.7368%	2.5836%	5.1234%	7.9533%
$5	0.0199%	0.7586%	2.5861%	5.2912%	7.9947%
$10	0.0199%	0.7587%	2.6236%	5.3052%	7.9948%
$15	0.0204%	0.7835%	2.6573%	5.3192%	8.0150%
$20	0.0207%	0.7933%	2.6574%	5.3671%	8.0429%
$25	0.0207%	0.7963%	2.6575%	5.3673%	8.0513%
$30	0.0208%	0.7977%	2.6576%	5.3675%	8.0597%
$35	0.0208%	0.7990%	2.6577%	5.3752%	8.0680%
$40	0.0208%	0.8004%	2.6578%	5.3893%	8.0764%
$45	0.0216%	0.8109%	2.6579%	5.4023%	8.0901%
$50	0.0224%	0.8112%	2.6642%	5.4023%	8.1139%
$55	0.0225%	0.8115%	2.6925%	5.4023%	8.1244%
$60	0.0225%	0.8118%	2.6934%	5.4310%	8.1349%
$65	0.0226%	0.8120%	2.8017%	5.4327%	8.1658%
$70	0.0226%	0.8123%	2.8241%	5.4739%	8.1664%
$75	0.0226%	0.8126%	2.8250%	5.5161%	8.2436%
$80	0.0227%	0.8129%	2.8402%	5.5178%	8.2438%
$85	0.0227%	0.8397%	2.8407%	5.5194%	8.2447%
$90	0.0228%	0.8581%	2.8631%	5.5277%	8.2449%
$95	0.0228%	0.8689%	2.8680%	5.5281%	8.2450%
$100	0.0229%	0.8690%	2.8681%	5.5822%	8.2452%
$105	0.0229%	0.8690%	2.8682%	5.6361%	8.2801%
$110	0.0232%	0.8691%	2.8684%	5.6362%	8.2819%
$115	0.0239%	0.8691%	2.8804%	5.6364%	8.3180%
$120	0.0239%	0.8691%	2.9679%	5.7583%	8.4715%
$125	0.0239%	0.8692%	2.9681%	5.7635%	8.4733%
$130	0.0239%	0.8702%	2.9684%	5.7687%	8.4751%
$135	0.0239%	0.8702%	2.9687%	5.8671%	8.4768%
$140	0.0241%	0.8702%	2.9689%	5.8673%	8.4786%
$145	0.0261%	0.8702%	3.0112%	5.8674%	8.4804%
$150	0.0261%	0.8708%	3.0113%	5.8676%	8.6113%

APPENDIX B

Full Tables of Average Probabilities of Default by Scenario

Average Marginal Probability of Default by Year and Carbon Tax (Base Case Highlighted in Blue)

	1 Year	2 Years	3 Years	4 Years	5 Years
$5	0.03%	0.03%	0.04%	0.05%	0.07%
$10	0.05%	0.05%	0.08%	0.10%	0.13%
$15	0.06%	0.08%	0.11%	0.16%	0.20%
$20	0.07%	0.10%	0.15%	0.21%	0.26%
$25	0.08%	0.12%	0.19%	0.26%	0.32%
$30	0.10%	0.14%	0.22%	0.30%	0.38%
$35	0.11%	0.16%	0.26%	0.35%	0.44%
$40	0.12%	0.19%	0.30%	0.40%	0.49%
$45	0.13%	0.21%	0.33%	0.45%	0.55%
$50	0.14%	0.23%	0.37%	0.50%	0.61%
$55	0.15%	0.26%	0.41%	0.54%	0.66%
$60	0.16%	0.28%	0.44%	0.59%	0.72%
$65	0.17%	0.31%	0.48%	0.64%	0.77%
$70	0.18%	0.33%	0.51%	0.68%	0.82%
$75	0.19%	0.35%	0.55%	0.73%	0.88%
$80	0.20%	0.38%	0.59%	0.77%	0.93%
$85	0.21%	0.40%	0.62%	0.82%	0.98%
$90	0.22%	0.43%	0.66%	0.86%	1.03%
$95	0.23%	0.45%	0.69%	0.91%	1.08%
$100	0.24%	0.48%	0.73%	0.95%	1.13%
$105	0.26%	0.50%	0.77%	0.99%	1.18%
$110	0.27%	0.53%	0.80%	1.04%	1.23%
$115	0.28%	0.55%	0.84%	1.08%	1.28%
$120	0.29%	0.58%	0.87%	1.12%	1.33%
$125	0.30%	0.60%	0.91%	1.16%	1.38%
$130	0.32%	0.63%	0.94%	1.21%	1.42%
$135	0.33%	0.66%	0.98%	1.25%	1.47%
$140	0.34%	0.68%	1.01%	1.29%	1.52%
$145	0.35%	0.71%	1.05%	1.33%	1.56%
$150	0.37%	0.73%	1.08%	1.37%	1.61%

Median Marginal Probability of Default by Year and Carbon Tax (Base Case Highlighted in Blue)

	1 Year	2 Years	3 Years	4 Years	5 Years
$5	0.0000%	0.0002%	0.0005%	0.0010%	0.0016%
$10	0.0000%	0.0003%	0.0011%	0.0020%	0.0031%
$15	0.0000%	0.0005%	0.0016%	0.0030%	0.0047%
$20	0.0000%	0.0007%	0.0022%	0.0042%	0.0065%
$25	0.0000%	0.0009%	0.0027%	0.0052%	0.0081%
$30	0.0001%	0.0010%	0.0033%	0.0063%	0.0097%
$35	0.0001%	0.0012%	0.0039%	0.0073%	0.0114%
$40	0.0001%	0.0014%	0.0045%	0.0083%	0.0130%
$45	0.0001%	0.0015%	0.0050%	0.0094%	0.0146%
$50	0.0001%	0.0017%	0.0056%	0.0104%	0.0162%
$55	0.0001%	0.0019%	0.0061%	0.0115%	0.0178%
$60	0.0001%	0.0020%	0.0067%	0.0125%	0.0195%
$65	0.0001%	0.0023%	0.0073%	0.0138%	0.0211%
$70	0.0001%	0.0025%	0.0078%	0.0148%	0.0227%
$75	0.0001%	0.0026%	0.0084%	0.0159%	0.0243%
$80	0.0001%	0.0028%	0.0089%	0.0170%	0.0259%
$85	0.0002%	0.0030%	0.0095%	0.0180%	0.0276%
$90	0.0002%	0.0032%	0.0101%	0.0194%	0.0293%
$95	0.0002%	0.0033%	0.0107%	0.0209%	0.0310%
$100	0.0002%	0.0035%	0.0112%	0.0221%	0.0327%
$105	0.0002%	0.0037%	0.0118%	0.0232%	0.0343%
$110	0.0002%	0.0039%	0.0124%	0.0243%	0.0360%
$115	0.0002%	0.0041%	0.0129%	0.0254%	0.0376%
$120	0.0002%	0.0042%	0.0135%	0.0265%	0.0393%
$125	0.0002%	0.0044%	0.0141%	0.0276%	0.0409%
$130	0.0002%	0.0046%	0.0146%	0.0287%	0.0425%
$135	0.0003%	0.0048%	0.0152%	0.0298%	0.0442%
$140	0.0003%	0.0049%	0.0158%	0.0309%	0.0458%
$145	0.0003%	0.0051%	0.0163%	0.0320%	0.0474%
$150	0.0003%	0.0053%	0.0169%	0.0331%	0.0491%

APPENDIX C

Relative Carbon Tax Burdens Overall and by Industry

Carbon Tax Liability as a Percentage of Liabilities

	1 Year	2 Years	3 Years	4 Years	5 Years
5	0.59%	0.88%	1.18%	1.47%	1.77%
10	1.18%	1.77%	2.36%	2.95%	3.54%
15	1.77%	2.65%	3.54%	4.42%	5.31%
20	2.36%	3.54%	4.72%	5.89%	7.07%
25	2.95%	4.42%	5.89%	7.37%	8.84%
30	3.54%	5.31%	7.07%	8.84%	10.61%
35	4.13%	6.19%	8.25%	10.32%	12.38%
40	4.72%	7.07%	9.43%	11.79%	14.15%
45	5.31%	7.96%	10.61%	13.26%	15.92%
50	5.89%	8.84%	11.79%	14.74%	17.68%
55	6.48%	9.73%	12.97%	16.21%	19.45%
60	7.07%	10.61%	14.15%	17.68%	21.22%
65	7.66%	11.49%	15.33%	19.16%	22.99%
70	8.25%	12.38%	16.51%	20.63%	24.76%
75	8.84%	13.26%	17.68%	22.11%	26.53%
80	9.43%	14.15%	18.86%	23.58%	28.29%
85	10.02%	15.03%	20.04%	25.05%	30.06%
90	10.61%	15.92%	21.22%	26.53%	31.83%
95	11.20%	16.80%	22.40%	28.00%	33.60%
100	11.79%	17.68%	23.58%	29.47%	35.37%
105	12.38%	18.57%	24.76%	30.95%	37.14%
110	12.97%	19.45%	25.94%	32.42%	38.91%
115	13.56%	20.34%	27.12%	33.90%	40.67%
120	14.15%	21.22%	28.29%	35.37%	42.44%
125	14.74%	22.11%	29.47%	36.84%	44.21%
130	15.33%	22.99%	30.65%	38.32%	45.98%
135	15.92%	23.87%	31.83%	39.79%	47.75%
140	16.51%	24.76%	33.01%	41.26%	49.52%
145	17.09%	25.64%	34.19%	42.74%	51.28%
150	17.68%	26.53%	35.37%	44.21%	53.05%

APPENDIX D

Loan Losses by Scenario

Unscaled Bank Losses – 0% Recovery

($MM)

	1 Year	2 Years	3 Years	4 Years	5 Years
$5.00	320	317	427	578	734
$10.00	508	570	826	1,136	1,439
$15.00	658	812	1,223	1,686	2,124
$20.00	791	1,053	1,619	2,228	2,793
$25.00	916	1,295	2,015	2,764	3,448
$30.00	1,034	1,538	2,411	3,294	4,091
$35.00	1,150	1,784	2,807	3,819	4,723
$40.00	1,264	2,032	3,202	4,339	5,346
$45.00	1,376	2,282	3,598	4,855	5,960
$50.00	1,489	2,534	3,993	5,367	6,565
$55.00	1,601	2,789	4,387	5,874	7,164
$60.00	1,713	3,046	4,782	6,377	7,755
$65.00	1,827	3,305	5,175	6,877	8,339
$70.00	1,941	3,566	5,568	7,373	8,916
$75.00	2,056	3,829	5,960	7,865	9,487
$80.00	2,172	4,094	6,352	8,354	10,052
$85.00	2,289	4,360	6,742	8,840	10,611
$90.00	2,408	4,628	7,132	9,322	11,165
$95.00	2,529	4,897	7,521	9,800	11,712
$100.00	2,651	5,168	7,908	10,276	12,254
$105.00	2,774	5,440	8,295	10,748	12,791
$110.00	2,899	5,713	8,681	11,217	13,323
$115.00	3,026	5,987	9,065	11,682	13,849
$120.00	3,155	6,263	9,449	12,145	14,370
$125.00	3,285	6,539	9,831	12,604	14,886
$130.00	3,417	6,815	10,211	13,060	15,398
$135.00	3,551	7,093	10,591	13,513	15,905
$140.00	3,687	7,371	10,969	13,963	16,407
$145.00	3,825	7,649	11,346	14,410	16,904
$150.00	3,964	7,929	11,722	14,854	17,397

Scaled Bank Losses (Commercial and Industrial) – 0% Recovery

($MM)

	1 Year	2 Years	3 Years	4 Years	5 Years
$5.00	759	753	1,013	1,371	1,741
$10.00	1,204	1,351	1,959	2,694	3,413
$15.00	1,560	1,926	2,900	3,997	5,037
$20.00	1,876	2,497	3,839	5,282	6,622
$25.00	2,171	3,070	4,778	6,553	8,175
$30.00	2,452	3,647	5,716	7,810	9,699
$35.00	2,727	4,229	6,655	9,055	11,198
$40.00	2,996	4,817	7,593	10,289	12,674
$45.00	3,263	5,410	8,530	11,511	14,130
$50.00	3,529	6,009	9,467	12,724	15,566
$55.00	3,796	6,613	10,402	13,927	16,985
$60.00	4,062	7,222	11,337	15,120	18,386
$65.00	4,331	7,837	12,270	16,305	19,771
$70.00	4,601	8,455	13,201	17,481	21,140
$75.00	4,874	9,079	14,131	18,648	22,494
$80.00	5,150	9,706	15,059	19,808	23,834
$85.00	5,428	10,338	15,985	20,959	25,159
$90.00	5,710	10,973	16,909	22,102	26,471
$95.00	5,996	11,612	17,831	23,237	27,769
$100.00	6,285	12,254	18,750	24,364	29,055
$105.00	6,577	12,898	19,667	25,483	30,327
$110.00	6,874	13,546	20,582	26,595	31,587
$115.00	7,175	14,196	21,493	27,699	32,835
$120.00	7,480	14,848	22,402	28,795	34,071
$125.00	7,789	15,503	23,308	29,884	35,295
$130.00	8,103	16,159	24,211	30,966	36,508
$135.00	8,420	16,817	25,111	32,040	37,709
$140.00	8,742	17,476	26,008	33,106	38,900
$145.00	9,068	18,137	26,901	34,166	40,079
$150.00	9,398	18,798	27,792	35,218	41,247

Scaled Bank Losses (Commercial, Industrial and Industrial Real Estate) – 0% Recovery

($MM)

	1 Year	2 Years	3 Years	4 Years	5 Years
$5.00	1,477	1,465	1,971	2,668	3,389
$10.00	2,344	2,629	3,814	5,243	6,642
$15.00	3,037	3,748	5,644	7,778	9,803
$20.00	3,652	4,860	7,471	10,281	12,888
$25.00	4,225	5,975	9,298	12,754	15,910
$30.00	4,773	7,098	11,125	15,201	18,876
$35.00	5,307	8,231	12,952	17,624	21,794
$40.00	5,832	9,375	14,778	20,025	24,668
$45.00	6,351	10,530	16,602	22,404	27,501
$50.00	6,869	11,695	18,425	24,764	30,296
$55.00	7,387	12,871	20,246	27,105	33,057
$60.00	7,907	14,057	22,065	29,428	35,784
$65.00	8,429	15,252	23,881	31,734	38,479
$70.00	8,955	16,457	25,694	34,023	41,144
$75.00	9,486	17,670	27,503	36,295	43,780
$80.00	10,023	18,891	29,309	38,551	46,387
$85.00	10,565	20,120	31,112	40,791	48,967
$90.00	11,113	21,357	32,910	43,016	51,520
$95.00	11,669	22,600	34,704	45,225	54,047
$100.00	12,231	23,849	36,493	47,418	56,548
$105.00	12,802	25,104	38,278	49,597	59,025
$110.00	13,379	26,364	40,057	51,761	61,478
$115.00	13,965	27,629	41,832	53,909	63,906
$120.00	14,558	28,899	43,601	56,043	66,312
$125.00	15,160	30,172	45,364	58,163	68,694
$130.00	15,770	31,450	47,121	60,268	71,054
$135.00	16,388	32,730	48,873	62,358	73,393
$140.00	17,014	34,013	50,618	64,434	75,709
$145.00	17,649	35,299	52,357	66,496	78,004
$150.00	18,292	36,587	54,090	68,544	80,279

Unscaled Bank Losses – 69% Recovery

($MM)

	1 Year	2 Years	3 Years	4 Years	5 Years
$5.00	99	98	132	179	228
$10.00	157	177	256	352	446
$15.00	204	252	379	523	659
$20.00	245	326	502	691	866
$25.00	284	401	625	857	1,069
$30.00	321	477	747	1,021	1,268
$35.00	357	553	870	1,184	1,464
$40.00	392	630	993	1,345	1,657
$45.00	427	707	1,115	1,505	1,847
$50.00	461	786	1,238	1,664	2,035
$55.00	496	865	1,360	1,821	2,221
$60.00	531	944	1,482	1,977	2,404
$65.00	566	1,025	1,604	2,132	2,585
$70.00	602	1,106	1,726	2,286	2,764
$75.00	637	1,187	1,848	2,438	2,941
$80.00	673	1,269	1,969	2,590	3,116
$85.00	710	1,352	2,090	2,740	3,290
$90.00	747	1,435	2,211	2,890	3,461
$95.00	784	1,518	2,331	3,038	3,631
$100.00	822	1,602	2,452	3,186	3,799
$105.00	860	1,686	2,571	3,332	3,965
$110.00	899	1,771	2,691	3,477	4,130
$115.00	938	1,856	2,810	3,622	4,293
$120.00	978	1,941	2,929	3,765	4,455
$125.00	1,018	2,027	3,047	3,907	4,615
$130.00	1,059	2,113	3,166	4,049	4,773
$135.00	1,101	2,199	3,283	4,189	4,930
$140.00	1,143	2,285	3,400	4,329	5,086
$145.00	1,186	2,371	3,517	4,467	5,240
$150.00	1,229	2,458	3,634	4,605	5,393

Scaled Bank Losses (Commercial and Industrial) – 69% Recovery

($MM)

	1 Year	2 Years	3 Years	4 Years	5 Years
$5.00	235	233	314	425	540
$10.00	373	419	607	835	1,058
$15.00	484	597	899	1,239	1,561
$20.00	582	774	1,190	1,637	2,053
$25.00	673	952	1,481	2,031	2,534
$30.00	760	1,131	1,772	2,421	3,007
$35.00	845	1,311	2,063	2,807	3,471
$40.00	929	1,493	2,354	3,189	3,929
$45.00	1,012	1,677	2,644	3,569	4,380
$50.00	1,094	1,863	2,935	3,944	4,826
$55.00	1,177	2,050	3,225	4,317	5,265
$60.00	1,259	2,239	3,514	4,687	5,700
$65.00	1,343	2,429	3,804	5,055	6,129
$70.00	1,426	2,621	4,092	5,419	6,553
$75.00	1,511	2,814	4,381	5,781	6,973
$80.00	1,596	3,009	4,668	6,140	7,388
$85.00	1,683	3,205	4,955	6,497	7,799
$90.00	1,770	3,402	5,242	6,851	8,206
$95.00	1,859	3,600	5,528	7,203	8,609
$100.00	1,948	3,799	5,813	7,553	9,007
$105.00	2,039	3,999	6,097	7,900	9,401
$110.00	2,131	4,199	6,380	8,244	9,792
$115.00	2,224	4,401	6,663	8,587	10,179
$120.00	2,319	4,603	6,945	8,927	10,562
$125.00	2,415	4,806	7,226	9,264	10,942
$130.00	2,512	5,009	7,505	9,599	11,317
$135.00	2,610	5,213	7,784	9,932	11,690
$140.00	2,710	5,418	8,062	10,263	12,059
$145.00	2,811	5,622	8,339	10,591	12,424
$150.00	2,914	5,828	8,615	10,918	12,787

Scaled Bank Losses (Commercial, Industrial and Industrial Real Estate) – 69% Recovery

($MM)

	1 Year	2 Years	3 Years	4 Years	5 Years
$5.00	458	454	611	827	1,051
$10.00	727	815	1,182	1,625	2,059
$15.00	941	1,162	1,749	2,411	3,039
$20.00	1,132	1,507	2,316	3,187	3,995
$25.00	1,310	1,852	2,882	3,954	4,932
$30.00	1,480	2,200	3,449	4,712	5,852
$35.00	1,645	2,552	4,015	5,463	6,756
$40.00	1,808	2,906	4,581	6,208	7,647
$45.00	1,969	3,264	5,147	6,945	8,525
$50.00	2,129	3,625	5,712	7,677	9,392
$55.00	2,290	3,990	6,276	8,403	10,248
$60.00	2,451	4,358	6,840	9,123	11,093
$65.00	2,613	4,728	7,403	9,838	11,929
$70.00	2,776	5,102	7,965	10,547	12,755
$75.00	2,941	5,478	8,526	11,251	13,572
$80.00	3,107	5,856	9,086	11,951	14,380
$85.00	3,275	6,237	9,645	12,645	15,180
$90.00	3,445	6,621	10,202	13,335	15,971
$95.00	3,617	7,006	10,758	14,020	16,754
$100.00	3,792	7,393	11,313	14,700	17,530
$105.00	3,968	7,782	11,866	15,375	18,298
$110.00	4,148	8,173	12,418	16,046	19,058
$115.00	4,329	8,565	12,968	16,712	19,811
$120.00	4,513	8,959	13,516	17,373	20,557
$125.00	4,700	9,353	14,063	18,030	21,295
$130.00	4,889	9,749	14,608	18,683	22,027
$135.00	5,080	10,146	15,151	19,331	22,752
$140.00	5,274	10,544	15,692	19,975	23,470
$145.00	5,471	10,943	16,231	20,614	24,181
$150.00	5,670	11,342	16,768	21,249	24,886

APPENDIX E

Losses by Financial Institution

Derivation of Institution Loan Losses

Bank	Losses ($MM)	Loan Base Accounted For ($MM)	Global Loan Base ($MM)	Percentage of American Revenue	American Loan Base ($MM)	Adjusted Losses ($MM)
JP Morgan	681.39	163,590.56	649,583.00	76.08%	494,201.04	2,058.46
Bank of America	601.83	153,507.41	499,335.00	88.36%	441,232.60	1,729.86
Citibank	528.97	108,972.48	387,044.00	48.90%	189,271.17	918.75
Wells Fargo & Co	270.66	104,804.13	347,064.00	100.00%	347,064.00	896.30
US Bancorp	262.98	56,328.65	131,343.00	100.00%	131,343.00	613.20
Comerica Bank	63.32	5,115.85	44,185.00	100.00%	44,185.00	546.91
PNC Bank NA	147.82	51,178.51	167,203.00	100.00%	167,203.00	482.92
Truist	171.15	62,773.03	170,189.00	100.00%	170,189.00	464.03
KeyBank	127.80	20,851.07	69,993.00	100.00%	69,993.00	428.99
Compass Bank	38.59	5,615.59	40,170.40	100.00%	40,170.40	276.06
Goldman Sachs & Co	685.21	107,356.65	64,050.00	61.73%	39,539.66	252.36
Regions Bank	50.62	11,907.12	53,669.00	100.00%	53,669.00	228.16
Huntington Bank	19.53	4,922.03	41,537.00	100.00%	41,537.00	164.80
Fifth Third Bank	96.65	42,173.28	63,182.00	100.00%	63,182.00	144.79
Capital One Bank	18.69	17,302.18	75,780.00	100.00%	75,780.00	81.85
Northern Trust	31.21	6,058.26	15,262.00	71.52%	10,915.15	56.24
Morgan Stanley Bank NA	1.94	5,182.07	103,351.00	72.65%	75,086.97	28.18
Bank of New York Mellon	11.18	4,837.29	18,730.00	63.12%	11,822.36	27.31
Ally Commercial Finance LLC	0.02	360.72	24,324.00	97.96%	23,828.61	1.33

APPENDIX F

Python Code for Calculating Probabilities of Default

```
#Import statements
import numpy as np
import csv
import math
import sqlite3
from scipy.stats import norm
from scipy import optimize
from sympy.solvers import solve
from sympy import Symbol
from sympy import log as sympyLog

#Sets up database access
db = sqlite3.connect("thesis.sqlite")
db.row_factory = sqlite3.Row
cursor = db.cursor()

#Assigns average yearly emissions taxbase. First, checks CDP data to see if
company is included. If not, assigns emissions based on closesest SIC
industry average
def getEmissions(SICCode, ticker, revenue, individualMarketCap):

    #Sets variables
    majorCount = 0
    majorEmissions = 0
    industryCount = 0
    industryEmissions = 0

    #Checks if company is in CDP data
    query = """SELECT AVG(D.Scope1Emissions)
                FROM CDPAccountInfoV2 AI, CDPDataV2 D
                WHERE D.AccountNumber = AI.AccountNumber AND AI.Ticker =
"""+"\""+ticker+"\""+""" AND CAST(D.Scope1Emissions AS INTEGER) >= 0 AND
AI.Country = "United States of America" """
    cursor.execute(query)

    companyEmissions = cursor.fetchall()

    #Returns emissions of company is in CDP data
    if companyEmissions[0][0]!= None:
        print("actual emissions")
        print(SICCode)
        return companyEmissions[0][0]

    #Gets the emissions data for all industries that are in the same SIC
major group (meaning that the first two digits of the SIC code match)
    SICCode2="\""+str(SICCode)[0:2]+"%\""
    query = """SELECT AI.Industry, avg(D.Scope1Emissions)/avg(AI.Revenue) as
CO2ePerRevDollar
                    FROM CDPAccountInfoV2 AI, CDPDataV2 D
                    WHERE AI.AccountNumber = D.AccountNumber AND AI.Industry
<> "(Invalid Identifier)" AND AI.Revenue <> "(Invalid Identifier)" AND
AI.Revenue > 0 AND CAST(D.Scope1Emissions AS INTEGER) >0 AND AI.Industry
LIKE"""+SICCode2+"""
```

```
                    GROUP BY AI.Industry
                    ORDER BY CO2ePerRevDollar DESC"""
    cursor.execute(query)
    emissionsPerDollar = cursor.fetchall()

    #returns 0 if there is no CDP data on the major SIC group
    if len(emissionsPerDollar) == 0:

        print("no match")
        print(SICCode)
        return -1
    for row in emissionsPerDollar:
        SicCode = str(row[0])
        #returns emissions if there is data on the exact 4-digit SIC code
        if int(SicCode) == int(SICCode):
            print("actual industry")
            return row[1]*revenue
        #If there is not data on the exact SIC code, proceeds to calculate
industry/major average
        if SicCode[0:3] == str(SICCode)[0:3]:
            industryCount+=1
            industryEmissions+=row[1]
            continue
        majorCount+=1
        majorEmissions+=row[1]

    #returns emissions if there is data on the 3-digit SIC industry
    if industryCount > 0:
        print("3 digits")
        return industryEmissions*revenue/industryCount
    #returns emissions if there is data on the 2-digit SIC major
    print("2 digits")
    return majorEmissions*revenue/majorCount



def mertonSolver(initAssetVolatility, initAssetValue, companyLiabilities,
riskFreeRate, Time,equityValues,mertonCount, tradingDays, marketCap,
equityVolatility):

    if mertonCount > 50:
        print("fail")
        return -1

    #formulas from Black-Scholes model
    assetValues = []
    for i in equityValues:
        def equations(AssetValue):
            d1 = (np.log(AssetValue[0]/companyLiabilities) +
(riskFreeRate+initAssetVolatility**2/2)*Time)/(initAssetVolatility *
np.sqrt(Time))
            d2 = (np.log(AssetValue[0]/companyLiabilities) +
(riskFreeRate+initAssetVolatility**2/2)*Time)/(initAssetVolatility *
np.sqrt(Time)) - initAssetVolatility * np.sqrt(Time)
            nd1 = norm.cdf(d1)
            nd2 = norm.cdf(d2)
```

```
            equityValue0 = AssetValue[0]*nd1 - np.exp(-
riskFreeRate*Time)*companyLiabilities*nd2
            return abs(i - equityValue0)
        ans = optimize.root(equations, [initAssetValue])
        #print(i+companyLiabilities)
        #print(ans)
        if not ans.success:
            print("failure")
            print(ans.message)
            print("")
            return -1
        assetValues.append(ans.x[0])

    assetReturns = []
    count = 0
    for i in assetValues:
        if count == 0:
            count +=1
            continue
        assetReturns.append(assetValues[count-1]/i)
        count+=1

    lnAssetReturns = []
    count = 0

    for i in assetReturns:
        lnAssetReturns.append(np.log(float(i)))
    newAssetVolatility = np.nanstd(lnAssetReturns)*math.sqrt(tradingDays)

    if (abs(newAssetVolatility - initAssetVolatility) < .001):

        #print("new asset Volatility")
        #print(newAssetVolatility)
        ans = [newAssetVolatility, assetValues[0]]
        return ans
    #print("old asset volatility")
    #print(initAssetVolatility)
    #print("new asset volatility")
    #print(newAssetVolatility)
    mertonCount +=1
    return mertonSolver(newAssetVolatility, assetValues[0],
companyLiabilities, riskFreeRate, Time,equityValues, mertonCount,
tradingDays, marketCap, equityVolatility)



def solvePD(carbonTax, years):

    #array to be returned with results in form [[ticker1, PD1], [ticker2,
PD2], ... [tickerN, PDN]]
    results = []


    #arrays that will hold the standard deviation of natural log of returns
and tickers at the same indexes

    nonZeroMarketCaps = []
```

```
    rawMarketCaps = []
    lnReturns = []
    stdvLnReturns = []
    liabilities = []
    tickers = []
    marketCap = []
    borrowerIDs = []
    sicCodes = []
    revenues = []

    #number of trading days used to calculate yearly volatility
    tradingDays = 252
    riskFreeRate = 0.02
    Time = 1
    minimumTradingDays = 40

    with open('lnEquityReturns_v3.csv') as csv_file:
        #puts tickers in array
        csv_reader = csv.reader(csv_file, delimiter=',')
        count = 0
        for row in csv_reader:
            if row[0]!="" and count>0:
                tickers.append(row[1])

            count+=1

        #takes input of ln returns for 1 year and ads standard deviation to
stdvLnReturns. At this point, daily volatility is in stdvLnReturns
        my_data = np.genfromtxt('lnEquityReturns_v3.csv', delimiter=',')
        for row in my_data:
            if not np.isnan(row[3]):
                rawMarketCaps.append(row[7:-1])
                liabilities.append(row[3])
                marketCap.append(row[4])
                sicCodes.append(row[0])
                revenues.append(row[5])
                borrowerIDs.append(row[6])


        #Gets rid of all days without data
        for row in rawMarketCaps:
            tempArray = []
            for mc in row:
                if mc !=0:
                    tempArray.append(mc)
            nonZeroMarketCaps.append(tempArray)

        #Finds daily ln(returns)
        for row in nonZeroMarketCaps:
            tempArray = []
            count = 0
            for mc in row:
                if count == 0:
                    count +=1
                    continue
                lnRet = np.log(row[count-1]/mc)
                #Handles case if market cap didn't change day-over-day
```

```
                if lnRet != 0:
                    tempArray.append(lnRet)
                count +=1
            lnReturns.append(tempArray)


        # Calculates yearly equity volatility, inputing -1 if there are less
than minimumTradingDays of usable data
        for row in lnReturns:
            if len(row)<minimumTradingDays-1:
                stdvLnReturns.append(-1)
                continue
            stdvLnReturns.append(np.nanstd(row)*math.sqrt(tradingDays))

    count = 0
    zeroliabilities= 0
    for i in stdvLnReturns:

        #Accounts for companies without sufficient data
        #if count > 4:
         #    count+=1
          #   continue
        if i == -1:
            count+=1
            continue
        volatility = i
        ticker = tickers[count]
        revenue = revenues[count]
        equityValue = marketCap[count]
        companyLiabilities = liabilities[count]
        emissions = getEmissions(sicCodes[count], ticker, revenue,
equityValue)
        print(ticker)

        if companyLiabilities == 0 or companyLiabilities == np.nan or
emissions == -1 or revenue == 0:
            zeroliabilities+=1
            count+=1
            continue
        initAssetValue = equityValue+companyLiabilities
        initAssetVolatility = equityValue*volatility/initAssetValue

        if initAssetVolatility == np.nan:
            count+=1
            continue

        mertonOutput = mertonSolver(initAssetVolatility, initAssetValue,
companyLiabilities, riskFreeRate, Time, nonZeroMarketCaps[count], 0,
tradingDays, equityValue, volatility)

        if mertonOutput == -1:
            count+=1
            continue

        assetValue = mertonOutput[1]
        assetVolatility = mertonOutput[0]
        secondRiskFreeRate = 0.08
```

```
        for y in years:
            Time = y
            for tax in carbonTax:
                taxLiability = (emissions*tax/1000000)+
(emissions*tax/1000000)*(Time-1)/2
                if Time == 1:
                    taxLiability = emissions*tax/1000000

                d1 = (np.log(assetValue/(companyLiabilities+taxLiability)) +
(secondRiskFreeRate+assetVolatility**2/2)*Time)/(assetVolatility *
np.sqrt(Time))

                d2 = d1 - assetVolatility * np.sqrt(Time)
                nd1 = norm.cdf(d1)
                nd2 = norm.cdf(d2)

                result = [ticker,tax, y, 1-nd2, borrowerIDs[count],
taxLiability, companyLiabilities, sicCodes[count], emissions]
                results.append(result)
        count+=1
    return(results)
allResults = solvePD([0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65,
70, 75, 80, 85, 90, 95, 100, 105, 110, 115, 120, 125, 130, 135, 140, 145,
150], [1,2,3,4,5])

cursor.execute("""DROP TABLE IF EXISTS preCarbonTaxPDs""")
cursor.execute("""DROP TABLE IF EXISTS postCarbonTaxPDs""")

cursor.execute("""
    CREATE TABLE preCarbonTaxPDs (
    Ticker String,
    carbonTax Int,
    year Int,
    pd Float,
    borrowerCompanyID Int,
    taxLiability Int,
    Liabilities Int,
    sicCode Int,
    emissions Int
    )
""")

for result in allResults:
    cursor.execute("""INSERT INTO preCarbonTaxPDs VALUES (?, ?, ?, ?, ?, ?,
?,?, ?)""", (result[0], result[1], result[2], result[3], result[4],
result[5], result[6], result[7], result[8]))

db.commit()
db.close()
```

APPENDIX G

Derivation of Black Scholes Option Pricing

The Black Scholes option pricing model is a formula for calculating the price of European all options. European call options are contracts that give holders the options to buy an equity at a fixed price (strike price) on a fixed date (exercise date). The general intuition for this model is that such an option should be worth the difference between the share price on the exercise date and the strike price, discounted back to the present. Because the Black Scholes model assumes a risk-free world (meaning that all stocks should grow at the risk-free rate), if all stocks grow at the same rate, the price of the call option should be represented by Formula 1, where c is the price of the call option, S_0 is the current stock price, r is the risk-free rate, t is the time before the exercise date, and k is the strike price. In this model, where all equities grow at the same rate, the price of the option is the maximum of zero and difference between the stock price and discounted strike price.

Formula 1

$$c = Max((S_0 e^{rt} - k)e^{-rt}, 0)$$

Formula 1 can then be simplified as shown in Formula 2.

Formula 2

$$c = Max(S_0 - ke^{-rt}, 0)$$

However, not all equities grow at the same rate, and Formula 2 can be modified to include the possibility some equity values grow at a rate different than the risk-free rate. By introducing uncertainty in equity performance, one can no longer know whether the option holder will pay the strike price or what the equity value will be on the exercise date. Therefore, one must weight ke^{-rt} (the discounted strike price) by the probability that the option will be exercised, and one must weight S_0 (how much the investor expects to get from selling the stock after exercising the option) by the probability that the option is worth less than zero, assuming returns follow a normal distribution. The probability that the option will be exercised (i.e., the probability that the stock will be higher than the strike price) is equal to the cumulative normal function of d_2, as described in Formula 4, and the probability the amount the investor expects to get from selling the call option is equal to the cumulative normal function of d_1, as described in Formula 5. In both these equations, σ is equal to equity volatility.

Formula 3

$$d_1 = \ln\left(\frac{S_0}{k}\right) + \frac{r + \frac{\sigma^2}{2} * t}{\sigma * \sqrt[2]{t}}$$

Formula 4

$$d_2 = d_1 - \sigma * \sqrt[2]{t}$$

Putting Formulas 3 and 4 together with Formula 2, one can derive that the price of a European call option is equal to Formula 5.

Formula 5

$$c = S_0 * N(d_1) - ke^{-rt} * N(d_2)$$

APPENDIX H

Relative Loan Losses

Commercial, Industrial, and Commercial Real Estate Bank Losses as a Percentage of 2020 CCAR Losses – 0% Recovery

(%)

	1 Year	2 Years	3 Years	4 Years	5 Years
$5.00	0.32	0.32	0.43	0.58	0.74
$10.00	0.51	0.57	0.83	1.15	1.45
$15.00	0.66	0.82	1.23	1.70	2.14
$20.00	0.80	1.06	1.63	2.25	2.82
$25.00	0.92	1.31	2.03	2.79	3.48
$30.00	1.04	1.55	2.43	3.32	4.12
$35.00	1.16	1.80	2.83	3.85	4.76
$40.00	1.27	2.05	3.23	4.37	5.39
$45.00	1.39	2.30	3.63	4.89	6.01
$50.00	1.50	2.55	4.02	5.41	6.62
$55.00	1.61	2.81	4.42	5.92	7.22
$60.00	1.73	3.07	4.82	6.43	7.82
$65.00	1.84	3.33	5.22	6.93	8.41
$70.00	1.96	3.59	5.61	7.43	8.99
$75.00	2.07	3.86	6.01	7.93	9.56
$80.00	2.19	4.13	6.40	8.42	10.13
$85.00	2.31	4.39	6.80	8.91	10.70
$90.00	2.43	4.66	7.19	9.40	11.25
$95.00	2.55	4.94	7.58	9.88	11.81
$100.00	2.67	5.21	7.97	10.36	12.35
$105.00	2.80	5.48	8.36	10.83	12.89
$110.00	2.92	5.76	8.75	11.31	13.43
$115.00	3.05	6.04	9.14	11.78	13.96
$120.00	3.18	6.31	9.52	12.24	14.48
$125.00	3.31	6.59	9.91	12.70	15.01
$130.00	3.44	6.87	10.29	13.16	15.52
$135.00	3.58	7.15	10.68	13.62	16.03
$140.00	3.72	7.43	11.06	14.07	16.54
$145.00	3.86	7.71	11.44	14.52	17.04
$150.00	4.00	7.99	11.82	14.97	17.54

Minimum CET1 Ratio Under 2020 CCAR Severely Adverse Scenario with Climate Losses – 0% Recovery, Scaled to Commercial, Industrial, and Commercial Real Estate

(%)

	1 Year	2 Years	3 Years	4 Years	5 Years
$5.00	9.59	9.59	9.59	9.58	9.58
$10.00	9.59	9.59	9.58	9.57	9.56
$15.00	9.58	9.58	9.57	9.56	9.54
$20.00	9.58	9.57	9.56	9.54	9.53
$25.00	9.58	9.57	9.55	9.53	9.51
$30.00	9.57	9.56	9.54	9.51	9.49
$35.00	9.57	9.55	9.53	9.50	9.48
$40.00	9.57	9.55	9.52	9.49	9.46
$45.00	9.56	9.54	9.51	9.47	9.44
$50.00	9.56	9.53	9.50	9.46	9.43
$55.00	9.56	9.53	9.49	9.45	9.41
$60.00	9.56	9.52	9.47	9.43	9.40
$65.00	9.55	9.51	9.46	9.42	9.38
$70.00	9.55	9.51	9.45	9.41	9.37
$75.00	9.55	9.50	9.44	9.39	9.35
$80.00	9.54	9.49	9.43	9.38	9.34
$85.00	9.54	9.49	9.42	9.37	9.32
$90.00	9.54	9.48	9.41	9.36	9.31
$95.00	9.53	9.47	9.40	9.34	9.29
$100.00	9.53	9.46	9.39	9.33	9.28
$105.00	9.53	9.46	9.38	9.32	9.26
$110.00	9.52	9.45	9.37	9.31	9.25
$115.00	9.52	9.44	9.36	9.29	9.24
$120.00	9.52	9.44	9.35	9.28	9.22
$125.00	9.51	9.43	9.34	9.27	9.21
$130.00	9.51	9.42	9.33	9.26	9.20
$135.00	9.51	9.41	9.32	9.25	9.18
$140.00	9.50	9.41	9.31	9.23	9.17
$145.00	9.50	9.40	9.30	9.22	9.16
$150.00	9.50	9.39	9.29	9.21	9.14

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