A contingent claims approach to climate stress testing

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A growing body of literature attempts to understand the impact of climate policies on the value of financial sector assets. Typically, these studies focus at gains and losses on equity instruments, while for banks the majority of their exposures is debt. We calibrate a Merton contingent claims model to assess the impact of adverse asset valuation shocks on the market value of corporate debt and residential mortgages. We then proceed by performing a climate stress test, using detailed exposure data on the Dutch banking sector. We find that carbon tax scenarios ranging between EUR 50-200 per tonne lead to a decline in the market value of banks' assets that is equivalent to 3-70% of their core capital.

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1. Introduction

Studies within the environmental sciences show that there is a substantial gap between Green House Gas (GHG) emission paths that are consistent with keeping global warming well below two degrees Celsius and emissions paths that result from currently implemented and announced climate policies (Rogelj et al., 2016; Rogelj, McCollum, Reisinger, Meinshausen, & Riahi, 2013). In recent years this gap between policy goals and practice has moved central banks and financial supervisors to investigate both the financial risks that are related to a changing climate as well as the financial risks that arise from transitioning towards a low-carbon economy (Campiglio et al., 2018; Nieto, 2019). With respect to the latter class of transitional risks, much more stringent climate policies could be implemented in the future, if governments follow up on their commitments that were made as part of the 2015 Paris Agreement (Monasterolo and Raberto, 2019).

Decarbonizing the economy comes however at an economic cost, at least in the short run (Acemoglu, Aghion, Bursztyn, and Hemous, 2012; Nordhaus, 1992). Depending on policy choices (e.g., the type of climate policy and the distribution of potential tax proceeds) a share of the cost of the transition to a low-carbon economy will likely be borne by owners of financial assets, including banks, insurance companies, and pension funds (Ganapati, Shapiro, and Walker, 2016). For example, higher taxes on GHG emissions can lead to additional costs for firms in GHG-intensive sectors and more rapid write-off of their capital investments, reducing firm's market value and increasing credit risk. These costs can be substantial and range across a wide variety of sectors and asset classes (Leaton, 2011). Estimations on implied prices per tonne of CO2-equivalent (CO2e) emissions to limit global warming to below two degree Celsius with greater than 66 percent probability range between USD 15 to USD 360 in 2030 and USD 45 to USD 1000 in 2050 (Stiglitz et al., 2017).

From a financial sector perspective, a key question is what the potential impact of climate policies is on the balance sheets of financial institutions. It is well understood that carbon pricing can affect the value of firms and, consequentially, the value of financial assets that fund those firms (e.g., Bassen & Rothe, 2009; Scholtens & Van Der Goot, 2014; Smale, Hartley, Hepburn, Ward, & Grubb, 2006). However, it is much less clear what the different channels are that lead to changes in in the value of financial assets, what the functional form is of the relationship between economic and financial variables, and to what extend climate policies can affect the solvency of financial institutions. To this end, several authors have started to explore whether climate policies have the potential to adversely affect the value of financial institutions' balance sheets and, for extreme scenarios, can cause systemic financial crises. For example, Battiston et al. (2017) perform a climate stress test for Eurozone banks, looking at the impact of climate policies on the equity exposures of European banks while allowing for second-round effects (resulting from exposures between financial institutions). Furthermore, a recent paper by Vermeulen et al. (2019) propose a framework for analysing climate-related financial stress that builds on macro-economic stress test methods. This climate-focused work fits into a broader literature on financial sector stress testing (e.g, Gray, Merton, and Bodie, 2007; Henry and Kok, 2013; Upper, 2011).

Our research contributes to the emergent climate stress test literature by explicitly modelling the impact of industry valuation shocks on the value of debt and equity exposures. A typical firm is funded with equity (e.g. shares) and debt (e.g. bonds and loans) which are held by financial institutions and other investors. Senior claims, such as bonds and loans, will only stop paying out promised cash flows when a counterparty defaults (or sometimes as a result of pre-default restructuring).[2] The contingent claims approach in this paper allows us to investigate the effects of carbon taxation on corporate debt (bonds and loans) and residential real-estate (mortgages), in addition to the much better understood effects on equity exposures. This is important since much of the existing literature focuses on equity exposures (often due to lack of suitable data), while the majority of bank assets consist of debt instruments. For example, in the euro area, at least 85% of all banking assets consist of debt, while only 2% is equity (see table 1). Not including the debt valuation channel in impact assessments could hence lead to a substantial underestimation of potential losses.

To investigate the financial channel based on both equity and debt exposures, this paper builds on the option valuation and structural credit risk modelling literature (Black & Scholes, 1973; Merton, 1974). Specifically, we employ the ideas by Merton (1974), who models the structural factors that determine the market value of debt. A key insight in that paper is that equity can be viewed as a residual claim on assets after debt has been repaid. This implies that the equity holder has a call option on the value of the firm's assets, where the payoff is either zero (in case of default) or the value of assets minus the face value of the debt. Conversely, the debt holder has a risk-free bond and is short a put option of the firm's assets. This then implies that a negative asset valuation shock will affect the value of both equity and debt in a non-linear way. The standard Merton (1974) model assumes that default occurs when at maturity the value assets V lies below the face value of debt L. For corporates, this is likely a valid approximation, although some extensions have been proposed to relax this assumption.[3] However, for mortgages, which represent an important asset class for banks, default is more complicated since these types of loans often have additional safeguards build in for the lender. Especially in the euro area, mortgages are common that do not only have recourse to the underlying real-estate, but also to the wealth and income of the borrower. This implies that, in a Merton setting, we need to adjust the default trigger for residential mortgages (Sy, 2014). Hence, for residential mortgages, we take an approach where default is conditional on both insolvency (i.e., the value of the house falling below the value of the mortgage) and delinquency (i.e., not having sufficient liquidity to make the periodical payment on a loan).

[2] Note that, from a market value perspective, adverse asset valuation shocks can affect the market value of debt even without default or restructuring.
[3] For example, Black and Cox (1976) look at the case where restructuring already occurs before V falls below L.

We perform our modelling in two steps. First, we calibrate a Merton contingent claims model to allocate asset valuation losses to junior (equity-like) and senior (debt like) claimholders of the firm. A specific feature of the contingent claims model is that asset valuation losses have an impact on the market value of bonds and loans that increases exponentially as the firm moves closer to insolvency (which is due to the put option that increases in value). We therefore pay specific attention to incorporating variation in the samples that we use for our calibration. For corporate exposures, we disaggregate exposures to a 2-digit NACE sectors and create for each sector a portfolio of representative firms. For residential mortgages, we disaggregate exposures to different types of dwelling (e.g., apartments, terraced houses and detached houses) and create for each type a representative mortgage portfolio based on a loan-level sample of Dutch residential mortgages. Second, we estimate asset valuation shocks per 2-digit NACE sector and per type of real-estate by comparing the impact of the carbon tax to the free cash flows of representative firms and households, which leads to valuation shocks per asset segment (industries and type of dwellings). The outcome of this two-step process is the market value losses per euro exposure for different asset classes (equity, loans and bonds) and per segment.

We then carry out a stress test for which we use detailed corporate and residential mortgage debt and loan data of the Dutch central bank. Data on mortgages are available on loan-level, while loan exposures are used for corporate loan and bond exposures to climate-sensitive industries (based on four-digit NACE codes). We define four tractable scenarios that differ in their severity and likelihood. Our baseline scenarios are all based on the introduction of a EUR 100 carbon tax, which lies well within current estimates of implied carbon prices that are needed to achieve the goals in the 2015 Paris Agreement. We differentiate our scenarios by assuming an either an abrupt (overnight) or smooth (10-year phase-in period) of the tax and by assuming either a regional application (no cost pass-through from firms to consumers) or a global application (50% cost pass-through from firms to consumers). Some of these policy scenarios are severe and perhaps not immediately likely – but not entirely implausible. It will hence serve the purpose of investigating extreme policy scenarios which is a common practice in financial sector stress testing.

Our findings indicate that market value losses can amount to about one eight to one third (13% to 33%) of the available Common Equity Tier 1 (CET1) capital of the Dutch banking system, following an abrupt implementation of a sizeable carbon tax of EUR 100. If a carbon tax is phased-in over a ten-year period, this estimate drops to 6% to 17% of CET1. Total losses for the Dutch banking system range between EUR 7 and 40 billion. These losses can be seen as lower-bound (conservative) estimates, since we do not include second-round effects (e.g., due to increasing unemployment or exposures between financial institutions). By investigating different price levels, we show that market value losses increase exponentially with the size of the carbon tax, which is due to the exponentially increasing market value losses on debt when it asset valuation shocks increase, combined with highly debt based nature of the Dutch banking system.

2. Financial stress test model

In this section we develop the vulnerability model that underlies our stress test. We set out a general approach which we further develop in the subsequent two sections. We also discuss assumptions and possible extensions.

2.1 General set-up

The primary goal of our modelling is to determine the impact of stress scenarios on the value of debt and equity portfolios of banks. This will allow us to estimate stress test coefficients $\vartheta_{E,k}$ that can be applied to equity portfolios and stress test coefficients $\vartheta_{D,k}$ that can be applied to debt portfolios respectively as:

$$\vartheta_{E,k} = \frac{MV_{E,k}{}^{*}}{MV_{E,k}} \text{ and } \vartheta_{D,k} = \frac{MV_{D,k}{}^{*}}{MV_{D,k}} \tag{1}$$

In the above formula MV_k represents the market value of a group of assets *k* (from hereon: segment) that have similar vulnerability characteristics (e.g., carbon intensity) and an asterisk is used to denote the market value after the scenario shock has been applied. Using this definition gives us the fraction of the market value of the portfolio that remains after the stress scenario is applied. Hence, the expected market value loss per unit of exposure can be written as $1 - \vartheta$.[4]

Section 2.2 provides the modelling of $\vartheta_{D,k}$ and $\vartheta_{E,k}$ as functions of a set of calibration parameters Θ_i and an asset value shock ξ_k. For this base ourselves on the Merton (1974) structural credit risk model, which we extend to take into account more complicated default conditions that are characteristic of European mortgages with double recourse. The basic idea is to distribute the asset valuation shock ξ_k to holders of equity (E) and debt (D). This part of the stress test model can hence be viewed as covering the 'financial' or 'right' side of the balance sheet. Since we take the calibration parameters to differ per asset *i* and calculate the stress test coefficients per segment *k*, we sum the outcomes of *n* individual assets making up a segment using a weighting parameter ω_i.

$$\vartheta_{E,k}, \vartheta_{D,k} = \sum_{i=1}^{n} \omega_i * f_{Merton}(\xi_k, \theta_i) \tag{2}$$

[4] Since we are interested in the consequences for the market value of the bank balance sheet, we estimate the expected loss in risk-neutral terms (i.e., the probability of default is adjusted to reflect market participants' risk preferences).

In section 2.3 we put forward a stylized discounted cash flow model to determine a valuation shock ξ_k per segment. We model ξ_k such that it ranges between zero (no losses) and one (full loss of sector value). This can be viewed as the 'real economy' or 'left' side of the balance sheet, representing the value of a physical bundle of assets. We take ξ_k to be a function of the scenario variable $\tau_{k,t}$, which represents the euro tax amount per tonne of CO_2e emissions over time, and a set of vulnerability parameters $\Omega_{k,t}$ which we differentiate per segment *k* and that may vary over time *t*.[5]

$$\xi_k = f(\tau_{k,t}, \Omega_{k,t}) \tag{3}$$

2.2 Merton structural credit risk model

In a standard Merton structural debt framework, the market value of debt MV_D can be written as its risk-free value minus the risk-neutral expected loss (the latter being equivalent to a put option on the value of the assets). Following the notation of Giesecke (2002):

$$MV_D = Le^{-r(T-t)} - Le^{-r(T-t)}\big(N(-d_2)\big) - V_t N(-d_1) \tag{4}$$

with

$$d_1 = \frac{\ln\left(\frac{V_t}{L}\right) + \left(r + \frac{\sigma_V{}^2}{2}\right)(T-t)}{\sigma_V\sqrt{T-t}}$$

$$d_2 = \frac{\ln\left(\frac{V_t}{L}\right) + \left(r - \frac{\sigma_V{}^2}{2}\right)(T-t)}{\sigma_V\sqrt{T-t}}$$

Where N is the probability of the standard normal density function below *d*. Hence MV_D can be expressed as a function of asset value *V*, contracted repayment *L*, time to maturity *T-t*, the standard deviation of asset value σ_V and the risk-free interest rate *r*. Furthermore, under the Merton model's assumptions of geometric Brownian motion, the volatilities of the firm and its equity are given by:

$$\sigma_E = \frac{V}{E} N(d_1)\sigma_V \tag{5}$$

A typical problem that can be solved using these equations is to determine the unobserved value of the firm *V* and the standard deviation of the firm's assets σ_V. For our purposes, however, we will assume an instantaneous shock ξ on asset value such that immediately after the shock asset value V* is given as follows:

[5] Note that all our scenarios assume that the carbon tax applies equally to all segments *k*, hence for our analysis we can suffice by writing τ_t. This is however not a necessity (in practice climate policy often differentiates between industries). Vulnerability parameters in our analysis are the carbon footprint, the capacity to pass-on the carbon tax to consumers, adaptive capability, a sector specific discount rate, and (for mortgages) the probability of delinquency.

$$V^* = (1-\xi)V \tag{6}$$

Which gives the market value of debt after the shock as:

$$MV_D{}^* = Le^{-r(T-t)} - Le^{-r(T-t)}\big(N(-d_2^*)\big) - V_t^* N(-d_1^*) \tag{7}$$

Replacing V^* with $(1-\xi)V$, defining the ratio of contracted repayment to asset value (leverage ratio) as $R = L / V$ and dividing by the discounted exposure $Le^{-r(T-t)}$ we find that:

$$MV_D{}^* = 1 - \big(N(-d_2^*)\big) - ((1-\xi)/Re^{-r(T-t)})N(-d_1^*)$$

with

$$d_1^* = \frac{\ln\left(\frac{(1-\xi)}{R}\right) + \left(r + \frac{\sigma_V{}^2}{2}\right)(T-t)}{\sigma_V\sqrt{(T-t)}} \tag{8}$$

$$d_2^* = \frac{\ln\left(\frac{(1-\xi)}{R}\right) + \left(r - \frac{\sigma_V{}^2}{2}\right)(T-t)}{\sigma_V\sqrt{(T-t)}}$$

Hence,

$$\vartheta_D = \frac{MV_D{}^*}{MV_D} = \frac{1-\big(N(-d_2^*)\big)-((1-\xi)/Re^{-r(T-t)})N(-d_1^*)}{1-\big(N(-d_2)\big)-(1/Re^{-r(T-t)})N(-d_1)} \tag{9}$$

Thus, given a risk-free interest rate r, ϑ_D is a function of the asset valuation shock ξ, the leverage ratio *R*, asset value volatility σ_V and the time to maturity *T-t*. Moreover, equations 5 and 8 can be solved simultaneously in order to determine V and σ_V from E and σ_E. In a similar fashion, the Merton equation for equity is given by:

$$MV_E = V_t N(d_1) - Le^{-r(T-t)}N(d_2) \tag{10}$$

And following the same line of reasoning as for debt, we find that:

$$\vartheta_E = \frac{MV_E{}^*}{MV_E} = \frac{(1-\xi)N(d_1^*) - Re^{-r(T-t)}N(d_2^*)}{N(d_1) - Re^{-r(T-t)}N(d_2)} \tag{11}$$

2.2.1 Model limitations and extension

The Merton (1974) model is based on several assumptions[6], some of which have been challenged in subsequent research. One key assumption is that asset value follows a geometric Brownian motion, which implies that in a short interval of time, asset value can only change by a small amount (Merton, 1976). Several authors have noted that this is inconsistent with empirical observation, namely that in a short interval of time there can be large changes in stock prices or "jumps" (e.g., Cai and Kou, 2011). Moreover, in most industries, there are substantial costs associated with default that are not captured by the Merton model (i.e., the model assumes that there are no specific costs resulting from triggering default). To account for these costs, some authors explicitly introduce recovery values (e.g., Benos and Papanastasopoulos, 2007; Longstaff and Schwartz, 1995). Both of these assumptions in the standard Merton model lead to potentially higher losses as a result of an asset valuation shock, implying that our model is more likely to underestimate potential losses than to overestimate them.

On the other hand, specifically for mortgages, the Merton model may overestimate losses due to the recourse nature of most European mortgages. Recourse entitles the creditor to other household assets besides the value of the secured real-estate, including other assets and future income. In contrast to typical American mortgages, this implies that households are less prone to default on their mortgages in the face of asset valuation losses, even if the value of the real-estate is lower than the value of the mortgage.[7] To account for recourse, we model a more stringent default condition, rewriting equation 7 by dividing by the discounted exposure $Le^{-r(T-t)}$ and multiplying its last term by $N(-d_2)/\,N(-d_2)$:

$$MV_D/Le^{-r(T-t)} = 1 - N(-d_2)(1 - \frac{V_t}{Le^{-r(T-t)}} * \frac{N(-d_1)}{N(-d_2)}) \tag{12}$$

In this equation $N(-d_2)$ is the risk-neutral probability of default and $N(-d_1)/\,N(-d_2)$ is the expected discounted recovery rate (Sy, 2014). For residential mortgages, we can then introduce a more strict default trigger by replacing the Merton probability of default $N(-d_2)$, which could be thought of as representing insolvency, by a more broad probability of default that is a multiplication of $N(-d_2)$ and the probability that a household will not have sufficient wealth and/or income to pay their instalment *P(delinquent)*. In special case where we assume that there is no correlation between $N(-d_2)$ and *P(delinquent)*, equation 12 can then be rewritten as:

$$\frac{MV_D}{Le^{-r(T-t)}} = 1 - N(-d_2) * P(delinquent) * (1 - \frac{V_t}{Le^{-r(T-t)}} * \frac{N(-d_1)}{N(-d_2)}) \tag{13}$$

[6] For a full list of assumptions, see Merton (1974).

[7] We note here that although a mortgage may legally be full-recourse, in practice this full-recourse is not always (fully) applicable. An example is the case of Ireland where in the aftermath of a housing crisis the central bank implemented regulations that severely restricted the ability of banks to contact or harass delinquent borrowers, making the Irish residential mortgages *de facto* limited recourse contracts (Connor and Flavin, 2015).

Which leads to:

$$\vartheta_{D,M} = \frac{MV_D{}^*}{MV_D} = \frac{1-N(-d_2^*)*P(delinquent)^* *(1-(1-\xi)/Re^{-r(T-t)}*N(-d_1^*)/N(-d_2^*))}{1-N(-d_2)*P(delinquent)*(1-1/Re^{-r(T-t)}*N(-d_1)/N(-d_2))} \tag{14}$$

A similar reasoning applies to determine the impact of the market value of the equity portion of mortgage exposures (or in general, exposures where default is triggered by combined but uncorrelated insolvency and delinquency).

2.3 Asset valuation shocks

To determine asset valuation shocks, we take the yearly emissions connected to the segments' physical assets and multiply this by the carbon tax τ_t. The total valuation impact of the tax can then be determined by discounting the cash tax related cash flows, most of which occurring in the future, into a net present value using an appropriate discount rate. Without any response from any of the actors involved (such as adjustments in the production process, the quantity or the price of products and making energy efficiency investments in real-estate), an unanticipated shock in carbon tax rate would lead to a reduction in the value of the bundle of assets that is equal to the present value of the additional (negative) cash flows. Assuming that there are no net tax and funding cost effects, the impact of the tax shock on the net present value of a physical asset or firm can be thought of as follows:

$$NPV_{tax,\,k} = \sum_{t=0}^{T} (1-r_k)^t * \gamma_k(-\tau_t) \tag{15}$$

Of course, it can be expected that firms and households will respond in an attempt to offset the potential loss in their value after a carbon tax is announced. One response that is well-documented in the literature is the pass-through of increasing costs for firms (in this case the carbon tax) into product prices (Fabra and Reguant, 2013; Smale et al., 2006). This increase in price could partially offset the initial tax burden on producers. However, for most goods, an increasing price reduces the size of the market which potentially leads to firms exiting the market or lowering their production volumes.[8] We therefore allow within the asset valuation shock model the possibility that the amount of the tax that is passed on to consumer prices is a function over time, e.g., due to contract renewals after certain periods. Moreover, our model takes into account the possibility that firms and households adjust their physical assets and its use over time, for example by substituting inputs (e.g., green for brown electricity) and by making additional investments (e.g., energy savings technologies and technologies that avoid

[8] Note that this could not only lead to *stranded assets* (e.g., oil reserves and specialized capital goods) as often referred to in the literature, but also *stranded business* (i.e., future earnings that are priced into firm value but are not expected under the new climate policy regime).

atmospheric emissions such as carbon filters). We then arrive at the following expression for the valuation impact on the value of a physical asset or firm as:

$$NPV_{tax,k} = \sum_{t=0}^{T} (1 - r_k)^t * \gamma_{k,t}(1 - \varphi_{k,t})(-\tau_t) \tag{16}$$

In this equation $\varphi_{k,t}$ is the fraction of the tax that can be passed on to customers by increasing prices, which can change over time. $\gamma_{k,t}$ is the sector specific carbon footprint, which we allow to vary over time as a result of input substitution and additional investments in reducing carbon emissions (we hence add a subscript *t*). Finally, we relate the net present value of the tax shock to the total asset value, which gives us the fraction of the total asset value that is lost due to the carbon tax:

$$\xi_k = \frac{NPV_{tax,k}}{Total\ asset\ value} \tag{17}$$

3. Data and calibration

This section describes our data and calibration methods. We first describe the exposure data on the Dutch banking sector for corporate debt and residential mortgage portfolios. We then proceed by calibrating the contingent claims model for both these asset classes, by creating representative portfolios per segment *k* (i.e., per group of assets that have similar vulnerability characteristics). We opt for a representative portfolio approach and not for a representative firm approach since we want to include as much intra-group variability as possible. The reason for this is that the market value of debt declines exponentially when the value of assets declines. Hence using a representative firm approach could result in an underestimation of total market value losses when most exposures are debt-like (which is the case for the banking sector).

3.1. Exposure data

To perform our analysis, we combine two datasets available at the Dutch central bank, which provide exposure data on corporate equity and debt and residential real-estate respectively. These two asset classes combined make up 59% of the balance sheet of the Dutch banking sector (see table 1). Other major asset classes are government loans and debt (11%) and loans and debt to financial institutions (14%). Governments, however, have much more diversified and flexible balance sheets (e.g., due to taxing power) and are hence less likely to experience substantial market value losses on their debt instruments. There may be some governments of specialized economies (such as the oil producing Gulf-states) that may see a decrease in their creditworthiness, however the exposures of the Dutch banking sector to debt of these states is very limited. Financial institutions have low carbon footprints and hence will likely not experience a substantial burden from carbon taxes directly. However, exposure to financial institutions may lead to second-round effects when the market value of financial assets is affected (Battiston, Mandel, Monasterolo, Schütze, and Visentin, 2017)

For corporate loan and debt exposures we use a 2017 dataset on the sectorial classification of the asset holdings of Dutch banks. This dataset was obtained as part of a climate exposure survey and includes the exposures of three largest banks in the Netherlands, which together hold 79% of total assets in the Dutch banking sector. In this dataset, corporate loans and debt are categorized using a 4-digit NACE classification. Moreover, the data provides the remaining maturity of loans and debt per counterparty, which allow us to create a two-dimensional matrix of exposures, according to NACE classification and remaining maturity. For remaining maturity we create three buckets (less than one year, 1-5 years and more than 5 years). To keep the reported data manageable, we focus in the remainder of our analysis on the subset of NACE-industries that we classify as 'transition-sensitive'. We do this by selecting only those industries (at a 2-digit NACE level) that have a carbon intensity of more than 0.5 kg CO2-equivalent emissions per euro of gross operating surplus. Based on this dataset, the largest three Dutch banks have EUR 208 billion worth of assets in transition-sensitive industries, which equals 11.1% of their total assets. See table 2.

For residential real-estate loan exposures we use 2017 loan-level data on residential mortgages available at the Dutch Central Bank. This dataset covers 67% of the mortgages in the Dutch banking sector. In this dataset we categorize loans according to the type of building (e.g., apartment, town-house, detached), so we can link this data to energy use statistics (and hence carbon tax shocks) in a more granular way. Moreover, the data includes, at loan-level, statistics on the loan-to-value (LTV), remaining maturity and the last transaction price of the house. We consider the full set of mortgages to be 'transition-sensitive'.

3.2. Model calibration

We use two different approaches to obtain and estimate the required parameters for the Merton model, respectively for corporate exposures and real-estate exposures. The reason for this is that the structure of the data differs for the two types of portfolios. In our analysis, we take the risk-free interest rate to be constant at 2% and we have remaining maturity buckets available for banks' portfolios (for which we will assume no correlation with the other parameters, which implies a distribution of loan characteristics that is constant over time). We hence still need to obtain parameter values for the yearly standard deviation of asset value (from hereon: asset volatility) σ_V and the leverage ratio R for individual firms and real-estate.

3.1 Corporate exposures

For corporates, our exposure data does not include information on the asset volatility and the leverage of the underlying assets. For this reason, we use a representative portfolio approach, where we take a sample of Dutch firms from the Orbis database by Bureau van Dijk. This database contains balance sheet information on 6,595 Dutch firms in transition-sensitive industries with non-zero long-term debt exposures (which is the balance sheet post where we expect to find most bank loans). Furthermore, the Orbis database provides the same industry classification per firm so we are able to create representative portfolios per 2-digit NACE industry. For each firm, the database provides shareholder equity as a fraction of book value which gives us a reasonable estimate of the market value leverage of each firm (ideally, we would have used the market value of each firm, but since most firms are non-listed we found no good way of doing this). A key further challenge in the calibration process is to estimate the asset volatility of each firm that is part of the representative sample, most of which are non-listed and hence no yearly data is available on market values. To do this, we use data on listed firms for which an estimate of asset volatility can be made based on the observable volatility of its stocks.

Using only listed firms, however, could lead to an underestimation of the asset volatility of the smaller (non-listed) firms that are typically funded by banks. The rationale for this is that a larger balance sheet allows for diversification and hence a lower volatility of total assets. To account for this effect, we set-up a predictive model to estimate the asset volatility based on the characteristics of individual firms, for which data is available within Orbis. Several variants of the model are provided in table 4. The baseline model that we use to explain asset volatility (model 3) includes the logarithm of total assets (as a size indicator), the leverage ratio and the solvability ratio. We also include 2-digit industries and countries as dummy variables. We then use the estimated model to predict the asset volatility of the non-listed firms in our sample. Summary statistics on the sample of firms that we use for our stress test are provided in table 5.

3.2 Real-estate exposures

For real-estate exposures, our data includes all of the data to calibrate the standard Merton model except for the volatility of the value of the underlying real-estate assets. Next to that, we do also obtain an estimate for the probability of delinquency (to account for double recourse).

To estimate the volatility of real-estate assets we use indices of average sales prices that are obtained from the Dutch statistical office (CBS) Statline database. This data provides house price indices from 1995 to 2018 with yearly intervals. For the Netherlands as a whole, the average house price has an annual standard deviation of 6.1% over that period. Since this is an aggregate index, we do however not measure the idiosyncratic component of asset volatility. For this reason, and to obtain a measure for variation in asset volatility, we also look at a set of indices in the same Statline database for the capital cities of the Dutch provinces. The average annual standard deviation of these indices over the 1995-2018 period is 6.6%, with a standard deviation of 1.1%.

To estimate the probability of delinquency, we look at historical default rates on Dutch mortgages. This appears to be a valid approach, since defaults on mortgages in the Netherlands are only triggered in case of (prolonged) delinquency and not in case of insolvency. We take the long-run annual probability of default for the Dutch mortgages to be 0.96% (Stanga, Vlahu, and de Haan, 2017). We multiply this with the time to maturity of individual mortgages to obtain a probability of default over the lifetime of an average mortgage.

4. Climate stress test of the Dutch banking sector

In this section, we define the stress scenarios which we use to determine total market value losses for Dutch banks on their corporate debt and equity portfolios as well as on their mortgage portfolios

4.1 Shock scenarios

We define four baseline stress scenarios, which we all calibrate to be in line with the introduction of a EUR 100 per tonne CO_2e carbon tax. The scenarios differ in the timing of the shock and the extent to which corporates can pass on the carbon tax to consumers by increasing prices. With respect to the timing of the shock, we split the scenarios in two sets of two scenarios. In the first set, the carbon tax is applied overnight. In the other set, we relax this assumption and allow for a phase-in period of 10 years.

With respect to passing on the carbon tax to consumers, we divide both sets based on the amount of pass-through that takes place. This results in two scenarios where there is no pass-through of taxes to consumers. This could, for example, be caused by the limited geographical application of the tax whereby domestic firms cannot increase prices due to international competitive pressure. For the other two scenarios, we assume that most firms can pass-through 50% of taxes to consumers, with more limited pass-through for industries that have strong competition from renewable substitutes. This scenario reflects the situation in which a carbon tax is applied widely, and hence an international level playing field is maintained. The asset valuation shocks per industry are provided in table 6, and underlying assumptions in Appendix table A1.

For all scenarios, we assume that the carbon pricing policy comes on top of the set of climate policies that is already expected (and priced in by the market). We hence assume that the shock is unanticipated. Furthermore, we assume that the introduction of the carbon pricing policy does not affect market expectations about further climate policies to follow (i.e., this is a one-shot fix). This assumption is relevant, since changing expectations could alter the (expected) future asset volatility within industries and could in turn affect the market value of debt. Also, for all scenarios, we assume that the carbon pricing policy is applied to all emissions at their source (e.g., when fossil fuels are burned). We hence focus in our analysis on scope 1 emissions. We do, however, introduce an additional analysis for additional asset valuation shocks in the extractive industries, based on reduced demand for their products. We do this for coal, lignite, oil and natural gas extraction. This set of industry shocks is provided in Appendix table A2.

4.2 Shock calibration

We calibrate our shocks by relating the yearly negative cash flows resulting from the carbon tax to estimates of the yearly cash flows related to the firm or asset. For firms, we do this at an the 2-digit NACE industry level based on the total CO2e emissions and the gross operating surplus for each industry, both of which are supplied by Eurostat. We use the gross operating surplus instead of the gross added value (on the basis of which Eurostat provides their standard carbon intensity variable) since the latter does not account for personnel costs and hence makes an overestimation of the yearly cash flow and thereby the value of the firm. We then estimate the total value of the firm by calculating the value of the perpetuity based on the yearly gross operating surplus. By taking this approach to valuation we make the assumption that profitability within industries remains (on average) constant. We hence may make an overestimation of the impact of the carbon tax for growth industries, while we may underestimate the impact for industries that are shrinking over time in terms of profitability. Finally, we use a 5.5% discount rate in net present value calculations.

For real-estate, we calibrate the asset value shocks for different types of houses. For each category we obtain the average house price and the associated energy use. We then calculate the yearly cost of a EUR 100 carbon tax and relate this to the yearly capital costs, which we calculate based on a mortgage rate of 3% per annum. For the scenarios without cost pass-through we base the taxation costs on the use of natural gas only, since the full burden of the tax for electricity would fall onto the electricity producers. For the scenarios with 50% cost pass-through we base the taxation costs on the sum of the carbon costs of natural gas and 50% of the carbon costs related to the use of electricity.

4.3 Results

Results are shown in table 8. For the four scenarios we find total market value losses for the largest three Dutch banks to range between EUR 6 and EUR 31 billion. When we extrapolate these findings to the whole Dutch banking sector (using a factor of 1.27) [9], this yields losses between EUR 8 and EUR 40 billion. These market value losses are equal to 6.1% to 33.2% of Common Equity Tier-1 (CET1) capital in the Dutch banking sector. The majority of losses stem from losses on the corporate debt and loan portfolio, followed by losses on residential mortgages. Losses on equity exposures are a minor

[9] The largest three Dutch banks cover 79% of the total assets in the Dutch banking sector.

fraction of total losses, which is explained by the limited amount of equity exposures of Dutch banks to equity in transition-sensitive industries.

Additional results are shown in table 8. By looking at the same scenarios with lower (EUR 50) and higher (EUR 200) carbon prices, we investigate the sensitivity of our outcomes to the severity of the policy. We find that the market value losses for the Dutch banking sector increase exponentially with the size of the asset valuation shock. For example, for scenario I we find that at a price level of EUR 50 / tonne total market value losses amount to EUR 7.4 billion. This increases to EUR 39.8 billion for a price level of EUR 100 / tonne and to EUR 83.8 billion for a price level of EUR 200 / tonne. This reflects the specific nature of the Merton model, where the market value of debt is a concave function of the asset valuation shock.

Finally, we perform an additional partial analysis where we investigate stranded assets in the fossil fuel extraction industries (B.05 and B.06). Since the direct (scope 1) emissions of these sectors is limited they do not play a large role in driving the stress test results. However, in case of more stringent climate policies it is highly likely that these sectors are also affected, either by reduced demand or by other types of climate policies. For example, McGlade and Ekins (2015) find that, globally, a third of current oil reserves, half of gas reserves and over 80 percent of coals reserves should remain unused from 2010 to 2050 in order to meet the Paris Agreement target of keeping global warming below two degrees Celsius. Table 9 reports a shock that is in line with these outcomes and the corresponding market value losses to the Dutch banking sector. We find that market value losses amount to EUR 2.1 billion. Note that only the shock for B.06 influences our stress test results, since the largest three Dutch banks have no exposure to the mining of coal and lignite.

5. Conclusion and discussion

Current trajectories of carbon emissions lead to a global warming scenario of three to four degree Celsius. That is well beyond the safe boundary of keeping global warming below two degree Celsius. A sudden tightening of climate policies is therefore possible. Using the Merton methodology to assess the impact of an abrupt carbon tax of EUR 100 per tonne CO2e of emissions on equity- and debt-type assets allow us to calculate the impact on bank assets. Current studies of climate stress tests look primarily at losses on equities and thus underestimate carbon risk.

Our findings indicate that 6% to 32% of the available Common Equity Tier 1 capital of the Dutch banking system is wiped out in first round losses following an abrupt implementation of a sizeable carbon tax of EUR 100, depending on the geographical scope of application and abruptness of the policy. These estimates can be seen as a lower bound, as second-round effects could lead to further losses. Our findings hence suggest that climate policies pose a systemic risk to the financial sector. To mitigate the impact of climate policies, banks may wish to reduce the carbon intensity of their equity and debt portfolio and central banks may include regular carbon stress tests in their macroprudential toolbox (Schoenmaker and Van Tilburg, 2016).

Our analysis has a few important limitations. First, we focus our attention to market valuation effects that are an immediate result of asset valuation shocks. We hence do not account for general-equilibrium effects, such as potentially increasing unemployment, and second-round losses due to exposures between financial institutions. Second, the Merton model assumes no additional costs at bankruptcy and no sudden jumps in asset value. Both these limitations are likely to result in a conservative estimation of total losses, implying that our results are a lower bound estimate of total market value losses in the investigated scenarios. Third, our analysis assumes that, besides the asset value shock, the parameters in the Merton model remain constant. We hence implicitly assume that our scenario shocks do not alter asset value volatility and/or the risk-free interest rate.

Besides these limitations, our scenarios do not include potential valuation changes in industries that are not necessarily carbon intensive but that are dependent of carbon-intensive value chains (such as the traditional, fossil-fuel based, car industry) or that tend to benefit from climate policies (such as renewables and electric car producers). Incorporating the potential valuation shocks to such industries is in our opinion an important avenue for future research.

References

Acemoglu, B. D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The Environment and Directed Technical Change. *American Economic Review*, *102*(1), 131–166.

Bassen, A., & Rothe, S. (2009). Incorporating CO2 risks in valuation practice: A capital market approach for European utilities. *Proceedings of the 32nd IAEE International Conference*.

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). A climate stress-test of the financial system. *Nature Climate Change*, *7*(4), 283–288. https://doi.org/10.1038/nclimate3255

Benos, A., & Papanastasopoulos, G. (2007). Extending the Merton Model: A hybrid approach to assessing credit quality. *Mathematical and Computer Modelling*, *46*(1–2), 47–68. https://doi.org/10.1016/j.mcm.2006.12.012

Black, F., & Cox, J. C. (1976). Valuing corporate securities: some effects of bond indenture provisions. *The Journal of Finance*. https://doi.org/10.1111/j.1540-6261.1976.tb01891.x

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, *81*(3), 637–654.

Cai, N., & Kou, S. G. (2011). Option Pricing Under a Mixed-Exponential Jump Diffusion Model. *Management Science*, *57*(11), 2067–2081. https://doi.org/10.1287/mnsc.1110.1393

Campiglio, E., Dafermos, Y., Monnin, P., Ryan-Collins, J., Schotten, G., & Tanaka, M. (2018). Climate change challenges for central banks and financial regulators. *Nature Climate Change*, *8*(6), 1–13. https://doi.org/10.1038/s41558-018-0175-0

Connor, G., & Flavin, T. (2015). Strategic, unaffordability and dual-trigger default in the Irish mortgage market. *Journal of Housing Economics*, *28*, 59–75. https://doi.org/10.1016/j.jhe.2014.12.003

Fabra, N., & Reguant, M. (2013). Pass-through of emission costs in electricity markets. *American Economic Review*, *104*(9), 2872–2899. https://doi.org/10.1257/aer.104.9.2872

Ganapati, S., Shapiro, J. S., & Walker, R. (2016). Energy Prices, Pass-Through, and Incidence in U.S. Manufacturing. *NBER Working Paper*, (22281).

Giesecke, K. (2003). Credit Risk Modeling and Valuation: An Introduction. *Ssrn*, (607), 1–67. https://doi.org/10.2139/ssrn.479323

Gray, D. F., Merton, R. C., & Bodie, Z. (2007). New Framework for Measuring and Managing Macrofinancial Risk and Financial. *Nber Working Paper Series*, 1–32.

https://doi.org/10.1103/PhysRevB.74.041106

Henry, J., & Kok, C. (2013). A macro stress testing framework for assessing systemic risks in the banking sector. *ECB Occasional Paper Series*.

Leaton, J. (2011). Unburnable Carbon – Are the world' s financial markets carrying a carbon bubble? In *Carbon Tracker Initiative, Investor Watch*. https://doi.org/10.1108/meq.2013.08324eaa.003

Longstaff, F. A., & Schwartz, E. S. (1995). A Simple Approach to Valuing Risky Fixed and Floating Rate Debt. *The Journal of Finance*, *50*(3), 789–819. Retrieved from https://dl-web.dropbox.com/get/Literatur Ilmiah/Keuangan/Risk Premiums/Sovereign/1995 Lonstaff Schwartz JoF.pdf?w=c4013668

McGlade, C., & Ekins, P. (2015). The geographical distribution of fossil fuels unused when limiting global warming to 2 C. *Nature*, *517*(7533), 187.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, *29*(2), 449–470.

Merton, R. C. (1976). Option pricing when underlying stock returns are discontinuous. *Journal of Financial Economics*. https://doi.org/10.1016/0304-405X(76)90022-2

Monasterolo, I., & Raberto, M. (2019). The impact of phasing out fossil fuel subsidies on the low-carbon transition. *Energy Policy*, *124*(June 2018), 355–370. https://doi.org/10.1016/j.enpol.2018.08.051

Nieto, M. J. (2019). Banks, climate risk and financial stability. *Journal of Financial Regulation and Compliance*, *27*(2), 243–262.

Nordhaus, W. D. (1992). An optimal transition path for controlling greenhouse gases. *Science*, *258*(5086), 1315–1319.

Rogelj, J., Den Elzen, M., Höhne, N., Fransen, T., Fekete, H., Winkler, H., … Meinshausen, M. (2016). Paris Agreement climate proposals need a boost to keep warming well below 2 °c. *Nature*, *534*(7609), 631–639. https://doi.org/10.1038/nature18307

Rogelj, J., McCollum, D. L., Reisinger, A., Meinshausen, M., & Riahi, K. (2013). Probabilistic cost estimates for climate change mitigation. *Nature*, *493*(7430), 79–83. https://doi.org/10.1038/nature11787

Schoenmaker, D., & Van Tilburg, R. (2016). Financial Risks and Opportunities in the Time of Climate Change. *Bruegel Policy Brief*, (2). Retrieved from http://www.mejudice.nl/docs/default-source/bronmaterialen/pb-2016_02.pdf%5Cnhttp://aei.pitt.edu/74986/

Scholtens, B., & Van Der Goot, F. (2014). Carbon prices and firms' financial performance: An industry perspective. *Carbon Management*, *5*(5–6), 491–505. https://doi.org/10.1080/20430779.2015.1027862

Smale, R., Hartley, M., Hepburn, C., Ward, J., & Grubb, M. (2006). The impact of CO2emissions trading on firm profits and market prices. *Climate Policy*, *6*(1), 31–48. https://doi.org/10.1080/14693062.2006.9685587

Stanga, I., Vlahu, R., & de Haan, J. (2017). Mortgage Arrears, Regulation and Institutions: Cross-Country Evidence. *Ssrn*, (580). https://doi.org/10.2139/ssrn.3094242

Stiglitz, J., Stern, N., Duan, M., Edenhofer, O., Giraud, G., Heal, G. M., … Pangestu, M. (2017). *Report of the high-level commission on carbon prices*.

Sy, W. N. (2014). A Causal Framework for Credit Default Theory. *Ssrn*, (January 2007). https://doi.org/10.2139/ssrn.2389605

Upper, C. (2011). Simulation methods to assess the danger of contagion in interbank markets. *Journal of Financial Stability*. https://doi.org/10.1016/j.jfs.2010.12.001

Vermeulen, R., Schets, E., Lohuis, M., Kölbl, B., & Jansen, D. (2019). The Heat is on : A framework measuring financial stress under disruptive energy transition scenarios. *DNB Working Paper*, (625).

Table 1 – Aggregate assets in the euro area and Dutch banking sector

This table reports the aggregate balance sheet of banks in the euro area and the Netherlands. The shaded area shows the assets for which we have granular exposure data available and that are in scope of our analysis. These assets together represent 59% of the aggregated balance sheet of the Dutch banking sector. All data is for 2017 and obtained from the ECB Statistical Data Warehouse.

	Euro area		Netherlands	
	EUR trillion	Percentage of total	EUR trillion	Percentage of total
Equity exposures	0.54	2%	0.02	1%
Corporate loans and debt	5.08	23%	0.59	26%
Residential mortgages	3.84	17%	0.74	32%
Consumer loans (non-mortgage household loans)	1.88	8%	0.05	2%
Government loans and debt	2.82	13%	0.25	11%
Financial corporate loans and debt	3.38	15%	0.32	14%
Central bank loans and debt	1.84	8%	0.16	7%
Other	2.91	13%	0.15	7%
Total	22.30	100%	2.28	100%

Table 2 – Carbon footprint and exposures in the corporate loans and debt portfolio

This table reports corporate loan and debt exposure and carbon intensity per industry. For our analysis we focus on a subset of two-digit NACE industries that have carbon footprints higher than 0.5 (we refer to these industries from hereon as *transition-sensitive industries*). Carbon footprint data is based on Eurostat carbon intensity per gross value added and includes emissions of CO2, N2O and NH4 in CO2-equivalents (CO2e). We adjust the Eurostat carbon intensity data to reflect the profitability of industries as close as possible by subtracting personnel costs from gross value added, in order to arrive at carbon emissions per euro gross operating surplus.[10] Exposure amounts are based on a sample of the three largest Dutch banks, covering 79% of the assets in the Dutch banking sector. All figures are for the Netherlands and for 2017. Data is obtained from the Dutch Central Bank (DNB) and Eurostat.

		Carbon footprint (kg CO2e / euro gross operating surplus)	Exposure (EUR million)
A.01	Crop and animal production, hunting and related service activities	2.75	65,793
A.02	Forestry and logging	0.65	2,946
A.03	Fishing and aquaculture	1.39	1,117
B.05	Mining of coal and lignite	0.56*	0
B.06	Extraction of crude petroleum and natural gas	0.56*	11,307
B.07	Mining of metal ores	0.56*	0
B.08	Other mining and quarrying	0.56*	827
B.09	Mining support service activities	0.56*	9,404
C.10	Manufacture of food products	0.71*	26,499
C.11	Manufacture of beverages	0.71*	6,996
C.12	Manufacture of tobacco products	0.71*	1,018
C.17	Manufacture of paper and paper products	1.26	3,546
C.19	Manufacture of coke and refined petroleum products	9.51	7,153
C.20	Manufacture of chemicals and chemical products	3.24	10,109
C.23	Manufacture of other non-metallic mineral products	2.79	3,076
C.24	Manufacture of basic metals	9.75	3,427
D.35	Electricity, gas, steam and air conditioning supply	10.08	20,434
E.37	Sewerage	5.02*	22
E.38	Waste collection, treatment and disposal activities; materials recovery	5.02*	1,778
E.39	Remediation activities and other waste management services	5.02*	134
H.49	Land transport and transport via pipelines	1.56	9,272
H.50	Water transport	3.96	20,932
H.51	Air transport	8.82	2,284

[10] The standard reported carbon intensity by Eurostat is based on gross value added and taken from the Eurostat Structural Business Statistics (SBS). We use the same SBS database to construct carbon intensities based on gross operating surplus instead of based on gross value added. The principle difference between gross value added and gross operating surplus is that the latter includes personnel costs, hence providing a closer approximation of an industry's profitability. Data to make this adjustment is not available for Agriculture, forestry and fishing (A.01 to A.03). For these industries we estimate the carbon intensity based by taking the ratio of gross operating surplus and gross value added from the Dutch national accounts provided by the Dutch Statistical Office (CBS). Not all Eurostat carbon intensity data is available at a 2-digit NACE industry level. Industries for which only a higher level of aggregation is available are denoted with an asterisk (*).

Table 3 – Carbon footprint and exposures in the residential mortgages portfolio

This table reports residential mortgages exposure and carbon footprint per type of dwelling. Exposure amounts are based on a sample of 9 Dutch banks, covering 67% of the total aggregated residential mortgages exposure on the balance sheets of Dutch banks. To calculate the carbon footprint, we use the average natural gas (per M3) and electricity consumption (in kWh) per housing type for 2017 from the Dutch Statistical Office (CBS) Statline database. We combine this data with emission factors of 1.9 kg CO2e/M3 for natural gas and 0.355 kg CO2e/kWh for electricity. For the carbon footprint of electricity, the emission factor accounts for the energy mix in the Netherlands and is taken from CE Delft.[11] The reported carbon intensities are based on annual capital cost which we derive from average sales prices per housing type, also obtained from CBS Statline, assuming a 3% per annum mortgage interest rate (hence multiplying the average sales price by 0.03). We exclude residential mortgage exposure for which there is no classification for the type of dwelling or the type of dwelling is of an uncommon nature (e.g., land-only and bungalows). The omitted exposure equals EUR 18,145 million (3.6% of total reported exposures).

	Carbon footprint (kg CO2e / euro annual capital cost)		Exposure (EUR million)
	Based on natural gas consumption	Based on total energy consumption	
Flat/Apartment	0.25	0.36	65,022
Terraced House	0.31	0.45	51,210
Detached or semi-detached	0.36	0.48	363,103

[11] CE Delft report, *emissiekentallen elektriciteit*, published in 2015 (https://www.ce.nl/publicaties/download/1786)

Table 4 – Model to estimate asset volatility of non-listed firms

This table reports the OLS-regression results for different models to predict the yearly standard deviation of asset value (asset volatility). We base our analysis on a sample of 2,346 listed firms in the EU-15 in transition-sensitive industries, obtained from the Bureau van Dijk Orbis database. All variables except asset volatility are directly taken from the Orbis database. We also obtain for all firms their ISIN code, which we use to obtain the yearly standard deviation of equity value (based on the return index of stock prices between 2006 and 2018) via Thomson Reuters Datastream. We then transform the standard deviation of equity into asset volatility by using the Merton equations as put forward in section 2.2 (i.e., simultaneously solving for equations 5 and 8). We exclude firms for which there are more than 3 missing values in the 12-year period based on which we calculate the standard deviation of equity value. Furthermore, we exclude firms with the 1% largest and smallest values for asset volatility and the 1% of firms with largest leverage. This results in an estimation sample of 1,548 firms. We perform F-tests to confirm the significance of the sets of dummy variables in the full model. The F-statistic for the country dummy variables is 2.15 (prob > F = 0.0077) and for the industry dummy variables 4.20 (prob > F = 0.0000), based on the full model (Model 2). T-values are reported within brackets, *** denotes a significance-level of 1%.

	Model 1	Model 2	Model 3	Model 4
Total assets (natural logarithm)	-0.031*** (-9.54)	-0.016*** (-4.88)	-0.019*** (-6.32)	-0.031*** (-10.02)
Return on assets	-0.000 (-0.30)	-0.001*** (-2.64)	-	-
Leverage ratio	-	-0.502*** (-13,88)	-0.486*** (-13.66)	-
Liquidity ratio	-	0.005*** (3.41)	0.005*** (3.50)	-
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
R-squared	0.26	0.37	0.37	0.26
N	1,532	1,521	1,537	1,548

Table 5 – Corporate loans and debt calibration sample (summary statistics)

This table reports the summary statistics for the sample of firms that we use to calibrate the Merton model. We base ourselves on all firms in the Orbis database that are registered in the Netherlands and that are funded by a non-zero amount of long-term debt (this is the category under which the majority of the bank exposures in our analysis would be accounted for). This results in a sample of 6,595 listed and non-listed firms in transition-sensitive industries. For the non-listed firms, we estimate the standard deviation of assets based on Model 3 as reported in table 4. We use the Winsorization-technique for the 5% lowest and highest predicted values, which results in a range of predicted values for asset variation of individual firms in the sample between 0.05 and 0.49. Note that, in line with the exposures of the largest three Dutch banks, there are no registered Dutch firms in the NACE industries B.05 and B.07 in the Orbis database.

			Standard deviation of assets (estimated based on Model 3)			Leverage		
		N	Mean	Standard deviation	Asset weighted mean	Mean	Standard deviation	Asset weighted mean
A.01	Crop and animal production, hunting and related service activities	2,316	0.23	0.13	0.19	0.56	0.25	0.54
A.02	Forestry and logging	18	0.22	0.15	0.23	0.58	0.27	0.50
A.03	Fishing and aquaculture	102	0.40	0.09	0.36	0.55	0.24	0.47
B.05	Mining of coal and lignite	0	-	-	-	-	-	-
B.06	Extraction of crude petroleum and natural gas	18	0.44	0.08	0.37	0.54	0.34	0.70
B.07	Mining of metal ores	0	-	-	-	-	-	-
B.08	Other mining and quarrying	42	0.43	0.08	0.43	0.61	0.24	0.56
B.09	Mining support service activities	56	0.38	0.11	0.32	0.48	0.26	0.37
C.10	Manufacture of food products	548	0.30	0.11	0.20	0.60	0.23	0.46
C.11	Manufacture of beverages	39	0.20	0.09	0.07	0.59	0.20	0.63
C.12	Manufacture of tobacco products	4	0.23	0.14	0.21	0.52	0.34	0.58
C.17	Manufacture of paper and paper products	107	0.29	0.10	0.16	0.63	0.21	0.70
C.19	Manufacture of coke and refined petroleum products	12	0.22	0.13	0.12	0.64	0.24	0.79
C.20	Manufacture of chemicals and chemical products	200	0.25	0.12	0.17	0.56	0.23	0.53
C.23	Manufacture of other non-metallic mineral products	172	0.26	0.11	0.11	0.63	0.21	0.71
C.24	Manufacture of basic metals	76	0.36	0.10	0.32	0.59	0.22	0.45
D.35	Electricity, gas, steam and air conditioning supply	310	0.24	0.13	0.25	0.74	0.25	0.49
E.37	Sewerage	24	0.23	0.13	0.20	0.57	0.27	0.57
E.38	Waste collection, treatment and disposal activities; materials recovery	235	0.22	0.12	0.17	0.66	0.24	0.63
E.39	Remediation activities and other waste management services	80	0.24	0.13	0.20	0.67	0.24	0.65
H.49	Land transport and transport via pipelines	1,649	0.24	0.11	0.16	0.67	0.21	0.57
H.50	Water transport	574	0.31	0.13	0.28	0.66	0.25	0.63
H.51	Air transport	13	0.26	0.14	0.07	0.68	0.26	0.90

Table 6 – Stress scenarios for firms under a EUR 100 carbon tax

This table reports the asset valuation shocks ξ_k that we use in four different scenarios. All shocks are reported as net present value losses as a fraction of total firm value, using equations 16 and 17. The scenarios differ based on the path of carbon prices τ_t and the share of the tax that firms are assumed to be able to pass-on to consumers $\varphi_{k,t}$. Scenarios I and II reflect the situation where there is no pass-through of costs to consumers (which can be thought of as more regional application, without a level-playing field), while scenarios III and IV reflect the situation where 50% of the cost of the tax are passed on to consumers (which can be thought of as more global application, where a level-playing field is largely maintained). Furthermore, scenarios I and III are based on an overnight application of the tax, which then remains constant at EUR 100 / tonne CO2e. Scenarios II and IV are based on a linear phase-in of the tax over a period of 10 years, after which it remains constant at EUR 100 / tonne CO2e. The assumed industry level adaptation parameters $\gamma_{k,t}$ are provided in Table A1 in the appendix. Carbon emissions are obtained from the Eurostat Air Emissions Accounts (AEA) database, while total asset value is based on the gross operating surplus as obtained from the Eurostat Structural Business Statistics (SBS) Database. All data is for the Netherlands and for 2017.

		I	II	III	IV
A.01	Crop and animal production, hunting and related service activities	0.25	0.18	0.13	0.09
A.02	Forestry and logging	0.06	0.04	0.03	0.02
A.03	Fishing and aquaculture	0.13	0.09	0.07	0.05
B.05	Mining of coal and lignite	0.05	0.04	0.03	0.02
B.06	Extraction of crude petroleum and natural gas	0.05	0.04	0.03	0.02
B.07	Mining of metal ores	0.05	0.04	0.03	0.02
B.08	Other mining and quarrying	0.05	0.04	0.03	0.02
B.09	Mining support service activities	0.05	0.04	0.03	0.02
C.10	Manufacture of food products	0.06	0.05	0.03	0.02
C.11	Manufacture of beverages	0.06	0.05	0.03	0.02
C.12	Manufacture of tobacco products	0.06	0.05	0.03	0.02
C.17	Manufacture of paper and paper products	0.11	0.08	0.06	0.04
C.19	Manufacture of coke and refined petroleum products	0.87	0.64	0.46	0.32
C.20	Manufacture of chemicals and chemical products	0.30	0.22	0.16	0.11
C.23	Manufacture of other non-metallic mineral products	0.25	0.19	0.14	0.09
C.24	Manufacture of basic metals	0.89	0.66	0.48	0.33
D.35	Electricity, gas, steam and air conditioning supply	0.83	0.60	0.64	0.46
E.37	Sewerage	0.46	0.34	0.25	0.17
E.38	Waste collection, treatment and disposal activities; materials recovery	0.46	0.34	0.25	0.17
E.39	Remediation activities and other waste management services	0.46	0.34	0.25	0.17
H.49	Land transport and transport via pipelines	0.14	0.09	0.07	0.05
H.50	Water transport	0.36	0.24	0.18	0.12
H.51	Air transport	0.80	0.59	0.43	0.30

Table 7 – Stress scenarios for residential real-estate under a EUR 100 carbon tax

This table reports the asset valuation shocks ξ_k that we use in four different scenarios. All shocks are reported as net present value losses as a fraction of total real-estate value, using equations 16 and 17. The scenarios differ based on the path of carbon prices τ_t and the amount of the tax that firms are assumed to be able to pass-on to consumers $\varphi_{k,t}$. In the scenarios (I and II) where there is no pass-through of costs to consumers we base the asset valuation shock on the use of natural gas only (since electricity is assumed not to increase in price). In the scenarios (III and IV) where there is 50% pass-through of costs to consumers, we base the asset valuation shock on the total use of energy (natural gas and electricity). Furthermore, scenarios I and III are based on an overnight application of the tax, which then remains constant at EUR 100 / tonne CO2e. Scenarios II and IV are based on a linear phase-in of the tax over a period of 10 years, after which it remains constant at EUR 100 / tonne CO2e. All data is for 2017 and obtained from the Dutch statistical office (CBS).

	I	II	III	IV
Apartment	0.023	0.018	0.028	0.022
Terraced house	0.028	0.022	0.035	0.027
Detached or semi-detached house	0.033	0.026	0.038	0.030

Table 8 – Market value losses under EUR 100 carbon tax scenarios, in EUR million

This table reports the stress test results for our four carbon tax scenarios. Total market value losses are reported for the sample of the three largest banks and extrapolated to the entire Dutch banking sector. The total Common Equity Tier-1 (CET1) capital for the entire Dutch banking sector was EUR 120 billion in 2017. Total assets were EUR 2,381 billion.

EUR 100 / tonne carbon tax	Scenario I • Regional • Abrupt	Scenario II • Regional • Phase-in	Scenario III • Global • Abrupt	Scenario IV • Global • Phase-in
Corporate loans and debt	31,245	15,771	12,364	5,657
Corporate equity	1	0	0	0
Residential mortgages	130	101	155	119
Total (exposure sample)	31,376	15,872	12,519	5,776
Total (market estimate)	39,848	20,157	15,889	7,336
% of CET1 capital	33,2%	16,8%	13,2%	6,1%
% of total assets	1,7%	0,8%	0,7%	0,3%

Table 9 – Market value losses under EUR 50 and EUR 200 carbon tax scenarios, in EUR million

This table reports the stress test results for our four carbon tax scenarios, under different carbon prices. Total market value losses are reported for the sample of the three largest banks and extrapolated to the entire Dutch banking sector. The total Common Equity Tier-1 (CET1) capital for the entire Dutch banking sector was EUR 120 billion in 2017. Total assets were EUR 2,381 billion.

	Scenario I • Regional • Abrupt	Scenario II • Regional • Phase-in	Scenario III • Global • Abrupt	Scenario IV • Global • Phase-in
EUR 50 / tonne carbon tax				
Corporate loans and debt	7,349	3,956	2,893	1,584
Corporate equity	0	0	0	0
Residential mortgages	62	48	73	57
Total (three largest banks)	7,411	4,004	2,966	1,641
Total (market estimate)	9,412	5,085	3,767	2,084
% of CET1 capital	7,8%	4,2%	3,1%	1,7%
% of total assets	0,4%	0,2%	0,2%	0,1%
EUR 200 / tonne carbon tax				
Corporate loans and debt	65,726	48,554	39,633	26,857
Corporate equity	1	1	1	0
Residential mortgages	290	218	351	262
Total (three largest banks)	66,017	48,773	39,985	27,119
Total (market estimate)	83,842	61,942	50,781	31,441
% of CET1 capital	69,9%	51,6%	42,3%	28,7%
% of total assets	3,5%	2,6%	2,1%	1,4%

Appendix

Table A1 – Parameter assumptions for adaptation

This table reports the parameter assumptions for adaptive capacity γ_t over time. For all industries we take a linear reduction of carbon footprint over a period of 5 years. We assume the maximum reduction to be 10% for all industries unless the industry has strong potential for electrification (land and water transport) or strong potential to capture emissions (electric power generation). In those cases, we take adaptation potential to be 20%.

NACE Rev. 2	Industry	Adaptation (γ_t)
A.01	Crop and animal production, hunting and related service activities	10% (5 yr)
A.02	Forestry and logging	10% (5 yr)
A.03	Fishing and aquaculture	10% (5 yr)
B.05	Mining of coal and lignite	10% (5 yr)
B.06	Extraction of crude petroleum and natural gas	10% (5 yr)
B.07	Mining of metal ores	10% (5 yr)
B.08	Other mining and quarrying	10% (5 yr)
B.09	Mining support service activities	10% (5 yr)
C.10	Manufacture of food products	10% (5 yr)
C.11	Manufacture of beverages	10% (5 yr)
C.12	Manufacture of tobacco products	10% (5 yr)
C.17	Manufacture of paper and paper products	10% (5 yr)
C.19	Manufacture of coke and refined petroleum products	10% (5 yr)
C.20	Manufacture of chemicals and chemical products	10% (5 yr)
C.23	Manufacture of other non-metallic mineral products	10% (5 yr)
C.24	Manufacture of basic metals	10% (5 yr)
D.35	Electricity, gas, steam and air conditioning supply	20% (5 yr)
E.37	Sewerage	10% (5 yr)
E.38	Waste collection, treatment and disposal activities; materials recovery	10% (5 yr)
E.39	Remediation activities and other waste management services	10% (5 yr)
H.49	Land transport and transport via pipelines	20% (5 yr)
H.50	Water transport	20% (5 yr)
H.51	Air transport	10% (5 yr)

Table A2 – Stress scenario for unburnable carbon

This table reports asset valuation shocks for the extractive industries (coal, lignite, crude petroleum and natural gas) that are based on the fraction of fossil fuel reserves that cannot be burned if global warming is to be limited to two degrees Celsius, as reported by McGlade and Ekins (2015).[12]

		2-degrees alignment of fossil fuel extraction
B.05	Mining of coal and lignite	0.85
B.061	Extraction of crude petroleum	0.34
B.062	Extraction of natural gas	0.50

Table A3 - Market value losses for the unburnable carbon scenario, in EUR million

This table reports the outcome for a partial stress test based on the shocks presented in table A2.[13] Total market value losses are reported for the sample of the three largest banks and extrapolated to the entire Dutch banking sector. The total Common Equity Tier-1 (CET1) capital for the entire Dutch banking sector was EUR 120 billion in 2017. Total assets were EUR 2,381 billion.

	2-degrees alignment of fossil fuel extraction
Corporate loans and debt	1,680
Total (three largest banks)	1,680
Total (market estimate)	2,134
% of CET1 capital	1,8%
% of total assets	0,1%

[12] We take the average value for scenarios with and without Carbon Capture and Storage (CCS).
[13] Note that our sample does not include any exposure to B.05 (mining of coal and lignite).