A finance approach to climate stress testing*

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Abstract

There is increasing interest in assessing the impact of climate policies on the value of financial sector assets, and consequently on financial stability. Prior studies either take a "black box" macro-financial approach or focus solely on equity instruments – though banks' exposures predominantly consist of debt. We develop a more tractable finance (valuation) approach at the industry-level and use a Merton contingent claims model to assess the impact of a carbon tax shock on the market value of equity and debt instruments. We calibrate our model using detailed firm-level vulnerability data and apply the model to 2-digit sectoral exposures of Dutch banks. We find declines in the market value of banks' assets of 3-14% of core capital for a €100 carbon tax shock, increasing to 9-32% for a €200 carbon tax shock.

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"Changes in climate policies, new technologies and growing physical risks will prompt reassessments of the values of virtually every financial asset."

Mark Carney, Governor of the Bank of England[1]

1. Introduction

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 current climate policies (Rogelj et al., 2018). In recent years, this gap between practice and policy goals has led central banks, financial supervisors, and researchers to investigate the financial risks stemming from climate change ("physical risks") and from transitioning towards a low-carbon economy (Campiglio et al., 2018; Nieto, 2019). The latter "transition risks" may primarily arise if much more stringent climate policies are implemented by governments to follow up on the 2015 Paris Agreement (Batten et al., 2016).

Decarbonizing the economy is expected to come at an economic cost, at least in the short run (Acemoglu et al., 2012; Nordhaus, 1992). Depending on policy choices, some of these costs will likely be borne by owners of financial assets, including banks, insurance companies, and pension funds (Smale et al., 2006; Scholtens and Van Der Goot, 2014). 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 (i.e., "stranded assets"), reducing firms' market values and increasing their credit risk. These costs can be substantial and range across a wide variety of sectors and asset classes (Leaton, 2011). Estimates of the implied price of CO2-equivalent (CO2e) emissions needed to limit global warming to below two degree Celsius range from \$15-\$360 per tonne in 2030 and from \$45-\$1000 per tonne in 2050 (Stiglitz et al., 2017).

[1] Speech at the 2019 Task Force on Climate-related Financial Disclosures TCFD Summit, Tokyo (Oct. 8, 2019).

From the perspective of both financial institutions and regulators concerned with financial stability, a key question is what the potential impact of climate policies is on the solvency and liquidity of banks. Several studies have started to explore how climate policies adversely affect the value of financial institutions' balance sheets and, for extreme scenarios, can cause systemic financial crises (e.g., Battiston, Mandel, Monasterolo, Schütze, and Vistentin, 2017; Vermeulen, Schets, Lohuis, Kölbl, and Jansen, 2019). These studies however either use indirect and generally intractable macro-financial models to determine financial sector impacts or focus exclusively on equity instruments while assuming that the value of certain financial instruments evaporates completely.[2] Especially for banks, it is crucial to understand the effects of climate policies on debt instruments, since the majority of bank assets are subordinated in nature. For example, in the euro area, at least 85% of all banking assets consist of debt, while only 2% is equity (see Table 1, panel A).

Our main contribution to the emerging literature on climate stress testing is two-fold. First, we develop a novel approach to estimate the impact of adverse carbon pricing scenarios on bank solvency. Specifically, we develop a vulnerability model that links carbon tax scenarios to the market value of equity and debt, using a tractable finance (valuation) approach that combines an industry-level discounted cash flow model with a Merton-style structural credit risk model. We do this using a change in industry asset value as the main intermediate variable (instead of more indirectly through macro-economic variables such as GDP and employment). A key advantage of our finance approach to climate stress testing is that it is straightforward to implement and facilitates meaningful discussions about the underlying assumptions. In contrast, the large macro-financial models traditionally used in stress tests are

[2] Macro-financial stress testing typically estimates the impact of scenarios on GDP and other macro-variables first and then uses those variables as inputs into financial risk models (see, for example, Upper, 2011; Henry et al., 2013; Ong, 2014). Results are obtained through several layers of modelling employing a large and complex set of equations, increasing the potential for modelling error and making it harder to intuitively interpret results. Moreover, this approach assumes that changes in macro-economic variables have similar effects on financial sector variables (e.g., non-performing loans), regardless of the cause of the economic shock.

essentially black boxes in the sense that it is hard to trace the outcomes to underlying assumptions and obtain a clear intuition why certain outcomes obtain and how they would vary when assumptions change. We furthermore extend our model to account for recourse, allowing us to incorporate residential mortgages in our analysis. Our second contribution is an illustration of the use of our model by performing a stress test of the Dutch banking sector, based on proprietary and granular loan exposure data obtained from the Dutch Central Bank.[3] We calibrate our model using representative samples of firms aggregated to a 2-digit sectoral level and for mortgages with different types of dwellings as collateral. To our knowledge, we are the first to carry out such a climate stress test using a financial vulnerability model at a sectoral level.

For our analysis, we construct a set of scenarios that are based on an unexpected €100 or €200 carbon tax shock, 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 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 but not implausible. They hence serve the purpose of investigating extreme policy scenarios, which is a common practice in financial sector stress testing (Cihák, 2007).

Our approach consists of two steps, by first estimating shocks in asset value and then allocating those asset value shocks to the holders of equity and debt. In the first step, we estimate asset valuation shocks per 2-digit industry and real estate segment by comparing the negative cash flows of a carbon tax to total asset value. Shocks for firms are calibrated using

[3] To assess the external validity of this empirical analysis, we compare our exposure data for the Netherlands with 1-digit industry exposure data for the euro area as a whole (Table 1, Panel B). Exposures are broadly similar for Dutch banks and euro area banks, however Dutch banks have higher exposures to agriculture (11% for Dutch banks compared to 4% for the euro area) and lower exposure to manufacturing (8% for Dutch banks compared to 14% for the euro area). We thus believe that the results of our analysis are relevant also for the European banking sector as a whole, although naturally caution should be applied in the translation of our results to other contexts.

firm-level carbon emissions data (scope 1) obtained from Trucost and firm-level financial statement data obtained from the Bureau van Dijk Orbis database. We proceed by calibrating the Merton contingent claims model to allocate asset valuation losses to junior (equity-like), and senior (debt-like) claim holders of the asset. We use representative samples from the Orbis database to obtain estimates of leverage and asset volatility for firms by sector. For listed firms, we link these samples to Thomson Reuters Datastream to obtain market estimates for asset volatility. For non-listed firms, we estimate asset value volatility using a cross-sectional regression model. For residential mortgages, we disaggregate exposures to different types of dwellings (i.e., apartments, terraced houses, and detached houses) per loan-to-value (LTV) bucket and per remaining maturity bucket. We also obtain estimates for house price value volatility and the probability of delinquency. With minor exceptions, all our data are for 2017 and 2018.

Our intermediate results show that industries and real estate segments starkly differ in their asset valuation shocks as a result of a carbon tax. For a €100 carbon tax, firm valuation shocks range between minus 3% (0.03) and minus 81% (0.81). Industries that are experiencing the largest decline in asset value are waste collection, treatment and disposal activities (E.38), air transport (H.51), forestry and logging (A.02), the manufacture of basic metals (C.24), and the manufacture of coke and refined petroleum products (C.19). Shocks for these industries range between 0.54 and 0.81 for the most severe scenario and 0.22 and 0.50 for the least severe scenario. For the real-estate segments, asset valuation shocks range between a relatively modest 0.018 and 0.038.

To allocate asset valuation shocks to the holders of equity and debt in the second step of our analysis, we build on the option valuation and structural credit risk modelling literature (Black and Scholes, 1973; Merton, 1974). Specifically, we employ the ideas by Merton (1974), who models the structural factors that determine the market value of debt. Merton's key insight is that equity can be viewed as a residual claim on assets after the 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 the maximum between zero (since a corporation has limited liabilities) and the value of bank's 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. Overall, Merton's contingent claims approach implies that a negative asset valuation shock will affect the value of both equity and debt in a non-linear manner. We modify the standard Merton (1974) model to account for mortgages that have additional safeguards built-in for the lender. Specifically, the traditional Merton model assumes that default occurs when at maturity the value assets V lies below the face value of debt L. For firms, this is likely a valid approximation, although some extensions have been proposed to relax this assumption.[4] However, for mortgages, which represent an important asset class for banks, default is more complicated since these often have additional safeguards built-in for the lender, such as recourse 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. Building on Sy (2014), we take an approach where mortgage 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). Furthermore, we also run our model with additional discontinuous jumps in asset value over time, using a jump diffusion process.

Next, using our calibrated model, we estimate potential market value losses for the banking sector in the Netherlands, for which we use detailed and proprietary exposure data on corporate loans and residential mortgages from the Dutch central bank (DNB).[5] Our exposure dataset includes the three largest banks in the Netherlands that collectively cover 79% of total

[4] For example, Black and Cox (1976) look at the case where restructuring already occurs before V falls below L.
[5] Our data includes residential mortgages from the DNB loan-level database and corporate loan, debt, and equity data that are aggregated to 4-digit NACE sector level. Total assets in the Dutch banking sector were €2,381 billion in 2017.

assets in the Dutch banking sector. We find that, depending on the policy scenario, market value losses range from €3.8 billion to €17.2 billion following the implementation of a carbon tax of €100. In the most severe scenario, in which carbon taxation is applied abruptly and there is no pass-through (e.g., due to regional application of the tax), losses amount to 14% of the available Common Equity Tier 1 (CET1) capital in the Dutch banking system and to 0.7% of total assets. When carbon taxation is instead phased-in over ten years, the losses as fractions of CET1 capital and total assets decline to 8.5% and 0.4%, respectively. For a €200 per tonne carbon tax, the market value losses increase exponentially, ranging from €10.2 billion to €37.9 billion. In the most severe scenario, this equals 31.6% of CET1 capital and to 1.6% of total assets. When carbon taxation is instead phased-in over ten years, the losses as fractions of CET1 capital and total assets decline to 23.3% and 1.2%, respectively.

Our findings furthermore shed light on vulnerable asset classes and sectors. We find that first-order market value losses for Dutch banks are primarily driven by exposures to corporate loans and debt, and to a lesser extent by residential mortgages and equity. Principal reasons for this finding are the low exposures of Dutch banks to equity instruments in carbon-intensive industries (i.e., less than 1% of total assets) and the low net present value of carbon taxes for most types of housing compared to their valuation, combined with recourse to a borrowers income on top of the recourse to the underlying real estate (which puts market value losses on real estate mostly as a burden to households and to a lesser extent on the banking sector). In the €100 carbon tax scenarios, the largest absolute contributions to market value losses are, in declining order, obtained for the manufacture of coke and refined petroleum products (C.19), air transport (H.51), the extraction of crude petroleum and natural gas (B.06), waste collection, treatment and disposal activities (E.38), and electricity, gas, steam and air conditioning supply (D.35). Taken together, these five industries drive between 62% and 48% of the total market value losses, depending on the choice of scenario.

Overall, our results point to the substantial impact that climate-related policies can have on the market value of assets on the balance sheets of banks in the Netherlands. By tractably modelling the vulnerability of financial assets to carbon taxation, our analysis highlights the importance of debt exposures for their contribution to overall losses, and in particular the corporate loans and debt portfolio. In severe scenarios, climate policies may lead to substantial losses in the banking sector and our research, therefore, underlines the importance of adequately addressing the interlinkages between climate policies and financial stability (e.g., steering away from investments in long-term assets that are not compatible with a low carbon economy).

Our study has several important limitations. Chief amongst those is the limited availability of firm-level carbon-related data to calibrate our model. We hence have to make assumptions on relevant parameters and on the representativeness of our samples for all firms in a given industry (e.g., some information is only available for listed and often larger firms). Moreover, our study focuses on the first-order effects of carbon taxation on asset valuation and then on banks. We hence do not account for second-order effects, such as effects on other firms along the value chain or in the rest of the economy (e.g., due to the use of tax proceeds for subsidies and increased demand for low-carbon substitutes).[6] Our outcomes are thus likely conservative. We furthermore rely on several standard assumptions commonly used in financial modelling. We address the latter by conducting a range of sensitivity analyses.

2. Financial vulnerability model

We develop our vulnerability model in two steps, by first estimating shocks in asset value and then allocating those asset value shocks to the holders of equity and debt. We separate the

[6] We partially deal with this issue by separately investigating the impact of phasing out fossil fuel industries (that have little emissions themselves, but are an integral part of the carbon intensive supply chain).

aggregate exposures of banks into equity exposure and debt exposure in groups of assets k (from hereon: segments) that share similar vulnerability characteristics (e.g., carbon intensities). In principle, k can be at the level of an individual firm or any other real economy asset. However, given the vulnerability and exposure data that we have available, we will take k to represent industries (for firms) and real estate of a similar dwelling type. The total market value loss for banks is given by:

$$Total\ market\ value\ loss = \sum_{k=1}^{n} \vartheta_{E,k} * exposure_{E,k} + \vartheta_{D,k} * exposure_{D,k}, \tag{1}$$

with stress test coefficients $\vartheta_{E,k}$ for equity and $\vartheta_{D,k}$ for debt defined as follows:

$$\vartheta_{E,k} = \frac{MV_{E,k}{}^{*}}{MV_{E,k}} \text{ and } \vartheta_{D,k} = \frac{MV_{D,k}{}^{*}}{MV_{D,k}} \tag{2}$$

In the above formula, $MV_{E,k}$ and $MV_{D,k}$ represent the current market value of equity (E) and debt (D) to segment k. An asterisk (*) is used to denote the future market value after the scenario shock has been applied. Using this definition for ϑ 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 $1 - \vartheta$.

Our general modelling strategy is as follows. In section 2.1, we put forward a stylized discounted cash flow model to estimate the 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 (left-hand) side of the corporate 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 CO2e emissions over time, and a set of vulnerability parameters $\Omega_{k,t}$ which we differentiate per segment k and which may vary over time t.[7]

[7] 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 policies often differentiate 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.

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

Section 2.2 sets out the modelling of $\vartheta_{D,k}$ and $\vartheta_{E,k}$ as functions of a set of calibration parameters Θ_k and an asset value shock ξ_k. Here, we follow Merton's (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 (right-hand) side of the corporate balance sheet. For our main analysis we use a representative asset approach, where we take both the asset value shocks and the calibration parameters at segment level k (averaging the calibration parameters Θ for the assets in that segment):

$$\vartheta_{E,k}, \vartheta_{D,k} = f_{Merton}(\xi_k, \theta_k) \tag{4}$$

Additionally, we perform sensitivity analyses where we obtain θ_k on a firm level and aggregating the outcomes to an industry level. We do this to account for non-linear effects of firm-level asset valuation shocks on the market value of equity and debt (which may cause higher or lower estimates of total market value losses depending on the heterogeneity of firms' characteristics within the segment). We also vary the Merton function, f_{Merton}, to include the possibility of discontinuous jumps in asset prices, in line with the Merton (1976) jump diffusion model.

2.1 Asset valuation shocks

To model our asset valuation shocks ξ_k, we start by taking the yearly CO2-equivalent (CO2e) greenhouse gas emissions connected to the segments' activities γ_k (i.e., the segment-specific carbon footprint) and multiply this by the carbon tax τ_t. The total first-order valuation impact of the tax can then be obtained by discounting the tax-related cash flows into a net present value using an appropriate discount rate per segment r_k. Without a response from any of the actors involved (such as adjustments in the production process, the quantity or the price of products and/or making energy efficiency investments in real estate), an unanticipated shock to the 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 effects from other sources, the impact of the carbon tax shock on the net present value of a physical asset or firm can be thought of as follows:

$$NPV_{tax,k} = \sum_{t=0}^{T} (1 - r_k)^t * \gamma_k(-\tau_t) \tag{5}$$

Besides the first-order effects, it can be expected that firms and households respond in an attempt to offset the potential loss in their value after a carbon tax is announced. We account for this in two ways. First, 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, Hartley, Hepburn, Ward, and Grubb, 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] Therefore, in some of our scenarios, we allow for a non-zero amount of pass-through that can change over time (e.g., due to contract renewals after certain periods), denoted by $\varphi_{k,t}$.[9] Second, our model takes into account the possibility that firms and households adjust their physical assets and their use over time, for example by substituting inputs (e.g., green for brown electricity) and by making additional investments

[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).

[9] We will define two sets of scenarios with respect to pass-through. One will assume no pass through, which resembles the situation in which carbon taxation is only applied regionally and there is free trade between regions. In such a case, producers that are taxed are (for most products) expected not to be able to pass on the cost to consumers. Another set will assume 50% pass through, resembling the situation in which the tax is applied more widely and hence inter-regional competition will be less of a constraint to passing on the tax to consumers.

(e.g., energy savings technologies and technologies that avoid atmospheric emissions such as carbon filters). We do this by allowing the carbon intensity per segment γ_k, and thereby the tax burden, to change over time. We hence add a subscript *t*. We then arrive at the following expression for the valuation impact on the value of a physical asset or firm as:

$$NPV_{tax,k} = \sum_{t=0}^{T} (1 - r_k)^t * \gamma_{k,t}(1 - \varphi_{k,t})(-\tau_t) \quad (6)$$

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:

$$\xi_k = \frac{NPV_{tax,k}}{Total\ asset\ value_k} \quad (7)$$

2.2 Market value of equity and debt

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):

$$MV_D = Le^{-r(T-t)} - Le^{-r(T-t)}\big(N(-d_2)\big) - V_t N(-d_1) \quad (8)$$

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, following Jones, Mason and Rosenfeld (1984), under the assumption that asset values follow a geometric Brownian motion, the volatilities of the firm and its equity are given by:

$$\sigma_E = \frac{V}{E} N(d_1)\sigma_V \quad (9)$$

For our purposes, we will assume an instantaneous shock ξ on asset value such that immediately after the shock asset value V^* is given by:

$$V^* = (1 - \xi)V, \tag{10}$$

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

$$MV_D{}^* = Le^{-r(T-t)} - Le^{-r(T-t)}\big(N(-d_2^*)\big) - V_t^* N(-d_1^*) \tag{11}$$

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

$$d_1^* = \frac{\ln\left(\frac{(1-\xi)}{R}\right) + \left(r + \frac{\sigma_V{}^2}{2}\right)(T-t)}{\sigma_V\sqrt{(T-t)}} \tag{12}$$

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

Hence,

$$\vartheta_D = \frac{MV_D{}^*}{MV_D} = \frac{1-\big(N(-d_2^*)\big)-((1-\xi)/Re^{-r(T-t)})N(-d_1^*)}{1-\big(N(-d_2)\big)-(1/Re^{-r(T-t)})N(-d_1)} \tag{13}$$

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 (9) and (12) 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:

$$MV_E = V_t N(d_1) - Le^{-r(T-t)}N(d_2) \tag{14}$$

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

$$\vartheta_E = \frac{MV_E{}^*}{MV_E} = \frac{(1-\xi)N(d_1^*)-Re^{-r(T-t)}N(d_2^*)}{N(d_1)-Re^{-r(T-t)}N(d_2)} \tag{15}$$

2.3 Extension for debt with recourse

Specifically for mortgages, the Merton model may overestimate potential 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 financial 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.[10] To account for recourse, we define a more stringent default condition, rewriting equation (11) by dividing by the discounted exposure $Le^{-r(T-t)}$ and multiplying its last term by $N(-d_2)/\, N(-d_2)$:

$$MV_D/Le^{-r(T-t)} = 1 - N(-d_2)(1 - \frac{V_t}{Le^{-r(T-t)}} * \frac{N(-d_1)}{N(-d_2)}) \tag{16}$$

In this equation, $N(-d_2)$ is the 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 stricter default trigger by replacing the Merton probability of default $N(-d_2)$, which could be thought of as representing insolvency, by a 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)*. As long as there is no correlation between $N(-d_2)$ and *P(delinquent)*, equation (16) can then be rewritten as:

$$\frac{MV_D}{Le^{-r(T-t)}} = 1 - N(-d_2) * P(delinquent) * (1 - \frac{V_t}{Le^{-r(T-t)}} * \frac{N(-d_1)}{N(-d_2)}), \tag{17}$$

which leads to:

$$\vartheta_{D,M} = \frac{MV_D{}^*}{MV_D} = \frac{1 - N(-d_2^*) * P(delinquent)^* * (1 - (1-\xi)/Re^{-r(T-t)} * N(-d_1^*)/N(-d_2^*))}{1 - N(-d_2) * P(delinquent) * (1 - 1/Re^{-r(T-t)} * N(-d_1)/N(-d_2))} \tag{18}$$

[10] 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).

Similar reasoning can be applied 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).

3. Stress test for the Dutch banking sector

We proceed to set and calibrate relevant parameters and perform a stress test of the Dutch banking sector to a set of adverse carbon tax scenarios. To this end we collect data on the exposure of financial institutions to different asset segments (i.e., industries and types of real estate), data on the vulnerability of these segments to a carbon tax (i.e., carbon intensity), and data to calibrate the contingent claims model (e.g., leverage and asset volatility). We start by setting out several carbon tax scenarios. We then describe our data and calibration process in the following three sub-sections. As part of our calibration, we estimate the asset volatility of non-listed firms, which is non-observable and is not our market-based calibration data.

The choice for our data sources is to a large extent driven by the availability of breakdowns that match the segment classification of our exposure data. For corporate exposures, these are industries according to a 2 or 4-digit NACE industry classification, while for mortgages we use a segmentation based on the type of dwelling (e.g., terraced houses, detached houses and apartments). All data is for 2017 or 2018, using the latest available, except the sectorial exposures to equity for which we only have 2016 data available. For corporate exposures, we report outcomes for industries at the 2-digit NACE division with a carbon intensity of more than 50 tonne CO2e / $ revenue. This includes subsectors within agriculture, forestry and fishing (A), mining and quarrying (B), manufacturing (C), electricity, gas, steam and steam conditioning supply (D), water supply, sewerage, waste management and remediation activities (E), and transportation and storage (H). The choice of these industries is in line with other papers (e.g., Battiston et al. 2017; Vermeulen et al. 2019). We refer to this group as "carbon-intensive industries".[11]

3.1 Shock scenarios

We start by defining a set of scenarios which we employ in our stress test. As is common in financial sector stress tests, we aim to investigate a set of scenarios that are severe, but still plausible. We define our scenarios based on three characteristics: the level of the carbon tax (i.e., the price per tonne of CO2e emissions), the timing of the tax (e.g., overnight versus phased-in over time), and the scope of its application (e.g., in a confined region versus globally). The latter reflects the ability of firms to pass on part of the cost of the carbon tax, where regional application limits cost pass-through due to competitive pressures from outside the carbon tax jurisdiction (assuming no adjustments at borders).

For all scenarios, we assume that the carbon tax comes on top of the set of climate policies that are already expected (and priced in by the market). In other words, we 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 segments and could, in turn, affect the market value of debt. Also, for all scenarios, we assume that the carbon tax is applied to all emissions at their source (e.g., when fossil fuels are burned).

To link the scenarios to our model, we relate our scenario assumptions to the parameters in equation (6). Specifically, we vary 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 $\varphi_{k,t}$. For scenarios I and III (overnight application) we set τ_t equal to the level of the carbon tax for all years *t*. For scenarios II and

[11] The full list of carbon-intensive industries can amongst others be found in Table 2.

IV we set τ_t to increase linearly from zero to the level of the carbon tax during the first 10 years, and equal to the level of the carbon tax for all years thereafter. For scenarios I and II we set $\varphi_{k,t}$ to zero for all industries *k* and all time periods *t*. For scenarios III and IV we set $\varphi_{k,t}$ to 0.5 for all industries *k* and all time periods *t* except for the first year in which we assume no pass-through ($\varphi_{k,1} = 0$), hence implying a one-year period before repricing can occur.

For real estate the pass-through parameter $\varphi_{k,t}$ is zero in all cases. However, to ensure consistency in the scenarios, we adjust the taxation costs for households. For the scenarios without cost pass-through (I and II), we base the taxation costs that are linked to real estate 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 (III and IV), we base the taxation costs that are linked to real estate on the sum of the carbon costs of burning natural gas and 50% of the carbon costs related to the use of electricity. In all scenarios, we assume the interest rate r_k to be constant at 2% and the adaptation parameters $\gamma_{k,t}$ to linearly increase from 0% to 10% or 20% over a period of 5 years, the maximum reduction depending on the potential for electrification and the potential to cost-effectively capture emissions.[12] We conservatively 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 abatement potential to be 20%.

To determine shocks per unit of asset value, we first calculate the net present value of the carbon tax (equation 6) and then divide by total asset value (equation 7). For firms, carbon emission data is not available for all entities. We hence base our industry estimates on the average of a sample of firms in the European Union (the region to which Dutch banks have most of their loan exposures). Specifically, we obtain all available firms from the Trucost

[12] Since we lack the data to estimate the adaptation potential over time in all industries, we make conservative assumptions. We also note that the adaptation parameter reflects the net effect of both savings due to lower carbon emissions (i.e., less tax) and additional costs to achieve those savings.

database for which scope 1 carbon emission data is available.[13] We then link this data to the Orbis database from which we obtain a measure of total asset value by taking the sum of the market capitalization and total liabilities and debt (for listed firms) or total assets (for non-listed firms). For the discount rate in the net present value formula, we obtain estimates for the industry specific weighted average cost of capital in Europe.[14]

The resulting asset valuation shocks per segment are provided in Tables 2 and 3. These tables report the asset valuation shocks ξ_k, per segment (rows) and scenario (I to IV, columns). For a €100 carbon tax, firm valuation shocks range between minus 3% (0.03) and minus 81% (0.81). For each industry, shocks are greatest under scenario I (overnight application, no pass-through), followed by scenario III (overnight application, 50% pass-through), scenario II (10 years phase-in, no pass-through, and scenario IV (10 years phase in, 50% pass-through). Industries that are experiencing the highest decline in asset value are waste collection, treatment and disposal activities (E.38), air transport (H.51), forestry and logging (A.02), the manufacture of basic metals (C.24), and the manufacture of coke and refined petroleum products (C.19). Shocks for these industries range between 0.54 and 0.81 for the most severe scenario and 0.22 and 0.50 for the least severe scenario. For the real-estate segments, asset valuation shocks range between a relatively modest 0.018 and 0.038. The greatest asset valuation shocks are observed under scenario III, which for detached or semi-detached houses yields an asset valuation shock of 0.038, followed by terraced houses (0.035) and apartments (0.028). We note that even modest real estate asset valuation losses can result in substantially increased default risk since most households finance their homes with significant leverage.

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[13] We prefer the Trucost data over data provided by Eurostat, since the latter does not provide granular breakdowns to industries. Since the Trucost data is at firm level, we can aggregate scope 1 carbon emissions for firms at a 2-digit NACE level.

[14] http://people.stern.nyu.edu/adamodar/New_Home_Page/datacurrent.html#discrate

3.2 Merton model calibration

To calibrate the Merton model, we need estimates per industry and real estate segment for four parameters: leverage, asset value volatility, remaining time to maturity, and the risk-free interest rate. In addition, for mortgages, we need an estimate of the probability of delinquency. The time to maturity is available as part of our exposure data, providing averages per industry at the 2-digit NACE level and buckets with different times to maturity for mortgages (i.e., 0-5 year, 5-10 year, 10-20 year, 20-30 year, and more than 30 years). Furthermore, loan-to-value (LTV) ratios are available as part of a further breakdown of exposure data for residential real estate, providing the exposure per segment in 10 LTV buckets. These provide an indicator for leverage within mortgage loans. We assume a constant risk-free interest rate of 2% over time and provide results for a 0% interest rate over time in the sensitivity analysis.

To obtain estimates of the leverage per industry, we create a representative sample of firms obtained from the Orbis van Dijk database. Since most of the exposures of the Dutch banking sector are in the Netherlands, we obtain the full sample of Dutch firms that are present within the Orbis van Dijk database and then restrict the sample to those firms that have a non-zero and positive amount of long-term debt (the closest indicator in the database of firms being bank-funded). For all firms, we divide total debt by total assets to obtain a measure of the leverage ratio. Moreover, we obtain, for each firm in the sample, their respective 2-digit NACE industry classification code. This allows us to link the sample data to the exposure data.

The volatility of asset values is not directly observable for most firms in the Orbis van Dijk sample of Dutch firms. For each firm in the sample that is publicly listed, we hence determine the implicit asset value volatility based on the observable volatility of its listed stock. We do this by linking the listed firms in the Orbis van Dijk sample to Thomson Reuters Datastream using their ISIN-codes and obtaining the standard deviation of yearly total equity returns including dividends (computed using the Datastream return index) between 2006 and

2017. We choose this 12-year period to minimize the number of firms for which there is no complete time series available, while still including the variation caused by the global financial crisis in 2007 and 2008. We then transform the standard deviation of equity into implied asset volatility by using the Merton equations in section 2.2 (i.e., simultaneously solving for equations (9) and (12)). We exclude firms for which there are more than three missing values in the 12-year period.

To obtain a measure 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 dataset 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 not measure the idiosyncratic component of asset volatility. For this reason, we also look at a set of house price indices in the same Statline database for the 12 capital cities of the Dutch provinces. The average annual standard deviation of these indices over the 1995-2018 period is 6.6% (with a cross-sectional standard deviation of 1.1% across the 12 cities). We use the 6.6% for our further analysis.

For the probability of delinquency, we base ourselves on the historical default rates on Dutch mortgages. We believe that this provides a sensible estimate since defaults on mortgages in the Netherlands are only triggered in case of (prolonged) delinquency. 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 an estimate of the probability of default over the lifetime of an average mortgage.

3.3 Listed versus non-listed firms

In case of non-listed firms, we cannot observe the standard deviation of yearly total equity returns. Excluding non-listed firms from the sample can be problematic, however, as this will likely lead to sample bias (as non-listed firms are typically smaller, and may make different choices with regards to risk-taking and leverage). Specifically, smaller firms that are typically non-listed may have higher asset volatility than larger firms that are more often listed, due to fewer diversification opportunities within their business boundaries. To obtain an as valid estimate for asset volatility as possible for non-listed firms, we estimate a predictive model for the asset volatility of non-listed firms based on relevant financial and size characteristics that are available within the Orbis database. We first estimate the model using data for listed firms and the used to predict the asset volatility of non-listed firms.

We estimate four models based on a sample of 2,346 listed firms in the EU-15 in carbon-intensive industries, including size, profitability, leverage and liquidity as predictors of asset volatility. All variables except asset volatility are directly obtained from the Orbis database, while asset volatility is obtained via Datastream using the same methodology as for the listed Dutch firms only (described in the previous paragraph). We also include country and industry fixed effects (based on 2-digit NACE industries).

The results for four variants of the OLS-regression are provided in Table 5. For each model, we report the estimated coefficient as well as its t-value. We start with a simple model (model 1) that includes only the natural logarithm of total assets as an explanatory variable, as well as country and industry fixed effects.[15] Total assets are found to be negatively related to asset volatility (-0.031), implying that smaller firms indeed have higher asset volatility than larger firms. This relationship is statistically significant at the p<0.01 level. We then introduce several other potentially relevant variables: the return on assets in model 2 and the leverage and liquidity ratios in model 3. Model 4 provides a full model that includes total assets, return on assets, the leverage ratio and the liquidity ratio. Profitability (i.e., return on assets) is

[15] An F-test confirms the significance of the fixed effects. The F-statistic for the country fixed effects is 2.15 (p-value = 0.0077) and for the industry fixed effects F = 4.20 (p-value = 0.0000).

significant in the full specification (model 4) but does not add substantially to the explained variance – the R^2 of model 4 and model 3 are similar at 0.37, while model 3 is simpler by excluding return on assets. For this reason, we use model 3 as our baseline model to estimate the asset value volatility of the non-listed firms.

Table 6 reports the summary statistics for the standard deviation of assets (for the combined set of listed and non-listed firms) and leverage for each sector. The summary statistics are based on a sample of 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 both listed and non-listed firms in carbon-intensive industries. To exclude outliers, we use the winsorization technique for the 5% lowest and highest predicted values. This results in the standard deviation of assets between 0.17 (E.36 water collection, treatment and supply) and 0.44 (B.06 extraction of crude petroleum and natural gas). With respect to leverage, we find that mean values per industry range between 0.48 (B.09 mining support service activities) and 0.74 (D.35 electricity, gas, steam and air conditioning supply).

3.4 Exposure data

We use two proprietary datasets of the Dutch central bank that provide detailed breakdowns of corporate and residential real estate exposures. Combined, these two asset classes make up 59% of the balance sheet of the Dutch banking sector.[16] For corporate debt exposures, we use a 2017 dataset on the industry classification of the asset holdings of Dutch banks. This dataset is obtained as part of a 2017 climate exposure survey and includes the exposures of the three largest banks in the Netherlands, which together hold 79% of total assets in the Dutch banking

[16] Other major asset classes that are outside the scope of our analysis are government loans and debt (11%) and loans and debt to financial institutions (14%) – see Table 1.

sector. In this dataset, corporate loans and debt are categorized using a 4-digit NACE classification. For each 4-digit NACE class, the dataset provides total exposure and average remaining maturity. For our analysis, we aggregate these exposures to the 2-digit NACE division, in order to match them with Eurostat data on carbon intensity. We calculate the average remaining maturity for each 2-digit NACE division based on the exposure-weighted average remaining maturity. For equity exposures, we use a dataset on the sectorial classification of debt and equity, which was part of a 2016 survey on climate-related exposures. This dataset includes the same set of banks as the 2017 data.

Based on these datasets, the largest three Dutch banks hold €208 billion worth of corporate debt and equity in carbon-intensive industries, which equals 11.1% of their total assets. Looking at the 2-digit NACE sectors in carbon-intensive industries, the largest three Dutch banks have, in declining order, the highest exposure to agriculture (A.01), water transport (H.50), electricity, gas, steam and air conditioning supply (D.35), the extraction of crude petroleum and natural gas (B.06), and the manufacture of chemicals and chemical products (C.20). Further details are provided in table 4.

For residential real estate loan exposures, we use 2017 loan-level data on residential mortgages from the Dutch Central Bank. This dataset covers 67% of the mortgages in the Dutch banking sector. In this dataset, we segment loans according to the type of building (e.g., apartment, town-house, detached). The database includes, at loan-level, the loan-to-value (LTV), remaining maturity, and the last transaction price of the house. The total exposure in the dataset is €497 billion, which equals 32% of total assets in the Dutch banking sector. With respect to residential real estate, the majority of the exposure consists of detached or semi-detached houses which make up about three quarters (76%) of the total residential real estate portfolio. For a full summary of this data, see table 4.

4. Results

Our main results are shown in Table 8. This table reports the stress test results for our four carbon tax scenarios, at two carbon tax levels: €100 / tonne, and €200 / tonne. We report both the market value losses for the sample of the three largest Dutch banks, as well as an extrapolation based on market share for the entire Dutch banking sector.[17] The table also presents the market value losses per major asset class, including corporate loans and debt, corporate equity, and residential mortgages. Finally, the table reports the market value as fractions of total Common Equity Tier 1 (CET1) capital in the Dutch banking sector and the total assets in the Dutch banking sector.

From the table, we distil two main findings. First, for the main estimates for a €100 per tonne carbon tax, total market value losses for the whole Dutch banking system range between €3.8 billion and €17.2 billion, depending on policy choices made. In the most severe scenario (I), in which carbon taxation is applied abruptly, and there is no pass-through (e.g., due to regional application), losses amount to 14.3% of CET1 capital and to 0.7% of total assets. When carbon taxation is instead phased-in over ten years (scenario II), losses as fractions of CET1 capital and total assets decline to 8.5% and 0.4%, respectively. When carbon taxation is applied abruptly and allowing for 50% pass-through (scenario III), losses as fractions of CET1 capital and total assets are 5.5% and 0.3%. Finally, for the least severe scenario (IV), in which carbon taxation is phased-in over ten years and allowing for 50% pass-through, losses as fractions of CET1 capital and total assets are 3.2% and 0.2%. These losses are substantial: comparing outcomes to regular stress test exercises by financial regulators, we find that the market value loss under the most severe policy assumptions (scenario I) is of the same order of magnitude (15-20%) as the impact on CET1 capital in the most severe scenarios employed

[17] Using a factor of 1.27. The largest three Dutch banks cover 79% of the total assets in the Dutch banking sector. The total Common Equity Tier 1 (CET1) capital for the entire Dutch banking sector was €120 billion in 2017. Total assets were €2,381 billion.

in regular financial sector stress testing. For example, the 2018 stress test by the European Banking Authority (EBA) found that, on aggregate, the CET1 capital of EU banks declines by 19.2% in their adverse scenario, while the EBA also stated that the 2018 stress test was more severe than any previous EU-wide exercise.[18] Additionally, the 2019 stress test by the Federal Reserve found that, on aggregate, the Tier 1 leverage ratio of US banks declines by 19.8% in their severely adverse scenario.[19]

Second, losses for the Dutch banking sector are primarily driven by exposures to corporate loans and debt. In the €100 carbon tax scenarios, the fraction of losses that are driven by residential mortgages and equity is only between 1% and 2% of total losses. Principal reasons for this finding are the low exposures of Dutch banks to equity instruments in carbon-intensive industries (i.e., less than 1% of total assets) and the low net present value of carbon taxes for most types of housing compared to their valuation, combined with recourse to a borrower's income next to recourse to the underlying real estate (which puts market value losses of real estate mostly as a burden to households and not to the banking sector). Looking at the corporate loans and debt exposure in more detail, the majority of losses for our €100 / tonne estimates are driven, in declining order, by exposure to the manufacture of coke and refined petroleum products (C.19), air transport (H.51), the extraction of crude petroleum and natural gas (B.06), waste collection, treatment and disposal activities (E.38), and electricity, gas, steam and air conditioning supply (D.35). Together, these five industries drive between 46% and 60% of total market value losses in the corporate and mortgage portfolios across the

[18] https://eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing/2018. In the adverse scenario, the fully loaded CET1 capital declines from 1,176 billion to 950 billion, which is equivalent to a decline of 19.2%. Key features of the adverse scenario of the EBA 2018 stress test were: a cumulative fall in GDP over 3 years by 2.7%, unemployment reaching 9.7% in 2020, cumulative inflation over 3 years standing at 1.7%, and a cumulative fall in residential and commercial real estate prices over 3 years of 19.1% and 20% respectively.

[19] https://www.federalreserve.gov/publications/files/2019-dfast-results-20190621.pdf. In the adversely severe scenario the Tier 1 leverage ratio declines from 8.6% to 6.9%, which is equivalent to a decline in CET1 capital of 19.8% if other liabilities are constant. The scenario assumes a global recession with the U.S. employment rate rising by more than 6 percentage points to 10 percent, accompanied by a large decline in real estate prices (-25% for house prices and -35% for commercial real estate) and elevated stress in corporate loan markets.

four scenarios. The market value losses for all sectors are reported at a 2-digit NACE aggregation level in Table 9.

Besides our main results, we provide the results for a specific scenario that estimates the market value losses for the Dutch banking sector in case a major share of fossil fuel assets becomes stranded. To this end, we perform an additional analysis where we investigate stranded assets in the fossil fuel extraction industries covering coal, lignite, oil and natural gas extraction (B.05 and B.06). Since the direct (scope 1) emissions of these sectors are limited, they do not play a large role in driving the main 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 the gas reserves and over 80 per cent of coal reserves should remain unused from 2010 to 2050 in order to meet the Paris Agreement target of keeping global warming below two degrees Celsius. We use these estimates for our industry valuation shocks as reported in Table 7: 0.85 for the mining of coal and lignite (B.05), 0.34 for the extraction of crude petroleum (B.061), and 0.50 for the extraction of natural gas (B.062). Results are reported in Table 10. We find that market value losses for this specific scenario amount to €2.1 billion. This equals 1.8% of total CET1 capital in the Dutch banking sector and 0.1% of total assets. Hence an unburnable carbon scenario alone does not seem to affect the Dutch banking sector severely.

5. Sensitivity analysis

We test the sensitivity of the outcomes of our stress test to changes in key assumptions. Table 11 presents the outcomes of our €100 carbon tax scenarios, based on alternative assumptions relating to the risk-free interest rate, the ease with which firms can adapt to the carbon tax (e.g., by investing in carbon abatement technologies), allowing for firm-level variation in leverage and asset volatility (instead of taking the average leverage and asset volatility for the entire industry), and by allowing discontinuous jumps in asset value based on Merton (1976). The first two represent parameters in our modelling that are relatively hard to determine, either because they are not known yet (i.e., the future risk-free interest rate) or because the estimates of the parameters are not readily available (i.e., the industry-specific abatement curves that determine the rate with which firms can reduce their carbon footprint γ_t). The latter two represent refinements of our modelling.

The first panel (A) of Table 11 reports outcomes based on a risk-free interest rate that is constant over time at a rate of 0%, instead of 2% which is assumed in our main analysis. This assumption reflects a ‘low-for-long’ scenarios with respect to risk-free interest rates in the euro area. We find that lowering the risk-free interest rate to 0% increases the market value losses in all four scenarios; however, not to the same extent. Losses as a fraction of CET1-capital are 16.7% (scenario I), 10.4% (scenario II), 7.5% (scenario III), and 4.6% (scenario IV). These represent increases over the baseline scenario of 16.4%, 22.5%, 35.0%, and 45.3%, respectively. These increases are, to a large extent, driven by market value losses for residential mortgages, and is primarily due to their relatively long duration *k*.

The second panel (B) of Table 11 reports outcomes based on an increased ability of firms to cost-effectively reduce their carbon footprint. Specifically, we double the adaptation parameters. This results in adaptation parameters between 20% and 40%, depending on the potential for electrification and the potential to capture emissions. We find that increasing the ability to reduce carbon footprints decreases the market value losses for banks. Losses as a fraction of CET1-capital are 13.7% (scenario I), 8.3% (scenario II), 5.1% (scenario III), and 3.0% (scenario IV). These represent decreases over the baseline scenario of 4.1%, 2.5%, 7.7%, and 5.7%, respectively.

The third panel (C) of Table 11 reports the outcomes where we introduce firm-level variation in leverage and asset volatility in the corporate loan portfolio. One challenge to our results is that we employ a "representative firm" approach, by defining average parameter values for leverage and asset volatility per industry (e.g., a 2-digit NACE industry). To check whether this has a substantial impact on results, we estimate our model for each of the 6,595 firms in our sample individually. These include 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 (which is the category under which the majority of bank lending would be accounted for). We estimate an asset valuation shock for each of these firms, and then aggregate these shocks by taking the long-term debt weighted average for all firms within an industry. We find that this approach increases the market value losses for banks. Losses as a fraction of CET1-capital are 15.9% (scenario I), 9.6% (scenario II), 6.2% (scenario III), and 3.6% (scenario IV). These represent increases over the baseline scenario of 11.1, 13.1%, 12.1%, and 13.3%, respectively. We thus show that a representative firm approach may underestimate shocks in a Merton setting, albeit to a limited extend.

Finally, the fourth panel (D) of Table 11 reports the outcomes when allowing for sudden adjustments in asset value based on the Merton Jump Diffusion (MJD) model. One key assumption in the Merton (1974) model 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. 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" when new information becomes available to market participants (e.g., Cai and Kou, 2011). The standard Merton (1974) hence does not account for other jumps in asset value that stem from other sources, which means that it likely overestimates the market value of debt. We hence include two different calibrations for the Merton (1976) jump diffusion model, which allows for discontinuous jumps in asset value. Calibration parameters for the MJD model are obtained from Zhou (2001) and Wong and Li (2006) and are adjusted to account for the lower volatility of total assets compared to equity (using a factor 0.4 for the jump mean and standard deviation). For relatively infrequent but large jumps, based on Zhou (2001), we find that outcomes are only marginally higher compared to results obtained under the standard Merton (1974) model. Total estimated losses on corporate loans and debt are between €25 million and €36 million higher depending on the scenario. This represents an increase of total losses between 0.3% and 0.9%. For more frequent but smaller jumps, based on Wong and Li (2006), we find that outcomes differ more substantially, with estimated losses on corporate loans and debt being €984 million and €1,551 million higher depending on the scenario. This represents an increase of total losses between 10.3% and 28.0%.

5. Conclusion and discussion

Current trajectories of carbon emissions could potentially lead to a global warming scenario of three to four degree Celsius (Rogelj et al., 2013). That is well beyond the safe boundary of keeping global warming below two degrees Celsius. A sudden tightening of climate policies is therefore possible. Using the Merton methodology to assess the impact of the introduction of a carbon tax on equity- and debt-type assets allows us to calculate the impact on bank assets. Current studies of climate stress tests that take an industry-level approach look primarily at losses on equities and thus underestimate carbon risk, while macro-econometric approaches are intractable and rely on strong assumptions regarding GDP channels. Overall, our results point to the substantial impact that climate-related policies can have on the market value of assets on the balance sheets of banks. We find that 3.8% to 29.9% of the available Common Equity Tier 1 (CET1) capital of the Dutch banking system is wiped out in first-round losses following the implementation of a sizeable carbon tax of €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. Moreover, first-round losses increase exponentially with the size of the carbon tax. A carbon tax of €200 leads to first-round losses of 14.9% to 62.6% of the available CET1 capital of the Dutch banking system.

Our findings are relevant to macro-prudential supervisors, micro-prudential supervisors, and other financial sector participants. For macro-prudential supervisors, our results show that strong carbon pricing policies have the potential to substantially alter the market value of a broad range of assets on banks' balance sheets. This is in line with previous findings in Battiston et al. (2017) and Vermeulen et al. (2019). As a consequence, from a systemic mandate, macro-prudential authorities may wish to engage in an ongoing dialogue with climate policymakers in order to achieve orderly decarbonization of the economy. For micro-prudential supervisors, our results point to those assets and industries that are of a heightened risk of losing their value in an energy transition. This could have implications for the risk scoring of individual financial institutions that are, to a greater extent, exposed to these industries (e.g., specialized banks such as agricultural banks). And finally, our results have implications for financial institutions in their assessment and pricing of transition-related financial risks. In particular, it provides estimates of market value losses in the tail-end of the distribution. This can help financial institutions set risk limits, and could provide input into their loan origination, investment, and pricing decisions.

Our study has several important limitations. Chief amongst them is the limited availability of carbon-related firm-level data to calibrate our model.[20] We hence have to make some assumptions on relevant parameters and on the representativeness of our samples for all firms in a given industry (e.g., some information is only available for listed and often larger

[20] Specifically, we identify three main data gaps: (1) carbon emission data for smaller – mostly non-listed – firms, (2) data on the adaptive capabilities of firms and sectors (i.e., the possibility of firms to cost-effectively reduce their carbon emissions) and, (3) data on the vulnerability to carbon taxes of firms in the value chain.

firms). Furthermore, we focus on market value effects that are an immediate result of asset valuation shocks. We hence do not account for general-equilibrium effects, such as potentially increasing unemployment, as well as other second-round losses due to exposures between financial institutions. Also, our scenarios do not include potential valuation changes in industries that are not necessarily carbon intensive but that are dependent on 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 view, an important avenue for future research. Finally, we rely on several standard assumptions commonly used in financial modelling. We address the latter by conducting a range of sensitivity analyses.

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

This table reports the aggregate balance sheet (panel A) and sectoral breakdown of corporate loans and debt (panel B) of banks in the euro area and the Netherlands. The shaded area shows the exposure data on which we base our stress test, detailed in Table 4. All other data is for 2019 and obtained from the ECB Statistical Data Warehouse.

	Euro area		Netherlands	
	€ trillion	Percentage of total	€ trillion	Percentage of total
(A) Aggregate balance sheet				
Equity	0.45	2%	0.02	1%
Corporate loans and debt	5.63	24%	0.60	26%
Residential mortgages	4.24	18%	0.75	32%
Consumer loans (non-mortgage household loans)	2.14	9%	0.05	2%
Government loans and debt	2.87	12%	0.25	11%
Financial corporate loans and debt	3.08	13%	0.30	13%
Central bank loans and debt	1.77	7%	0.18	8%
Other	3.60	15%	0.18	8%
Total	23.77	100%	2.33	100%
(B) Sectoral breakdown of corporate loans and debt				
A - Agriculture, forestry and fishing	0.19	4%	0.03	11%
B - Mining and quarrying	0.02	0%	0.00	0%
C - Manufacturing	0.63	14%	0.03	8%
D, E - Electricity, gas, water, and waste	0.23	5%	0.01	2%
F - Construction	0.31	7%	0.01	3%
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	0.57	13%	0.04	12%
H, J - Transportation and storage; information and communication	0.37	8%	0.01	4%
I - Accommodation and food service activities	0.15	3%	0.00	2%
L, M, N - Real estate; professional activities; administrative and support service activities	1.68	38%	0.12	38%
Other	0.31	7%	0.06	19%
Total	4.46	100%	0.30	100%

Table 2 – Estimated asset valuation shocks by industry for the €100 carbon tax scenario

This table reports the asset valuation shocks ξ_k aggregated by industry in four different scenarios. All shocks are reported as net present value losses as a fraction of total firm value, using equations (6) and (7). 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 is passed through 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 €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 €100 / tonne CO2e. Firm-level carbon emissions are obtained from Trucost's Environmental Register for a sample of 793 firms in Europe, which we match the Bureau van Dijk Orbis Database from which we obtain a measure of total asset value by taking the sum of the market capitalization and total liabilities and debt (for listed firms) or total assets (for non-listed firms). For the discount rate in the net present value formula, we obtain estimates for the industry specific weighted average cost of capital in Europe from the website of Aswath Damodaran at NYU Stern (http://people.stern.nyu.edu/adamodar/New_Home_Page/datacurrent.html). We aggregate the firm-level data to industries using a weighted average by total assets.

		I	II	III	IV
A.01	Crop and animal production, hunting and related service activities	0.15	0.12	0.08	0.06
A.02	Forestry and logging	0.66	0.49	0.35	0.24
B.05	Mining of coal and lignite	0.05	0.04	0.03	0.02
B.06	Extraction of crude petroleum and natural gas	0.31	0.22	0.16	0.11
B.07	Mining of metal ores	0.19	0.13	0.10	0.06
B.08	Other mining and quarrying	0.26	0.18	0.14	0.09
B.09	Mining support service activities	0.30	0.21	0.16	0.11
C.16	Manufacture of wood and of products of wood and cork	0.08	0.05	0.04	0.03
C.17	Manufacture of paper and paper products	0.13	0.10	0.07	0.05
C.19	Manufacture of coke and refined petroleum products	0.54	0.40	0.32	0.22
C.20	Manufacture of chemicals and chemical products	0.18	0.14	0.11	0.08
C.23	Manufacture of other non-metallic mineral products	0.54	0.47	0.42	0.35
C.24	Manufacture of basic metals	0.60	0.56	0.54	0.50
D.35	Electricity, gas, steam and air conditioning supply	0.35	0.27	0.21	0.16
E.36	Water collection, treatment and supply	0.51	0.39	0.27	0.19
E.38	Waste collection, treatment and disposal activities	0.81	0.58	0.43	0.29
H.49	Land transport and transport via pipelines	0.11	0.09	0.07	0.05
H.50	Water transport	0.20	0.15	0.11	0.08
H.51	Air transport	0.74	0.52	0.39	0.26

Table 3 – Estimated asset valuation shocks for residential real estate for the €100 carbon tax scenario

This table reports the asset valuation shocks ξ_k estimated for residential real estate in four different scenarios. All shocks are reported as net present value losses as a fraction of total real estate value, using equations (6) and (7). 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 €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 €100 / tonne CO2e. To calculate carbon emissions, we use the average natural gas (per M3) and electricity consumption (in kWh) per housing type. We combine these data with emission factors of 1.9 kg CO2e/M3 for natural gas and 0.355 kg CO2e/kWh for electricity. We assume a mortgage interest rate of 3%. All data is for 2017 and obtained from Dutch Statistical Office (CBS) Statline and 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 4 – Banking sector exposures to corporate debt, corporate equity and residential mortgages

This table reports exposures per industry and type of residential mortgage. For firms, exposure amounts (both debt and equity) are obtained from a sample of the three largest Dutch banks, covering 79% of the assets in the Dutch banking sector. Exposure amounts for mortgages 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. 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 €18,145 million (3.6% of total reported exposures). All figures are for the Netherlands and for 2017. Data is obtained from the Dutch central bank (DNB).

		Loan and debt exposure (€ million)	Equity exposure (€ million)
A.01	Crop and animal production, hunting and related service activities	65,793	-
A.02	Forestry and logging	2,946	-
B.05	Mining of coal and lignite	0	-
B.06	Extraction of crude petroleum and natural gas	11,307	-
B.07	Mining of metal ores	0	-
B.08	Other mining and quarrying	827	-
B.09	Mining support service activities	9,404	-
C.16	Manufacture of wood and of products of wood and cork	1,724	-
C.17	Manufacture of paper and paper products	3,546	-
C.19	Manufacture of coke and refined petroleum products	7,153	0.06
C.20	Manufacture of chemicals and chemical products	10,109	-
C.23	Manufacture of other non-metallic mineral products	3,076	-
C.24	Manufacture of basic metals	3,427	-
D.35	Electricity, gas, steam and air conditioning supply	20,434	-
E.36	Water collection, treatment and supply	1,324	-
E.38	Waste collection, treatment and disposal activities	1,778	-
H.49	Land transport and transport via pipelines	9,272	-
H.50	Water transport	20,932	0.85
H.51	Air transport	2,284	-
-	Detached or semi-detached house	65,022	-
-	Apartment	51,210	-
-	Terraced house	363,103	-

Table 5 – Prediction model for 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 carbon-intensive 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 (9) and (12)). We exclude firms for which there are more than three 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 1% of firms with the 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 6 – Summary statistics of corporate loans and debt calibration sample

This table reports summary statistics by industry 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 carbon-intensive industries. For the non-listed firms, we estimate the standard deviation of assets based on Model 3, as reported in table 5. We winsorize 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.

Table 6, continued

			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
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.16	Manufacture of wood and of products of wood and cork	202	0.28	0.11	0.17	0.66	0.21	0.74
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.36	Water collection, treatment and supply	16	0.17	0.10	0.12	0.65	0.23	0.79
E.38	Waste collection, treatment and disposal activities; materials recovery	235	0.22	0.12	0.17	0.66	0.24	0.63
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 7 – Asset valuation shocks for unburnable carbon in fossil fuel stranded assets scenario

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). We take the average value for scenarios with and without Carbon Capture and Storage (CCS).

		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 8 – Market value losses for different carbon tax scenarios, in € 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 (market estimate). The total Common Equity Tier 1 (CET1) capital for the Dutch banking sector was €120 billion in 2017. Total assets were €2,381 billion.

	Scenario I • Regional • Abrupt	Scenario II • Regional • Phase-in	Scenario III • Global • Abrupt	Scenario IV • Global • Phase-in
€100 / tonne carbon tax				
Corporate loans and debt	13,428	7,919	5,068	2,884
Corporate equity	0	0	0	0
Residential mortgages	152	117	181	139
Total (three largest banks)	13,580	8,036	5,249	3,023
Total (market estimate)	17,190	10,172	6,647	3,827
% of CET1 capital	14.3%	8.5%	5.5%	3.2%
% of total assets	0.7%	0.4%	0.3%	0.2%
€200 / tonne carbon tax				
Corporate loans and debt	29,637	21,816	14,300	7,741
Corporate equity	0	0	0	0
Residential mortgages	335	253	405	303
Total (three largest banks)	29,972	22,069	14,705	8,044
Total (market estimate)	37,939	27,935	18,614	10,182
% of CET1 capital	31.6%	23.3%	15.5%	8.5%
% of total assets	1.6%	1.2%	0.8%	0.4%

Table 9 – Market value losses per industry, in € billion (€100 / tonne carbon tax)

This table reports the contribution of individual industries to total market value losses in the four main €100 / tonne carbon tax scenarios, for the total sample of the three largest Dutch banks. The largest absolute contributions to market value losses are, in declining order, obtained for the manufacture of coke and refined petroleum products (C.19), air transport (H.51), the extraction of crude petroleum and natural gas (B.06), waste collection, treatment and disposal activities (E.38), and electricity, gas and air conditioning supply (D.35).

		I	II	III	IV
A.01	Crop and animal production, hunting and related service activities	0.63	0.41	0.26	0.18
A.02	Forestry and logging	0.93	0.38	0.17	0.08
B.05	Mining of coal and lignite	0.00	0.00	0.00	0.00
B.06	Extraction of crude petroleum and natural gas	1.46	0.92	0.64	0.40
B.07	Mining of metal ores	0.00	0.00	0.00	0.00
B.08	Other mining and quarrying	0.07	0.04	0.03	0.02
B.09	Mining support service activities	0.29	0.16	0.11	0.06
C.16	Manufacture of wood and of products of wood and cork	0.02	0.01	0.01	0.01
C.17	Manufacture of paper and paper products	0.06	0.04	0.02	0.01
C.19	Manufacture of coke and refined petroleum products	2.83	1.55	0.90	0.35
C.20	Manufacture of chemicals and chemical products	0.04	0.02	0.01	0.01
C.23	Manufacture of other non-metallic mineral products	1.01	0.67	0.49	0.26
C.24	Manufacture of basic metals	0.73	0.59	0.53	0.44
D.35	Electricity, gas, steam and air conditioning supply	1.20	0.75	0.46	0.30
E.36	Water collection, treatment and supply	0.28	0.11	0.04	0.02
E.38	Waste collection, treatment and disposal activities; materials recovery	1.21	0.53	0.23	0.09
H.49	Land transport and transport via pipelines	0.02	0.02	0.01	0.01
H.50	Water transport	1.05	0.72	0.51	0.36
H.51	Air transport	1.57	0.97	0.63	0.29
-	Detached or semi-detached house	0.12	0.09	0.14	0.11
-	Apartment	0.02	0.01	0.02	0.02
-	Terraced house	0.02	0.01	0.02	0.02

Table 10 - Market value losses for unburnable carbon, in € million

This table reports the outcome for a partial stress test in a fossil fuel stranded assets scenario based on the shocks presented in Table 7. 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 €120 billion in 2017. Total assets were €2,381 billion. We note that our sample does not include any exposure to B.05 (mining of coal and lignite).

	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%

Table 11 – Sensitivity analysis, in € million

This table reports market value losses for the €100 carbon tax scenarios, using alternative assumptions. Panel (A) reports outcomes based on a risk-free interest that is constant over time at a rate of 0% instead of 2%. Panel (B) reports outcomes assuming double the potential for cost-effective carbon abatement (20% or 40%). Panel (C) reports outcomes by running the Merton model at the firm level in the corporate portfolios, thereby allowing for variation in the leverage and asset volatility parameters. Panel (D) reports outcomes using a Merton jump diffusion (MJD) model. Calibration parameters for the MJD model are obtained from Zhou (2001) and Wong and Li (2006) and adjusted to account for the lower volatility of total assets compared to equity (using a factor 0.4 for the jump mean and standard deviation). The underlined percentages report the difference compared to the main estimate outcome in Table 8.

	Scenario I • Regional • Abrupt	Scenario II • Regional • Phase-in	Scenario III • Global • Abrupt	Scenario IV • Global • Phase-in
€100 / tonne carbon tax (main estimate)				
Corporate loans and debt	13,428	7,919	5,068	2,884
Corporate equity	0	0	0	0
Residential mortgages	152	117	181	139
Total (three largest banks)	13,580	8,036	5,249	3,023
Total (market estimate)	17,190	10,172	6,647	3,827
% of CET1 capital	14.3%	8.5%	5.5%	3.2%
% of total assets	0.7%	0.4%	0.3%	0.2%
(A) risk-free interest rate at 0%				
Corporate loans and debt	14,912	9,148	6,027	3,568
Corporate equity	0	0	0	0
Residential mortgages	897	698	1,060	823
Total (three largest banks)	15,809	9,846	7,087	4,391
Total (market estimate)	20,011	12,463	8,971	5,558
% of CET1 capital	16.7%	10.4%	7.5%	4.6%
% of total assets	0.8%	0.5%	0.4%	0.2%
<u>Difference (compared to main estimate total)</u>	<u>16.4%</u>	<u>22.5%</u>	<u>35.0%</u>	<u>45.3%</u>
(B) +100% abatement potential				
Corporate loans and debt	12,871	7,717	4,664	2,712
Corporate equity	0	0	0	0
Residential mortgages	152	117	181	139
Total (three largest banks)	13,023	7,834	4,845	2,851
Total (market estimate)	16,485	9,916	6,133	3,609
% of CET1 capital	13.7%	8.3%	5.1%	3.0%
% of total assets	0.7%	0.4%	0.3%	0.2%
<u>Difference (compared to main estimate total)</u>	<u>-4.1%</u>	<u>-2.5%</u>	<u>-7.7%</u>	<u>-5.7%</u>

Table 11, continued

(C) including firm-level variation in leverage and asset volatility				
Corporate loans and debt	14,931	8,975	5,706	3,286
Corporate equity	0	0	0	0
Residential mortgages	152	117	181	139
Total (three largest banks)	15,083	9,092	5,887	3,425
Total (market estimate)	19,092	11,509	7,452	4,335
% of CET1 capital	15.9%	9.6%	6.2%	3.6%
% of total assets	0.8%	0.5%	0.3%	0.2%
Difference (compared to main estimate total)	11.1%	13.1%	12.1%	13.3%

(D) based on Merton jump diffusion (MJD) process				
Corporate loans and debt, based on MJD (0.05 jumps per year, 0 jump mean, and 0.1 jump standard deviation).	13,464	7,950	5,097	2,909
Difference (compared to main estimate for corporate loans and debt)	0.3%	0.4%	0.5%	0.9%
Corporate loans and debt, based on MJD (10 jumps per year, -0.02 jump mean, and 0.04 jump standard deviation).	14,979	9,238	6,196	3,868
Difference (compared to main estimate for corporate loans and debt)	10.3%	15.0%	18.0%	28.0%