Green House Gas Emissions and Bank Risk in the Euro-Area

Emmanuel C. Mamatzakis*

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Abstract

Financial services industry, and in particularly the EU banking industry, has recently been confronted with climate change-related issues that need them to transition to low-carbon, or even zero-carbon, emission operations by 2050. The EU has established legally enforceable thresholds for greenhouse gas emissions with expensive compliance costs and significant fines for non-compliance. These costs and fines would have a negative impact on bank's cash flows and increase liabilities, which would contribute to higher bank risk. We propose a new model to measure of bank risk based on the first order conditions of a flexible indirect von Neumann Morgenstern utility function with respect to outputs. By estimating input and output elasticities, with both parametric and non-parametric techniques, we find increasing bank risk due to uncertainty regarding greenhouse gas emissions among banks would result in sizeable bank output losses.

Keywords: Green House Gas Emissions; Bank Risk; Bank Output Losses; Euro-Area.

JEL: C14, D22, G21, G01.

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*Birkbeck Business School, University of London, Malet Street, Bloomsbury, London WC1E 7HX, UK. E-mail: e.mamatzakis@bbk.ac.uk.

1 Introduction

Recent climate change-related challenges have forced the financial services sector, and particularly the banking sector, to transition to low-carbon, or even zero-carbon, emission operations by 2050 in the case of EU. With costly compliance expenses and significant fines for non-compliant Member States, the EU has taken the initiative and established legally enforceable thresholds for greenhouse gas emissions by country and industry. The expenses and penalties resulting from greenhouse gas emissions would reduce bank cash flows and increase liabilities, which would raise bank risk. Because of the legal necessity for them to cut emissions, the climate risks are real because they are connected to decreasing profitability and increasing operating expenses. For instance, the main EU objective for 2030 is to raise the share of renewable energy by at least 32 percent while reducing greenhouse gas emissions by at least 40 percent(from 1990 levels). These EU environmental goals are implemented via the EU Emissions Trading System, and they are monitored by the EU Effort Sharing Regulation (see EU [2021], the EU European Climate Law, and EU [2023]). These objectives are projected to be accomplished through reducing emissions and getting rid of machinery that heavily relies on fossil fuels. Due to the higher expenses associated with reducing greenhouse gas emissions, achieving those goals would surely put businesses at risk. Due to the underlying cost of reducing emissions, prior research demonstrates that greenhouse gas emissions could be seen as a systematic risk factor (Calabrese et al. [2024]; Tsionas et al. [2020]; Matsumura et al. [2014]; Krueger et al. [2020]; Ilhan et al. [2021]. Growing bodies of literature, including those by Baker et al. [2019], Krueger et al. [2020], have recently focused on the environmental performance of businesses and found a correlation between high environmental performance and high profitability. Tobin's Q is a commonly used metric for gauging profitability. Environmental investing is known to help businesses in terms of long-term operational costs as well as in terms of regulatory compliance and Tobin's Q. Climate-related risks and strategic decisions to remove polluting assets and replace them with green assets could contribute to bank risk. For example, banks with polluting assets would have to replace them and as such polluting assets need to be depreciated more quickly or written off. This could lead to higher bank losses. Banks will need to provide disclosures in its financial statements about their greenhouse gas emissions reductions that adds to the cost of managing emissions. This study covers a gap in the literature by examining whether greenhouse gas emissions are positively associated with bank output losses as a way to deal with higher bank risks associated with climate-change and strict EU climate regulations.

Defining and measuring bank risk has been subject to much controversy, also because of the intrinsic difficulties in disentangling its underlying determinants. To this date, there is no universally accepted way of conceptualising bank risk (Diamond and Dybvig [1983]; Santomero [1997], let alone of measuring it Diamond and Rajan [2005]; Brunnermeier [2009]; Acharya et al. [2013]; Acharya and Mora [2015]. There have been attempts of course to shed more light on bank risk. Going back to Santomero [1997] there is the argument that bank risk can either be related to financial assets that cannot be easily transferred to a third party, and due to this absence of secondary markets there is also no counter party risk or related to other assets and/or activities that are associated with high return. To better understand systemic financial stability Elsinger et al. [2006] for example develop a framework which relies mainly on easily

observable market data and which provides an early warning system by computing the 'value at risk' for a lender of last resort. They find that the funds necessary to prevent contagion are surprisingly small. As in Elsinger et al. [2006] other research on bank risk has evolved around the issues of early warning mechanisms and prediction of banking crises (e.g., Lawrence et al. [2006]; Barrell et al. [2010]; Aebi et al. [2012]; El-Shagi et al. [2013]. Lehar [2005] for example estimates the dynamics and correlations between bank asset portfolios. To obtain measures for the risk of a regulator's portfolio, the individual liabilities that the regulator has vis-à-vis each bank are modelled as contingent claims on each bank's assets. He finds that larger and more profitable banks have lower systemic risk and that additional equity capital reduces systemic risk but only for banks that are constrained by regulatory capital requirements. Cornett et al. [2011] on the other hand emphasise the importance of liquidity as they report that it dried up during the financial crisis of 2007-2009. Banks that relied more heavily on core deposit and equity capital financing, which are stable sources of financing, continued to lend more relative to other banks. Banks that held more illiquid assets on their balance sheets, in contrast, increased asset liquidity and reduced lending. Off-balance sheet liquidity risk materialised on the balance sheet and constrained new credit origination as increased takedown demand displaced lending capacity. They conclude that efforts to manage the liquidity crisis by banks led to a decline in credit supply.

As evident from this literature review, there is no research when it comes to the underlying bank risk due to greenhouse gas emission based on micro foundations, though previous studies provide measures of risk based on micro-foundations Glasserman and Kang [2014]; Tsionas [2016]; Tsionas et al. [2020] (see also Tsionas [2017]). Our model aims to fill this gap. Following the categorisation of risky financial assets in Santomero [1997], we provide a theoretical model of bank risk with micro foundations tethered to the uncertainty regarding prices due to greenhouse gas emissions in the three broad categories of bank outputs, i.e., loans, other earning assets and off balance sheet items and fees. Bank risk is endogenous to bank managers who aim to maximise expected profit without regarding its variability. The model follows (Froot and Stein [1998] who analyse the capital allocation and capital structure decisions facing financial institutions. Their model incorporates two key features: value maximising banks want to manage risks and not all the risks they face can be frictionlessly hedged in financial markets. Departing from their approach we develop a model of bank level risk that factors into the pricing of greenhouse gas emissions that cannot be easily hedged. In our model risk is bank specific and as such we are able to explicitly measure bank risk exposure due to greenhouse gas emissions as derived from a profit maximisation process where uncertainty regarding input and output price elasticities due to greenhouse gas emissions determines the bank's risk. In fact, standard micro foundations suggest that the expected utility under profit maximisation relies on the entire distribution of risky activities. As in Freixas and Parigi [1998] we build on the notion that the expected price of bank outputs is uncertain because of greenhouse gas emissions. And, as in Appelbaum and Ullah [1997] bank risk will be measured based on the first order conditions of a flexible indirect von Neumann Morgenstern utility function with respect to outputs. Our model further builds on the concept that with more risk due to greenhouse gas emissions loans, other earning assets and off balance sheet items and fees would be lower, and that the converse would also be true. This

is an effective way of measuring bank risk due to uncertainty around greenhouse gas emissions in expected output prices, as we clearly identify it for the case of loans, for other earning assets and for off balance sheet items and fees. The simplicity of such identification lies on measuring bank output losses due to bank risk associated with greenhouse gas emissions, in terms of lower loans, other earning assets and off balance sheet items and fees. Despite its conceptual simplicity, the estimation of our new measure of bank risk is rather cumbersome. As such we contribute to the literature by providing both parametric and non-parametric estimations of bank risk and thus bank output losses. In addition. Moreover, in the empirical application we provide evidence on bank risk due to greenhouse gas emissions in the Euro-Area

The remainder of the paper is structured as follows: Section 2 presents the theoretical model, whilst section 3 discusses the Euro-area banking industry and the data set. Section 4 reports and discusses the estimations and the last section offers some concluding remarks.

2 The Bank Indirect Utility of Profits under Climate Risk

Our paper builds on the expected utility of profit maximisation, relaxing the assumption that the utility function is known as in Hughes et al. [2001]. Whilst Tsionas [2016] proposes a theoretical model with a Taylor approximation, we extend this analysis beyond the Taylor approximation as we focus on bank output price uncertainty and the direct influence of climate risk (noted as CO2 emissions).

2.1 The General Formulation

The production technology is described by a general transformation function $F(X,Y) \geq 1$, where $X \in \mathbb{R}_+^K$ is a set of inputs, $Y \in \mathbb{R}_+^M$ is a set of outputs, with banking technology as follows:

$$F(X,Y) \geq 1 \tag{1}$$

Then, the bank would maximise the expected utility of profits:

$$\max_{X \in \mathbb{R}_+^K, Y \in \mathbb{R}_+^M} \mathbb{E}\left[U\left(P'Y - W'X - C\right)\right] \tag{2}$$

where C represents fixed costs and $U(\cdot)$ is a von-Neumann Morgenstern utility function with $U' > 0$, the input prices $W \in \mathbb{R}_+^K$ are known to the bank, but output prices $P \in \mathbb{R}_+^M$ are unknown before decisions are made.

Our basic stochastic assumption about bank output prices is:

$$P = \mu + \varepsilon \tag{3}$$

where $\mu \in \mathbb{R}_+^M$ represents expected prices, and $\varepsilon \in \mathbb{R}^M$ is a vector random variable whose distribution is $G(\varepsilon)$, with expectation zero.

Using duality, and assuming that fixed costs are C, the problem can be expressed in terms

of an indirect von Neumann–Morgenstern utility function as follows:

$$V(W,\mu,C;M) = \max_{x\in\mathbb{R}^K_+,\, y\in\mathbb{R}^M_+} E\big\{U\big((\mu+\varepsilon)'\,y - W'x - C\big)\big\} \quad \text{s.t.} \quad F(X,Y)\geq 1. \tag{4}$$

Here M denotes higher order moments of the distribution of the general transformation function $F(X,Y)$. The functional form of $F(X,Y)$ is not known. By applying the envelope theorem it yields:

$$\frac{\partial V}{\partial W_k} = -E\big[U'(\Pi)\big]\,X_k, \qquad k=1,\ldots,K, \tag{5}$$

$$\frac{\partial V}{\partial \mu_m} = E\big[U'(\Pi)\big]\,Y_m, \qquad m=1,\ldots,M, \tag{6}$$

$$\frac{\partial V}{\partial C} = -E\big[U'(\Pi)\big]. \tag{7}$$

Input demand and output supply functions can be obtained as follows (using the envelope relations above):

$$X_k \;=\; \frac{\partial V/\partial W_k}{\partial V/\partial C}, \quad k=1,\ldots,K, \qquad Y_m \;=\; -\frac{\partial V/\partial \mu_m}{\partial V/\partial C}, \quad m=1,\ldots,M. \tag{8}$$

It is easier to work in log terms to obtain corresponding 'shares' in terms of fixed costs:

$$s_k \;=\; \frac{W_k X_k}{C} \;=\; \frac{\partial \log V}{\partial \log W_k}, \qquad k=1,\ldots,K, \quad \text{and} \quad r_m \;=\; \frac{P_m Y_m}{C} \;=\; \frac{\partial \log V}{\partial \log \mu_m}, \quad m=1,\ldots,M. \tag{9}$$

We have, of course, the additional complication that higher moments $M = \{\mu^{(j)}\}_{j=1,\ldots,J}$ enter into the definition of the indirect utility function in (4), where $\mu^{(j)} = E(p^j|x)$ (conditional moments). A simple way of dealing with such complications is for $\mu^{(1)}$ to obtain the mean, then for $\mu^{(2)}$ to obtain the second moment, and so on. By doing so, all moments could be obtained.

Moreover, we assume the following:

$$p_m = D(p_{-m}, z) + \nu, \tag{10}$$

that represent demand functions for the various outputs, p_{-m} represents the output price vector excluding the m^{th} element, $z \in \Re^D$ is a vector of predetermined variable and specifically greenhouse gas emissions and ν is a $D-$dimensional random vector with zero mean.

Using nonparametric estimation we can compute moments of the form $E(p_m^j \mid z), j = 1,...,J, m = 1,...,M$ easily. Our specification for the indirect utility function in (4) is a flexible, translog, functional form (where small letters w, p, c represents logs of W, P and C respectively).[1]

[1] We drop μ as an argument of V as it is implicitly included in M.

$$\begin{aligned}\log V(W,C;M) = \alpha_0 + \sum_{k=1}^{K}\alpha_k w_k + \tfrac{1}{2}\sum_{k=1}^{K}\sum_{k'=1}^{K}\alpha_{kk'}w_k w_{k'} + \\ \sum_{j=1}^{J}[\sum_{m=1}^{K}\beta_m^{(j)}\mu_m^{(j)} + \tfrac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M}\beta_{mm'}^{(j)}\mu_{m'}^{(j)}\mu_{m'}^{(j)} + \\ \sum_{k=1}^{K}\sum_{m=1}^{M}\gamma_{km}^{(j)}w_k\mu_m^{(j)} + c\sum_{k=1}^{K}\delta_k^{(j)}w_k + \psi_1 c + \tfrac{1}{2}\psi_2 c^2 \\ c\sum_{m=1}^{M}\zeta_m^{(j)}\mu_m^{(j)}] + \tfrac{1}{2}\sum_{j=1}^{J}\sum_{j'=1}^{J}\left|\sum_{m'=1}^{M}\sum_{m'=1}^{M}\eta_{mm'}^{(j,j')}\mu_m^{(j)}\mu_{m'}^{(j')}\right|.\end{aligned} \tag{11}$$

In this translog functional form included moments are $\mu_m^{(j)} = E(p_m^j \mid z), j = 1, ..., J, m = 1, ..., M$. The moments are, in fact, conditional moments (on some exogenous vector z) whose construction is detailed below.[2]

For simplicity, we include $j = 4$ moments for each one of the m^{th} output prices. The very last term in (11) captures interactions between moments of order j and $j'(j, j' = 1, ..., J)$ for the various output prices p_m and $p_{m'}(m, m' = 1, ..., M)$.

Given data $\{p_{mi}, z_i, i = 1, ..., n\}$ we can estimate:

$$\mu_m^{(1)} = \sum_{i=1}^{n} p_i \Omega_i(z), \tag{12}$$

where $\Omega_i(z) = K\left(\frac{z-z^*}{k}\right) / \sum_{i=1}^{n} K\left(\frac{z-z^*}{k}\right)$, $K(\cdot)$ is a kernel function and h is the bandwidth parameter. Following standard practice we take $h = n^{-(4+D)}$ when the data is normalised by their standard deviations. When z is a vector we use a product kernel, $K_D(z) = \prod_{d=1}^{D} K(z_d)$ where for K we use an Epanechnikov kernel. For $r > 1$, we use:

$$\mu_m^{(J)} = \sum_{i=1}^{n} p_i' \Omega_i(z), j = 2, ..., J. \tag{13}$$

The asymptotic correctness of these estimators is established in Singh and Tracy [1970].

Bank risk μ_m can be measured as in Appelbaum and Ullah [1997] using a simple device. From the first order conditions with respect to outputs, we have: $E\big[U'(\Pi)(\mu_m + \varepsilon_m)\big] = \frac{\partial C(w,y)}{\partial y_m}$, $m = 1, ..., M$,[3] which implies:

$$\mu_m = \frac{\partial C(w,y) \,/\, \partial y_m}{E\big[U'(\Pi)\big]}, m = 1, ..., M. \tag{14}$$

This is equivalent to the condition: $\mu_m = \frac{\partial C(w,y)}{\partial y_m} + \lambda_m$, where $\lambda_m = -\frac{\text{cov}(U', P_m)}{E(U')} > 0$, provided we have bank risk. Therefore, under risk due to greenhouse gas emissions output will be lower and the converse is also true. Setting $\mu_m^{(J)} = 0$, $j = 2, ..., M$ in (11) results in

[2]The first moment $\mu_m^{(1)}$ is included in logs as is always positive. We do not follow this rule for moments higher than the first despite the fact that the second moment is also positive.

[3]Notice that problem (4) is equivalent to:
$V(W, \mu, C; M) = y \in \Re_+^W \max : E\big[U\big((\mu + \varepsilon)Y - C(W,Y) - C\big)\big]$, where $C(W,Y)$ is the usual cost function.

the case with no uncertainty. If output is higher in the no-uncertainty case, then bank risk is present. This is broadly consistent with Stiroh [2006] who finds that banks most reliant on activities that generate non-interest income do not earn higher average equity returns, and are much more risky as measured by return volatility (both total and idiosyncratic) and market betas. It is also consistent with Altunbas et al. [2000] who find that optimal bank size is considerably smaller when risk and quality factors are taken into account when modelling the cost characteristics of Japanese banks.

Regarding the returns to scale, if we define returns to scale, $RTS = \sum_{m=1}^{M} \frac{\partial \log C(W,Y)}{\partial \log Y_m}$, expected marginal utility can be recovered from (14) as:

$$E\big[U'(\Pi)\big] = \frac{RTS}{ER/C}, \tag{15}$$

where $ER = \sum_{m=1}^{M} \mu_m' Y_m$ is the expected revenue. The ratio ER/C is a return to dollar expression keeping in mind that dollar includes only fixed costs.

2.2 The parametric estimation

Following from the discussion of identifying shares, see equations (9) and the derivatives of (11), we estimate the following system of equations:

$$S_k = \frac{\alpha_k + \sum\limits_{k'=1}^{K} \alpha_{kk'} w_{k'} + \sum\limits_{j=1}^{J} \left[\sum\limits_{m=1}^{M} \gamma_{km}^{(j)} \mu_m^{(j)} + c\delta_k^{(j)} \right]}{\sum\limits_{j=1}^{J} \left[\sum\limits_{k=1}^{K} \delta_k^{(j)} w_k + \sum\limits_{m=1}^{M} \zeta_m^{(j)} \mu_m^{(j)} + \psi_1 + \psi_2 c \right]} + \xi_k, \quad k = 1, ..., K, \tag{16}$$

$$r_m = -\frac{\sum\limits_{j=1}^{J} \left[\beta_m^{(j)} + \sum\limits_{m'=1}^{M} \beta_{mm'}^{(j)} \mu_{m'}^{(j)} + \sum\limits_{k=1}^{K} \gamma_{km}^{(j)} w_k + c\zeta_m^{(j)} \right] + \sum\limits_{j'=1}^{J} \sum\limits_{m'=1}^{M} \eta_{mm'}^{(j,j')} \mu_{m'}^{(j)}}{\sum\limits_{j=1}^{J} \left[\sum\limits_{k=1}^{K} \delta_k^{(j)} w_k + \sum\limits_{m=1}^{M} \zeta_m^{(j)} \mu_m^{(j)} \right] + \psi_1 + \psi_2 c} + \xi_{K+m}, \quad m = 1, ..., M, \tag{17}$$

where ξ is a $(K + M) \times 1$ vector error term that we add for statistical purposes.[4]

The econometric estimation is embedded within a bootstrap scheme for bias reduction but also for considering when high-order moments of output prices are related to conventional and unconventional monetary policy.

Notice that we cannot drop an equation from this system as shares do not add up to unity. In the interest of simplicity, we omit the observation index, which is, in fact, $i = 1, ..., B$ for individual banks and $t = 1, ..., T_i$ for time.

From duality theory it follows that the indirect utility function, V, must be non-decreasing in W, C and non-increasing in expected output prices $\mu_m^{(j)}$. This implies the following specific constraints:

[4] As the system is homogeneous of degree one in the parameters we impose the identification constraint $\psi_1 = -1$.

$$\alpha_k + \sum_{k'=1}^{K} \alpha_{kk'} w_{k'} + \sum_{j=1}^{J} \left\{ \sum_{m=1}^{M} \gamma_{km}^{(j)} \mu_m^{(j)} + c\delta_k^{(j)} \right\} \geq 0, \quad k = 1, ..., K, \tag{18}$$

$$\sum_{j=1}^{J} \left\{ \sum_{k=1}^{K} \delta_k^{(j)} w_k + \sum_{m=1}^{M} \zeta_m^{(j)} \mu_m^{(j)} \right\} + \psi_1 + \psi_2 c \geq 0, \tag{19}$$

$$\sum_{j=1}^{J} \left[\beta_m^{(j)} + \sum_{m'=1}^{M} \beta_{mm'}^{(j)} \mu_{m'}^{(j)} + \sum_{k=1}^{K} \gamma_{km}^{(j)} w_k + c\zeta_m^{(j)} \right] + \sum_{j'=1}^{J} \sum_{m'=1}^{M} \eta_{mm'}^{(j,j')} \mu_{m'}^{(j)} \leq 0, \quad m = 1, ..., M. \tag{20}$$

We do not use maximum likelihood as this requires questionable normality and homoskedasticity assumptions in (16) and (17). Instead, we opt for the Generalised Method of Moments (GMM), which, however, cannot be used under the observation specific constraints (18) to (20). To address this, we impose, first, the restrictions (18) to (20) at the sample means $\bar{x}$. For simplicity in presentation, let $\bar{x}_i = [w_{k,i}, c_i, \mu_{m,i}^{(j)}]^T$. We then apply the continuously updated estimator (CUE) version of GMM (see Hansen et al. [1996]).[5] We keep adding constraints at the points $\bar{x} \pm hs$ (where the vector of standard deviations is denoted by s for $h = 0.1, 0.2, ...$ until 99% of the data satisfy the constraints. Eventually, almost all data points satisfy the constraints for $h = 1.7$.

Our instruments are input prices, all four observation specific moments of P and country, bank and time effects. In the list of instruments, we include squares and cross products of all input prices, all four moments of P as well as all cross-product terms along with cross product terms with bank specific and time specific effects. Time effects are introduced to account for other exogenous shifts in the demand functions. Hansen (1982)'s J statistic for testing the over identifying restrictions had a p value no less than 0.30 in all cases for which we present empirical results. Moments are estimated using (10) where z includes total loans, other earning assets and off-balance sheet items and fees, greenhouse gas emissions, a measure of consumer's income (real GDP per capita), a measure of prices of other commodities (the GDP deflator), as well as country and time effects.

In Appendix I we present the non-parametric of bank risk in some detail. In the empirical section, we shall present parametric and non-parametric estimations, whilst we also compare the fitness of the two estimations.

2.3 Bank risk measure

The starting point is to focus on demand and supply elasticities, with respect to output prices, that are given as follows:

$$E_{kmp}^{x} = \frac{\partial \log X_k}{\partial \log \mu_m^{(j)}} = \frac{\alpha_{kk'}}{\rho_m} - \frac{\zeta_m^{(j)}}{D_e}, \quad k = 1, ..., K, \quad j = 1, ..., J, \tag{21}$$

[5] We used the filterSD software which is written in Fortran77 and is released as open source code under the Eclipse Public License (EPL). It is available from the COINOR initiative. The code has been written by Roger Fletcher. The COIN project leader is Frank E. Curtis. For more details, see https://projects.coinor.org/filterSD.

$$E^{y}_{mm'j} = \frac{\partial \log Y_m}{\partial \log \mu^{(j)}_m} = \frac{\beta^{(j)}_{mm'}}{D_{\mu_m}} - \frac{\zeta^{(j)}_m}{D_e} - \Delta_{jj'}, \quad m, m' = 1, ..., M, \quad j, j' = 1, ..., J, \tag{22}$$

where $D_k = \frac{\partial \log V}{\partial \log W_k}, \quad k = 1, ..., K, \quad D_e = \frac{\partial \log V}{\partial \log C}, \quad D_{\mu_m} = \frac{\partial \log V}{\partial \log \mu^{(j)}_m}$, and $\Delta_{jj'} = 1$ if $j = j'$ and zero otherwise is a Kronecker's 'delta'.

These elasticities are meaningful empirical outcomes of the model. Equation (21) provides input demand elasticities with respect to moments of the bank output price distribution. More importantly, (22) provides elasticities of bank outputs Y_m with respect to the various moments $\mu^{(j)}_m$. These in the generalised sense are

$$\frac{\partial \log Y_m}{\partial \log \mu^{(j)}_m} = \frac{\partial Y_m}{\partial \mu^{(j)}_m} \frac{\mu^{(j)}_m}{Y_m},$$

implying a way of identifying uncertainty regarding bank output prices.

Moreover, bank input price elasticities can be computed easily:

$$E^{x}_{kk'} = \frac{\partial \log X_k}{\partial \log W_{k'}} = \frac{\alpha_{kk'}}{\rho_k} - \frac{\zeta^{(j)}_k}{D_e} - \Delta_{kk'}, \quad k, k' = 1, ..., K, \tag{23}$$

$$E^{y}_{mm'} = \frac{\partial \log Y_m}{\partial \log \mu^{(j)}_m} = \frac{\eta^{(j,1)}_{mm'}}{D_{\mu_m}} - \frac{\zeta^{(j)}_k}{D_e}, \quad m, m' = 1, ..., M. \tag{24}$$

It must be noted that cross price elasticities of input demand are not symmetric and under uncertainty they may not have the same sign. Moreover, demand and supply functions that are upward sloping with respect to expected output prices but downward sloping with respect to second moments of prices, are consistent with risk averse banks with decreasing absolute risk aversion. That is to say that demand for bank inputs would increase as the expected bank output prices increase, and the same follows for bank supply, but one the other hand an increase in the volatility of bank output due to greenhouse gas emissions would result to a decline in both bank input demand and bank supply.

To compute output under the assumption of no uncertainty we use (11) and impose the restrictions that it is linearly homogeneous with respect to $w, \mu^{(j)}, c$, $\frac{\partial V}{\partial C} = -1$ and moments of order $j = 2, ..., J$ disappear from the model. Output 'shares' can be computed from (17) and therefore expected or fitted outputs can be computed under the no risk case, denoted as $\tilde{y}_m$. In the case of presence of risk (i.e., in output prices), then we could, also, compute from (17) expected or fitted outputs as $\hat{y}_m$. Under bank risk aversion, we expect that $\tilde{y}_m > \hat{y}_m, \quad m = 1, ..., M$, or $\tilde{y}_m > \hat{y}_m$ in log terms.

To see by how much bank risk due greenhouse gas emissions decreases outputs we opt for:

$$\overline{D}_m = (nT)^{-1} \sum_{i=1}^{n} \sum_{t=1}^{T} \left(\tilde{y}_{m,it} - \hat{y}_{m,it} \right), \quad m = 1, ..., M, \tag{25}$$

which is the sample average percentage difference of outputs between the no uncertainty and uncertainty (due to greenhouse gas emissions) cases.

This measure provides an overall measure of the effects of uncertainty due to greenhouse gas

emissions and thereby also a direct way of counting for its effects on bank risk. In the empirical application, one could employ (25) to measure bank risk as time varying, bank specific and/or country specific. Most of the banking literature has focused on risk as the latter derives from one particular bank output, that is problem loans. There are several hypotheses around problem loans; if problem loans are exogenous then we have the 'bad luck' hypothesis, if endogenous to bank management then the 'bad management' or 'skimping' (Berger and DeYoung [1997]). The aforementioned hypotheses have also led to 'moral hazard' hypothesis (Gorton and Rosen [1995], counting for the case that under-capitalised banks could issue further loans, some risky, so as to enhance counter-party risk. Koutsomanoli-Filippaki and Mamatzakis [2009] test for these hypotheses and find evidence for the 'moral hazard' hypothesis in EU. To this day, no analysis has been proposed to deal with the micro foundations of bank output, and thereby bank loans. Our model shows that the bank output price uncertainty would lead to bank output losses. Appendix I presents an extension to this measure, providing for a non-parametric estimation method.

3 The Data Set

Given these striking developments the Euro-area is a region of particular interest to examine bank risk-taking. In this study, we employ a comprehensive data set based on IBCA Bankscope that contains all commercial, cooperative, savings, investment and real estate banks operating in the Euro-area between 2001 and 2021. We examine the database for any reporting errors and other inconsistencies and end up with an unbalanced panel of 23,917 observations, which comprises 3,103 banks.

Moreover, as we derive our bank risk measure based on the duality theory we employ, what is now standard in the literature, the "financial intermediation approach" (see Sealey and Lindley [1977], Badunenko and Kumbhakar [2017]) for determining bank inputs and outputs. Based on this approach, banks act as intermediates and thereby have deposits, by employing labor, physical and financial capital, and thereafter produce three bank outputs that cover the vast majority of banking activity: loans and other earning assets (also as part of sensitivity we include off balance sheet items and fees).

Descriptive statistics of the data set are provided in Table 1. For this study we focus on Member States of the Euro-area, i.e., Austria, Belgium, Cyprus, Finland, France, Germany, Greece, Italy, Ireland, Luxembourg, Malta, Netherlands, Portugal, Slovenia and Spain.

In our analysis we consider three different inputs, i.e., physical capital, labor and financial capital, and three outputs, i.e., loans, other earning assets (which include government securities, bonds, equity investments, CDs, T-bills, and equity investment), and off balance sheet items and fees. In line with previous studies (Koutsomanoli-Filippaki and Mamatzakis [2009]; Mamatzakis et al. [2015]; Quaranta et al. [2018] we define the price of physical capital as other administrative expenses to fixed assets, of labor as personnel expenses to total assets, of financial capital as the total interest expenses over total interest bearing borrowed funds, of loans as interest income to total loans, and of other earning assets as total non interest income to total other earning assets. We take as fixed cost the value of total fixed total assets. We also include in our analysis

Table 1: **Table 1. Bank Level Profit Function Data Descriptive Statistics.**

Variable	Obs	Mean	Std. Dev.	Min	Max
Physical Capital	23,917	0.0260914	1.105047	-4.73994	8.65039
Labor	23,917	0.3211268	0.9792036	-4.46483	7.82897
Financial Capital	23,917	4.257574	1.234154	-1.49298	14.5828
Other Earning Assets	23,917	4.553891	1.139462	-1.52765	14.7553
Profit	23,917	14.82286	1.786711	3.95042	22.6753
Loans	23,917	13,87796	1.877915	7.965091	21.82188
lnZ-score	23,917	1.856529	0.9348321	0	5.6529
Size	23,917	13.91126	1.898264	7.31003	21.9074
Asset diversification	23,917	0.2409229	0.158111	0	0.995758
Liquidity ratio	23,917	0.163665	0.164085	0	1
Revenue diversification	23,917	0.2093403	0.2918759	-21.062	0.999886
Cost to income ratio	23,917	0.7990322	0.9983081	0.012794	105.875
GDP growth	23,917	0.0020949	0.0285425	-0.091325	0.078114

Note: Authors' data.

variables such as loan loss provisions, loan loss reserves, and non-performing loans to directly take into account problem loans into our modelling. Other bank specific variables that we consider are: equity to total assets, net interest revenue, and net interest margin.

In Europe, there is strong support for responding to climate change without any further delay, while enforcement mechanisms are in place, varying from fines to denying grants. Particularly, the EU countries are committed to dealing with climate change and for this reason, they have adopted stringent GHG regulations (see **?**, Climate and Energy Package). In turn, those regulations provide the momentum for firms to enhance their efforts towards reducing their emissions footprint. Figure 1 provides over time greenhouse gas emissions for all EU (EU-27) in financial services industry, indicating that although there was a deep till 2014 there is worryingly upwards trend since (reaching the max level of above 7000000 tones in 2019). There is some correction in 2020, but the upwards trend rebounded thereafter.

EU countries have been highly committed to dealing with climate change. Table 2 provides an overview of how emissions have been developed by country at the EU level over time. The highest polluting country in the EU remains Germany followed by the France, though over time both countries clearly follow a negative trend. Other main industrial countries, like France, Netherlands, Spain, and Italy also have high emissions with a negative trend as well. There are also some new member states Poland with high GHG emissions and some persistence over time. Other member states also report a decline in emissions over time, see for example Austria, Portugal, and Ireland.

Tackling greenhouse gas emissions in the EU highlights the need to decrease the firms' emissions footprint. EU 2020 Climate and Energy Package have set as target a 20 percent reduction in emissions by 2020 compared with 1990 levels. This is not an easy task by any means and if one takes 2005 as the benchmark year then the equivalent target reduction is of the magnitude of 14 percent. These emission targets are also part of the Emissions Trading Scheme (ETS) and the Effort Sharing Decision (ESD) (**?**, EPA [2019]). Moving further ahead, the EU has an even more ambitious long-term objective of a 2030 climate and energy policy framework

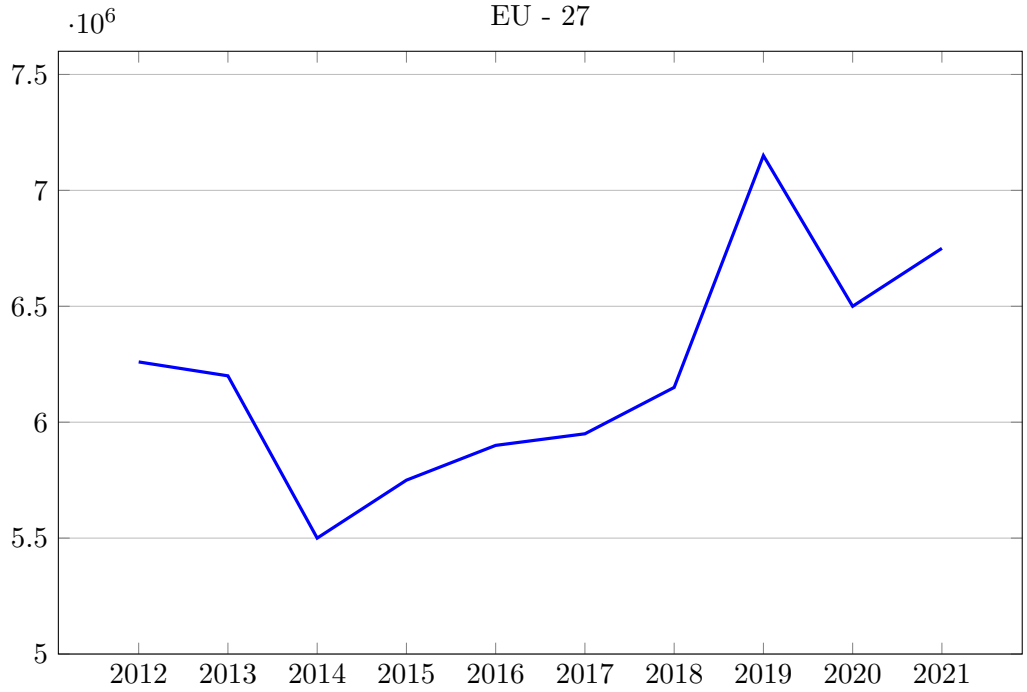


Figure 1: *
Note: Eurostat. Air emissions accounts by NACE Air pollutants and greenhouse gases: Carbon dioxide. Unit of measure: Tonne.

Table 2: **Green House Gas Emissions by Member States, financial and insurance activities.**

Member State	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Austria	31,569	30,850	26,070	24,654	24,894	25,531	29,702	36,454	41,395	44,155
Belgium	306,073	319,740	260,072	292,216	293,803	287,175	285,899	260,996	224,460	253,728
Cyprus	7,436	8,709	5,678	7,831	8,046	8,458	7,627	10,894	11,952	12,008
Denmark	58,853	55,651	51,117	50,891	59,982	57,463	57,338	52,597	49,304	47,066
Finland	211,141	225,700	191,596	191,092	137,360	92,964	108,651	135,791	140,334	140,192
France	970,065	915,653	856,597	912,286	932,535	950,661	973,708	979,971	831,500	895,746
Germany	1,611,873	1,826,895	1,576,200	1,489,381	1,523,441	1,502,675	1,332,959	1,356,777	1,245,731	1,220,629
Greece	19,447	13,464	7,924	9,912	10,764	9,834	8,760	8,671	11,789	12,135
Ireland	62,279	43,670	28,373	36,196	34,593	44,112	45,416	56,135	56,406	53,068
Italy	493,550	485,422	415,867	538,126	535,894	554,919	580,081	603,701	491,022	501,947
Lux.	176,633	164,754	112,800	131,423	160,062	187,300	208,800	244,500	136,100	137,949
Malta	232	199	265	253	301	485	532	529	423	429
Netherlands	458,327	443,094	381,005	396,210	434,487	451,485	436,324	393,803	341,016	355,969
Portugal	97,000	100,700	92,500	90,300	81,600	69,600	43,800	45,300	50,500	53,291
Slovakia	43,648	7,833	8,167	10,675	16,986	26,573	31,899	56,537	51,000	53,420
Slovenia	41,595	42,884	47,094	51,289	52,883	55,287	57,299	57,984	53,431	54,646
Spain	270,788	222,266	190,660	247,639	269,091	255,895	263,003	228,472	192,091	194,496

Note: **?**,Eurostat. Air emissions accounts by NACE Air pollutants and greenhouse gases: Carbon dioxide. Unit of measure: Tonne.

that would involve a 40percent domestic reduction in emissions as a minimum compared with 1990 levels, where a 43 percent reduction would be in the ETS sectors, and a 30percent reduction would be in the Effort Sharing sectors compared with 2005 levels. On factual observation progress towards the targets has been observed as the EU's emissions were 21.7 percent in 2017 lower than 1990 levels, totalling 4,483 megatons (Mt) of carbon dioxide equivalent (CO2). According to estimates, emissions fell by 2 percent from 2017 to 2018. With these latest values, the EU was 23.2percent below 1990 levels in 2018 and therefore remained on track to meet its upcoming target of a 20percent reduction in GHG emissions by 2020. In the present analysis, we consider the total greenhouse gas emissions of the financial industry:

$$\ln \mathrm{GHG}_{i,t} = \ln(\text{Total emissions } \mathrm{CO}_2 \text{ equivalent}_{i,t}),$$

where i denotes the Euro-area Member State and t the year. Total CO_2 emissions can be decomposed to **direct emissions** (Scope 1), which represent the emissions owned or operated directly by the company (e.g., combustion of fuel), and **indirect emissions** (Scope 2), which are related to the electricity consumption. We employ two more alternative measures for greenhouse gas emissions as explanatory variables.

Following Misani and Pogutz [2015], we scale emission to total assets:

$$\ln \mathrm{GHGTA}_{i,t} = \ln\left(\frac{\text{Total emissions } \mathrm{CO}_2 \text{ equivalent}_{i,t}}{\text{Total Assets}_{i,t}}\right),$$

and to market value:

$$\ln \mathrm{GHGMV}_{i,t} = \ln\left(\frac{\text{Total emissions } \mathrm{CO}_2 \text{ equivalent}_{i,t}}{\text{Market Value}_{i,t}}\right).$$

Higher values correspond to higher emissions. Our variables avoid high skewness and at the same time control for the size of the bank.

4 Empirical Results

4.1 The Parametric inputs and output elasticities

First, we present our results on the various elasticities at the point of approximation, which is the sample mean of the data. First we estimate elasticities $\mathrm{E}_{i,j}$ denote an elasticity of input $I \in \{K, L, F\}$ standing for physical capital, labor and financial capital with respect to the j^{th} moment j=1,...,4 in the output price. Results show that all input elasticities are positive with respect to the first moment, the expected output price, and turn negative with respect to the second moment, the volatility of the output price. This implies that for all inputs, that is physical capital, labor and financial capital, an increase in the expected output price would also increase the demand for inputs, but higher volatility in output price would lead to lower demand. Similarly, it is reported that the third and fourth moment is positive and negative, respectively.

Input elasticities with respect to output prices are all positive and significant in line with the parametric estimations. Note that the higher the volatility of output prices, the lower

the demand for bank inputs as the elasticity of inputs with respect to the second moment is negative. The elasticities with respect to the third and fourth moments are positive and negative, respectively. These elasticities are, generally, quite different across the three sub-periods. These results reveal that during the times of uncertainty regarding bank output prices due to greenhouse gas emissions has severe effects on bank inputs demand. All other results are available upon request.

Over time we note a decline in demand for labor, physical and financial capital for all Member States in the Euro-area, but it is quite considerable for the periphery, i.e., Greece, Ireland, Italy, Portugal and Spain. There is some recovery in bank input demand over the period 2012-2017, but this is rather anaemic, whereas for some Member States negative trends in bank input demand persist (see Austria, France, Germany, Greece, Ireland, Italy, the Netherlands and Portugal). Indeed, there is evidence of "multi-dipping" in the demand for bank inputs. Also it is worth noting that demand for labor is negative, in particular during and after the crisis for Greece, Ireland, Portugal and Spain.

In Table 3 we report output elasticities $\mathrm{E}_{O,j}$, where $O \in \{Loans, OEA\}$ standing for loans, other earning assets (OEA), with respect to the j^{th} price moment j=1,...,4. Output elasticities are at the point of approximation, which is the sample mean of the data. Results show that higher expected output prices due to greenhouse gas emissions increase the supply of bank loans, bank other earning assets, but that this effect is subdued over time, whereas volatility in output prices has the opposite outcome. Output elasticities with respect to the 3^{rd} and 4^{th} moment are, as expected, positive and negative respectively. These output elasticities reveal similar patterns to input elasticities. Non-parametric estimations of output elasticities confirm the above and are available under request.

Table 3: **Parametric output elasticities with respect to moments.**

Elasticity of Output:	**Loans**				**OEA**			
wrt to Moment (j)	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Belgium	0.796	-0.620	0.336	-0.418	0.205	-0.217	0.447	-0.202
Germany	0.542	-0.528	0.295	-0.354	0.169	-0.234	0.326	-0.328
Ireland	1.821	-0.237	1.455	-0.284	0.179	-0.423	0.196	-0.626
Greece	1.683	-0.155	1.508	-0.370	0.164	-0.544	0.249	-0.490
Spain	1.610	-0.246	1.550	-0.329	0.172	-0.564	0.171	-0.387
France	0.810	-0.558	0.252	-0.465	0.207	-0.303	0.286	-0.169
Italy	1.794	-0.239	1.373	-0.205	0.096	-0.498	0.236	-0.469
Cyprus	0.538	-0.495	0.347	-0.436	0.191	-0.250	0.296	-0.235
Luxembourg	1.719	-0.166	1.440	-0.239	0.272	-0.579	0.154	-0.528
Malta	0.646	-0.597	0.314	-0.464	0.207	-0.249	0.326	-0.233
Netherlands	0.914	-0.567	0.370	-0.379	0.241	-0.381	0.281	-0.154
Austria	0.524	-0.634	0.245	-0.390	0.183	-0.242	0.266	-0.278
Portugal	1.761	-0.250	1.447	-0.285	0.134	-0.553	0.287	-0.482
Slovenia	0.510	-0.606	0.376	-0.440	0.115	-0.191	0.290	-0.334
Finland	0.536	-0.545	0.419	-0.317	0.170	-0.395	0.346	-0.276

Note: Authors' estimations.

In order to compare the parametric vs the non-parametric estimations in a formal way

note that we estimate p-values that show that both parametric and non-parametric estimations perform well in terms of accuracy overall. For larger banks non-parametric estimations provide a higher accuracy.

The reported findings suggest that the Euro-area banking industry has been subject to some severe head winds as both bank input demand and bank output supply have been subject to uncertainty due to greenhouse gas emissions, and there is some persistence in recent years too. The results show that the Euro-area banking industry has faced escalating uncertainties in bank output prices and that thereby bank risk has been increasing.

4.2 The bank output loss: parametric estimations

We now turn to estimating any loss of bank output due to changes in bank risk triggered by the uncertainty in output prices. To this end, we employ equation (25). The results of loss bank of output are reported in Table 4 as D_m, where m = loans, OEA (Other Earning Assets). Since logs are used the measures are in percentage terms. Any deviations from risk neutrality towards risk aversion due to uncertainty in output prices associated with greenhouse gas emissions would lead to loss of output. Thus, bank outputs under certainty should be higher than under uncertainty. This implies that the larger the estimates of D_m the higher the loss of output due to uncertainty in output prices associated with greenhouse gas emissions.

Table 4: **Bank loss of output due to risk associated with greenhouse gas emissions.**

Loss in Output, in %	**2012-2014**		**2015-2018**		**2019-2021**	
	Loans	**OEA**	**Loans**	**OEA**	**Loans**	**OEA**
Belgium	21.423	21.423	14.425	9.343	10.627	6.627
Germany	23.707	23.707	12.506	3.238	12.205	6.586
Ireland	20.207	20.207	7.562	12.119	19.601	18.756
Greece	22.941	22.941	10.705	11.729	24.836	28.141
Spain	28.153	28.153	8.116	14.133	13.823	16.646
France	19.709	19.709	11.142	7.424	11.962	6.606
Italy	21.318	21.318	12.000	16.194	11.361	13.804
Cyprus	21.986	21.986	11.795	7.871	11.794	7.563
Luxembourg	22.334	22.334	13.882	6.958	11.495	6.111
Malta	22.627	22.627	11.533	7.783	10.646	5.828
Netherlands	21.754	21.754	12.897	6.850	10.580	5.693
Austria	22.054	22.054	10.097	8.506	10.646	5.828
Portugal	21.108	21.108	8.739	13.048	16.857	22.595
Slovenia	19.180	19.180	13.578	7.974	9.648	11.828
Finland	21.423	21.423	14.425	9.343	10.627	6.627

Notes. The table reports the loss of output calculated with equation (25) which represents the difference of output between the no-uncertainty (no greenhouse gas emissions) case and the uncertainty case, and which can be interpreted as the change in bank risk. OEA are Other Earning Assets and off balance sheet items and fees

Table 4 shows that, we have considerable loss of bank output, both in terms of bank loans, other earning assets. The loss of bank output is quantitatively important, for EU Member States and for France and Germany (the largest Euro-area Member State) during the period 2012-2021. This is also the case for other Member States of the Euro-area, with that of Spain

being rather striking as bank loans (but also other earning assets and off balance sheet items and fees) under certainty in Spain would have been around 24 percent higher during the post crisis period from 2012 to 2014. Worryingly, for some Member States in the Euro-area the output loses persist well after the crisis, notably in the case of Belgium Greece, Cyprus (and to a less extend for Germany) for which the losses have been aggravated. Alas, results show that bank output losses persist over the period though they decline over the years.

These findings reveal an unpleasant reality as the Euro-area banking industry is facing large output losses as a result of uncertainty in bank output prices in recent years. It is true that output losses were high during the crisis across all Euro-area Member States (including the large Member States such as France and Germany that were supposed to weather the crisis well), yet their persistence thereafter is troublesome. What we observe is evidence of bank 'risk averse management', that is bank managers in the face of uncertainty in bank output prices opt for lower bank output, whether as bank loans or other earning assets. This attitude towards lower bank output has been emerging since the financial crisis, and we do not detect a reversion, suggesting that the financial cycle has been prolonged in the Euro-area. Some significant bank output loss is reported prior to the crisis as the average bank loss in loans (other earning assets) is 12 percent (10 percent) in the period 2012 to 2021. And despite the fact that bank output loss increased up to 24 percent early in the last decade, it is worryingly that since then bank out loss remains at high levels (see Table 4). This persistence in bank output loss is potentially alarming. One might raise the question whether intervention is warranted to mitigate the effects of persistence in bank risk aversion. It could be the case that ECB's monetary policy could come to aid.

Clearly though, since 2019 there is a considerable bank output loss due to climate risk in the Euro-area, casting doubts over the soundness of the industry. We provide evidence herein that uncertainty in output prices or uncertainty in rates of return on bank outputs, such as bank loans, other earning assets, would be considered as the main drivers of bank risk therefore in the Euro-area. We also reveal, rather alarmingly, that bank output losses is widely spread across all of the Euro-area in recent years.

5 Conclusions

This paper formulates an indirect utility function to estimate the first four moments of the output prices' distribution parametrically and non-parametrically. Our new estimation techniques are then applied to Euro-area banking. The results indicate that input and output elasticities differ widely. Rising uncertainties in bank output prices due to greenhouse gas emissions lead to an increasing bank risk, in turn, to increases in bank output losses. Policy interventions ought to look at financial stability, but not only focus on capital requirements. It may be necessary to reduce uncertainty regarding bank output return/prices.

Although research on the effects of greenhouse gas emissions on performance of listed firms is available, little is known about how the latter may affect bank risk. Emissions would have a detrimental effect on bank risk because they are increasing bank output prices that would lead to bank output losses. Our results must be understood in light of the EU's most recent adoption

of more stringent greenhouse gas emission rules. These stricter rules' severe fines may have an immediate effect on banks costs, cash flows, and profits. However, stricter greenhouse gas emission limits can also give certain banks a competitive advantage. The context is necessary to comprehend our results. In order to address challenges related to climate change, which are crucial for the global community, the EU decided to set aggressive greenhouse gas emissions targets for all EU sector, including financial services. According to our findings, the banking sector would be impacted because greenhouse gas emissions would raise bank production prices and increase bank risk. Reducing greenhouse gas emissions could thereby lessen bank risk.

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Appendix I. The non-parametric estimation of bank risk

The system in (16) and (17) results for a parametric (translog) specification as in (11). Although the translog is a flexible functional form and has proved itself adequate in many areas of applied economics, the possibility of misspecification is always present.

For this reason, we propose in this section a nonparametric specification:

$$s_k = f_k(w, c, M) + \epsilon_k, \quad k = 1, ..., K, \tag{A.1}$$

$$r_m = f_{k+m}(w, c, M) + \epsilon_{k+m}, \quad m = 1, ..., M, \tag{A.2}$$

where w is the vector of factor prices in logs, c is fixed costs in logs and $M = [\mu^{(j)}, j = 1, ..., J]$. Here, $f_j(\cdot), j = 1, ..., K + M$ denote unknown functional forms. The vector error term $\epsilon = [\epsilon_1, ..., \epsilon_{k+M}]'$. The number of variables in each equation is $K+2MJ+1$, as we have K input prices, one variable representing fixed costs and $2MJ$ moments (J moments for each of the M output prices). We feel that this is an important extension of (16) and (17) and Appelbaum and Ullah [1997] as we make no parametric assumptions about (i) the joint distribution of output prices, and (ii) the parametric form of the (indirect) utility function that does not involve any approximations at all.

Let us suppose for the sake of simplicity in presentation that $\epsilon \sim N_{k+M}(0, \Sigma)$. Then the parametric likelihood of (A.1), (A.2) if we knew the functional forms would have been given by the following:

$$L = (2\pi)^{-nT(K+M)/2}|\Sigma|^{-nT/2} \exp\left\{-\frac{1}{2}\sum_{i=1}^{n}\sum_{t=1}^{T}[\psi_{it} - f(w_{it}, c_{it}, M_{it})]'\Sigma^{-1}[\psi_{it} - f(w_{it}, c_{it}, M_{it})]\right\}, \tag{A.3}$$

where $\psi_{it} = [s_{1,it}, ..., s_{k,it}, r_{1,it}, ..., r_{M,it}]'$, $f(\cdot) = [f_1(\cdot), ..., f_{k+M}(\cdot)]'$, and indices i, t stand for individual banks and time respectively. Of course, as the functional forms are unknown, the parametric likelihood is not of much use. We use the method of Local Linear Maximum Likelihood (LLML) to convert (A.3) to a nonparametric likelihood.

Denote $x_{it} = [w'_{it}, c_{it}, M'_{it}]'$. The method of LLML specified each function as follows:

$$\tilde{f}_j(x; \alpha) = \alpha_{0j} + \alpha'_j(x - x_i), \quad j = 1, ..., K + M, \tag{A.4}$$

where α_{0j} is a constant and $\alpha_j \in \Re^{K+2MJ+1}$, $j = 1, ..., K + M$ are parameter vectors. To avoid the normality assumption we introduce heteroskedasticity of unknown form as follows.

Given the Cholesky decomposition $\Sigma(x) = H(x)'H(x)$ we assume that each element of $H(x)$, denoted by $h_s(x), s = 1, ..., \frac{(K+M)(K+M+1)}{2}$, has the following representation:

$$h_s(x, x_i; \alpha) = \alpha_{0s} + \alpha'_{(h),s}(x - x_i), \quad s = 1, ..., \frac{(K+M)(K+M+1)}{2}, \tag{A.5}$$

where α_{0s} is a constant and $\alpha_{(h),s} \in \Re^{K+2MJ+1}$ are parameter vectors. We denote the entire vector of local parameters by α.

Given these specifications the conditional local log likelihood function for the linear local fit at x is defined as follows:

$$\log L_x(a) = \sum_{i=1}^{n} \sum_{t=1}^{T} l_{it}(a); \tag{A.6}$$

$$l_{it}(a) = -\tfrac{1}{2} \log |\Sigma(x - x_i; \alpha)| - \tfrac{1}{2} \Big[\psi_{it} - \tilde{f}(x - x_i; \alpha)\Big]' \Sigma(x - x_i; \alpha)^{-1} \Big[\psi_{it} - \tilde{f}(x - x_i; \alpha)\Big] \cdot K_B(x - x_i), \tag{26}$$

where $K_B(x)$ is a kernel function, and $\tilde{f}(\cdot) = \Big[\tilde{f}_1(\cdot), ..., \tilde{f}_{K+M}(\cdot)\Big]^T$ as defined in (A.4).

We choose:

$$K_B(u) = \mid B \mid^{-1} \; K(B^{-1}u), \tag{A.7}$$

where B is a bandwidth matrix.

For the kernel function we assume:

$$\int K(u)du = 1, \quad \int uu'K(u)du = m_2 I, \tag{A.8}$$

for some positive constant m_2. The kernel function is chosen as a product of univariate kernels along the lines of section 2.3 in Kumbhakar (2007).

Specifically, we use:

$$K(u) = \prod_{j=1}^{D} K_o(u_j), \tag{A.9}$$

where $K_o(u)$ is a symmetric univariate probability function (the standard normal in our case) and D denotes the dimensionality.

In this case:

$$\int uu'K(u)du = \left(\int u_o^2 K_o(u_o)du_o \right) I_D. \tag{A.10}$$

The log likelihood in (A.6) can be maximised using standard numerical optimisation techniques to yield local linear estimates $\hat{\alpha}(x_{it})$. The local linear estimator at x is $\hat{\alpha}_0(x)$ where $\hat{\alpha}(x)$ maximises (A.6). The asymptotics of the estimator under general regularity conditions are provided in Theorem 2.2 of **?**. Initial conditions are chosen as described in Section 3.1 there in connection to **?**.[6]

[6] We used again the filterSD software which is written in Fortran77.

Regarding bandwidth selection, we choose $B = b \otimes I_D$ where the vector $b = b_o S_x (nT)^{-1/5}$ where S_x is the vector of sample standard deviations of the covariates and b_o is a constant. Therefore, the bandwidth is adjusted for different scales of the variables and different sample sizes. To choose the value of b_o we use cross validation as in section 3.2 of **?**. As the sample size is quite large, we leave out 500 observations randomly for a total of 50 times and for a grid of 20 values of b_o. Our final optimal value for this parameter was 1.70.

As LLML provides a fit for every observation in the sample, it is quite easy to compute (numerically) elasticities of the form (21), (22), and (23) as well. This is, in fact, a great advantage over parametric procedures.

II. Comparison of parametric and non-parametric fits

The implications of the non-parametric specification in terms of elasticities and output loss are similar, although quantitatively different, of course. To assess the parametric model (16), (17) we can compare with the nonparametric specification (A.1), (A.2). Suppose $\psi_{it}^{(P)}$ and $\psi_{it}^{(NP)}$ denote the fits of the parametric and the nonparametric model, respectively.

We consider the statistic:

$$D_\psi = \sum_{(i,t)\in S} \frac{\mid \psi_{it}^{(P)} - \psi_{it}^{(NP)} \mid}{\frac{1}{2}\left\{\psi_{it}^{(P)} + \psi_{it}^{(NP)}\right\}}, \tag{A.11}$$

where S is a certain subset of the observations.

The statistic is a relative difference of fits in terms of the average fit. We use the average fit, as the choice of $\psi_{it}^{(P)}$ and $\psi_{it}^{(NP)}$ in the denominator of (A.11) would have been arbitrary. We compute the statistic over certain percentiles of the data (which constitute the set S) defined by total assets. To compute the p-value of the D_ψ statistic we use a block bootstrap, and different lengths of blocks are tried: When the data are ordered according to total assets we pretend that there is no natural way to define blocks (for example countries or banks). With N observations per percentile the length of blocks is defined as $B = bN$ and the total number of bootstrap replications is 5,000. In a second approach, we apply the bootstrap, but we keep together time series observations belonging to the same bank. To distinguish between the two approaches, we call them A and B.

We find p-values of the D_ψ statistic in (A.11) that compares the fits from the parametric model (16) and (17) and the nonparametric specification (A.1) and (A.2). A large p-value indicates that the fits are close. With N observations per percentile the length of blocks is defined as $B = bN$ and the total number of bootstrap replications is 5,000.

From the results it turns out that the parametric model behaves well at the lower 5 and 10 percentiles, the fit is marginally acceptable for the lower 25 percentile, but this is not so for banks whose total assets are above the median. Therefore, for larger banks the non-parametric model behaves better, and its results should be considered as more accurate. The relative size of the block, b, does not have a significant impact on the results.