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Keywords

multi-product banks, market power, Lerner index, consistent aggregation

JEL Classification

D43, L13, G21

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Measuring multi-product banks' market power using the Lerner index

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Abstract

The aggregate Lerner index is a popular composite measure of multi-product banks' market power, based on the assumption that banks' single aggregate output factor is total assets. This study identifies three limitations of the aggregate Lerner index that potentially distort its interpretation as a composite measure of market power. We investigate the empirical relevance of these limitations for a sample of U.S. banks covering the years 2011–2017. We establish an economically relevant bias in the value of the aggregate Lerner index and show that this bias may also affect regressions that use the Lerner index as a dependent or explanatory variable.

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1. Introduction

According to Blair and Sokol (2014, p. 325), "the standard measure of market power, at least by economists, has come to be the Lerner index". The historical and theoretical foundations of the Lerner index have been extensively discussed in the literature (Amoroso, 1933; Lerner, 1934; Amoroso, 1938, 1954; Landes and Posner, 1981; Elzinga and Mills, 2011; Giocoli, 2012; Shaffer and Spierdijk, 2017). A firm's Lerner index compares the market output price with the firm's marginal costs of production, where marginal-cost pricing is referred to as the 'social optimum that is reached in perfect competition' (Lerner, 1934, p.168). A positive Lerner index is generally associated with the presence of market power and reduced consumer welfare.

The Lerner index was originally derived for a firm producing a single product. The multi-product extension of the Lerner index comprises separate Lerner indices for each product category. This is follows from the result that product-specific marginal-cost pricing also characterizes the long-run competitive equilibrium of multi-product firms (Baumol et al., 1982; MacDonald and Slivinski, 1987).[1] Consequently, t

Multi-product measures of market power are relevant for the banking sector, where banks earn a substantial part of their income from investments and off-balance sheet activities, in addition to lending. For instance, for U.S. commercial banks with total assets exceeding $ 100 million, the sum of securities income and realized capital gains was about 14% of operating income during the 2011–2017 period, on average. For the same group of banks, non-interest income constituted about 18% of operating income during this period, on average.[2] For an overview of such trends in the European banking sector, see e.g. Lepetit et al. (2008).

Despite the multi-product character of banks, the aggregate Lerner index has remained popular in banking, though.[3] This Lerner index is based on the assumption that banks' single aggregate output factor is total assets. Under this assumption, banks' output price is typically calculated by the average revenue (i.e., the total revenue divided by total assets), while the estimate of marginal costs is based on an aggregate cost function with total assets as the single output factor. Product-specific Lerner indices–based on the average revenue per product and a multi-product cost function –have only

[1]Baumol et al. (1982) and MacDonald and Slivinski (1987) show this for markets with multi-product firms only and for markets with both single- and multi-product firms, respectively. Their proofs make use of the concept of a perfectly contestable market (PCM). They show that, for both single- and multi-product firms in a PCM market, the first-order conditions imply marginal-cost pricing. This argument then carries over to competitive equilibrium, which is a specific form of a PCM.

[2]Source: authors' own calculations using Call Report data for the 2011–2017 period; see Appendix A.

[3]Non-Lerner multi-product measures of market power have not yet gained much popularity either, even though some of them have already been proposed decades ago (e.g., Gelfand and Spiller, 1987; Suominen, 1994; Shaffer, 1996; Barbosa et al., 2015).

been used occasionally in banking. Other studies make use of a weighted-average of product-specific Lerner indices.

Table 1 provides an overview of recent banking studies using the Lerner index. These studies, published between 2013–2018, are grouped into three categories on the basis of the type of Lerner index used: the aggregate Lerner index (upper panel), product-specific Lerner indices (middle panel) and a weighted-average of product-specific Lerner indices (lower panel).

Table 1: Recent Lerner index studies in banking

author(s)	**journal/book**	**sample period**	**country/region**
Aggregate Lerner index			
Spierdijk and Zaouras (2018)	Journal of Banking & Finance	2000–2014	U.S.
Feng and Wang (2018)	Journal of Banking & Finance	2004–2014	U.S. and Europe
Biswas (2017)	Journal of Financial Stability	1995–2004	13 countries
Cubillas et al. (2017)	Journal of Financial Intermediation	1989–2007	104 countries woldwide
Fosu et al. (2017)	Journal of Financial Stability	1995–2013	U.S.
Leroy and Lucotte (2017)	Journal of Int. Fin. Markets, Inst. and Money	2004–2013	97 large European banks
Shaffer and Spierdijk (2017)	Handbook of Competition in Banking and Finance	1976–2014	Dewey county, U.S.
Delis et al. (2016)	Journal of Money, Credit and Banking	1997–2009	131 countries
Carbó-Valverde et al. (2016)	Journal of Money, Credit and Banking	1994–2010	Spain
Calderon and Schaeck (2016)	Journal of Financial and Quantitative Analysis	1996–2010	124 countries
Dong et al. (2016)	European Journal of Operational Research	2002–2013	China
McMillan and McMillan (2016)	Journal of Financial Services Research	1994–2009	U.S.
Anginer et al. (2014)	Journal of Financial Intermediation	1997–2009	63 countries
Fu et al. (2014)	Journal of Banking & Finance	2003–2010	14 Asia Pacific countries
Mirzaei and Moore (2014)	Journal of Int. Fin. Markets, Inst. and Money	1999–2011	146 countries
Beck et al. (2013)	Journal of Financial Intermediation	1994–2009	79 countries
Hainz et al. (2013)	Journal of Financial Services Research	2000–2005	70 countries
Weill (2013)	Journal of Int. Fin. Markets, Inst. and Money	2002–2010	27 EU countries
Product-specific Lerner indices			
Spierdijk and Zaouras (2018)	Journal of Banking & Finance	2010–2014	U.S.
Degl'Innocenti et al. (2017)	European Journal of Finance	1993–2011	Italy
Huang et al. (2017)	Quarterly Review of Economics and Finance	1998–2010	5 European countries
Titotto and Ongena (2017)	Handbook of Competition in Banking and Finance	2000–2014	28 EU countries
Forssbæck and Shehzad (2015)	Review of Finance	1995–2007	48 countries
Weighted-average Lerner index			
Tsionas et al. (2018)	European Journal of Operational Research	1984–2007	U.S.
Ahamed and Mallick (2017)	Journal of Financial Stability	1994–2012	India
Das and Kumbhakar (2016)	Empirical Economics	1991–1992, 2000–2001, 2009–2010	India
Bolt and Humphrey (2015)	Journal of Banking & Finance	2008–2010	U.S.
Hakenes et al. (2015)	Review of Finance	1995–2004	Germany
Inklaar et al. (2015)	Review of Finance	1996–2006	Germany
Kick and Prieto (2015)	Review of Finance	1994–2010	Germany
Fu et al. (2014)	Journal of Banking & Finance	2003–2010	14 Asia Pacific countries
Restrepo-Tobón and Kumbhakar (2014)	Journal of Applied Econometrics	1976–2007	U.S.
Buch et al. (2013)	Review of Finance	2003–2006	Germany

Notes: This non-exhaustive table lists some recent studies (published since 2013) using aggregate, product-specific or weighted-average Lerner indices. Studies that appear more than once employ different Lerner indices.

To our best knowledge, the literature has not yet analyzed the properties of the aggregate Lerner index as a composite measure of market power and its relation to the product-specific and weighted-average Lerner indices. We are aware of only one study that is critical about the aggregate Lerner index. Gischer et al. (2015) analyze European banks' lending activities and mention several inconsistencies in the calculation of the aggregate Lerner index' average revenue.

The goal of this study is to explore the aggregate Lerner index' properties as a composite measure of multi-product banks' market power. Our main contribution to the literature is that we derive testable conditions under which the aggregate Lerner index boils down to a weighted-average of product-specific Lerner indices. In this way, our study provides the missing link between three different Lerner indices used in the literature.

Our approach is as follows. By relating a multi-product bank's aggregate Lerner index to the product-specific and weighted-average Lerner indices, we identify three limitations of the aggregate Lerner index. These limitations potentially distort its interpretation as a composite measure of market power. The economic relevance of these limitations is ultimately an empirical matter, though. We investigate this for a sample of U.S. commercial banks observed during the 2011–2017 period. Here we distinguish between three lines of business of multi-product banks: lending, investments and off-balance-sheet activities.

We find the following theoretical results. The three limitations of the aggregate Lerner index that we identify are the use of **[L1]** an inconsistent measure of aggregate output, **[L2]** an inconsistent measure of total revenue, and **[L3]** a potentially misspecified aggregate cost function. **[L1]** and **[L2]** stem from the specific empirical calculation of the aggregate Lerner index as employed in the literature. They can be circumvented by adjusting the calculation. By contrast, the relevance of **[L3]** is an empirical matter, which applies if banks' multi-product cost function does not satisfy certain testable parameter restrictions. If these restrictions do not hold, the aggregate cost function inconsistently aggregates the individual outputs into a composite measure of output, resulting in a misspecified cost function. Otherwise, the aggregate cost function is correctly specified and the aggregate Lerner index boils down to a weighted-average of product-specific Lerner indices.

Our empirical results are based on a sample of U.S. commercial banks. We reject the parameter restrictions on the multi-product cost function by means of a statistical test. We therefore conclude that **[L3]** indeed applies. We show that especially **[L1]** and **[L3]** cause an economically relevant bias in the value of the aggregate Lerner index as a composite measure of a multi-product bank's market power. This bias has two main implications. First, it distorts the aggregate index' interpretation as a composite measure of market power. Second, we show that it affects the sign and magnitude of the correlation between the aggregate Lerner index and several bank-specific variables. This may distort the outcomes of a regression analysis that uses the aggregate index as a dependent or explanatory variable.

We recommend the weighted-average Lerner index in situations where a composite Lerner index is desired for multi-product banks. In all other cases, we recommend the product-specific Lerner indices. Because some information about individual components inevitably gets lost in a composite index, the product-specific indices are more informative about multi-product banks' market power than a weighted average.

We emphasize that this study focuses on the Lerner index' limitations due to inconsistent aggregation of outputs. We do not address the conceptual limitations of the Lerner index as a measure of market power, related to issues such as inefficiency and economies of scale (e.g., Scitovsky, 1955; Cairns, 1995; Koetter et al., 2012; Spierdijk and Zaouras, 2018).

The setup of the remainder of this study is as follows. Section 2 contains the theoretical framework and shows derives the conditions under which the aggregate Lerner index boils down to a weighted-average of product-specific Lerner indices. Section 3 formalizes the limitations **[L1]**, **[L2]** and **[L3]**. The estimation of banks' total and marginal cost functions is discussed in Section 4. The setup of the empirical application to U.S. commercial banks is outlined in Section 5, while the empirical results are discussed in Section 6. Finally, Section 7 concludes.

2. Theoretical framework

This section derives the conditions under which the aggregate Lerner index reduces to a weighted-average of product-specific Lerner indices.

2.1. Aggregate Lerner index

The starting point of the aggregate Lerner index is a single-output production technology with aggregate output factor $y = \sum_{j=1}^{n} y_j \geq 0$. The associated total cost function is written as $C(y, \mathbf{w})$, with $\mathbf{w} = (w_1, \ldots, w_K)$ a vector of exogenous input prices. The marginal cost function is denoted $MC_A(y, \mathbf{w}) = \partial C(y, \mathbf{w})/\partial y$. For $y > 0$, a bank's aggregate Lerner index is defined as the relative markup of the aggregate market output price P_A^* over marginal costs:

$$L_A(y; \mathbf{w}) = \frac{P_A^* - MC_A(y, \mathbf{w})}{P_A^*}. \tag{1}$$

The empirical calculation of the aggregate Lerner index typically uses the average revenue as the output price, i.e., $P_A^* = AR_A = \sum_{j=1}^{n} P_j^* y_j / \sum_{j=1}^{n} y_j = R/y$ (see the studies listed in the upper panel of Table 1).

2.2. Product-specific Lerner indices

Given a multi-product cost technology, we assume a total cost function $C(\mathbf{y};\mathbf{w})$, where $\mathbf{y} = (y_1,\ldots,y_n)$. Here $y_j \geq 0$ denotes the level of a bank's j-th output ($j = 1,\ldots,n$). The partial derivatives with respect to each output are denoted $MC_j(\mathbf{y};\mathbf{w}) = \partial C(\mathbf{y};\mathbf{w})/\partial y_j > 0$. The Lerner index is defined separately for the j-th output (assuming $y_j > 0$) and captures the relative markup of the realized market output price P_j^* over marginal costs:

$$L_j(\mathbf{y};\mathbf{w}) = \frac{P_j^* - MC_j(\mathbf{y};\mathbf{w})}{P_j^*}. \tag{2}$$

The product-specific Lerner indices that have been used in the literature use loans, securities and off-balance sheet items as output factors y_j (see the studies in the middle panel of Table 1).

Because product-specific output prices are often not available for banks, the average revenue earned on each output factor is typically used in the empirical calculation of product-specific Lerner indices; i.e., $P_j^* = AR_j = R_j/y_j$.[4]

2.3. Weighted-average Lerner index

Given $n \geq 2$ product-specific Lerner indices, the weighted-average Lerner index is defined as

$$L_{WA}(\mathbf{y};\mathbf{w}) = \sum_{j=1}^{n} \omega_j L_j(\mathbf{y};\mathbf{w}), \tag{3}$$

with revenue shares as the weights ω_j, as suggested by Encaoua et al. (1986):

$$\omega_j = \frac{P_j^* y_j}{\sum_{i=1}^{n} P_i^* y_i} = \frac{R_j}{R}. \tag{4}$$

By rewriting (3), we find

$$\begin{aligned} L_{WA}(\mathbf{y};\mathbf{w}) &= \sum_{j=1}^{n} \omega_j L_j(\mathbf{y};\mathbf{w}) = \sum_{j=1}^{n} \left[\frac{P_j^* y_j}{\sum_{i=1}^{n} P_i^* y_i} \frac{P_j^* - MC_j(\mathbf{y};\mathbf{w})}{P_j^*} \right] \\ &= \frac{\sum_{j=1}^{n} P_j^* y_j - \sum_{j=1}^{n} MC_j(\mathbf{y};\mathbf{w}) y_j}{\sum_{j=1}^{n} P_j^* y_j} && (5) \\ &= \frac{AR_A - \sum_{j=1}^{n} MC_j \tilde{\omega}_j}{AR_A}, && (6) \end{aligned}$$

[4] As shown in Shaffer (1983), the average revenue can reflect any two-part tariffs or nonlinear pricing schedules. Average revenue also has the advantage of reflecting actual transaction prices even when they deviate from posted prices (due to errors, idiosyncratic negotiations with selected counterparties, etc.).

where $\tilde{\omega}_j = y_j / \sum_{i=1}^n y_i$ is the output share of the i-th output. From (6) it becomes clear that L_{WA} can be viewed as a single-output Lerner index with AR_A as the output price and weighted-average marginal costs as marginal costs. The weighted-average Lerner index has recently been used by the studies listed in the lower panel of Table 1.[5]

2.4. *Relation between the aggregate and product-specific Lerner indices*

There is no general mathematical relation between the aggregate Lerner index and the product-specific Lerner indices. In particular, this relation depends on the cost function used for the estimation of marginal costs. We can derive such a relation under certain conditions, though.

Brown et al. (1979) define a separable multi-product cost function as a cost function of the form $C(\mathbf{y}, \mathbf{w}) = g(h(\mathbf{y}), \mathbf{w})$, where $h(\mathbf{y})$ is referred to as the output aggregation function. This function aggregates the vector of outputs $\mathbf{y}$ into a scalar measure of aggregate output. If a multi-product cost function is separable, it reduces to an aggregate cost function in terms of aggregate output $h(\mathbf{y})$; see e.g. Kim (1986).

The use of the sum of the individual outputs as the aggregate output factor requires a specific aggregation function, namely the identity function $h(\mathbf{y}) = \sum_{i=1}^n y_i$. We will refer to this type of separability as "IF"-separability, where IF stands for the identity function.

Assumption 1 *[IF-separability of the multi-product cost function] The multi-product cost function is IF-separable in aggregate output $y = \sum_{j=1}^n y_j$ and input prices $\mathbf{w} = (w_1, \ldots, w_K)$, such that $C(\mathbf{y}, \mathbf{w}) = C(y; \mathbf{w})$ for $\mathbf{y} = (y_1, \ldots, y_n)$.*

Using short-hand notation, it is readily seen that, under Assumption 1,

$$MC_j = \frac{\partial C(\mathbf{y}, \mathbf{w})}{\partial y_j} = \frac{\partial C(y, \mathbf{w})}{\partial y} = MC_A \qquad [j = 1, \ldots, n]. \tag{7}$$

Because $\sum_{j=1}^n \tilde{\omega}_j = 1$ and $MC_j = MC_A$ under Assumption 1, we can rewrite the last expression in (6) to find

$$L_{WA}(\mathbf{y}; \mathbf{w}) = \frac{AR_A - MC_A}{AR_A} = L_A(y; \mathbf{w}). \tag{8}$$

We can now formulate our main result:

[5] In some of these studies, the weighted-average Lerner index is written as $L_{WA} = (R - C \sum_{k=1}^n e_k)/R$, where $R = \sum_{k=1}^n P_k^* y_k$ is the total revenue and $e_k = \partial \log (C(\mathbf{y}; \mathbf{w}))/\partial \log (y_k)$ the cost elasticity with respect to the k-th output.

Result 1 *[Relation between Lerner indices] Under Assumption 1, the aggregate Lerner index reduces to the weighted-average of product-specific Lerner indices; i.e.,* $L_A = L_{WA} = \sum_{j=1}^{n} \omega_j L_j(y_j)$*, with* ω_j *the revenue share of output* $j = 1, \ldots, n$*.*

3. The aggregate Lerner index' limitations

Result 1 shows that, under Assumption 1, the aggregate Lerner index has a sound interpretation as a weighted-average Lerner index. We will now formalize limitations **[L1]** and **[L2]**. Subsequently, we will show how the violation of Assumption 1 directly relates to limitation **[L3]**.

*3.1. The use of an inconsistent measure of aggregate output (**[L1]**)*

Our theoretical analysis of the various Lerner indices has shown that, for the aggregate Lerner index to have a sound interpretation, total output $y = \sum_{j=1}^{n} y_j$ must be the aggregate output factor. However, the empirical calculation of AR_A and MC_A in L_A is typically based on total assets instead of total output; see the studies listed in the upper panel of Table 1. It is the non-equivalence between total output and total assets that causes **[L1]** and that makes total assets an inconsistent measure of aggregate output. Our theoretical analysis of the various Lerner indices has shown that **[L1]** would not apply if total output instead of total assets were used as the aggregate output factor.

The source of the non-equivalence between total assets and total output comes from two directions. Some components of total assets are not considered an output, while other components are viewed as an output but are not part of total assets. The precise non-equivalence will depend on the adopted banking model, such as the intermediation or production model of banking. For instance, total assets include fixed assets, which are considered an input instead of an output according to the intermediation model of banking (Klein, 1971; Monti, 1972; Sealey and Lindley, 1977). By definition, off-balance sheet activities are not included in total assets, while they are considered to be an output factor (e.g., DeYoung and Rice, 2004; Wheelock and Wilson, 2012). These two factors work in opposite directions regarding the mismatch between total assets and total output, so total assets could potentially either overstate or understate total output for individual banks. We will later present sample statistics to further illustrate this non-equivalence for our sample of banks.

*3.2. The use of an inconsistent measure of total revenue (**[L2]**)*

Our theoretical analysis has shown that, for the aggregate Lerner index to have a sound interpretation, the sum of the product-specific revenue earned on all outputs must be the measure of total revenue. The average revenue used in the empirical calculation of L_A is based on a different measure of 'total' revenue, typically the sum of interest and non-interest income (see the studies in the upper panel of Table 1). Depending on the adopted model of banking, this measure of total revenue is generally not equal to the sum of the product-specific revenue earned on all outputs. It is this non-equivalence that causes **[L2]** and that makes the sum of interest and non-interest income an inconsistent measure of total revenue. Our theoretical analysis of the various Lerner indices has shown that **[L2]** would not apply if the correct measure of total revenue were used.

The direction of the non-equivalence between the measure of total revenue and the sum of all product-specific revenue is potentially twofold. First, service fees on deposits are part of non-interest income, but deposits are not considered an output according to the intermediation model of banking. Second, capital gains on securities are neither part of interest income nor non-interest income; they are listed as a separate item on banks' income statement. Yet securities are included in total assets and part of their revenue stems from these capital gains. We will later present sample statistics to illustrate the magnitude of this non-equivalence for our sample. We notice that **[L2]** would persist even if we used total output instead of total assets as the aggregate output factor.

*3.3. The use of a potentially misspecified aggregate cost function (**[L3]**)*

For the aggregate cost function to be consistent with a multi-product technology, the underlying multi-product cost function should be IF-separable. Only then the individual outputs y_j can be consistently aggregated into the composite output measure $y = \sum_{j=1}^{n} y_j$. This means that we have to distinguish between two cases. If Assumption 1 holds true, the aggregate cost function is based on consistent aggregation and the aggregate Lerner index boils down to a weighted average of product-specific Lerner index. If Assumption 1 does not hold true, the aggregate cost function is misspecified due to inconsistent aggregation of outputs. In this case, the aggregate Lerner index does not have a sensible economic interpretation as a composite index of market power.

3.4. Adjusted aggregate Lerner index

It is easy to circumvent **[L1]** and **[L2]** by defining an adjusted aggregate Lerner index L_A^*. The difference between L_A and L_A^* is that the latter index is based on total output $y = \sum_{j=1}^{n} y_j$ instead of total assets, and the sum of all product-specific revenue as the measure of total revenue. If Assumption 1 holds, $L_A^* = L_{WA}$ such that the adjusted index has a sound interpretation as a weighted average. If Assumption 1 does not hold, only limitation **[L3]** applies to L_A^*. In our empirical analysis later on, L_A^* will be calculated to isolate the effect of **[L3]**.

4. Multi-product cost functions

We now turn to the specification, estimation and testing of multi-product banks' cost functions, which are needed for the calculation of the marginal-cost component in the Lerner index.

Multi-product cost functions have a long history in banking (e.g., Benston et al., 1982; Shaffer, 1984). It is well-known that the popular translog cost function–introduced by Christensen et al. (1971, 1973)– requires a relatively homogeneous sample in terms of bank size and product mix to provide an accurate fit (McAllister and McManus, 1993). In a multi-product setting, the problem of size heterogeneity is amplified due to the presence of multiple outputs. Even if the translog cost function is estimated separately for relatively homogeneous samples of banks in terms of total output, there can still be substantial variation across banks in terms of one or more individual outputs. This is because the various outputs are not perfectly correlated. For instance, there are banks that are large in terms of loans, but small in terms of securities.

Although nonparametric methods have proven their usefulness in the modeling of cost functions in banking (e.g., Wheelock and Wilson, 2012), we confine our analysis to a parametric approach. The main reason for this choice is that we want to run some statistical tests on the cost functions' coefficients in order to assess the validity of the aggregation into a single output factor.

To circumvent the problems associated with the translog cost function, we consider an alternative flexible parametric form in addition to the translog: the generalized Leontief cost function (Diewert, 1971; Fuss, 1977). Generalized Leontief technologies have been widely used in banking and other fields, both in a single- and a multi-product context (e.g., Thomsen, 2000; Gunning and Sickles, 2011; Martín-Oliver et al., 2013; Miller et al., 2013). Multi-product Leontief cost functions date back to Hall (1973).

Because a multi-product cost function can always be seen as a single-product cost function for given levels of the remaining outputs, it is no loss of generality to start with generic forms of the translog and Leontief single-product cost functions to illustrate their basic properties.

4.1. The generic translog cost function

The generic single-output translog cost function is given by

$$\log(C(y)) = a + b\log(y) + (c/2)\log(y)^2, \tag{9}$$

where $y > 0$ denotes the bank's output level. This cost function is generic in the sense that the precise dependence of a, b and c on input prices is omitted for the sake of exposition. We assume $c \geq 0$, corresponding to a well-behaved cost function that is convex in output. Because $C(y) \to \infty$ for $y \to 0$ if $c > 0$ and $C(y) \to 0$ for $y \to 0$ if $c = 0$, fixed costs are either infinite or zero. The average-cost (AC) function equals $AC(y) = \exp(a + (b-1)\log(y) + (c/2)\log(y)^2)$. The AC-function is U-shaped for $c > 0$ and monotonically decreasing (increasing) for $c = 0$ and $b < 1$ ($b > 1$). The marginal-cost

(MC) function is given by $MC(y) = [b + c\log(y)]AC(y)$, showing that $MC(y) \to -\infty$ for $y \to 0$. The first derivative of the MC-function equals

$$MC'(y) = \frac{AC(y)}{y}\left[(b-1)b + c + c(2b-1)\log(y) + c^2\log(y)^2\right] \tag{10}$$

The part of $MC'(y)$ between brackets is an upward-opening parabola in $\log(y)$ for $y > 0$. Hence, the MC-function is increasing for $c > b(1-b)$ and non-monotonic for $c < b(1-b)$ if $b < 1$. For $b > 1$, it is increasing for any $c > 0$. In case of non-monotonicity, the MC-function increases from $-\infty$ to a relatively large value, after which it decreases to a minimum before starting to increase again (increasing-decreasing-increasing). Hence, the MC-function will only be monotonically increasing if the cost function itself is sufficiently convex in case of $b < 1$; i.e., if c is sufficiently positive. If there is only little convexity, the MC-curve will turn out non-monotonic, with high values for small output values. These high values arise because $MC(y) = [b + c\log(y)]AC(y)$, with $AC(y) \to \infty$ for $y \to 0$.

4.2. *The generic generalized Leontief cost function*

The generic single-output generalized Leontief cost function is a convex, quadratic function of bank output $y \geq 0$, given by

$$C(y) = \alpha + \beta y + (\gamma/2)y^2, \tag{11}$$

for $\alpha \geq 0$ (non-negative fixed costs) and $\gamma \geq 0$ (convexity). The corresponding AC-function equals $AC(y) = \beta + \alpha/y + (\gamma/2)y$, which is U-shaped for $\alpha > 0$ and $\gamma > 0$ and hyperbolically decreasing for $\alpha > 0$ and $\gamma = 0$. The associated MC-function is given by $MC(y) = \beta + \gamma y$, showing that the MC-function is a linearly increasing ($\gamma > 0$) or constant ($\gamma = 0$) function of output.

4.3. *Banking model*

Before turning to empirically more relevant specifications, we must specify the banking model and the associated cost technology. Our choice of banking technology is based on the intermediation model for banking (Klein, 1971; Monti, 1972). We assume that banks employ a technology with four inputs and three output factors. The four inputs we consider are purchased funds, core deposits, labor services, and physical capital (Wheelock and Wilson, 2012). The corresponding input prices are (i) the price of purchased funds of bank $i = 1, \ldots, N$ in year $t = 1, \ldots, T$ ($w_{1,it}$), (ii) the core deposit interest rate ($w_{2,it}$), (iii) the wage rate ($w_{3,it}$), and (iv) the price of physical capital ($w_{4,it}$). Total operating costs (C_{it}) are defined as the sum of expenses on purchased funds, core deposits, personnel, and physical capital. The three output factors we consider are total loans and leases ($y_{1,it}$), total securities ($y_{2,it}$) and off-balance sheet activities ($y_{3,it}$).

4.4. *Empirical specification: translog*

We consider a translog cost function similar to Koetter et al. (2012) and many others. As usual, we impose linear homogeneity in input prices by normalizing total costs and input prices with the price of purchased funds ($w_{1,it}$). This results in the following four-input and two-output translog cost function for bank i in year t:

$$\begin{aligned}
\log(\widetilde{C}_{it}) &= \alpha_i + \sum_{j=2}^{4} \beta_{j,w} \log(\widetilde{w}_{j,it}) + (1/2) \sum_{j=2}^{4} \sum_{k>j}^{4} \beta_{jk,ww} \log(\widetilde{w}_{j,it}) \log(\widetilde{w}_{k,it}) \\
&+ \sum_{j=2}^{4} \sum_{k=1}^{3} \beta_{jk,wy} \log(\widetilde{w}_{j,it}) \log(y_{k,it}) + \sum_{k=1}^{3} \beta_{k,y} \log(y_{k,it}) + (1/2) \sum_{k=1}^{3} \beta_{k,yy} \log(y_{k,it})^2 \\
&+ \sum_{j=1}^{3} \sum_{k>j} \beta_{jk,yy} \log(y_{j,it}) \log(y_{k,it}) + \beta'_{CF} \log(CF_{it}) + \sum_{t=2}^{T} \beta_t d_t + \varepsilon_{it}, \qquad (12)
\end{aligned}$$

with α_i a bank-specific effect, d_t a time dummy for year $t = 2, \ldots, T$, CF_{it} a vector of control factors (such as the equity ratio), and ε_{it} a zero-mean error term that is orthogonal to the regressors. Throughout, variables with a tilde have been normalized with the price of purchased funds prior to taking the logarithmic transformation to ensure linear homogeneity. Marginal costs equal

$$\begin{aligned}
MC_{k,it} &= \frac{C_{it}}{y_{k,it}} \frac{\partial \log C_{it}}{\partial \log y_{k,it}} \\
&= \frac{C_{it}}{y_{k,it}} \left[\sum_{j=2}^{4} \beta_{jk,wy} \log(\widetilde{w}_{j,it}) + \beta_{k,y} + \beta_{k,yy} \log(y_{k,it}) + \sum_{j<k} \beta_{jk,yy} \log(y_{j,it}) \right], \qquad (13)
\end{aligned}$$

for output $k = 1, 2, 3$.

Aggregate cost function. To calculate L_A, we estimate the following single-output translog cost function in terms of total output or total assets (Y):

$$\begin{aligned}
\log(\widetilde{C}_{it}) &= \alpha_i + \sum_{j=2}^{4} \beta_{j,w} \log(\widetilde{w}_{j,it}) + (1/2) \sum_{j=2}^{4} \sum_{k=2}^{4} \beta_{jk,ww} \log(\widetilde{w}_{j,it}) \log(\widetilde{w}_{k,it}) \\
&+ \sum_{j=2}^{4} \beta_{j,wy} \log(\widetilde{w}_{j,it}) \log(y_{it}) + \beta_y \log(y_{it}) + (1/2) \beta_{yy} \log(y_{it})^2 \\
&+ \beta'_{CF} \log(CF_{it}) + \sum_{t=2}^{T} \beta_t d_t + \varepsilon_{it}. \qquad (14)
\end{aligned}$$

Such a single-output aggregate translog cost function has been used in many Lerner studies in banking (see the studies listed in the upper panel of Table 1). Marginal costs equal

$$MC_{A,it} = \frac{C_{it}}{y_{k,it}} \frac{\partial \log C_{it}}{\partial \log y_{it}} = \frac{C_{it}}{y_{k,it}} \left[\sum_{j=2}^{4} \beta_{j,wy} \log(\widetilde{w}_{j,it}) + \beta_y + \beta_{yy} \log(y_{it}) \right]. \tag{15}$$

Conditions for IF-separability. We view the aggregate translog cost function as a second-order approximation to an arbitrary multi-product cost function in the sense of Diewert (1971). Necessary conditions for IF-separability of the true underlying cost function can be derived as in Denny and Pinto (1978) and Kim (1986). Assuming separability of the true multi-product cost function with aggregation function $h(\mathbf{y}) = \sum_{j=1}^{3} y_j$, we approximate $C(\mathbf{y}; \mathbf{w}) = C(h(\mathbf{y}); \mathbf{w})$ by a second-order Taylor expansion of $\log(C) = \log(C(h(\log(\mathbf{y})); \log(\mathbf{w})))$. The resulting necessary parameter constraints for IF-separability are $\beta_{k,y}/\beta_{\ell,y} = \beta_{jk,wy}/\beta_{j\ell,wy} = 1$ for $j = 2, \ldots, 4$ and $k, \ell = 1, 2, 3$; i.e. $\beta_{k,y} = \beta_y$ and $\beta_{jk,wy} = \beta_{j,wy}$. We test the resulting eight linearly independent constraints using a Wald test.

4.5. *Empirical specification: generalized Leontief*

We now turn to an empirically more realistic specification of the generalized Leontief cost function. We consider a variation of the multi-product non-homothetic generalized Leontief (NHT-GL) cost function (Fuss, 1977). With four-inputs and three-outputs, the total input-factor costs of bank i in year t are given by:

$$\begin{aligned} C_{it} &= \alpha_i + \sum_{j=1}^{4} \beta_{j,w} w_{j,it} + \sum_{j=1}^{4} \sum_{k>j} \sum_{\ell=1}^{3} \beta_{jk\ell,wwy} w_{j,it}^{\frac{1}{2}} w_{k,it}^{\frac{1}{2}} y_{\ell,it} + \sum_{j=1}^{4} \sum_{\ell=1}^{3} \beta_{j\ell,wy} w_{j,it} y_{\ell,it} \\ &+ \frac{1}{2} \sum_{j=1}^{4} \sum_{\ell=1}^{3} \beta_{j\ell,wyy} w_{j,it} (y_{\ell,it})^2 + \sum_{j=1}^{4} \sum_{\ell=1}^{3} \sum_{m>\ell} \beta_{j\ell m,wyy} w_{j,it} y_{\ell,it} y_{m,it} \\ &+ \beta_{CF}' CF_{it} + \sum_{t=2}^{T} \beta_t d_t + \varepsilon_{it}. \end{aligned} \tag{16}$$

Here α_i denotes a bank-specific effect, CF_{it} a vector of control factors, d_t a time dummy for year $t = 2, \ldots, T$ and ε_{it} a zero-mean error term that is orthogonal to the regressors. The NHT-GL cost function is linearly homogeneous in input prices. Marginal costs are given by

$$\begin{aligned} MC_{\ell,it} &= \frac{\partial C_{it}}{\partial y_{\ell,it}} = \sum_{j=1}^{4} \sum_{k>j} \beta_{jk\ell,wwy} w_{j,it}^{\frac{1}{2}} w_{k,it}^{\frac{1}{2}} + \sum_{j=1}^{4} \beta_{j\ell,wy} w_{j,it} + \sum_{j=1}^{4} \beta_{j\ell,wyy} w_{j,it} y_{\ell,it} \\ &\quad + \sum_{j=1}^{4} \sum_{m>\ell} \beta_{jk\ell,wyy} w_{j,it} y_{m,it}, \end{aligned} \tag{17}$$

for output $\ell = 1, 2, 3$.

Aggregate cost function. To calculate L_A, we estimate the following single-output NHT-GL cost function in terms of total output or total assets (Y):

$$\begin{aligned} C_{it} &= \alpha_i + \sum_{j=1}^{4} \beta_{j,w} w_{j,it} + \sum_{j=1}^{4} \sum_{k>j} \beta_{jk,wwy} w_{j,it}^{\frac{1}{2}} w_{k,it}^{\frac{1}{2}} y_{it} + \sum_{j=1}^{4} \beta_{j,wy} w_{j,it} y_{it} \\ &+ \frac{1}{2} \sum_{j=1}^{4} \beta_{j,wyy} w_{j,it} (y_{it})^2 + \beta_{CF}' CF_{it} + \sum_{t=2}^{T} \beta_t d_t + \varepsilon_{it}. \end{aligned} \tag{18}$$

Marginal costs equal

$$MC_{A,it} = \frac{\partial C_{it}}{\partial y_{it}} = \sum_{j=1}^{4} \sum_{k>j} \beta_{jk,wwy} w_{j,it}^{\frac{1}{2}} w_{k,it}^{\frac{1}{2}} + \sum_{j=1}^{4} \beta_{j,wy} w_{j,it} + \sum_{j=1}^{4} \beta_{j,wyy} w_{j,it} y_{it}. \tag{19}$$

Conditions for IF-separability. We view the aggregate NHT-GL cost function as a second-order approximation to an arbitrary multi-product cost function (Fuss, 1977). Necessary conditions for IF-separability of the true underlying cost function can be derived as in Denny and Pinto (1978) and Kim (1986). Assuming separability of the true multi-product cost function with aggregation function $h(\mathbf{y}) = \sum_{j=1}^{3} y_j$, we second-order approximate $C(\mathbf{y}; \mathbf{w}) = C(h(\mathbf{y}); \mathbf{w})$ by a NHT-GL cost function. The resulting necessary parameter constraints for IF-separability are $\beta_{jk\ell,wwy} = \beta_{jk,wwy}$ and $\beta_{j\ell,wy} = \beta_{j,wy}$ for $j, k = 1, \ldots, 4$ and $\ell = 1, 2, 3$. We test the resulting twenty linearly independent constraints using a Wald test.

5. Empirical setting

To assess the empirical relevance of the aggregate Lerner index' limitations in a multi-product setting, we use year-end Call Report Data to create an unbalanced sample of U.S. commercial banks covering the 2011–2017 period. We restrict the samples to commercial banks that are part of a bank holding company, with a physical location in a U.S. state and subject to deposit-related insurance. We filter out inconsistent values and use some trimming to get rid of outliers. The exact filtering rules are listed in Appendix A. This appendix also explains how the Call Report series have been used to construct the variables required for our analysis.

5.1. Lerner indices

As mentioned in Section 4.3, we assume a cost technology with four inputs (purchased funds, core deposits, labor services, and physical capital) and three outputs (total loans and leases, total securities, and off-balance sheet activities) for each bank. Our empirical analysis will focus on five different Lerner indices: (i) L_{TLNS}: the Lerner index for total loans and leases; (ii) L_{TSEC}: the Lerner index for total securities; (iii) L_{OBS}: the Lerner index for off-balance sheet activities; (iv) L_{WA}: the weighted-average Lerner index with revenue shares as weights, and (v) L_A: the aggregate Lerner index based on the assumption that total assets is the single aggregate output.

For loans, we expect relatively high Lerner indices due the presence of locally limited borrowers (e.g, Petersen and Rajan, 2002; Degryse and Ongena, 2004; Brevoort and Hannan, 2006; Ho and Ishii, 2011) and loan screening and monitoring activities (Ruckes, 2004), among others.

Superficially, securities markets may look highly competitive due to the lack of entry barriers and the high degree of substitutability of well-diversified portfolios. Yet the literature has shown that asymmetric information between investors may result in imperfect competition (Grinblatt and Ross, 1985; Kyle, 1989; Holden and Subrahmanyam, 1992; Caballé and Krishnan, 1994; Back et al., 2000; Pasquariello, 2007). Another reason to expect positive Lerner indices for securities is the risk premium. Securities–like loans– generally have some risk of default. Assuming that risk is priced, it will show up in the Lerner index (e.g. Oliver et al., 2006; Spierdijk and Zaouras, 2017a). We therefore expect positive Lerner indices for securities, but generally lower than for loans.

The value of the Lerner index for off-balance sheet activities seems more of an empirical matter, because these bank activities tend to be quite diverse across banks. Such heterogeneity suggests product differentiation, which could promote market power and positive Lerner indices. On the other hand, some off-balance sheet activities may be offered primarily as a service or convenience to customers who are already using other banking products and, as such, may sometimes be priced at or below the bank's cost, which would tend to generate zero or negligible Lerner indices.

Several recent studies have established significant economies of scale even for the largest banks and bank-holding companies (e.g., Wheelock and Wilson, 2012; Hughes and Mester, 2013; Wheelock and Wilson, 2018). In the presence of economies of scale, product-specific marginal-cost pricing would imply negative profits for the firm.[6] In the presence of economies of scale, we may therefore expect relatively high Lerner indices for all outputs. Instead of contributing the entire margin to market power, we must realize that positive Lerner indices may simply reflect banks' need to earn non-negative profits (Lindenberg and Ross, 1981; Elzinga and Mills, 2011; Spierdijk and Zaouras, 2018).

5.2. Calculation of the average revenue

For total loans and leases, we use interest and lease income as revenue. For total securities (defined as the sum of hold-to-maturity and available-for-sale securities), we use interest and dividend income (also known as securities income) and realized capital gains on securities as revenue. We define the revenue from off-balance sheet activities as non-interest income minus service fees on de-

[6]For a bank with outputs $y_1, \ldots, y_n$, profit under marginal-cost pricing equals $\pi = C\Big(\sum_{k=1}^{n} e_k - 1\Big)$, with $e_k = \partial\log(\mathrm{C})/\partial\log(y_k)$. Hence, profits are negative for $\sum_{k=1}^{n} e_k < 1$.

posits (e.g., DeYoung and Rice, 2004; Boyd and Gertler, 1994). Due to a lack of direct output data, the output associated with the off-balance sheet revenue has to be obtained indirectly. We convert the adjusted non-interest income to non-interest income capitalization credit equivalents using the method of Boyd and Gertler (1994). This method measures off-balance sheet activities in units of on-balance sheet assets that would be required to generate the observed level of adjusted non-interest income. The resulting quantity serves as our output measure of off-balance sheet activities. The Boyd-Gertler method assumes that on- and off-balance sheet items are equally profitable. Clark and Siems (2002) argue that this assumption is reasonable in fairly competitive markets. In such markets, a reallocation of outputs would take place in case of unequal profit margins across different outputs. Lastly, we use the ratio of total interest and non-interest income to total assets as the average revenue for L_A and the sum of all product-specific revenue for L_A^*.

5.3. Dealing with negative Lerner indices

Under profit maximization, prices must weakly exceed marginal costs in equilibrium. Negative Lerner indices may therefore indicate that something is wrong. Various studies establish some negative values for the estimated Lerner indices, though (e.g. Fonseca and González, 2010; Jiménez et al., 2013; Coccorese, 2014; Huang et al., 2017). Coccorese (2014) focuses on the aggregate Lerner index for banks in several countries worldwide and emphasizes that non-negative Lerner indices must be a transitory phenomenon, related to e.g. predatory conduct. Huang et al. (2017) obtain product-specific Lerner indices for loans and investments for banks in several European countries. Both Coccorese (2014) and Huang et al. (2017) eventually resort to a restricted estimation approach that imposes non-negativity on the Lerner index.

Apart from short-run deviations from profit maximization (**[E1]**), there are several other explanations for negative Lerner indices. The estimated marginal cost may be subject to error if the underlying aggregate cost function is misspecified (**[E2]**). Also the average revenue that is used to calculate the Lerner index may be subject to error (**[E3]**). More permanent deviations from profit maximization may also give rise to negative Lerner indices (**[E4]**); see Spierdijk and Zaouras (2017b). For each of the cases **[E1]–[E4]**, imposing non-negativity on the Lerner index would be inappropriate. This is why the present study will only estimate unrestricted Lerner indices.

5.4. Size classes

As pointed out by McAllister and McManus (1993), global use of local approximations to cost functions functions may result in inaccurate results. We therefore use banks' total output in prices of the year 2017 to stratify our sample and distinguish between four size classes: (i) less than $ 100 million, (ii) \$ 100–500 million, (iii) \$ 500 million–1 billion, and (iv) more than \$ 1 billion. The next section will present empirical results for each size class.

6. Empirical results

We start with sample statistics. Table 2 provides (non-deflated) sample statistics on relevant variables, including output and revenue shares, output quantities, average revenue, and number of banks and bank-year observations. We highlight a few figures. On average, total loans have larger revenue and output shares than total securities and off-balance sheet activities, regardless of bank size. Banks in the last two size classes have relatively low average revenue and output shares for loans and securities, but higher average shares for off-balance sheet activities. Regardless of the size class, loans have the highest average revenue, followed by off-balance sheet activities and securities. Banks in the last two size classes have larger average shares of adjusted non-interest income and fiduciary services. They also have a higher wage rate on average. The dispersion in the absolute output levels is relatively large for banks in the fourth size class.

To illustrate the aforementioned non-equivalence between total assets and total output, Table 2 reports summary statistics for the ratio of total output to total assets, which ranges on average between 90%– 155%. The second size class has an average value below 100%, which shows that the effect of not including items such as fixed assets in total output outweighs the effect of including off-balance sheet activities for these banks, on average. The fourth size class has the largest average value, illustrating the more substantial output share of off-balance sheet activities for the largest banks. Also the dispersion in the ratio of total output to total assets is relatively large in this size class.

The non-equivalence between the sum of product-specific revenue and the sum of interest and non-interest income is illustrated by the summary statistics for the ratio of the latter two variables. This ratio is around 95% on average, showing that the sum of interest and non-interest income exceeds the sum of the product-specific revenue on average due to the included service fees on deposits.

6.1. Cost functions

We estimate both the translog and the NHT-GL cost functions separately for each size class. Throughout, we estimate all cost function using deflated level variables.[7] We use random-effects (RE) estimation to estimate Equations (12), (14), (16), and (18). The random effect α_i captures bank-specific heterogeneity, including time-invariant cost inefficiencies, uncorrelated with the cost function's explanatory variables. Any remaining time-varying cost inefficiencies are contained in the error

[7] We used the All Urban Consumer Price Index for deflation; see Appendix A.

Table 2: Sample statistics for U.S. commercial bank data (2011–2017)

	ALL		CLASS 1		CLASS 2		CLASS 3		CLASS 4	
	mean	*s.d.*	*mean*	*s.d.*	*mean*	*s.d.*	*mean*	*s.d.*	*mean*	*s.d.*
total loans ($TLNS$)	1,325,996	20,796,483	35,785	17,721	141,414	74,711	410,014	136,794	9,432,481	57,647,651
total securities ($TSEC$)	465,813	8,532,902	14,960	11,991	51,502	41,431	129,769	89,008	3,313,952	23,724,496
off-balance sheet items (OBS, asset equivalent)	1,263,169	32,892,009	5,337	5,786	31,486	33,288	123,233	96,137	9,682,341	91,763,741
off-balance sheet items (NII, adjusted non-interest income)	28,940	659,572	170	181	990	1,014	3,771	2,883	219,849	1,837,628
total assets (TA)	2,340,214	43,338,155	62,531	24,578	222,826	99,989	613,052	155,562	16,849,638	120,490,743
total costs (C)	47,032	826,296	1,505	673	5,349	2,608	14,896	4,669	332,469	2,296,058
equity ratio (EQ/TA)	10.8%	2.7%	11.1%	3.2%	10.7%	2.6%	10.5%	2.3%	10.9%	2.6%
revenu share total loans (ω_1)	75.5%	14.0%	78.1%	14.1%	76.1%	13.1%	73.9%	13.6%	69.5%	14.9%
revenue share total securities (ω_2)	13.8%	11.8%	15.4%	13.6%	14.0%	11.7%	12.0%	9.9%	11.5%	8.5%
revenue share off-balance sheet items (ω_3)	10.7%	10.0%	6.5%	6.1%	9.9%	8.3%	14.2%	11.2%	19.0%	14.7%
output share total loans ($\tilde{\omega}_1$)	62.7%	17.0%	64.2%	18.1%	63.3%	16.5%	61.9%	16.3%	57.6%	16.6%
output share total securities ($\tilde{\omega}_2$)	23.2%	15.6%	26.6%	17.8%	23.5%	15.3%	19.7%	13.0%	17.8%	10.9%
output share off-balance sheet items ($\tilde{\omega}_3$)	14.2%	12.4%	9.2%	8.4%	13.2%	10.5%	18.5%	13.6%	24.6%	17.3%
average revenue total loans (AR_{TLNS})	5.4%	1.0%	5.8%	1.0%	5.4%	0.8%	5.1%	0.9%	4.8%	1.1%
average revenue total securities (AR_{TSEC})	2.4%	1.3%	2.5%	1.7%	2.4%	1.1%	2.5%	1.2%	2.4%	1.0%
average revenue off-balance sheet items (AR_{OBS})	3.2%	0.6%	3.3%	0.7%	3.2%	0.6%	3.2%	0.7%	3.0%	0.7%
average revenue total assets (AR_{TA})	4.7%	1.4%	4.4%	1.0%	4.7%	1.1%	4.9%	1.5%	5.1%	2.5%
price of purchased funds (w_1)	1.2%	0.8%	1.1%	1.0%	1.2%	0.7%	1.3%	0.7%	1.4%	1.0%
price or core deposits (w_2)	0.4%	0.3%	0.4%	0.3%	0.4%	0.3%	0.4%	0.3%	0.4%	0.3%
wage rate (w_3)	68.1	18.0	62.3	15.5	67.1	16.3	72.9	18.9	79.7	21.7
price of physical capital (w_4)	34.5%	43.0%	44.8%	51.4%	30.1%	39.5%	30.5%	38.5%	33.6%	37.1%
adjusted non-interest income/operating income	16.9%	10.7%	13.0%	7.2%	16.1%	9.0%	20.3%	11.9%	25.6%	15.0%
deposit service fee/operating income	5.2%	4.1%	5.6%	3.9%	5.1%	3.7%	4.9%	4.5%	5.2%	5.2%
fiduciary services/operating income	0.8%	3.1%	0.1%	1.0%	0.6%	2.6%	1.7%	4.5%	2.4%	4.7%
total output/total assets	106.8%	357.1%	89.6%	14.6%	102.1%	34.7%	114.0%	52.5%	155.2%	995.6%
total revenue/(interest income + non-interest income)	94.1%	5.1%	92.7%	5.6%	94.6%	4.6%	95.1%	5.0%	94.7%	5.5%
# bank-years	30,185		7,973		15,010		3,360		3,842	
# banks	5,281		1,683		3,002		893		816	
# years	7		7		7		7		7	

Notes: The columns captioned 'mean' report sample means, while the columns captioned 's.d.' show sample standard deviations. All level variables are in thousands of $. We classify banks on the basis of their total output in 2017 prices. Some banks may switch from one size class to another over the years if their total output in 2017 prices changes. For this reason, the sum of the number of banks in each size class exceeds the number of banks in the entire sample.

term and do not have to be specified any further for consistent estimation. In all specifications we enter, both linearly and quadratically, bank age as an control factor to allow for different cost behavior of de novo banks (due to e.g. new technologies). We also include the equity ratio as a control factor, with the interpretation that equity is a quasi-fixed input (e.g., Mester, 1996).[8]

Table 3 reports the outcomes of the Wald tests for IF-separability, based on panel-robust covariance matrices. For both the translog and the NHT-GL cost functions, we reject for each size classand at each reasonable significance level the necessary parameter restrictions for IF-separability.[9] Hence, all aggregate cost functions are based on inconsistent aggregation of outputs and therefore misspecified; **[L3]** applies.

The adjusted R^2 for each estimated cost function is also reported in Table 3. The higher adjusted R^2 of the translog model indicates that the log of total cost can be very well predicted by this model, but it does not necessarily say much about the model's ability to yield a consistent estimate of marginal costs.[10] This will become more clear in the next subsection.

Table 3: Outcomes of Wald-test for IF-separability

	adj. R^2	**test stat.**	**d.f.**	**95% c.v.**	***p*-value**
Translog CLASS 1	0.98	33.16	8	15.51	0.0001
Translog CLASS 2	0.98	73.29	8	15.51	0.0000
Translog CLASS 3	0.99	40.38	8	15.51	0.0045
Translog CLASS 4	0.98	108.07	8	15.51	0.0000
NHT-GL CLASS 1	0.73	142.48	20	31.41	0.0000
NHT-GL CLASS 2	0.75	169.53	20	31.41	0.0000
NHT-GL CLASS 3	0.72	96.03	20	31.41	0.0000
NHT-GL CLASS 4	0.84	166.89	20	31.41	0.0000

Notes: The Wald test statistics are based on clustered covariance matrices that are robust against heteroskedasticity and autocorrelation. For the translog (NHT-GL) cost function, the IF-separability test involves 8 (20) linear constraints, so the associated 95% critical value ('c.v.') is based on a χ^2 distribution with 8 (20) degrees of freedom ('df'). Also the adjusted R^2 of each underlying cost regression is reported.

6.2. Lerner indices

Summary statistics for the estimated Lerner indices based on the translog cost function are displayed in Table 4, while those based on the NHT-GL cost function are shown in Table 5.

The lower panels of Tables 4 and Table 5 report the number of bank-years and banks used to estimate the translog cost function ('est.'). The NHT-GL cost functions have been estimated including bank-years with zero output levels, while these observations have been omitted for the estimation

[8]Estimation results based on fixed-effect estimation are similar and available upon request.

[9]If the necessary parameter constraints are rejected, we reject IF-separability of the underlying true cost function. If they are not rejected, we would have to derive and test for sufficient conditions; see e.g. Kim (1986). However, since we reject the necessary conditions in all cases, no further testing is required.

[10]The complete estimation results for the multi-product and aggregate cost functions are available upon request.

of the translog cost function. The lower panels of Tables 4 and Table 5 also report the number of bank-years and banks used in each size class for the calculation of the summary statistics is reported ('stats.'). We leave out observations with product-specific output levels less than \$ 100,000 (in prices of 2017) and output prices lower than 1% to obtain summary statistics for the Lerner indices. We do this because both the average revenue and the Lerner index are ratio variables, which may become erratic for small values of the denominator. In each size class, we use 90–96% of the full sample for that class to calculate the summary statistics.

For both the NHT-GL and the translog cost functions, Table 6 reports the percentages of bank-year observations with significantly negative Lerner indices. Also the percentages of negative estimates of marginal costs are reported. The summary statistics in this table are based on the same number of bank-year observations as reported in Tables 4 and 5 ('stats.').

Translog versus NHT-GL. The rows captioned 'mean s.e.' in the first panels of Tables 4 and 5 report the sample means of the standard errors of the estimated Lerner indices, based on a wild panel bootstrap (Cameron et al., 2008). These figures provide an indication of the amount of parameter uncertainty in the Lerner estimates. We see that the amount of parameter uncertainty in the estimates of L_{OBS} and especially L_{TSEC} is substantially larger in case of the translog cost function. This provides a first indication that the Leontief cost function provides a more accurate fit in terms of marginal costs.

Based on the translog cost function, the 5% quantile of L_{TSEC} turns out negative in each size class; see Table 4. As shown in more detail in the upper panel of Table 6, L_{TSEC} is significantly negative in 5–19% of the bank-years, depending on the size class. These results occur despite the fact that we allow for bank heterogeneity across size classes and use random-effects estimation (cf. McAllister and McManus, 1993). For the other Lerner indices, the percentage of negative values is negligible; see the middle panel of Table 6. Table 6 also shows that the translog cost function produces few negative estimates of marginal costs.

As explained in Section 5.3, negative estimates of the Lerner index may indicate that something is wrong. Before considering other explanations, we conjecture that misspecification of the translog cost function causes the negative values of L_{TSEC}. This suspicion is based on the observation that the negative values of L_{TSEC} occur mostly for small values of securities output. Because the multi-output translog cost function is only slightly convex in securities, the associated MC-curve tends to be non-monotonic with high marginal costs for small output values; see Section 4.1. This suggests that the functional form of the translog cost function may be too restrictive for securities, causing economically implausible estimates of marginal costs and the associated Lerner indices.[11] Our conjecture

[11] Adding flexible-Fourier output terms to the standard translog cost function does not solve the negativity issue.

Table 4: Summary statistics (in percentage) for the estimated Lerner indices and their components (translog)

	CLASS 1					CLASS 2					CLASS 3					CLASS 4				
	L_{TLNS}	L_{TSEC}	L_{OBS}	L_{WA}	L_A	L_{TLNS}	L_{TSEC}	L_{OBS}	L_{WA}	L_A	L_{TLNS}	L_{TSEC}	L_{OBS}	L_{WA}	L_A	L_{TLNS}	L_{TSEC}	L_{OBS}	L_{WA}	L_A
mean	63.4	45.9	55.2	64.5	57.9	59.2	35.9	66.4	59.5	57.5	59.3	46.9	86.4	62.3	64.3	54.2	33.2	72.3	57.4	61.3
median	64.4	58.3	58.6	64.7	58.0	60.0	42.6	65.5	59.6	57.7	60.3	50.1	75.5	62.1	64.4	58.0	21.2	73.0	57.1	60.9
IQR	9.1	42.0	27.1	8.3	8.9	10.1	52.4	22.1	8.9	9.1	10.0	41.9	11.4	8.1	9.3	13.9	64.2	20.9	9.1	8.0
5% quantile	49.8	-63.5	5.0	54.0	46.3	45.0	-96.4	20.5	47.8	45.4	44.0	-54.2	52.2	51.0	50.7	27.0	-160.2	23.5	45.1	50.1
95% quantile	74.5	83.7	83.2	74.4	69.0	71.5	76.2	84.3	71.0	69.2	72.8	80.9	87.1	74.5	77.1	73.3	65.2	93.0	70.9	72.9
mean s.e.	2.1	11.3	14.5	1.6	1.4	1.3	18.6	7.1	1.1	1.1	2.3	17.0	11.9	1.9	2.0	2.8	37.2	8.0	1.5	1.4
mean *MC*	2.1	1.2	1.4	1.8	1.9	2.2	1.4	1.1	1.9	2.0	2.1	1.1	0.4	1.7	1.7	2.2	0.3	0.9	1.8	2.0
median *MC*	2.0	1.0	1.3	1.7	1.8	2.1	1.4	1.1	1.9	1.9	2.0	1.2	0.8	1.7	1.7	2.0	1.9	0.8	1.7	1.8
IQR *MC*	0.7	0.8	0.9	0.6	0.6	0.6	1.1	0.7	0.6	0.6	0.7	0.9	0.4	0.5	0.6	0.8	1.3	0.7	0.5	0.6
5% quantile *MC*	1.3	0.4	0.5	1.2	1.2	1.4	0.6	0.5	1.2	1.3	1.3	0.5	0.4	1.1	1.0	1.2	0.8	0.2	1.1	1.1
95% quantile *MC*	3.1	3.3	3.1	2.6	2.7	3.1	3.9	2.6	2.7	2.8	3.1	3.2	1.6	2.5	2.6	3.6	5.2	2.4	2.5	3.1
mean *AR*	5.8	2.6	3.3	5.1	4.4	5.4	2.5	3.3	4.8	4.7	5.1	2.5	3.2	4.5	4.9	4.8	2.4	3.0	4.2	5.1
median *AR*	5.6	2.3	3.2	5.0	4.4	5.3	2.3	3.3	4.7	4.6	5.0	2.3	3.2	4.5	4.6	4.6	2.3	3.0	4.1	4.6
IQR *AR*	1.3	1.1	0.8	1.2	1.1	1.1	1.0	0.7	0.9	1.0	0.9	1.0	0.7	0.8	1.0	1.0	0.8	0.6	0.9	1.1
5% quantile *AR*	4.4	1.2	2.2	3.8	3.0	4.3	1.3	2.4	3.7	3.5	4.0	1.3	2.3	3.5	3.6	3.6	1.4	2.1	3.1	3.5
95% quantile *AR*	7.4	4.3	4.4	6.6	5.9	6.8	4.0	4.1	6.1	6.1	6.4	4.0	4.0	5.7	6.7	6.1	3.9	3.9	5.4	8.2
# bank-years (est.)	7,736					14,848					3,334					3,616				
# banks (est.)	1,649					2,974					890					774				
# bank-years (stats.)	7,207					14,241					3,208					3,487				
# banks (stats.)	1,597					2,924					861					757				

Notes: For each size class, the first row of this table reports the means of the bootstrap-based standard errors of the estimated Lerner indices, providing an indication of the amount of parameter uncertainty. The remaining rows report sample mean, median, interquartile range (IQR), 5% quantile and 95% quantile of the various estimated Lerner indices and the associated marginal costs and average revenue. The number of bank-year observations and included banks are reported on the basis of the amount used in the estimations ('est.') and in the calculation of the summary statistics ('stat.').

Table 5: Summary statistics (in percentage) for the estimated Lerner indices and their components (generalized Leontief)

	CLASS 1					CLASS 2					CLASS 3					CLASS 4				
	L_{TLNS}	L_{TSEC}	L_{OBS}	L_{WA}	L_A	L_{TLNS}	L_{TSEC}	L_{OBS}	L_{WA}	L_A	L_{TLNS}	L_{TSEC}	L_{OBS}	L_{WA}	L_A	L_{TLNS}	L_{TSEC}	L_{OBS}	L_{WA}	L_A
mean	61.0	53.3	71.8	61.5	57.9	58.9	42.1	68.8	58.5	58.3	59.8	49.9	74.6	61.8	68.4	62.3	33.3	68.5	60.7	67.8
median	62.7	56.8	72.9	62.9	59.2	60.1	46.5	70.6	59.7	59.7	61.7	54.3	77.3	63.1	69.9	63.7	38.6	72.1	62.2	69.4
IQR	14.5	22.2	11.3	13.5	15.2	13.3	25.0	10.5	12.1	13.0	13.1	26.6	13.5	11.3	11.9	13.4	30.6	19.4	12.2	10.9
5% quantile	39.8	15.8	53.4	42.6	37.1	40.5	-1.0	49.8	41.4	39.0	37.9	5.4	50.6	43.2	50.1	40.8	-16.1	35.2	40.7	48.5
95% quantile	76.5	77.6	85.5	75.7	74.5	73.5	70.3	81.0	71.9	72.8	75.1	78.9	89.1	75.5	81.5	78.2	68.5	90.7	75.3	81.9
mean s.e.	2.0	6.6	8.3	2.1	1.7	1.7	5.9	4.7	1.6	1.4	3.4	10.5	6.3	3.2	2.7	4.7	23.9	6.3	3.4	3.1
mean *MC*	2.2	1.1	0.9	1.9	1.8	2.2	1.3	1.0	1.9	1.9	2.0	1.1	0.8	1.7	1.5	1.7	1.5	0.9	1.6	1.5
median *MC*	2.1	1.0	0.9	1.8	1.8	2.1	1.3	0.9	1.9	1.8	1.9	1.1	0.7	1.6	1.4	1.7	1.4	0.8	1.5	1.5
IQR *MC*	0.7	0.4	0.3	0.7	0.6	0.6	0.5	0.3	0.6	0.5	0.7	0.5	0.4	0.5	0.5	0.6	0.5	0.6	0.5	0.4
5% quantile *MC*	1.4	0.6	0.5	1.2	1.1	1.5	0.8	0.6	1.3	1.3	1.3	0.5	0.3	1.1	0.9	1.1	0.9	0.3	1.0	1.0
95% quantile *MC*	3.2	1.6	1.4	2.8	2.6	3.1	2.0	1.5	2.7	2.7	3.1	1.9	1.5	2.6	2.3	2.5	2.3	1.8	2.2	2.2
mean *AR*	5.8	2.6	3.3	5.1	4.4	5.4	2.5	3.3	4.8	4.7	5.1	2.5	3.2	4.5	4.9	4.8	2.4	3.0	4.2	5.1
median *AR*	5.6	2.3	3.2	5.0	4.4	5.3	2.3	3.3	4.7	4.6	5.0	2.3	3.2	4.5	4.6	4.6	2.3	3.0	4.1	4.6
IQR *AR*	1.3	1.1	0.8	1.2	1.1	1.1	1.0	0.7	0.9	1.0	0.9	1.0	0.7	0.8	1.0	1.0	0.8	0.6	0.9	1.1
5% quantile *AR*	4.4	1.2	2.2	3.8	3.0	4.3	1.3	2.4	3.7	3.5	4.0	1.3	2.3	3.5	3.6	3.6	1.4	2.1	3.1	3.5
95% quantile *AR*	7.4	4.3	4.4	6.6	5.9	6.8	4.0	4.1	6.1	6.1	6.4	4.0	4.0	5.7	6.7	6.1	3.9	3.9	5.4	8.2
# bank-years (stats.)	7,207					14,241					3,208					3,487				
# banks (stats.)	1,597					2,924					861					757				

Notes: For each size class, the first row of this table reports the means of the bootstrap-based standard errors of the estimated Lerner indices, providing an indication of the amount of parameter uncertainty. The remaining rows display sample mean, median, interquartile range (IQR), 5% quantile and 95% quantile of the various estimated Lerner indices and the associated marginal costs and average revenue. The number of bank-year observations and included banks are reported on the basis of the amount used in the calculation of the summary statistics.

Table 6: Negative values of Lerner index and marginal costs (in percentage)

	Generalized Leontief				*Translog*			
	CLASS 1	**CLASS 2**	**CLASS 3**	**CLASS 4**	**CLASS 1**	**CLASS 2**	**CLASS 3**	**CLASS 4**
$L_{TSEC} < 0$ (sign.)	0.2	2.0	0.5	0.3	6.8	14.0	4.6	19.0
$L_{TSEC} > 0$ (sign.)	93.0	88.7	85.1	51.6	79.8	72.2	75.7	52.0
$L_{TSEC} > 1$ (sign.)	0.0	0.0	0.0	0.0	0.2	0.1	0.2	0.1
$L_{TLNS} < 0$	0.1	0.0	0.1	0.1	0.2	0.1	0.2	2.6
$L_{OBS} < 0$	0.1	0.1	0.1	0.7	4.2	2.3	0.2	2.6
$L_{WA} < 0$	0.0	0.0	0.0	0.2	0.0	0.0	0.1	0.0
L_A¡0	0.2	0.0	0.0	0.1	0.0	0.0	0.0	0.0
$MC_{TLNS} < 0$	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0
$MC_{TSEC} < 0$	0.0	0.1	0.3	0.4	0.9	0.8	0.8	0.7
$MC_{OBS} < 0$	1.0	0.0	0.3	0.6	1.5	1.3	1.5	2.5
$MC_W < 0$	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
$MC_{TA} < 0$	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Notes: For each size class, this table reports the percentage of (significantly) negative estimates of the various Lerner indices and the associated marginal costs. To determine the significance of the estimated Lerner indices for securities ('sign.'), we have used a panel wild bootstrap. The chosen significance level is 5%.

about the translog cost function is confirmed by the estimates based on the NHT-GL multi-product cost function, which are shown in Table 5. Switching to this alternative cost function solves the issue of significantly negative values of L_{TSEC}. The upper panel of Table 6 shows that the estimates of L_{TSEC} based on this cost function hardly ever turn out significantly negative. Apart from the negativity issue, the two cost functions lead to fairly similar results on average (with substantially higher estimation uncertainty for the translog cost functions, though). We therefore focus on the estimated Lerner indices based on the NHT-GL cost function in the remainder of the analysis.

Consistency with prior expectations. Table 5 shows that L_{TSEC} has the lowest median value among the three product-specific Lerner indices, followed by L_{TLNS} and L_{OBS}, respectively. The relatively low value of L_{TSEC} is in line with our prior expectations. On average, we observe fairly high product-specific Lerner indices for loans, securities and off-balance sheet activities. Because we also establish economies of scale for most banks, some caution is required here. As explained in Section 5.1, positive Lerner indices may simply reflect banks' need to earn non-negative profits instead of market power.

Size effects. Table 5 shows that the sample mean and median of L_{TSEC} are relatively low for banks in the fourth size class. Related to this, Table 6 indicates that the percentage of significantly positive values of L_{TSEC} varies between 85–93% in the first three size classes, while it is only 51.6% in the fourth size class. The latter percentage is consistent with the large average standard error of L_{TSEC} in the fourth size class, as reported in the row captioned 'mean s.e.' in the first panel of Table 5. For the other outputs, the percentage of significantly positive Lerner indices is almost 100% in each size class.

The reduced significance of L_{TSEC} in the fourth size class indicates relatively large amount of parameter uncertainty, caused by the modest amount of bank-year observations and the relatively large amount of output dispersion in the fourth size class. The row captioned 'mean s.e.' in the first panel of Table 4 shows that the estimates of L_{TSEC} based on the translog cost function are subject to even larger parameter uncertainty. For both the translog and the NHT-GL cost functions, the amount of parameter uncertainty in the fourth size class increases even further if the 53 banks with total output in excess of \$ 30 billion are included. On average, these banks have a total output of \$ 329 billion, while their average total assets equal \$ 241 billion. Although the other results remain about the same, these huge banks act as outliers in the sample and have a negative impact on the model fit. The results reported here for the fourth size class do therefore not include these banks.

Table 5 also reveals a size effect in the distribution of L_{TSEC}; the mean and median of L_{TSEC} are substantially lower in the fourth size class than in the other size classes. This size effect seems to be a direct consequence of the large estimation uncertainty in L_{TSEC}, though. That is, the size effect in the distribution of L_{TSEC} disappears if we calculate the sample means, medians and quantiles only over those bank-years for which L_{TSEC} differs significantly from zero.

Table 7: Summary statistics for L_A^* (in percentage)

	CLASS 1	**CLASS 2**	**CLASS 3**	**CLASS 4**
mean	63.8	61.3	67.2	67.4
median	65.3	62.5	68.4	69.6
IQR	13.5	11.3	9.8	11.1
5% quantile	44.0	44.8	50.9	48.1
95% quantile	78.3	73.8	78.6	79.9
mean *MC*	1.6	1.7	1.4	1.2
median *MC*	1.6	1.6	1.3	1.2
IQR *MC*	0.6	0.5	0.4	0.4
5% quantile *MC*	1.0	1.1	0.9	0.8
95% quantile *MC*	2.5	2.4	2.0	1.8
mean *AR*	4.6	4.4	4.2	3.9
IQR *AR*	1.2	0.9	0.8	0.8
5% quantile *AR*	3.3	3.3	3.2	2.9
95% quantile *AR*	6.1	5.6	5.3	5.0

Notes: For each size class, this table reports the sample mean, median, interquartile range (IQR), 5% quantile and 95% quantile of the adjusted aggregate Lerner index L_A^* and the associated marginal costs and average revenue (all in percentage).

6.3. *The economic relevance of* **[L1]**, **[L3]** *and* **[L3]**

In addition to L_A, we also report summary statistics for the adjusted aggregate Lerner index L_A^* in Table 7. The distributional differences between L_A, L_A^* and L_{WA} are substantial, suggesting that **[L1]**–**[L2]**–**[L3]** cause economically relevant distortions.

Relative differences. To quantify the economic relevance of the distortions due to **[L1]**, **[L2]** and **[L3]** in more detail, we will now examine relative differences. Table 8 reports the sample distribution of the relative difference $|L_A - L_{WA}|/L_{WA}$. This distortion is economically important (between 6–14% on average), especially for larger banks. The 95% sample quantiles indicate that more extreme differences may also occur. These results indicate that the distortion in L_A due to **[L1]**–**[L2]**–**[L3]** are economically relevant. Table 8 shows that the relative difference $|L_A^* - L_A|/L_A$ can be substantial as well, especially for banks in the first two size classes. On average, it ranges between 7–13%, depending on the size class. The 95% sample quantiles indicate that larger differences may also arise. These figures show that the distortion in L_A due to **[L1]**–**[L2]** is also economically relevant. The sample distribution of $|L_A^* - L_{WA}|/L_{WA}$ quantifies the distortion due to the misspecified aggregate cost function (**[L3]**), which causes L_A^* to deviate from L_{WA}. Again we observe an economically relevant bias (between 3–14% on average), particularly for larger banks. All in all, we conclude that the distortions due to **[L1]**–**[L2]** and **[L3]** are economically important, both individually and jointly.

Table 8: Sample distribution of the relative differences between L_A, L_A^* and L_{WA}

	5% Q	50% Q	95% Q	mean	5% Q	50% Q	95% Q	mean
	CLASS 1				**CLASS 2**			
$\lvert L_A - L_{WA}\rvert/L_{WA}$	0.5	5.6	24.7	5.7	0.4	4.2	19.5	6.3
$\lvert L_A^* - L_A\rvert/L_A$	1.1	9.2	33.1	12.8	0.6	6.3	26.4	8.8
$\lvert L_A^* - L_{WA}\rvert/L_{WA}$	0.7	5.1	15.9	2.8	0.8	5.8	16.7	7.0
	CLASS 3				**CLASS 4**			
$\lvert L_A - L_{WA}\rvert/L_{WA}$	1.4	10.3	38.1	14.0	1.6	10.5	39.4	13.4
$\lvert L_A^* - L_A\rvert/L_A$	0.4	4.7	22.2	6.8	0.4	5.3	27.8	7.8
$\lvert L_A^* - L_{WA}\rvert/L_{WA}$	1.8	9.0	26.1	10.9	2.8	11.8	32.4	14.1

Notes: For each size class, this table reports sample statistics for the relative differences (in percentage) between several composite Lerner indices. The reported statistics are the 5%, 50% and 95% sample quantiles and the sample mean.

We also calculate an adjusted version of the weighted-average Lerner index (denoted L_{WA}^e) by using the sum of interest and non-interest income as the total revenue instead of the sum of the product-specific revenue in (5). We calculate this index because it is the weighted-average Lerner index that is usually calculated in the empirical literature (see the studies in the third panel of Table 1). It is readily seen that L_{WA}^e is subject to **[L2]**. By comparing L_{WA} and L_{WA}^e, the distortive effect of **[L2]** is isolated; see Table 9. Our calculations show that the distortive contribution of **[L2]** is relatively small.[12]

Table 9: Limitations of the composite Lerner indices

index	*limitations*
L_A	**[L1]**, **[L2]**, **[L3]**
L_A^*	**[L3]**
L_{WA}^e	**[L2]**
L_{WA}	–

Notes: This table indicates the relevance of limitations **[L1]**–**[L2]**–**[L3]** for each of the four composite Lerner indices considered in our empirical analysis. The comparison of two indices isolates the following distortive effects: L_A vs. L_A^* (effects of **[L1]**–**[L2]**); L_A^* vs. L_{WA} (**[L3]**); L_{WA}^e vs. L_{WA} (**[L2]**), and L_A vs. L_{WA} (**[L1]**–**[L2]**–**[L3]**).

Correlations. Table 10 displays the Spearman rank correlations between the various Lerner indices, including the adjusted aggregate Lerner index L_A^*.

We first consider the five Lerner indices $L_{TLNS}, L_{TSEC}, L_{OBS}, L_{WA}$ and L_A. The relative magnitude of these correlations is quite consistent across the four size classes. In each size class, the highest sample correlations are found between L_{TLNS} and L_{WA}, L_{WA} and L_A, and L_{TLNS} and L_A. For these pairs, the rank correlations reveal a strong positive monotonic relation for banks in the first two size classes, with correlations above 0.85. In the last two size classes the correlations between L_{WA} and L_A and L_{TLNS} and L_A are somewhat lower, with values in the range 0.6–0.8. In each size class, the lowest

[12]These results are available upon request.

correlations are found between L_{TSEC} and L_{OBS}, L_{TSEC} and L_A and L_{TLNS} and L_{TSEC}. For these pairs, the rank correlations reveal a weakly positive monotonic relation. For the remaining pairs of Lerner indices the rank correlations are moderately positive.

Given the large revenue share of loans relative to total securities and off-balance sheet activities, it comes as no surprise that L_{WA} is strongly correlated with L_{TLNS} and much less with L_{TSEC} and L_{OBS}. As a weighted average, L_{WA} is dominated by the output with the largest revenue share. Consequently, some information about the other components gets lost. The positive but relatively low correlations between L_{TSEC} and L_{OBS} and between L_{TLNS} and L_{TSEC} indicate that there is only a weakly positive relation between multi-product banks' market power across different outputs.

Turning to the adjusted aggregate Lerner index L_A^*, we observe that it has a positive correlation with L_A in all size classes, with values in the range 0.65 and 0.9. We also see that L_A^* tends to be more strongly correlated with L_{WA} than L_A. This is because L_A^* is subject to a single distortion that causes deviations from L_{WA} (**[L3]**), while L_A is subject to all three distortions.[13]

Table 10: Sample correlations (in percentage) between various Lerner indices

	CLASS 1						CLASS 2					
	L_{TLNS}	L_{TSEC}	L_{OBS}	L_{WA}	L_A	L_A^*	L_{TLNS}	L_{TSEC}	L_{OBS}	L_{WA}	L_A	L_A^*
L_{TLNS}	100						100					
L_{TSEC}	32.7	100					35.1	100				
L_{OBS}	48.5	30.7	100				53.4	23.0	100			
L_{WA}	95.6	49.4	54.8	100			94.1	48.8	61.4	100		
L_A	86.2	39.6	54.7	88.4	100		79.0	36.0	62.3	88.1	100	
L_A^*	92.1	42.1	48.8	93.8	89.6	100	89.0	42.4	62.2	93.9	86.8	100
	CLASS 3						**CLASS 4**					
	L_{TLNS}	L_{TSEC}	L_{OBS}	L_{WA}	L_A	L_A^*	L_{TLNS}	L_{TSEC}	L_{OBS}	L_{WA}	L_A	L_A^*
L_{TLNS}	100						100					
L_{TSEC}	17.0	100					30.9	100				
L_{OBS}	44.2	35.3	100				26.9	17.8	100			
L_{WA}	92.4	39.9	57.2	100			84.0	48.9	47.4	100		
L_A	57.9	37.0	33.6	68.6	100		61.1	34.3	44.2	79.0	100	
L_A^*	84.3	36.6	58.0	88.3	72.6	100	78.8	43.0	63.5	84.9	64.8	100

Notes: The reported correlations (in percentage) are Spearman rank correlations. All correlations are significantly different from 0 at each reasonable significance level.

Even though the correlations in Table 10 are positive, it is an empirical matter to what extent the choice of the Lerner index affects the outcomes of a subsequent analysis where this index is used as a dependent or explanatory variable. To investigate this issue in more detail, Table 11 shows the Spearman rank correlations between the various Lerner indices and several bank characteristics in the entire

[13]The correlation between L_{WA}^e and L_{WA} exceeds 0.98 in each size class. Complete correlation results for L_{WA}^e are available upon request.

sample of banks. The bank properties that we consider have been used in various recent studies (e.g., Khan et al., 2017) and are the ratio of risk-weighted assets to total assets (RWA/TA, a measure of asset risk), the ratio of loan loss provisions to total loans and leases (LLP/TLNS, credit risk), the log of total assets (log(TA), scale), the equity ratio (EQ/TA, capitalization), the loan ratio (TLNS/TA, illiquidity), the return on assets (ROA, profitability), the ratio of interest income to total income (NI/TI, diversification of income), and the deposit ratio (TDEP/TA, funding liquidity risk). The various Lerner indices differ substantially in the way they correlate with certain bank characteristics, both in terms of sign and magnitude of the correlation. In particular, we observe notable differences in the way L_{WA}, L_A and L_A^* correlate with certain bank properties. For instance, L_{WA} correlates negatively with RWA/TA and TLNS/TA, while L_A and L_A^* correlate positively with these two bank characteristics. Because L_A and L_A^* are biased due to inconsistent aggregation, their correlations with the bank characteristics are also biased. Similar biases may arise in a regression analysis that uses L_A or L_A^* as a dependent or explanatory variable.

Table 11: Sample correlations (in percentage) between various Lerner indices and a selection of bank characteristics

	RWA/TA	LLP/TLNS	log(TA)	EQ/TA	TLNS/TA	ROA	NII/TI	TDEP/TA
L_{TLNS}	−18.5	6.0	7.6	4.8	−15.7	7.8	17.5	17.5
L_{TSEC}	−18.7	−3.6	−18.8	9.0	−22.4	3.5	3.6	3.0
L_{OBS}	−10.1	*1.1*	−6.3	4.1	−4.6	15.2	15.5	6.8
L_{WA}	−13.6	5.2	3.5	5.9	−10.0	11.3	23.8	15.6
L_A	9.0	10.6	33.1	*0.9*	13.9	17.4	54.1	2.1
L_A^*	2.5	9.0	19.7	3.6	7.8	13.1	20.8	8.8

Notes: This table reports the Spearman rank correlations (in percentage) between the Lerner indices L_{TLNS}, L_{TSEC}, L_{OBS}, L_{WA}, L_A and L_A^* and various bank characteristics in the entire sample of banks. The bank properties are the ratio of risk-weighted assets to total assets (RWA/TA), the ratio of loan loss provisions to total loans and leases (LLP/TLNS), the log of total assets (TA), the equity ratio (EQ/TA), the loan ratio (TLNS/TA), the return on assets (ROA), the ratio of non-interest income to total income (II/TI), and the deposit ratio (TDEP/TA). Correlations in italics are not significantly different from 0; the other ones are significant at each reasonable significance level.

6.4. Robustness checks

We perform various robustness checks with respect to the definition of revenue for both loans and securities. For loans, we include gains on the sales of loans (a form of non-intermediation income) in the revenue as a robustness check. For securities, we consider two alternative definitions of revenue. First, we exclude realized trading gains (a form of non-intermediation income) from the revenue. Second, we calculate the securities revenue as the sum of securities income, realized trading gains and unrealized holding gains on available-for-sale securities. These changes in the definitions of the revenue for loans and securities do not substantially alter the results. We also estimate some alternative cost functions. A two-output cost function (Koetter et al., 2012)–omitting off-balance sheet output–

yields similar results as before for the remaining two outputs. We also estimate a cost function with a single input price for funding, which gives also gives similar results as before. Lastly, we change the stratification based on size classes by using quartiles to form size classes. Also this change does not substantially alter the results.

7. Conclusions

Our analysis has identified three limitations of the popular aggregate Lerner index that may distort its interpretation as a composite measure of market power. The main limitation is the potentially inconsistent aggregation of the individual outputs into a composite measure of output.

The economic relevance of the aggregate Lerner index' limitations is ultimately an empirical matter, which we have investigated for a sample of U.S. multi-product banks observed during the 2011–2017 period. We have shown that the limitations cause economically relevant distortions in the aggregate Lerner index' value as a composite measure of market power. These distortions may also affect the outcomes of a subsequent regression analysis that uses the aggregate Lerner index as a dependent or explanatory variable.

The main implication of our analysis is that we can neither rely on the aggregate Lerner index' value, nor on its correlation with bank characteristics and related variables. We therefore recommend the weighted-average Lerner index in situations where a composite Lerner index is needed to assess multi-product banks' market power. In other cases, we recommend the product-specific Lerner indices, which are by definition more informative about multi-product banks' market power than any composite index.

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APPENDIX

A. Call Report data

Table A.1 explains how the Call Report Data, downloaded from the FFIEC website, have been used to define the variables used in the empirical part of this study. For the NHT-GL cost function, the sample is filtered by excluding banks that are not part of a bank holding company, not located in a U.S. state, have no deposit insurance, or are not commercial according to the charter type. We also remove bank-year observations with negative values for total loans and leases, total securities, off-balance sheet activities, total equity, total revenue on total loans and leases, or total revenue on securities. We also remove bank-years with non-positive values of input factor expenses or total assets. We leave out bank-year observations whose input price of core deposits falls below the 1% sample quantile, whose wage rate exceeds the 99% sample quantile, or whose price of physical capital exceeds the 99% sample quantile. We also delete bank-years with negative output prices and bank-years whose average revenue on securities exceeds the 99.9% quantile. For the translog cost function we employ the same filtering rules, but additionally remove bank-years that have zero prices or output quantities because of the logarithmic transformation. For the estimation of the translog and Leontief cost functions, all level variables have been deflated using the Consumer Price Index for All Urban Consumers (CPIAUCSL) downloaded from the website of the Federal Reserve Bank of St. Louis.

Table A.1: Definition of variables

Variable	**Series/Definition**
purchased funds	RCON2604 + RCFD2800 + RCFD3548 + RCFD3200 + RCFD3190 + RCFD2200 − RCON2200
total deposits	RCON2200
core deposits	RCON2200 − RCON2604
# of full-time equivalent employees on payrol	RIAD4150
premises and fixed assets	RCFD2145
expenses on purchased funds (interest)	RIAD4172 + RIAD4180 + RIADA517 + RIAD4185 + RIAD4200
expenses on core deposits (interest)	RIAD4170 − RIADA517 − RIAD4172
salaries and employee benefits	RIAD4135
expenses of premises and fixed assets	RIAD4217
total interest expense (IE)	RIAD4073
total loans and leases (TLNS)	RCFD1400
total securities (TSEC)	RCFD1754 + RCFD1773
total assets (TA)	RCFD2170
risk-weighted assets (RWA)	RCFAA223
total equity (EQ)	RCFD3210
interest income (II)	RIAD4107
loan income	RIAD4010
gains on the sales of loans	RIAD5416
lease income	RIAD4065
securities income (interest and dividend)	RIAD4218
capital gains on securities	RIAD3521 + RIAD3196
unrealized holding gains on available-for-sale securities	RCFD8434
deposit service fees	RIAD4080
fiduciary services	RIAD4070
total non-interest income (NII)	RIAD4079
operating income	II + NII − IE
adjusted non-interest income (ANII)	RIAD4079 − RIAD4080
loan loss provisions (LLP)	RIAD4230
non-interest income capitalization credit equivalents of OBS	ANII × TA/(II − IE − LLP)

Notes: This table explains how the variables in this study have been calculated from the data available in the Call Reports.

Table A.2: Definition of variables (continued)

Variable	Series/Definition
price of purchased funds	(expenses on purchased funds)/(purchased funds)
core deposit rate	(expenses on core deposits)/(core deposits)
wage rate	(salaries and employee benefits)/(# of full-time equivalent employees on payrol)
price of physical capital	(expenses of premises and fixed assets)/(premises and fixed assets)
total costs	sum of expenses on core deposits, purchased funds, labor and physical capital
average revenue on loans	(loan income + lease income)/TLNS
average revenue on loans (alternative)	(loan income + lease income + gains on the sales of loans)/TLNS
average revenue on securities	(securities income)/TSEC
average revenue on securities (alternative 1)	(securities income + realized capital gains)/TSEC
average revenue on securities (alternative 2)	(securities income + realized capital gains + unrealized holding gains)/TSEC
average revenue on OBS	ANII/(credit equivalent of ANII)
average revenue on total assets	(II + NII)/TA
FDIC bank certificate ID	RSSD9050
date	RSSD9999
charter type	RSSD9048
physical state code	RSSD9210
primary insurer	RSSD9424
is bank part of BHC?	RSSD9364

Notes: This table explains how the variables in this study have been calculated from the data available in the Call Reports.