Analyse

Measuring intra-bank complexity by (not) connecting the dots with LEI

A supervisor perspective

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Measuring intra-bank complexity by (not) connecting the dots with LEI. A supervisor perspective.

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1 Introduction

It is exactly 10 years ago that the Global Legal Entity Identifier System (GLEIS) has been endorsed by the Financial Stability Board (FSB) and the G-20, after the initiative was born out of the global financial crisis of 2007-2009.[1] In 2014 the Legal Entity Identifier (LEI) code, i.e. a unique identification code for legal entities that participate in financial transactions, was introduced by the GLEIS with the ambition to become the global standard (GLEIF, 2018). The introduction of the LEI was one of the global standards the FSB introduced after the collapse of Lehman Brothers in 2008. When Lehman failed, many market participants did not realize they were exposed to the bank, for example through its subsidiaries (Grody, 2018). The LEI contains information on the ownership structure of the entity and thereby does not only provide information on "who is who", but also on "who owns whom". The latter is very useful for, for example, getting a comprehensive view on the group structures of a firm and measuring intra-firm complexity. This study tests how useful the LEI data currently is for this purpose. The purpose of the LEI is however much broader, since is provides relevant information for both public and private parties.

The global financial crisis of 2007-2009 showed us that distress at large and complex banks undermined financial stability. The often complex group structures of financial institutions impeded oversight by regulatory authorities ex-ante and, at the same time, complicated crisis management and the resolvability of these institutions ex-post (Carmassi and Herring, 2016). The crisis led to more attention for transparency and systemic risk (IMF and BIS, 2010). Post-crisis regulatory measures were introduced, such as the aforementioned LEI code to identify legal entities and their intra-firm relationships, a framework to identify Global Systemically Important Banks (G-SIB), and recovery and resolution regimes to improve the resolvability of banks. These measures can support each other: for example, the LEI data can be used to get an overview of the group structure of a financial institution and as such provide relevant insights for recovery and resolution purposes. Combined with ever more granular reporting this also opens up the possibility to trace exposures through the financial system much more accurately (Van Lelyveld and Ullersma, 2022).

In this study we test the fitness of the current LEI data to produce an overview of intra-bank relationships by calculating complexity measures based on the LEI data and relating this to other data sources and findings in the existing literature. For the calculation of the complexity measures we apply the methodology proposed by Flood et al. (2020). In their study, the authors consider the intra-firm complexity of U.S. bank holding companies using data from the National Information Center (NIC) provided by the Federal Reserve System. We apply the same methodology to European bank holding companies by using the publicly available LEI data, and test for the fitness of this data for getting full insight into the intra-bank complexity of the largest bank holding companies.

We find that – at least currently – the coverage of LEI data is too limited to draw any conclusions on the complexity of European banks, both in the cross section and over time. However, our analysis does show the potential of the LEI data for measuring organizational complexity. The calculated complexity indicators are less correlated with size than the G-SIB classification, indicating its potential as a measure for organizational complexity distinct from the more traditional indicators that are often based on balance sheet information and are in some cases correlated with size by design.

[1] The GLEIS consists of the LEI regulatory Oversight Committee (ROC) and the Global Legal Entity Identifier Foundation (GLEIF). The primary objective of the ROC is oversight and policymaking for the GLEIS. The ROC policies are published on www.leiroc.org, and the ROC also publishes progress reports. The ROC publication of March 10, 2016 ("Collecting data on direct and ultimate parents of legal entities") is decisive for how corporate structures have to be reported.

Of course, one can think of other data – with a longer history and higher coverage – to measure the complexity of a bank holding company. Cetorelli and Goldberg (2014) measure organizational complexity by the number and geographic spread of an institution's affiliates. In a similar fashion, Carmassi and Herring (2016) consider the number of subsidiaries. The authors admit that while a simple count of subsidiaries may indicate a key challenge to an orderly resolution, this measure comes with some drawbacks . Most importantly, these measures don't contain information on the control hierarchies and interlinkages of legal entities within a company. Bank holding companies may have the same number of subsidiaries (and branches), but if one company has many more layers of ownership across different countries then this company would be more complex to resolve than a company with subsidiaries that all fall under the direct ownership of the ultimate parent and reside in the same country. Therefore, data on "who owns whom", i.e. the LEI data, is not only desired but actually much needed.

The focus of this study is the use of the LEI data for getting a better overview of group structures of banks. This directly links to the objective of the LEI to increase transparency around legal entities and their organizational structures. The potential of the LEI is however significant and its relevance is not limited to just supervisors and public authorities, but is also important for banks' internal risk management and the wider financial industry as pointed out by the ESRB (2021). Identified areas for possible further use as listed by the ESRB (2021) are, for example, to support the collection of data on sustainable finance by being able to track supply chains through the LEIs of suppliers or to help making anti-money laundering measures work more effectively by tracking parents and subsidiaries located in offshore centres. In addition, the LEI may also strengthen data standardization as well as support Straight Through Processing (STP) and Know Your Customer (KYC) processes (FSB, 2022).

To conclude, given the large potential of the LEI in combination with its current shortcomings – mainly linked to a low coverage – more attention should be given to increasing the usage of the LEI by institutions worldwide. As also mentioned by DNB governor Klaas Knot; we have seen the benefits of the use of the LEI in multiple areas, but the benefits should be reaped even more broadly (Knot, 2020). This requires effort by all market participants and a role for central banks and policymakers to support this.

2. Analysis on group structures and intra-bank complexity

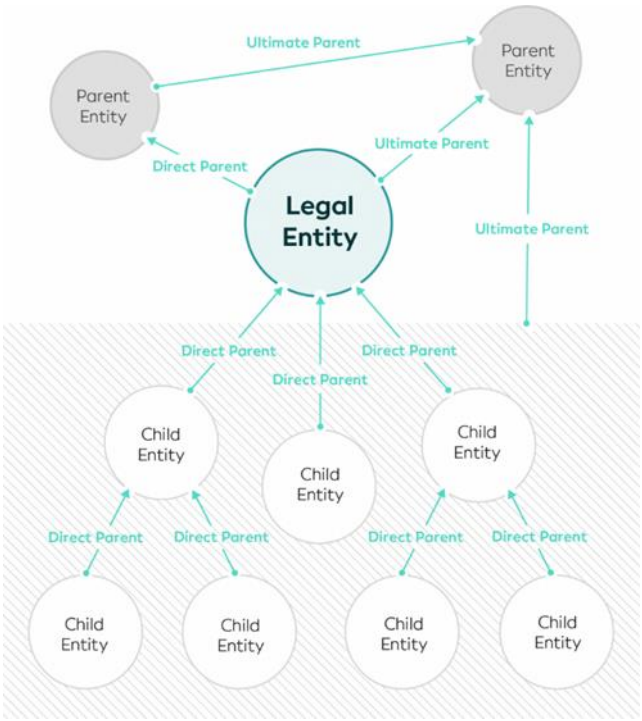
2.1 Data sources and definitions

Since we want to focus on intra-bank complexity, we need information on the organizational structures of banks. We obtain data on LEI codes from The Global Legal Entity Identifier Foundation (GLEIF): the foundation that is responsible for and makes the LEI data available. We focus on the so-called Level 2 data[2], that provides information on "Who owns Whom". All institutions that have a LEI code have to report their 'direct accounting consolidating parent', as well as their 'ultimate accounting consolidating parent'. The LEI data thereby enables connecting the dots within an entity and thus provides a complete overview of the ownership structure. Contrary to, for example, information on just the subsidiaries and branches, we can identify multiple layers of relationships within legal entities with LEI data (see Figure 1).

Although the LEI is a global standard, it is not yet compulsory for all financial entities to obtain a LEI.[3] Moreover, the LEI relies on self-registration. Multiple FSB jurisdictions have however implemented regulations referring to the LEI.[4] In a thematic review on the LEI, the FSB (2019) shows that this is paying off. Especially the November 2017 revision of the European Markets Infrastructure Regulation (EMIR), which made the LEI mandatory for entities engaged in derivates trading, led to a significant increase in the number of LEI codes.

Since we want to compare our measure of intra-bank complexity based on the LEI data with data on bank size (derived from Orbis) and its classification as G-SIB (FSB, 2021), we focus on the larger (and probably more complex) European banks. As such, our sample consists of 35 European banks with at least EUR 100 billion assets that report their financial data on a quarterly basis (See Table A.1 in the Appendix for a complete list). We consider data from 2018 onwards, to avoid the jump in the number of LEI codes in 2017 resulting from the EMIR revision.. The total assets of the 35 banks in our sample sum up to around 27 trillion euro or roughly 55% of total European banking assets (based on data from 2020).

Figure 1 Group structures in LEI



Source: GLEIF (Level 2 Data: Who Owns Whom)

[2] A distinction is made between Level 1 and Level 2 data. Level 1 data contains the most essential elements of identification and provides an answer to the question of "who is who?". Level 2 data contains information on the 'direct accounting consolidating parent' as well as on the 'ultimate accounting consolidating parent' of the legal entities with a LEI code. It thereby provides an answer to the question "who owns whom?".

[3] In many jurisdictions around the globe, public authorities rely on the LEI to evaluate risk, take corrective steps and, if required, minimize market abuse and improve the accuracy of financial data. However, GLEIF has no mandate to define the strategy for the use of the LEI by the public sector based on article 10 of the GLEIF Statutes (Hartsink, 2019).

[4] For an overview, see: LEI in Regulations - Solutions – GLEIF

2.2 Methodology

In our study, we focus on measuring intra-bank complexity. The intra-firm complexity of a bank is one of the elements that determines whether a bank is classified as a "globally systemically important institution" (G-SIB) by the Financial Stability Board and thus faces additional regulatory measures. As pointed out by Flood et al. (2020), a consistent way to measure organizational complexity is still lacking. The authors therefore propose to use a bank's organizational structure as a proxy for its complexity and come up with a set of indicators.[5] Their methodology, which we apply in our study, relies on network theory by applying *topological quotients*: a topological quotient collapses certain points of a network that share a common characteristic. In their study, the clusters of nodes (subsidiaries) of a specific bank network are collapsed based on geographical location.[6] As such, one gets insight in the coordination challenges across the clusters identified. We intuitively explain the concept using a relatively simple example.[7]

We focus on *cycle ranks*. Before explaining the different types of cycle ranks it is important to define the concept of nodes (sometimes also referred to as vertices) and edges. Figure 2 shows a hypothesized bank holding company. The figure on top shows the group structure of a company active in two countries – country A and country B – with a total of 9 entities. The entities – i.e. the total number of subsidiaries or branches – belonging to the bank holding company are called the '*nodes*'. The connections between the nodes of a bank holding company are referred to as '*edges*'. In the example, the number of edges equals 8.

Next, we discuss the concept of cycle ranks. A cycle rank reveals how many links of ownership and control a supervisor must sever to extract all entities – subsidiaries and branches – when resolving a distressed bank holding company (Flood et al., 2020). The cycle rank of a graph is defined as the number of edges minus the number of nodes plus the number of connected components. The group structure of a bank holding company is by definition connected, since all entities are – directly or indirectly – related to the bank holding company. Therefore, the number of connected components equals 1 by construction and consequently the cycle rank of the graph equals 0 in our example ((9-9)/1).

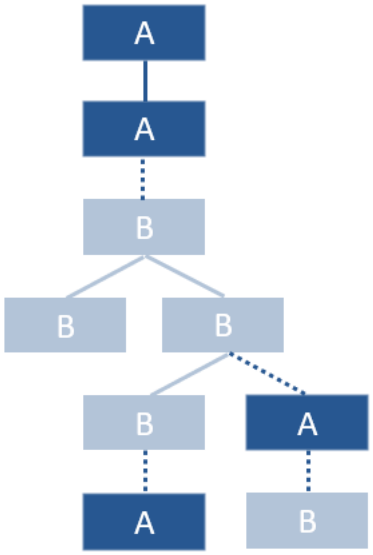
In addition to the cycle rank, we consider four other measures of complexity. Next to the cycle rank of the graph in its entirety, we consider the cycle ranks of the full quotient, heterogeneous quotient, condensed full quotient, and condensed heterogeneous quotient. The figures on the bottom of Figure 2 illustrate these concepts. As mentioned, a quotient collapses certain points of a network that share a common characteristic. In our study, the nodes are collapsed based on the country the entity resides. This is relevant information for resolution purposes: coordination, for example during failures, is complicated if entities are active in multiple countries. Since the bank holding company in this example is only active in two countries, the graph of the full quotient is a relatively simple one showing all relationships and two distinct labels (i.e., the two countries). The graph for the heterogeneous quotient only considers the relationships between nodes from different countries. Next, the condensed versions replace the multi relationships between or within different countries by a single one.

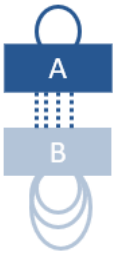
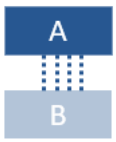
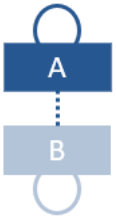
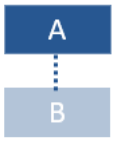
[5] In a recent study, Lumsdaine et al. (2021) also introduce a methodology – based on network theory – to measure the intrafirm complexity of financial institutions. Their measure is based on the distance of the majority-control hierarchy tree from a specific institution from their defined "ideal" supervisory or perfect tree structure.
[6] Flood et al. (2020) also collapse on the basis of entity type (e.g. bank, broker-dealer, insurer, etc.). Given the data structure of the LEI, we focus on the geographical location.
[7] For a thorough explanation of the methodology and the construction of the different variables that we show in the next section we refer to Flood et al. (2020).

The aim of our study is to test the current fitness of the LEI data for measuring intra-bank complexity. This is challenging because we don't have a perfect benchmark. We therefore relate the LEI data and the calculated intra-bank complexity scores to other data sources and previous findings.

Figure 1 Quotient graphs example

This figure provides an illustrated example of the definitions of the indicators in our study.



Full quotient	Heterogeneous quotient	Condensed full quotient	Condensed heterogeneous quotient
Cycle rank: 8-2+1 = **7**	Cycle rank = 4-2+1 = **3**	Cycle rank = 3-2+1 = **2**	Cycle rank = 1-2+1 = **0**
			

The figure is adapted from Flood et al. (2020).

2.3 Results

As mentioned before, we have used the LEI Level 2 data and applied the methodology by Flood et al. (2020) to calculate intra-bank complexity measures for 35 European banks. Table 1 below shows the descriptive statistics of these measures.

First, the average number of nodes represents the average number of entities – subsidiaries and branches – within a bank holding company with a unique LEI code. Table 1 indicates that there is quite some heterogeneity across the bank holding companies within our sample. The same holds for the number of edges. On average, the bank holding companies in our sample have entities with a LEI code in 57 different countries.

Cycle ranks show more interesting patterns. The median cycle rank of the graph of zero indicates that at least half of the group structures of the bank holdings companies in our sample are close to tree structures (with no cycles). However, on average the cycle rank of the bank holdings companies in our sample is 11. The higher the cycle rank, the higher the proportion of edges (relationships) to nodes (entities) and the higher the presence of co-ownership within a group structure. The average cycle rank of the heterogeneous quotient is substantially higher than zero, even for the bottom 10% of our sample. This implies – not surprisingly – that the number of parent-child relationships is higher than the number of countries bank holding companies in our sample are active in. In this statistic we exclude 'self-loops' (i.e. connections between entities in the same country) and the cycle rank of the heterogeneous quotient thus represents the number of connections between entities in different countries, and thereby indicates potential resolvability problems. The cycle ranks of the condensed graphs are – on average – also above zero. For all cycle ranks, Table 1 shows that there is quite some dispersion among the bank holding companies in our sample.

Table 1: Descriptives intra-bank complexity measures

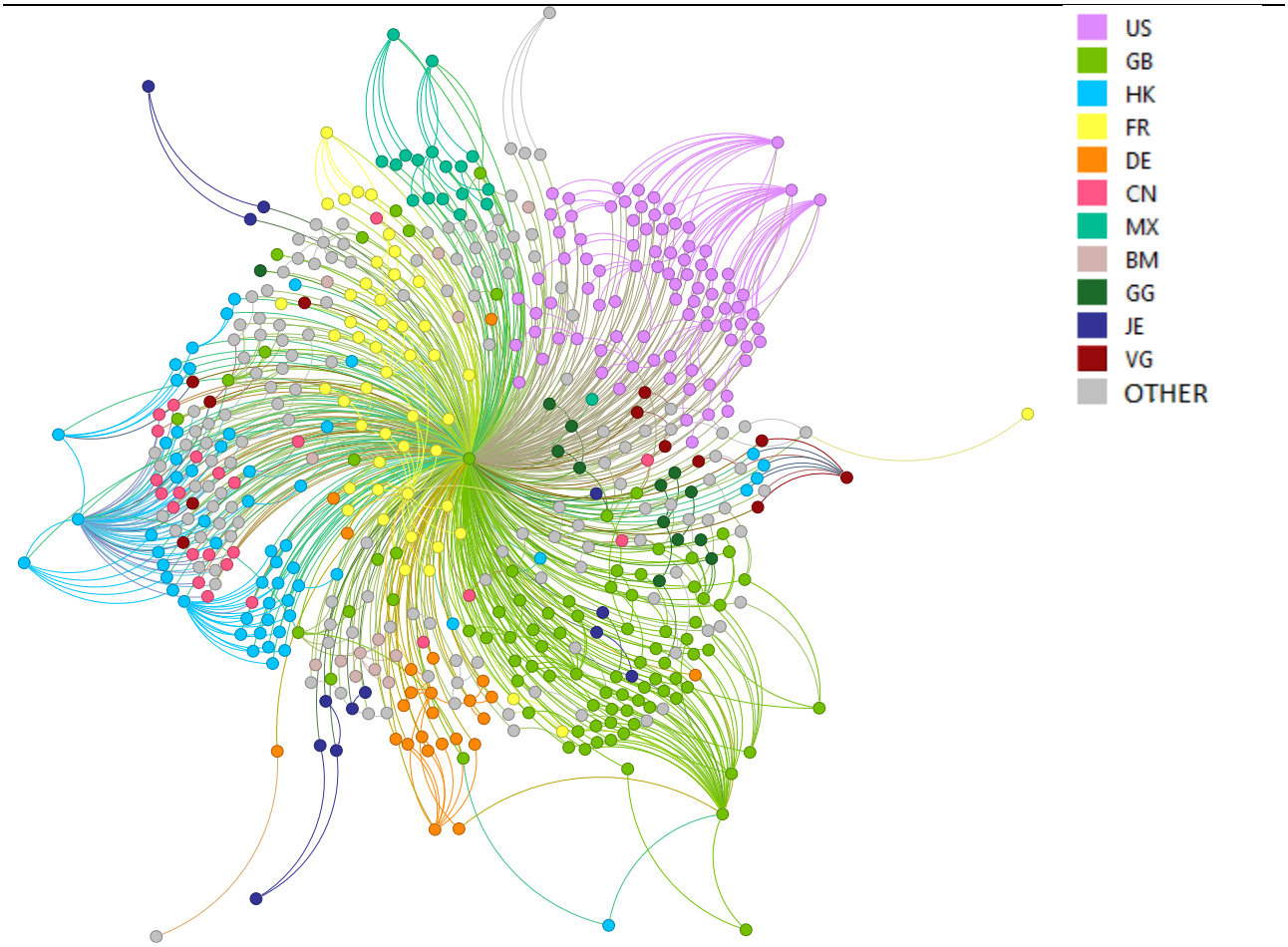
This table shows the descriptive statistics for the complexity measures for all 35 banks over the period 2018q1 – 2021q3.

	Mean	**Median**	**10%**	**90%**	**St. Dev.**
Number of nodes	154	60	7	492	194
Number of edges	163	62	6	513	208
Number of countries	57	19	2	172	83
Cycle rank of the graph	11	0	0	34	26
Cycle rank of the full quotient	147	50	4	482	195
Cycle rank of the heterogeneous quotient	47	9	0	164	81
Cycle rank of the condensed full quotient	8	3	1	25	12
Cycle rank of the condensed heterogeneous quotient	3	0	0	7	6

To get a better and more intuitive understanding of a bank holding's structure we shows a network graph based on the LEI data for HSBC, the largest European bank, in Figure 2 below. Every dot represents an entity with a LEI code that belongs to the ultimate parent entity HSBC Holdings PLC (the dot in the middle). The colors represent the home countries of the LEI reporting entities. This figure clearly shows how organizationally complex one parent institution can be. Multiple layers of ownership exist. While the graph shows a sort of clustering of countries (i.e. colors) the graph also shows cases where layers of ownership across different countries exist. As stated, such entities would be more complex to resolve than a company with subsidiaries that all fall under the direct ownership of the ultimate parent and reside in the same country.

Figure 3: The intra-bank network of HSBC

This figure plots the intra-entity network of HSBC. Every dot represents an entity with a LEI code that belongs to HSBC Holdings PLC (the dot in the middle). The colors of the nodes represent the country of the reporting entity.



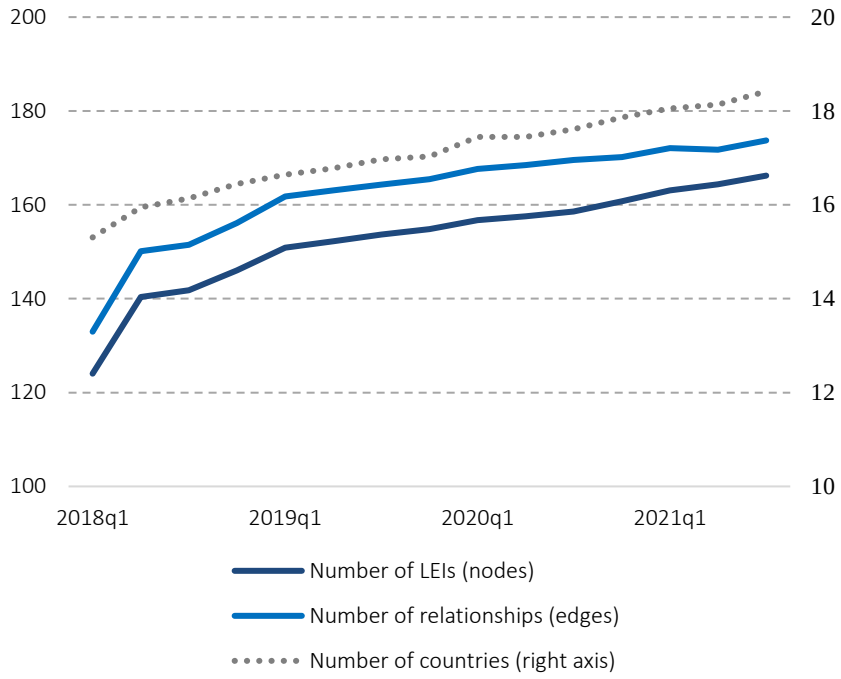
While all these statistics provide some intuitive insights in the intra-bank complexity of the largest bank holding companies in Europe, the question is whether they provide the full picture. For example, in the case of HSBC, based on the LEI data we can identify 50 different countries that HSBC has entities in (year end 2020). According to HSBC's annual report the number of countries should be 64. Depending on the relevance of the missing subsidiaries, Figure 3 might not show the full picture. For measuring intra-bank complexity, it is of utmost importance that the data is complete and that the coverage is comparable across bank holding companies. For example, if bank holding companies only obtain a LEI for their larger entities, for entities in specific regions or for entities that are active in particular markets (i.e., trading derivates), then the complexity measures likely underestimate the real intra-bank complexity of bank holding companies. Moreover, the data is more meaningful once considered in relation to something, e.g. an analysis over time or a comparison across bank holding companies. The next section therefore aims to validate the use of the LEI data for measuring intra-bank complexity.

2.4 Fitness of the LEI for measuring intra-bank complexity

The LEI data can – if consistently reported – provide great insight in the development of complexity over time. Figure 4 plots the average number of LEIs (nodes), relationships (edges) and countries in which the bank is active of the banks in our sample over the period 2018-2021. One can immediately observe that these main input variables to calculate the complexity measures, i.e. the cycle ranks, only increase over time. This is not only the case for the averages; actually for all banks in our sample the number of LEIs strictly increases over time. As such, one can question whether it is the complexity that is increasing or – simply – the reporting and thereby the coverage of the LEI data.

Figure 4: Main input variables over time (averages)

This figure shows the average number of LEIs (nodes), relationships (edges) and countries of a balanced panel of 35 banks in our sample for the period 2018q1 – 2021q4.



Source: GLEIF, own calculations

Currently, it is quite a challenge to conclude anything about the coverage of the LEI data for bank holding companies. A straightforward method would be to compare the number of obtained unique LEI codes for a bank holding company with the number of subsidiaries and branches belonging to that bank holding company. The former is equal to the number of nodes in our study.

There are however, at least, three caveats that come with this comparison. First of all, branches in the same country should operate under one umbrella LEI code. This implies that a check on the coverage based on the number of LEIs and the number of branches and subsidiaries or the number of subsidiaries is not that meaningful since the definitions do conflict. By only considering subsidiaries the average coverage equals 38% (i.e. dividing the number of unique LEI codes by the number of subsidiaries).This however results in an overestimation in case all institutions report a LEI, since the number of unique LEI codes will always be larger than the number of subsidiaries if the institution has branch companies. When comparing the number of subsidiaries and branches to the number of LEI codes (i.e. dividing the number of unique LEI codes by the number of subsidiaries and branches as reported in Orbis), we find that the average coverage equals 26% based on end-2020 data.

Second, we find that the coverage in our sample depending on the metric varies from 0% to 113% (and from 3% to 132% if we only consider subsidiaries). A coverage above 100% indicates that there are bank holding companies with more unique LEI codes than the number of reported subsidiaries and branches in Orbis. Third,

basing the coverage on the assets instead of the number of entities would economically be more meaningful, but this data is not always available.

As a last step we compare our calculated complexity indicators with data and findings from previous studies. The most relevant study is Flood et al. (2020). These authors calculate the complexity indicators for a sample of 149 firm-year observations over the years 2013-2018, based on data for the largest U.S. financial firms. They find that their calculated indicators are highly correlated with existing complexity indicators from the G-SIB framework that are not based on organizational structure. Moreover, their indicators are less correlated with size than these existing complexity measures.

Table 2: Correlation Matrix

	GSIB	Total assets	# of nodes	# of edges	CR (graph)	CR (full quot.)	CR (heter. quot.)	CR (cond. full quot.)	CR (cond. heter. quot)
GSIB	1								
Total assets	0.744	1							
# of nodes	0.374	0.633	1						
# of edges	0.392	0.659	0.994	1					
CR (graph)	0.351	0.552	0.495	0.585	1				
CR (full quotient)	0.358	0.633	0.994	0.998	0.575	1			
CR (heterog. quot.)	0.551	0.623	0.784	0.802	0.573	0.788	1		
CR (cond. full quot.)	0.502	0.681	0.673	0.722	0.760	0.694	0.691	1	
CR (cond. heterog. quot.)	0.441	0.607	0.562	0.623	0.797	0.599	0.629	0.967	1

Based on 2021, 12 out of our 35 banks are classified as a G-SIB. We therefore limit the analysis to the correlation of our complexity indicators with a G-SIB classification dummy. Table 2 shows the correlation matrix. Like Flood et al. (2020), we do find high correlations between the complexity indicators, size and the G-SIB classification. Moreover, the complexity indicators are correlated with size, but less than the G-SIB variable is. While the correlation between G-SIB and size equals 0.744, the correlation between size and the complexity indicators is also high, but a bit lower than the correlation between G-SIB and size, and lies between 0.552 and 0.681.

Table 3 further shows that G-SIBs are far more complex than non G-SIBs by presenting the average complexity measures for the different subgroups of banks depending on their G-SIB classification.

Table 3: Complexity measures G-SIB

	G-SIB	**No G-SIB**
# of nodes	250	99
# of edges	272	102
CR (graph)	23	4
CR (full quotient)	240	95
CR (heterog. quot.)	107	14
CR (cond. full quot.)	16	4
CR (cond. heterog. quot.)	6	1

3. Conclusion

The LEI data has a lot of potential for supervisors, financial markets and institutions, since it enables one to connect the corporate dots and get insight in the organizational structures of (financial) corporations globally. This is not only relevant for resolution and crisis management, but also fosters financial stability if the oversight challenges – that were present during the global financial crisis – can be reduced. In this study, we test the current fitness of the LEI for the purpose of getting insight in intra-bank complexity and group structures.

Let's start with some good news. The use of the LEI seems to increase over the last years. However, we also show that presently the coverage of the LEI data is too low to draw any conclusions on the complexity of European banks, both over time and in the cross section. This is a missed opportunity. For getting a complete overview of the financial landscape, it is of utmost importance that the data is complete and that the coverage is comparable across banks and corporations in general. Put it simply, connecting the dots is not that informative if we don't have a majority of the dots.

It turns out that it is even difficult to say something about the coverage of the LEI data based on public data sources for the largest European bank holding companies. We estimate that around 26% of the subsidiaries and branches of the 35 largest European bank holding companies have obtained a LEI code. The coverage varies greatly across companies, complicating the analysis on intra-bank complexity for the largest banks.

Our analysis does show the potential of the LEI data for measuring intra-bank complexity. The data allows for the creation of a measure for organizational complexity that is distinct from the more traditional indicators that are often based on balance sheet information (and are as such correlated with size). Applying the method by Flood et al. (2020) for European banks, we find that the calculated complexity indicators are correlated with the G-SIB classification, but less correlated with size than the G-SIB classification itself is.

The focus of this study has been on the use of the LEI for measuring intra-bank complexity. The value of the LEI is however much larger. As mentioned before, a broader adoption of the LEI could benefit banks in conducting their Know Your Customer processes or mitigate the risk in interbank relationships. On top, the LEI also has quite some value for multiple parties when it comes to cross-border activities. For example, Cleland and Hartsink (2020) mention its use in verifying identity in (cross-border) payments, and Hartsink (2022) discusses the relevance of the LEI for the securities industry.[8]

To conclude, given the large potential of the LEI in combination with its current shortcomings, mainly linked to low coverage, attention should be given to increasing the usage of the LEI by entities worldwide. The adoption of the LEI should therefore be better promoted, for example by adding the LEI as a requirement in new regulatory reporting standards as the EMIR regulation has shown that this is effective. The ESRB (2022) and ICC (2022) address current gaps in the adoption of the LEI, and a recent report by the FSB (2022) presents recommendations to increase the use of the LEI. The most promising of these is to foster mapping the LEI to domestic identifiers while at the same time increasing national coverage. This comes with a role for central banks and policymakers.

[8] For these cases, the GLEIF publishes LEI-to-ISIN (International Securities Identification Number) and LEI-to-BIC (Business Identifier Code) relationship files.

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5. Appendix

Table A.1 List of banks included in the analysis

Bank name	LEI code
ABN Amro Bank N.V.	BFXS5XCH7N0Y05NIXW11
Banca Monte dei Paschi di Siena S.p.A	J4CP7MHCXR8DAQMKIL78
Banco Bilbao Vizcaya Argentaria S.A.	K8MS7FD7N5Z2WQ51AZ71
Banco BPM S.p.A.	815600E4E6DCD2D25E30
Banco de Sabadell S.A	SI5RG2M0WQQLZCXKRM20
Banco Santander, S.A.	5493006QMFDDMYWIAM13
Barclays PLC	213800LBQA1Y9L22JB70
Bayerische Landesbank	VDYMYTQGZZ6DU0912C88
BNP Paribas S.A.	R0MUWSFPU8MPRO8K5P83
Caixabank S.A.	7CUNS533WID6K7DGFI87
Commerzbank AG	851WYGNLUQLFZBSYGB56
Credit Agricole S.A.	969500TJ5KRTCJQWXH05
Credit Suisse Group AG	549300506SI9CRFV9Z86
Danske Bank A/S	MAES062Z21O4RZ2U7M96
Deutsche Bank AG	7LTWFZYICNSX8D621K86
DNB ASA	5967007LIEEXZX78M803
Erste Group Bank AG	PQOH26KWDF7CG10L6792
HSBC Holdings PLC	MLU0ZO3ML4LN2LL2TL39
ING Groep N.V.	549300NYKK9MWM7GGW15
Intesa Sanpaolo S.p.A.	2W8N8UU78PMDQKZENC08
KBC Groep	213800X3Q9LSAKRUWY91
Kreditanstalt für Wiederaufbau (KfW)	549300GDPG70E3MBBU98
Landesbank Hessen-Thüringen Girozentrale	DIZES5CFO5K3I5R58746
Lloyds Banking Group PLC	549300PPXHEU2JF0AM85
Natwest Group PLC	2138005O9XJIJN4JPN90
Norddeutsche Landesbank Girozentrale	DSNHHQ2B9X5N6OUJ1236
Nykredit Realkredit A/S	LIU16F6VZJSD6UKHD557
Raiffeisen Bank International AG	9ZHRYM6F437SQJ6OUG95
Skandinaviska Enskilda Banken AB	F3JS33DEI6XQ4ZBPTN86
Societe Generale	O2RNE8IBXP4R0TD8PU41
Standard Chartered PLC	U4LOSYZ7YG4W3S5F2G91
Svenska Handelsbanken AB	NHBDILHZTYCNBV5UYZ31
Swedbank AB	M312WZV08Y7LYUC71685
Ubs Group AG	549300SZJ9VS8SGXAN81
Unicredit S.p.A.	549300TRUWO2CD2G5692