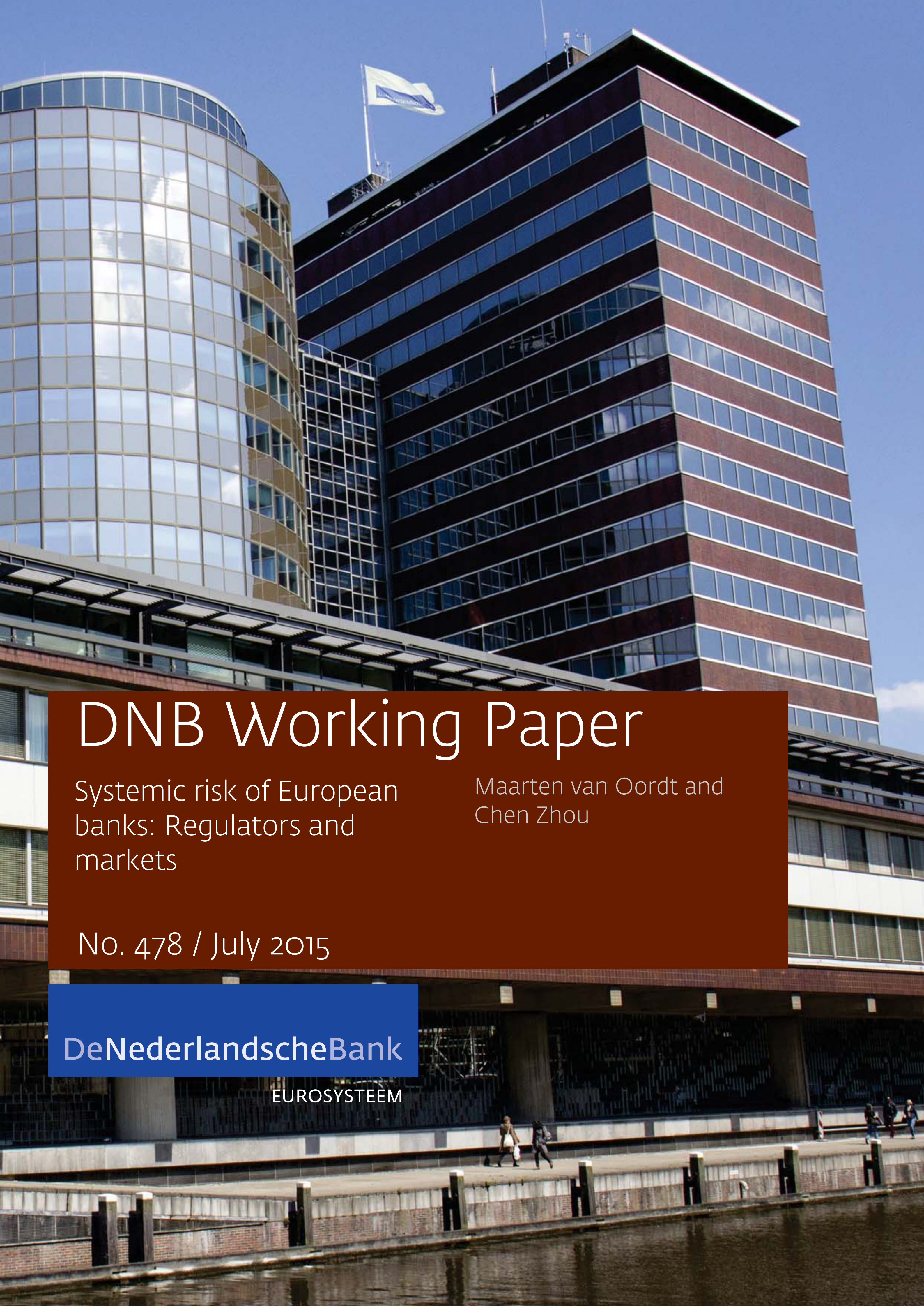

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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Systemic risk of European banks: Regulators and Markets[*]

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Abstract

Rules and regulations may have different impacts on risk-taking by individual banks and on banks' systemic risk levels. That is why implementing prudential rules and policies requires careful consideration of their impact on bank risk and systemic risk. This chapter assesses whether market-based measures of systemic risk and recent regulatory indicators provide similar rankings on the systemically importance of large European banks. We find evidence that regulatory indicators of systemic importance are positively related to systemic risk. In particular, banks with higher scores on regulatory indicators have a stronger link to the system in the event of financial stress, rather than having a higher level of bank risk.

Keywords: G-SIBs, financial stability, macroprudential regulation, systemic importance.
JEL classifications: G01, G21, G28.

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Views expressed do not necessarily reflect official positions of De Nederlandsche Bank.

1 Introduction

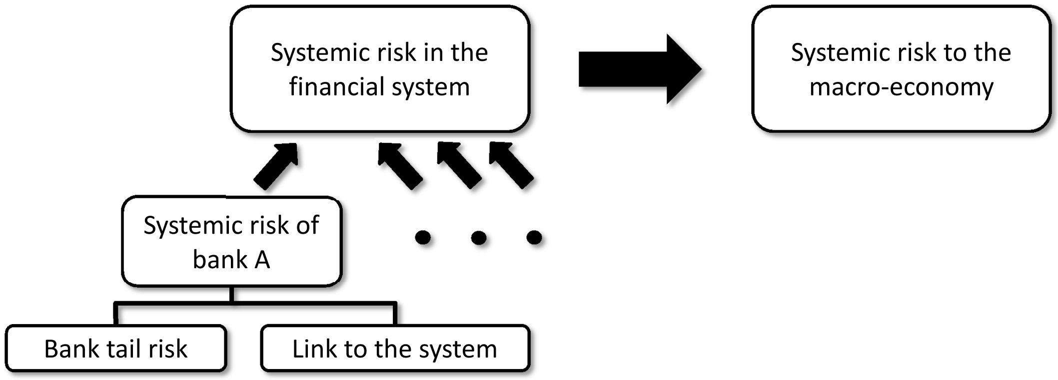
There is a general consensus that prudential regulation before the recent financial crisis focused mainly on the soundness of individual financial institutions. In other words, prudential regulation was primarily based on the microprudential objective of limiting the level of bank risk-taking. This might be one of the reasons why the recent financial crisis was not prevented. By contrast, the macroprudential objective of regulation is maintaining the stability of the financial system as a whole or, in other words, limiting systemic risk.

The ultimate concern of policy makers in the context of systemic risk is the macroeconomic cost of financial instability, i.e., the macroeconomic consequences of a serious disruption of the financial system; see Borio (2003). Evidence of such costs is documented by e.g. Peek and Rosengren (2000), Boyd et al. (2005) and Dell'Ariccia et al. (2008). The systemic risk to the macro-economy depends on the level of systemic risk in the financial system, which, in turn, depends on the systemic risk of individual financial institutions; see Figure 1. Gaining a full understanding of each of these layers of systemic risk is not without its challenges. That is why most studies focus on one single aspect of systemic risk.

Instead of measuring the ultimate macroeconomic cost of financial stability, a growing literature examines the level and determinants of systemic risk in the financial system, or, in other words, the likelihood of a collapse of the financial system and the potential magnitude of such a collapse. Examples are the studies on financial stress indicators and early warning indicators, which focus on evaluating the variation in systemic risk over time. Those papers are sometimes referred to as studies on systemic risk in the time dimension; see e.g. De Bandt et al. (2010) and Galati and Moessner (2013).

Rather than studying the time dimension, this chapter focuses on the cross-sectional dimension, i.e., the distribution of systemic risk across financial institutions. While there are many definitions of systemic risk, there is a general consensus that the health of some institutions is more essential to the stability of the financial system than that of others. Broadly speaking, the term "systemic risk" consists of two elements: "systemic" and

Figure 1: Systemic risk: a multi-layer concept



Note: The figure presents a diagram of the portfolio view on systemic risk explained in Borio (2003) and the decomposition of the systemic risk of financial institutions in Van Oordt and Zhou (2014).

"risk". Systemic risk thus not only depends on the risks taken by individual banks, but also on how these risks relate to other institutions in the system. For example, "common exposures" and "interlinkages" are also of paramount importance for systemic risk; see e.g. Borio (2003, 2014). That is why, conceptually, the systemic risk of a bank may be broken down into two subcomponents: the downside tail risk of the bank and its link to the rest of the system in the event of financial stress; see Figure 1.

The distinction between bank risk and systemic risk steers the ongoing debate about the micro- and macroprudential objectives of regulation. By focusing on bank risk, the microprudential objective of regulation considers one side of the "systemic risk coin" only. There is no guarantee that policies aimed at achieving the microprudential objective of regulation will simultaneously deal with the macroprudential objective, or vice versa. This depends on how policies with an impact on bank "risk" are related to the "systemic" component of "systemic risk".

One of the recently introduced policies in the context of macroprudential regulation is to identify global systemically important banks (G-SIBs) and to require them to fund themselves with more equity capital as an additional loss-absorbing buffer. Identification of the G-SIBs and the level of the additional capital buffer depend on the scores of banks in terms of systemic importance according to regulators; see BCBS (2013a, 2014a).

Regulators calculate the scores on the basis of information provided by the individual banks. Parallel to the regulatory approach, academic literature provides several measures of systemic risk on the cross-sectional dimension using market-based information. These market-based measures can also be used to rank financial institutions in terms of systemic risk.

This chapter assesses whether market-based measures of systemic risk and recent regulatory indicators provide similar rankings of systemically important banks. After a brief review of both approaches, we compare their rankings for a group of large European banks. We document evidence that regulatory scores used for the identification of G-SIBs have a positive relation to market-based measures of systemic risk. The positive relation to systemic risk is mainly because banks with higher regulatory scores on systemic importance have a much stronger link to the system in the event of financial stress, rather than having a higher level of bank risk.

2 Regulatory approach to systemic importance

Regulators worldwide haven taken several steps to enhance the stability of the global financial system. One of these steps is to require higher levels of Common Equity Tier 1 (CET1) funding for internationally active, systemically important banks (G-SIBs). The additional buffer requirement will be phased in between 2016 and 2019. The proposed additional buffer ranges from 1% to 3.5% of risk-weighted assets (RWA), but it may be further raised if institutions become more systemically important. The additional buffer requirement for an individual bank depends on its regulatory score for systemic importance.

The methodology for determining the systemic importance score of individual banks has been developed by the Basel Committee on Banking Supervision (BCBS). The method has an indicator-based approach and relies on measuring the extent to which banks are involved in certain activities. Large banks have to publish amounts for twelve G-SIB indicators grouped into five categories; see IMF/BIS/FSB (2009) and BCBS (2013a,

Table 1: Summary statistics of G-SIB indicators of large European banks (EUR billion)

Category	Indicator	Mean	Sd	Skewness
Size	Total exposures	1,379	654	0.9
Interconnectedness	Intra-financial system assets	102	98	1.3
	Intra-financial system liabilities	129	113	1.4
	Securities outstanding	276	82	0.3
Substitutability	Payments activity	11,527	33,130	3.4
	Assets under custody	874	1,357	1.8
	Underwriting activity	27	96	1.8
Complexity	OTC derivatives (RHS)	3,815	16,136	1.6
	Trading and AfS securities	27	59	1.5
	Level 3 assets	1	9	2.3
Cross-jurisdictional	Cross-jurisdictional claims	733	296	1.0
	Cross-jurisdictional liabilities	652	273	1.7

Note: Summary statistics of G-SIB indicators of 25 publicly traded large banks in the European Economic Area in EUR billion at the end of 2013. See Table 2 for the list of banks. Source: EBA (2014) and banks' websites.

2014a).[1] The European Banking Authority (EBA) collects these data for a number of large banks in the European Economic Area (EEA) and publishes them on its website; see EBA (2014). Our data set is based on the EBA data but also includes data on three large banks not included in the dataset published by the EBA.[2] Overall, our study considers the G-SIB indicators for 25 large listed banks in the EEA.

Table 1 presents the summary statistics of the G-SIB indicators for the 25 publicly listed large European banks included in our data set. The standard deviations indicate a considerable level of dispersion in the reported amounts across banks. Moreover, each of the indicators exhibits positive skewness, which suggests that the sample for each indicator includes, to a certain extent, several exceptionally high values.

The category "Size" captures the idea that the importance of a bank is positively related to the volume of services provided. This view is supported by the positive relation between bank size and systemic risk documented in e.g. Brunnermeier et al. (2012), López-Espinosa et al. (2012), Huang et al. (2012), Vallascas and Keasey (2012)

[1]The regulatory approach is still undergoing reviews and revisions; see e.g. BCBS (2015) for some recent changes.

[2]Given our intention to compare the regulatory approach with the market-based approach, we exclude six banks without a stock market listing from our data set, while adding three large EEA banks (with total exposures of more than EUR 200 billion) not included in the EBA dataset: Commerzbank, Danske Bank and Deutsche Bank. Their G-SIB indicator amounts were taken from their websites.

and Girardi and Ergün (2013). With size defined as total exposures, it also captures off-balance sheet items, rather than focusing on balance sheet exposures only.

The category "Interconnectedness" captures the view that linkages among financial institutions may increase contagion risk; see e.g. Allen and Gale (2000) and Freixas et al. (2000). The first two indicators, intra-financial system assets and liabilities, cover direct linkages to other financial institutions, including those resulting from deposits, credit lines and several other transactions; see BCBS (2014b). The indicator "Securities outstanding" represents the amount of securities issued by a bank, regardless of whether they are held by other financial institutions.

The potential harm caused by the collapse of a bank is incorporated in the category "Substitutability" by measuring the size of critical functions provided to the economy. This is a category with three indicators, viz. the amount of outgoing cash payments excluding those made through retail payment systems, the value of assets under custody held on behalf of clients, and the value of underwritten equity and debt instruments.

The category "Complexity" focuses on a bank's complexity and opacity, which are associated with potential fire sales or substantial haircuts in the event of severe market stress; see e.g. Brunnermeier (2009), Diamond and Rajan (2011) and Flannery et al. (2013). The first indicator is the notional amount of over-the-counter derivatives either cleared bilaterally or through a central counterparty. The second indicator is the amount of held-for-trading or available-for-sale securities that do not qualify as sufficiently high-quality liquid assets.[3] The third indicator is the amount of Level 3 assets, i.e. the amount of assets held at fair value that are difficult to value in the sense that the measurement is based on a pricing model using parameters that are not observable in the market.

The last category "Cross-jurisdictional activities" captures both the difficulties associated with the resolution of international financial institutions and the transmission of shocks across the globe through internationally active banks; see e.g. Goodhart and Schoenmaker (2009) and Cetorelli and Goldberg (2011).

[3]More specifically, high-quality liquid assets that qualify as Level 1 assets for liquidity coverage ratio (LCR) purposes are excluded. Assets that qualify as Level 2 assets receive a lower weight; for more details, see BCBS (2013b).

Table 2: Regulatory and market-based indicators of systemic risk of large European banks

Bank (country code)	Regulatory approach: Score	Bucket	Market-based approach: Bank risk	Link to system	Systemic risk
Banco Monte dei Paschi (IT)	22	0	1.60	0.61	0.98
Banco Santander (ES)	196	1	1.18	0.90	1.07
Barclays (UK)	384	3	1.85	0.83	1.54
BBVA (ES)	92	0	1.25	0.88	1.11
BNP Paribas (FR)	407	3	1.51	0.88	1.33
Caixabank (ES)	26	0	0.95	0.61	0.58
Commerzbank (DE)	121	0	1.78	0.76	1.35
Credit Agricole (FR)	218	1	1.68	0.82	1.38
Danske Bank (DK)	76	0	1.24	0.75	0.93
Deutsche Bank (DE)	417	3	1.36	0.80	1.10
DNB ASA (NO)	60	0	1.45	0.77	1.12
Erste Group Bank (AT)	33	0	1.62	0.74	1.20
HSBC (UK)	477	4	0.90	0.84	0.76
ING Bank (NL)	144	1	1.90	0.88	1.67
Intesa Sanpaolo (IT)	80	0	1.66	0.84	1.40
KBC Group (BE)	36	0	1.96	0.69	1.34
Lloyds Banking Group (UK)	98	0	1.84	0.73	1.35
Nordea Bank (SW)	121	0	1.31	0.84	1.10
Royal Bank of Scotland (UK)	238	2	1.75	0.80	1.40
SEB (SW)	58	0	1.49	0.81	1.21
Society Generale (FR)	225	1	1.72	0.84	1.45
Standard Chartered (UK)	133	1	1.11	0.76	0.84
Svenska Handelsbanken (SW)	45	0	1.18	0.76	0.89
Swedbank (SW)	32	0	1.63	0.81	1.32
Unicredit (IT)	148	1	1.86	0.80	1.48

Note: This table presents regulatory scores on systemic importance and market-based systemic risk measures for 25 publicly traded large banks in the European Economic Area at the end of 2013. The regulatory scores and buckets are obtained by applying the methodology described by BCBS (2014a) on the data released by EBA (2014) and individual banks' websites. The market-based measures are estimates based on daily stock market data data over the period 2009–2013 by applying the methodology of Van Oordt and Zhou (2014). Source: authors' calculations.

In order to express the systemic importance of each institution in a single score, regulators have to aggregate the twelve indicator values shown in Table 1. To normalize the reported amounts across different indicators, the score of a bank for an indicator is expressed in basis points of the total amount reported by all large banks. A bank's category score is obtained by averaging that bank's indicator scores within the category.[4] Finally, a bank's systemic importance score is the simple average of that bank's five category scores. In the first column of Table 2 we calculate the regulatory systemic

[4] An exception is the score for the category "Substitutability", which is capped at 500 basis points; see BCBS (2014a, subsection 3.3).

importance scores of European banks. Banks are allocated to a G-SIB bucket based on these scores, with the buckets determining the additional buffer capital requirement. Allocation to bucket 1 implies an additional CET1 loss absorbency requirement of 1% of RWA; a bank in bucket 4 faces an additional requirement of 2.5% of RWA.

3 Market-based approaches to systemic risk

This section discusses the market-based approaches to measuring systemic risk. There are both pros and cons of market-based approaches to estimating the systemic risk of financial institutions. The main advantages of using market data are their public nature and the low cost of data collection. Moreover, information based on market data is often available at a higher frequency and on a more timely basis than accounting-based measures, because of the higher frequency and the forward-looking nature of asset prices.

However, market-based measures could result in underestimation of systemic risk if prices incorporate potential responses of governments and regulators to a potential crisis. For example, bond prices and CDS spreads are directly affected by bailout expectations; see e.g. Flannery and Sorescu (1996) and Demirgüç-Kunt and Huizinga (2013). Market prices may also misrepresent actual risk levels given that they may be prone to panics, runs, illiquidity and fire sales. Moreover, regulators may have confidential information on the financial system that is not available to market participants. Nevertheless, regardless of whether market prices are in line with the information available to regulators, they may still provide information about the perceptions of market participants on the systemic risk of financial institutions. This information is valuable because it may reveal the willingness of investors and other agents in the economy to extend finance or roll-over existing debt of a bank once a large shock hits the financial system.

A difficulty with market-based measures is the identification of the origin of comovement in market prices. For example, joint failures of multiple banks may be caused by losses at one bank which are contagiously spread through the interbank market, or may be the consequence of losses on a common exposure. The distinction between the two is important for certain policy decisions. In the event of contagion through the interbank market, bailing out the bank suffering the initial loss would directly help the other banks survive. However, in case of a common exposure, bailing out any bank is unlikely to support the other institutions. It is difficult to distinguish between the two with the use of market information only. Nevertheless, even if market information only shows whether a bank is likely to face difficulties together with the rest of the system without revealing the cause, this information is still valuable because the bank's failure would place a larger burden on the economy during a banking crisis. Therefore, such information would still be useful for macroprudential regulation.

In recent years, many scholars have developed methods to measure the systemic risk of financial institutions based on market prices. Examples are the Volatility Contribution (VC) of Lehar (2005), the Conditional Value-at-Risk (CoVaR) of Adrian and Brunnermeier (2011), the Marginal Expected Shortfall (MES) of Acharya et al. (2009, 2012) and the Distressed Insurance Premium (DIP) of Huang et al. (2009, 2012). VC measures the risk contribution of a bank to the global regulator's portfolio, CoVaR is the level of risk in the financial system conditional on financial distress at a particular bank, or vice versa; MES is the expected loss of a bank's stock price conditional on a large shock to the financial system; and DIP measures the insurance premium required to cover the expected losses of an institution as a consequence of distress in the banking system. All these systemic risk measures help to differentiate financial institutions in the cross-sectional dimension based on market data.

The purpose of this chapter is to assess whether the regulatory approach and the market-based approach result in similar ranking orders of banks. The regulatory approach to measuring the systemic importance of financial institutions explicitly sets out to isolate systemic importance from the level of bank risk.

> "The Committee is of the view that global systemic importance should be measured in terms of the impact that a bank's failure can have on the global financial system and wider economy, rather than the risk that a failure could occur" BCBS (2013a, p. 5).

Therefore, when comparing rankings based on regulatory systemic importance scores with rankings based on market-based approaches, the relation between the two might be distorted by the differences in the level of bank risk. To achieve our goal, we will rely on a market-based approach for measuring systemic risk that can abstract from the level of bank risk.

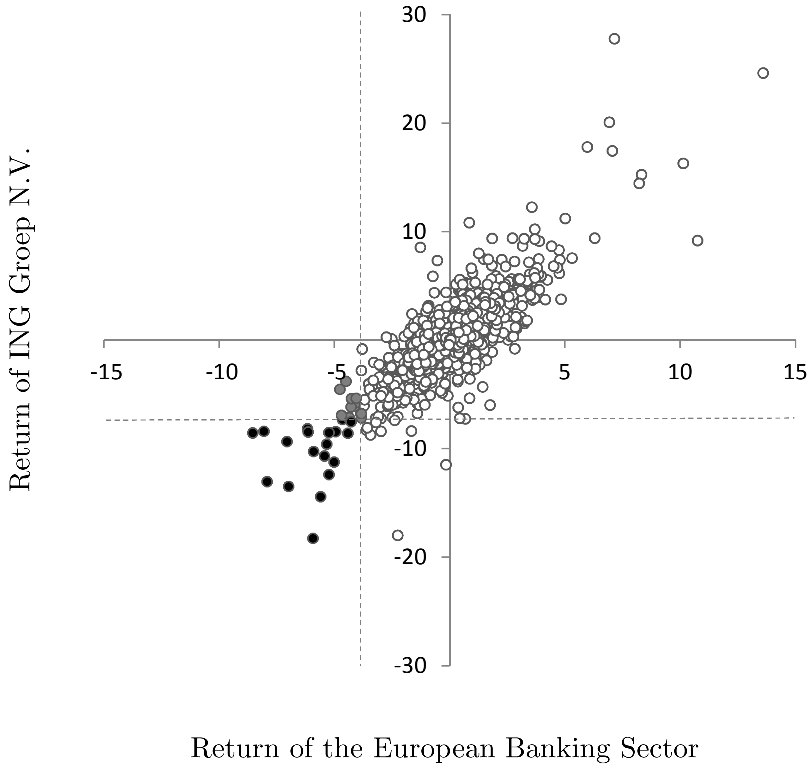
Van Oordt and Zhou (2014) introduce a methodology to estimate a market-based systemic risk measure that can be broken down into two subcomponents reflecting the level of bank risk ("bank tail risk") and the strength of the link of the bank to the system in the event of financial stress ("link to the system"). This breakdown is consistent with the conceptual framework in Figure 1. The "link to the system"-component measures the strength of the link between the bank and the system in the event of system-wide distress, without containing information on the risk level of the underlying bank. The fact that it abstracts from bank tail risk suggests that it might be closely related to the regulatory indicators of systemic importance.

The systemic risk of a bank is measured as the sensitivity of the bank's stock returns to extremely large adverse shocks in the financial system. Figure 2 provides an illustration by showing the scatter between the daily returns of ING Group and a European banking index (excluding ING Group). It uses euro-denominated stock market returns and market capitalizations of 25 large European banks for the period 2009-2013, collected from Datastream. The observations to the left of the dashed vertical line are regarded as observations corresponding to extremely adverse shocks in the banking system.[5] The systemic risk of ING Group is measured as the slope of a fitted line among the large losses in the banking system indicated by solid circles (both grey and black).

The sensitivity to large shocks in the banking system is closely related to the MES measure proposed by Acharya et al. (2009). Since MES stands for the expected loss of a financial institution conditional on a large loss in the system, the MES is estimated as the sample average of the observations indicated by the solid circles (both gray and

[5]More precisely, this chapter sets the threshold at such a level that the $k = 30$ worst returns of the European banking index out of $n = 1,304$ observations are regarded as extremely adverse shocks, which corresponds to $k/n \approx 2.3\%$ of the observations. The results remain qualitatively unchanged when using $k = 20$ or $k = 40$ instead.

Figure 2: Scatter of daily returns, 2009-2013



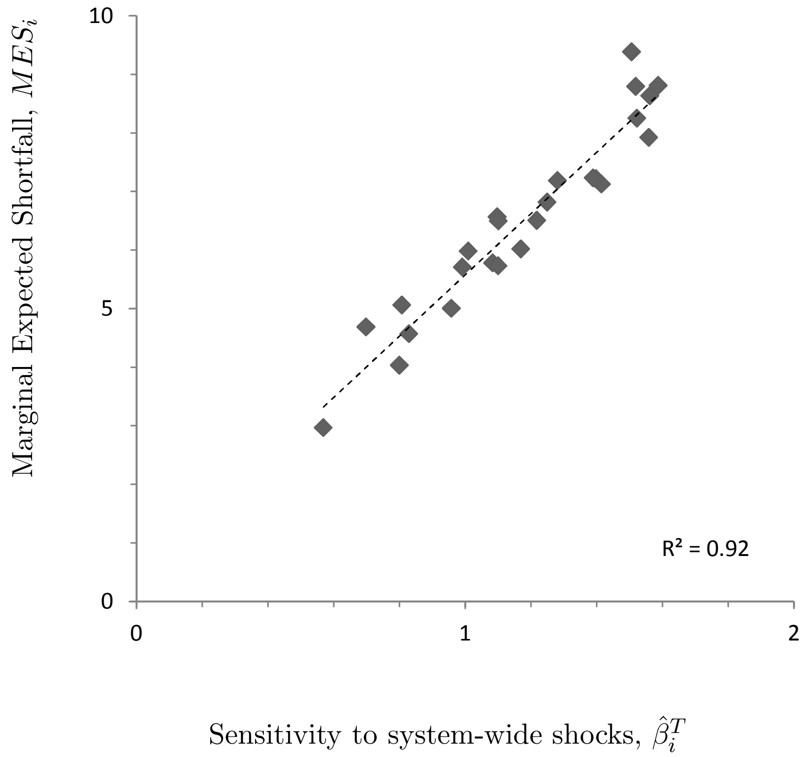
Note: The filled dots mark the 30 days during which the European banking sector index sustained the largest losses. Source: Datastream.

black). The MES not only depends on the slope of the fitted line among the large losses in the banking system, but also on the magnitude of the losses in the banking system. The close relation between the two is supported by the scatter plot between the MES of European banks and their sensitivity to large shocks in the banking system; see Figure 3. The R-squared of the trend line between the two is 0.92, which is in line with the theoretical argument that the sensitivity to large shocks in the banking system describes all cross-sectional dispersion in the MES across institutions; see Van Oordt and Zhou (2014).

Formally, we measure the sensitivity of bank i's stock returns, $R_{i,t}$, to large shocks in the financial system as the coefficient β_i^T in the following linear tail model

$$R_{i,t} = \beta_i^T R_{S^{-i},t} + \varepsilon_{i,t} \text{ for } R_{S^{-i},t} < -VaR_{S^{-i}}(\bar{p}), \tag{1}$$

Figure 3: Scatter of two market-based approaches to systemic risk, 2009-2013



Note: The figure presents a scatter between estimates of the sensitivity to systemic shocks and Marginal Expected Shortfall for 25 large European banks. Estimates are based on the 30 days with the largest market losses. For technical details on the estimation procedure, see the Appendix. See Table 2 for the list of banks. Source: Datastream and authors' calculations.

where $R_{S^{-i},t}$ is the return of the European banking index (excluding bank i), where $VaR_{S^{-i}}(\bar{p})$ is the Value-at-Risk of the system for some small probability $\bar{p}$, and where $\varepsilon_{i,t}$ are shocks that are assumed to be independent of $R_{S^{-i},t}$. The estimation of β_i^T does not rely on an ordinary least square regression conditional on extreme observations. Such an estimation strategy would have a relatively large estimation error due to the small number of observations and the heavy tails of stock returns; see e.g. Mikosch and De Vries (2013). Instead, we apply a methodology based on Extreme Value Theory (EVT), of which the technical details can be found in the Appendix. This method gives the estimator of the systemic risk measure in (1) as

$$\hat{\beta}_i^T = SL_i \times IR_i, \tag{2}$$

where SL_i measures the strength of the link between the bank and the system in the event of financial stress, and where IR_i measures the tail risk of a bank. Hence, the systemic risk measure β_i^T in (1) can be broken down into two subcomponents: the level of bank risk and the link to the system.

The intuition of the methodology to measure each subcomponent is described as follows. The subcomponent bank tail risk, IR_i, is the ratio between the Value-at-Risk of the bank and that of the banking system. The Value-at-Risk of the system is estimated by the threshold value of the vertical dashed line that indicates large losses to the banking index in Figure 2. We draw a similar dashed horizontal line, indicating the threshold below which we have the same number of extremely large losses for ING Group. The threshold value of this dashed line is an estimate of the Value-at-Risk of ING Group. The ratio between the two Value-at-Risks is a normalized measure of the downside tail risk of ING Group. The column "bank risk" in Table 2 presents this ratio for all banks in our sample.

The strength of the link between the bank and the system in the event of financial stress, SL_i, relies on the concept tail dependence and is measured as follows. The observations to the left of the vertical dashed line correspond to large adverse shocks in the banking system. Some of the large shocks in the system occurred at the same time as the extreme losses for ING Group. These observations are indicated in Figure 2 by the black solid circles. For the other large losses in the system, the link between ING Group and the banking system was not strong enough to coincide with an extreme loss for ING Group. The fraction of the co-extreme events (black solid circles) among all large shocks in the system (gray and black solid circles) is an estimator of the tail dependence between ING Group and the banking system.[6] The SL_i is a strictly increasing function of the tail dependence and takes a value between zero and one. The column "link to system" in Table 2 reports the level of SL_i for each bank.[7] The systemic risk measure $\hat{\beta}_i^T$, which is reported in the column "systemic risk", and can be obtained as the product of the values

[6]See Hartmann et al. (2007) and De Jonghe (2010) for two empirical banking studies on the level of tail dependence.

[7]Like the level of tail dependence, the SL_i is bounded between zero and one. See the Appendix for more details. The average value is 0.79 and suggests a relatively strong link between large banks and the system in financial stress. This is consistent with the finding of Mink and De Haan (2014) that a substantial part of the changes in market values of G-SIBs can be explained by G-SIBs as a group.

in the columns "bank risk" and "link to system".

The estimates in Table 2 show that neither a high level of bank risk nor a strong link to the system in the event of financial stress are a sufficient condition to have a high level of systemic risk. After abstracting from bank risk, Banco Santander's link to the financial system is strongest with a value of 0.90. However, because of a low risk level, this bank's systemic risk is still limited (1.07). Similarly, KBC Group has the highest level of bank risk with a value of 1.96, but it is not among the institutions with the highest sensitivity to large shocks in the financial system. This is because of a weaker link to the system. ING Group has the highest sensitivity to large shocks in the financial system because it ranks relatively high on both subcomponents of systemic risk.

4 Regulators and markets

Our aim is to assess whether the regulatory scores of systemic importance and the market-based systemic risk measure lead to similar rankings of systemically important banks. Therefore, we explore the empirical relation between the market-based measures of systemic risk and the regulatory scores of systemic importance and its categories. Because of the low number of observations, estimating a cross-sectional regression including the scores on each of the five G-SIB categories as explanatory variables is not feasible. Instead, we calculate Spearman rank correlations between the estimated market-based systemic risk measure and the banks' scores on each of the five G-SIB categories.[8] We further consider rank correlations between regulatory scores and the two subcomponents of systemic risk. Given the purpose of the regulatory approach to abstract from bank risk, we expect primarily a strong correlation between the scores for the G-SIB categories of systemic importance and the "link to the system"-component, because it abstracts from the "bank risk"-component in systemic risk.

Table 3 presents the results. The bank scores for each of the five G-SIB categories correlated positively with the market-based measure of systemic risk, with correlation

[8] We also conducted correlation analysis using the Pearson correlation coefficients between the market-based risk measures and the log-level of the scores on the regulatory categories and indicators. This leaves the results qualitatively unchanged.

Table 3: Rank correlations between G-SIB categories and market-based measures

Category	Bank risk	Link to system	Systemic risk
Size	0.02	0.59	0.27
Interconnectedness	0.02	0.60	0.26
Substitutability	0.03	0.56	0.25
Complexity	0.16	0.47	0.35
Cross-Jurisdictional Activity	-0.03	0.71	0.26
Total	0.04	0.65	0.30
G-SIB Bucket (Pearson correlation)	-0.11	0.41	0.07

Note: The table presents rank correlations between the scores of 25 large European banks for regulatory G-SIB categories and the market-based measures on risk and systemic risk in Table 2. Rejection of the null hypothesis of zero rank correlation (two-sided) at the 10%, 5% and 1% significance level is indicated by absolute values above 0.34, 0.40 and 0.51, respectively.

coefficients ranging from 0.25 to 0.35. Nevertheless, due to the small sample size, these coefficients cannot be regarded as statistically significant. However, after decomposing the systemic risk measure into the two subcomponents, the scores for all five G-SIB categories exhibit statistically significant positive correlations with the "link to the system"-component, ranging from 0.47 to 0.71. Each of these coefficients is statistically significant at the 5% level. This is in line with our expectation that the "link to the system"-component is stronger related to the regulatory approach to systemic importance as the regulatory approach aims to abstract from the level of bank risk. In contrast, we do not detect statistically significant relations between the five G-SIB categories and the level of bank tail risk component in our sample. The results weakly support the intention of the G-SIB categories to capture the level of banks' systemic importance without having a strong relation to bank risk. Moreover, the "link to the system"-component is also positively correlated to the G-SIB bucket allocation, with a Pearson correlation coefficient of 0.41, which is statistically significant at the 5% significance level.[9] In summary, the estimated systemic risk measures based on market data provide some support for the use of the G-SIB categories to measure banks' systemic importance.

To gain further insights into the relation between the regulatory approach to systemic

[9]Since the G-SIB Bucket is a categorical data item with a limited number of categories, a Spearman correlation is not feasible.

Table 4: Rank correlations between G-SIB indicators and market-based measures

Category	Indicator	Bank risk	Link to system	Systemic risk
Size	Total exposures	0.02	0.59	0.27
Interconnectedness	Intra-financial system assets	0.10	0.51	0.30
	Intra-financial system liabilities	0.12	0.56	0.33
	Securities outstanding	-0.13	0.67	0.15
Substitutability	Payments activity	0.10	0.47	0.28
	Assets under custody	-0.22	0.59	0.02
	Underwriting activity	-0.11	0.49	0.11
Complexity	OTC derivatives (RHS)	0.07	0.51	0.27
	Trading and AfS securities	-0.04	0.60	0.21
	Level 3 assets	0.22	0.26	0.31
Cross-Jurisdictional	Cross-jurisdictional claims	-0.10	0.70	0.20
	Cross-jurisdictional liabilities	-0.06	0.71	0.23

Note: The table presents rank correlations between the scores of 25 large European banks for regulatory G-SIB indicators and market-based measures on their level of risk and systemic risk in Table 2. Rejection of the null hypothesis of zero rank correlation (two-sided) at the 10%, 5% and 1% significance level is indicated by absolute values above 0.34, 0.40 and 0.51, respectively.

importance and systemic risk, we consider a parallel analysis for the twelve G-SIB indicators that are used to construct the scores for the five categories in Table 4. Similar to the results for G-SIB category scores, the correlations between the indicators and systemic risk are all positive (insignificant), ranging from 0.02 to 0.33. The correlations with the "link to the system"-component are all positive and statistically significant, with the only exception of the indicator "Level 3 assets" which has a statistically insignificant correlation coefficient of 0.26. For the other indicators, the rank correlations range from 0.47 to 0.71. The correlations with the level of bank tail risk remain insignificant, with Level 3 assets having the highest positive correlation. In summary, there are no qualitative changes in the results if we analyze G-SIB indicator scores rather than G-SIB category scores.

Although the indicator Level 3 assets is less correlated to the "link to the system"-component than the other G-SIB indicators, there is no reason to doubt its validity as an indicator for systemic importance. Because of the positive relation between Level 3 assets and bank risk, the indicator seems to be relatively strongly correlated to systemic risk before abstracting from bank risk (although insignificant). Level 3 assets may be considered as relatively opaque and relatively illiquid, which may be more vulnerable to fire sales than other assets. Market participants may regard banks with a higher exposure to these assets as more risky rather than considering those banks more strongly linked to the rest of the banking system. This may explain why Level 3 assets do not have a strong relation to the “link to the system”-component, but are still associated with a higher level of systemic risk.

5 Concluding remarks

Not all operations of banks that have an impact on the level of risk are similarly related to systemic risk. A single policy measure may have opposing effects on individual risk and systemic risk. That is why policy measures emanating from the microprudential objective of regulation – focusing on the risk of individual banks – may differ in scope and direction from policy measures that emanate from the macroprudential objective of regulation, and focus on systemic risk. Therefore, implementing prudential policies requires careful consideration of their impacts on bank risk and systemic risk.

Regulators worldwide have developed an approach to identify and categorize G-SIBs for higher loss absorbency requirements. This chapter contributes to the policy discussion by examining whether the regulatory approach to systemic importance is consistent with the perceptions of market participants. Our study provides some evidence supporting the regulators’ choice of systemic importance indicators. In particular, we evaluate the relation between G-SIB categories and indicators, on the one hand, and market-based (systemic) risk measures on the other, for a sample of large banks in the EEA. The results support all G-SIB categories and most G-SIB indicators used to measure banks’ systemic importance.

Appendix

This appendix presents technical details on how the market-based measure of systemic risk and its two subcomponents are estimated. Because of the small number of banks in our sample, we follow López-Espinosa et al. (2012) and construct for each bank i an index of the European banking system S^{-i} based on the 24 other banks. Let $R_{i,t}$ denote the stock return of bank i on day t. We construct the return of S^{-i} as

$$R_{S^{-i},t} = \frac{\sum_{j \neq i} e_{j,t-1} R_{j,t}}{\sum_{j \neq i} e_{j,t-1}}, \tag{3}$$

where $e_{j,t-1}$ is the market capitalization of bank j at the end of the previous trading day, and where $R_{j,t}$ is the return of bank j on day t.

Following Van Oordt and Zhou (2014), we measure the systemic risk of a bank by evaluating its sensitivity to large shocks in the European banking system. The coefficient β_i^T is estimated based on the EVT approach proposed by Van Oordt and Zhou (2011). More specifically, let $R_{i,t}$ and $R_{S^{-i},t}$ follow heavy-tailed distributions with tail indices ζ_i and $\zeta_{S^{-i}}$, respectively.[10] Under the weak conditions $\zeta_{S^{-i}} < 2\zeta_i$ and $\beta_i^T \geq 0$, β_i^T can be estimated by

$$\hat{\beta}_i^T := \widehat{\tau}_i(k/n)^{1/\hat{\zeta}_{S^{-i}}} \frac{\widehat{VaR}_i(k/n)}{\widehat{VaR}_{S^{-i}}(k/n)}, \tag{4}$$

where the tail index $\zeta_{S^{-i}}$ is estimated by the estimator proposed in Hill (1975); $\widehat{VaR}_i(k/n)$ and $\widehat{VaR}_{S^{-i}}(k/n)$ are estimated by the $(k+1)th$ worst return on the bank's stock and the European banking index; and $\widehat{\tau_i(k/n)}$ is the non-parametric estimator of tail dependence between $R_{i,t}$ and $R_{S^{-i},t}$ established in multivariate EVT, see Embrechts et al. (2000), as

$$\widehat{\tau}_i(k/n) = \frac{1}{k} \sum_{t: R_{S^{-i},t} < -\widehat{VaR}_{S^{-i}}(k/n)} \mathbf{1}(R_{i,t} < -\widehat{VaR}_i(k/n)). \tag{5}$$

The estimator of β_i^T can be decomposed into two subcomponents reflecting measures of the strength of the link of bank i to the system in the event of financial stress and the level of bank tail risk, respectively. With the subcomponent measuring the link to the system defined as $SL_i = \widehat{\tau}_i(k/n)^{1/\hat{\zeta}_{S^{-i}}}$, and with the subcomponent measuring bank i's risk level as $IR_i = \widehat{VaR}_i(k/n)/\widehat{VaR}_{S^{-i}}(k/n)$, the estimator of β_i^T in (4) can be rewritten as Eq. (2).

[10] Formally, the distribution of $R_{i,t}$ is heavy-tailed if $\Pr(R_{i,t} < -u) = u^{-\zeta_i} l_i(u)$ with $\lim_{u \to \infty} \frac{l_i(tu)}{l_i(u)} = 1$ for all $t > 1$. To guarantee the consistency of $\hat{\beta}_i^T$ in (4), theoretically, k is a sequence depending on n such that $k := k(n) \to \infty$ and $k(n)/n \to 0$ as $n \to +\infty$.

Following Acharya et al. (2009), we estimate the MES_i in Figure 3 as

$$\widehat{MES}_i(k/n) = -\frac{1}{k} \sum_{t:R_{S-i,t} < -\widehat{VaR}_{S-i}(k/n)} R_{i,t}. \tag{6}$$

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