Monitoring Ireland's Payments using TARGET2

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Abstract

With the aim to develop indicators to better understand the interconnectedness of the Irish banking system and to identify the build-up of potential systemic risks, this article describes TARGET2-IE, Ireland's component of the Eurosystem's large value payment system (TARGET2). In doing so, we seek to highlight how close monitoring of payments data can confer a deeper understanding of the components that contribute to the smooth functioning of the Irish economy and a stable financial system. Following a description of TARGET2-IE, we highlight the underlying topology (map) of Ireland's interbank and customer payment networks. We identify key bank connections arising from payment flows between banks and introduce indicators for systemic risk monitoring. The indicators provide information on the relative importance of banks in the networks, liquidity conditions, key connections and payment inflows and outflows.

1 The views expressed in this article are those of the authors and are not necessarily those held by the Central Bank of Ireland or the ESCB.

1. Introduction

Significant amounts of economic transactions are ultimately settled via money transfers between banks taking place on large-value payment systems. In this manner, payments data reflect economic activity and the health of a financial system. A necessary condition for the functioning of the economy is that payment transactions are settled smoothly and securely. TARGET2[2] fulfils this role for euro denominated payments. Given its importance to the smooth functioning of the economy, a key priority of the Eurosystem – including the Central Bank of Ireland – is ensuring that the infrastructures for payments and securities settlement are safe, resilient and efficient and that participants can readily access such systems. It is through this close monitoring and oversight that payment system infrastructures proved resilient even during the most recent financial crisis.

Payment systems can also be beneficial in identifying the 'too-interconnected-to-fail' institutions, i.e. the 'systemically important' institutions that have become an increasing focus of regulators and policy-makers alike following the Global Financial Crisis (GFC).[3] The GFC highlighted that regulators had limited information about the direct and indirect connections between financial institutions. Furthermore, little was understood on how these connections affected financial stability. Encouragingly, there have been considerable empirical and theoretical contributions since the GFC aiding a better understanding of these issues (see Section 2).

In this article, we introduce TARGET2-IE, the Irish component of TARGET2. We highlight how analysis of payment flows to and from Irish banks can be utilised for financial stability purposes, by enabling a deeper understanding of credit institutions' behaviour and their key connections. Specifically, data from TARGET2-IE are used to present, for the first time, a network topology of both customer payment flows and interbank payment flows involving Irish banks.

We consider how this analysis can feed into the identification of idiosyncratic or system-wide risks and to illustrate, we introduce some indicators that aid in this task. This is especially important in an Irish context, given that liquidity concerns during the GFC resulted in substantial Central Bank liquidity provision to banks (both through regular operations and by way of Emergency Liquidity Assistance) and ultimately public interventions via capital injections.

The article is structured as follows: Section 2 discusses relevant literature; Section 3 introduces TARGET2; Section 4 describes TARGET2-IE and presents some summary statistics; Section 5 presents the network for TARGET2-IE, highlighting the key connections between institutions, while Section 6 discusses indicators for systemic risk monitoring. Section 7 concludes.

2. Related Literature

Relevant literature in the context of this article is vast and growing but can be broadly summarised as focusing on the following areas: systemic risk; financial crisis; contagion; interbank markets and payments network theory. This article builds on earlier work in an Irish context by Hallissey (2016) who examined Irish banking sector interlinkages using a number of regulatory data sources. The author finds that banks with a domestic retail focus have much lower levels of interconnectedness with the global financial sector than the internationally-focussed foreign-owned banks, in part driven by the intragroup exposures of the foreign-owned banks. The author also noted the need for improvements in data availability to better capture all exposures and connections. Payments data can aid in this regard.

A related strand of literature examines the major role of interconnectedness among banks in the propagation of financial distress. Seminal contributions by Allen and Gale (2000) and Freixas et al. (2000) suggest that

2 TARGET stands for Trans-European Automated Real-time Gross settlement Express Transfer system

3 EBA Guidelines on the criteria for the assessment of Other Systemically Important Institutions (O-SIIs) pursuant to Article 131 (3) of Directive 2013/36/EU require, for example, the use of payments data as a mandatory indicator.

a more interconnected architecture enhances the resilience of the system to the insolvency of any individual bank. Allen and Gale, for example, argue that, in a 'complete' structure, which they describe as one in which every bank has symmetric links with all other banks – contagion is less likely to occur. If every bank lends to every other bank, the impact of one bank defaulting is diluted among other banks – making the network more resilient. In contrast, they find that a ring network, in which each bank borrows from exactly one other bank and 'incomplete' structures, where banks have links only with a few neighbouring banks, are particularly fragile. The findings of Freixas et al. are similar. They note that interbank connections generally enhance the resilience of the financial system as interbank credit lines provide an implicit subsidy to an insolvent bank, allowing it to share losses with other banks.

A further strand of literature (Gai and Kapadia, 2010) finds that modern financial networks display 'robust-yet-fragile'[4] features. Higher interconnectedness allows for innocuous absorption of most shocks, reducing the overall probability of systemic failure. However, when extreme, high impact events occur, such as during a crisis, the shocks are more amplified than in less connected networks. Acemoglu et al. (2015) also support this view and find that the same factors that contribute to resilience under certain conditions may function as significant sources of systemic risk under others.

In this article we explore the topological features of the Irish payment networks over time. We follow the approach of Bech and Rørdam (2008), who use Danish payments data, by focusing on two distinct network topologies – one for customer payments and another for interbank payments. Other topological studies have been completed for large value payment systems in other jurisdictions: Japan (Inaoka et al., 2004); US Fedwire (Soramäki et al., 2007); UK CHAPS (Becher et al., 2008); Hungary (Lubloy, 2006) and Austria (Boss et al., 2004). Iori et al. (2008) analyse the network topology of the Italian money market and investigate the evolution of the network over time while Martinez-Jaramillo et al. (2014) present topologicial measures to monitor systemic risk for the Mexican payment system.

Further, this article is related to elements of research completed by other European Central Banks using TARGET2. Heijmans et al. (2011) using data from the Dutch portion of TARGET2 (TARGET2-NL) have developed indicators for signs of liquidity shortages and potential financial problems of banks in the Netherlands. Pröpper et al. (2008) use network theory to examine the Dutch payment system with special focus on systemic stability issues. Network measures proposed in the comprehensive study on contagion in financial networks presented by Glasserman and Young (2016) provided inspiration for some of the indicators we examine.

Finally, the latter part of this article relates to the literature on extracting indicators from payments data. Gaffney (forthcoming) highlights how payments data can be useful in tracking price and quantity effects in the Irish interbank market. The author applies an algorithm developed by Furfine (1999) to identify interbank payments between Irish banks. Given that prices and counterparties to money market transactions are generally unobservable, this approach provides a novel means of identifying salient trends in Irish interbank lending – thus providing indicators on liquidity and changing perceptions of counterparty risk over time. Related studies using the Furfine algorithm to identify interbank loans have been widely used in other euro area countries (Frutos et al. (2016); Bräuning and Fecht 2012; Heijmans et al. (2011); Saldanha and Soares (2015)) as well as for other countries (Demiralp et al. (2006); Armantier and Copeland (2012)). Furthermore, by comparing the algorithm's outcomes with observable interbank loans from the Italian e-MID platform, Arciero et al. (2014) were able to verify that the matching was reliable in identifying unsecured interbank loans of up to three-month maturities.

4 Speech given in April 2009 by Andrew Haldane, Executive Director for Financial Stability at the Bank of England.

3. TARGET

TARGET2 is the large value payment system of the Eurosystem. It is used to settle almost all euro denominated payment transactions.[5] By providing the technical infrastructure for the safe and reliable settlement of euro denominated payments on a real-time basis TARGET2 facilitates efficient inter-country payments; it plays a pivotal role in ensuring the smooth conduct of Eurosystem monetary policy operations and in ensuring financial stability in euro area countries.

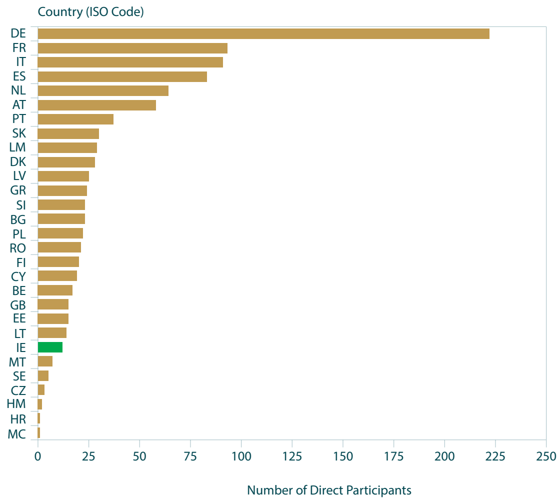
As all settlements are conducted in real time and with immediate finality[6], a receiving institution to a payment transaction in TARGET2 has full certainty with regard to the receipt of funds. This feature of TARGET2 allows the receiving institution to immediately reuse the funds received for its own purposes. In value terms, the largest payment types settled in TARGET2 relate to monetary policy operations. The next largest payment type by value in TARGET2 is interbank transactions – defined as those exclusively involving credit institutions – and the settlement of transactions relating to other payment and securities settlement systems (known as ancillary systems). In volume terms, customer payments – defined as those processed on behalf of a non-bank party, either individual or corporate – represent the largest type of payments settled.

In 2015, the latest year for which full data is available, TARGET2 processed a daily average of around 345,000 payments, representing a daily average value of €1.8 trillion.[7] The average transaction value in TARGET2 in 2015 was €5.3 million, although most payments (two-thirds) settled via TARGET2 had a value less than €50,000 each.

Types of participation in TARGET2 vary depending on the institutions' needs but can be broadly categorised as either direct or indirect. A direct participant can initiate payments on their own or on their customers' behalf. Indirect participants, on the other hand must operate through a direct participant to make payments. In total, there were 1,004 direct participants in TARGET2 at end 2015 (Chart 1).

The TARGET2 system is based on a single shared platform. Three eurosystem central banks – the Banca d'Italia; the Banque de France and the Deutsche Bundesbank jointly operate this single shared platform (the technical infrastructure behind TARGET2) on behalf of the Eurosystem. However, in a business sense, TARGET2 operates in a decentralised manner and each connected central bank is responsible for the operation of its system component and maintains the business relationships with its local counterparties.

Chart 1: Number of TARGET2 Direct Participants by Country



Source: ECB (www.ecb.europa.eu). ECB Target 2 directory January 2016.

4. TARGET2 – IE

The Irish component of TARGET2, referred to in this article as TARGET2-IE had 12 direct participants and 10 indirect participants (Table 1) at end 2015. Of the 12 direct participants, 9 were credit institutions, with the remainder

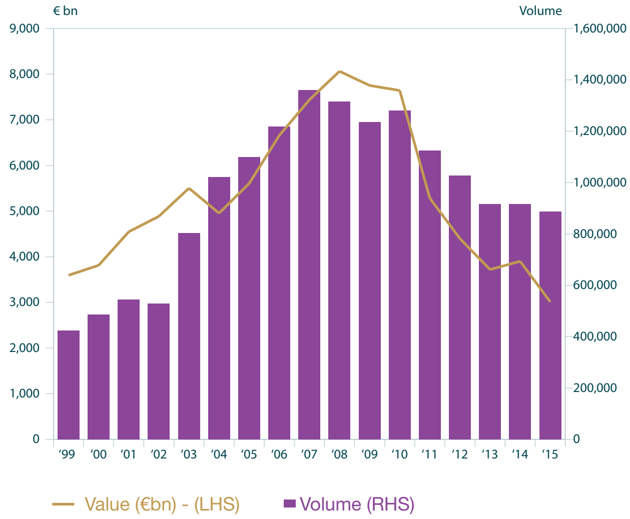
5 According to the ECB's annual report on TARGET2 for 2015, TARGET2 processed 91% of the value all euro payments in 2015.

6 Settlement finality in payment and securities settlement systems, Directive 98/26/EC of the European Parliament.

7 ECB TARGET2 annual report for 2015.

consisting of the Central Bank of Ireland, the National Treasury Management Agency (NTMA) and the Irish Paper Clearing Company.[8] TARGET2-IE accounted for just 1 per cent and 0.01 per cent respectively of the total value and volume of payments processed in all of TARGET2 in 2015. Chart 2 displays the evolution of payment values and volumes for TARGET2-IE since 1999. Both volume and value for TARGET2-IE peaked in 2007 and 2008 respectively. A contraction in the value of payments in TARGET2-IE is observable from 2010 onwards. This largely reflects a decrease in interbank activity. The volume of payments, which is dominated by customer activity, also declined since 2010, but has stabilised in more recent years. The trends in Ireland's payment system often mirror activity in the broader Irish economy and monitoring such activity can provide insights for financial stability and payment system oversight.

Chart 2: Value and Volume of Payments in TARGET2-IE.



Source: ECB TARGET2 Annual Reports 2000-2015.
Prior to February 2008, TARGET was in operation.

Table 1: TARGET2-IE Listed Participant Names by Participation Type

Direct	Indirect
• The Royal Bank of Scotland plc. • Allied Irish Banks plc. • Bank of Ireland Treasury • Danske Bank • Depfa Bank plc. • EBS Limited • Permanent TSB plc. • Investec Bank plc. • Ulster Bank Ireland Ltd. • Central Bank of Ireland • Irish Paper Clearing • NTMA	• Intesa Sampaolo • Bank of America • Merrill Lynch • Citibank Europe plc. • DZ Bank Ireland plc. • KBC Bank Ireland plc. • ING Bank NV Dublin Branch • KBC Bank NV • Scotiabank Ireland Ltd • Rabobank Ireland plc. • EAA Covered Bond Bank plc.

Source: ECB (www.ecb.europa.eu). ECB TARGET2 Directory January 2016.

4.1 TARGET2-IE Descriptive Statistics

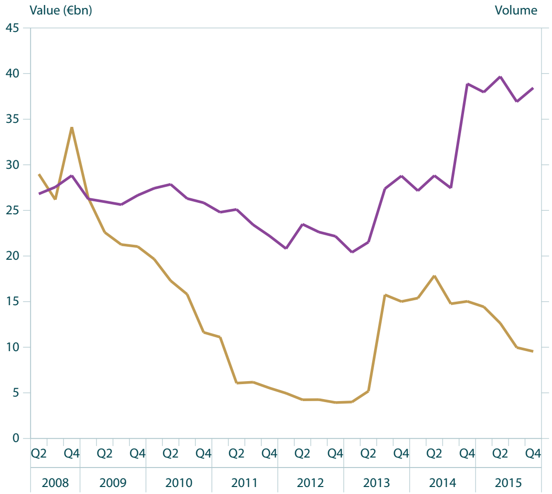
From Chart 2, we see that, in 2015 TARGET2-IE processed almost 880,000 transactions and this represented a total value of around €3 trillion.

The largest payment type by value in TARGET2-IE is interbank payments exclusively involving credit institutions, with €9.5bn per day on average in 2015 (Table 2). Customer payments processed on behalf of corporates and individuals account for the largest number of payments in TARGET2-IE, with almost seven thousand per day on average in 2015. The sharp fall in value of interbank payments from 2008 onwards is clear in Chart 3, reflecting well-known disruptions to wholesale funding markets access experienced by the Irish banks during the financial crisis. While access has improved in recent years, activity is still well below pre-crisis levels. This somewhat reflects the changing composition of domestic banks' funding – there is now a greater dependence on more stable retail deposits rather than on wholesale markets.[9]

8 The Irish Paper Clearing Company maintain and operate a payment, clearing and settlement system for domestic paper debits and credits e.g. cheques.

9 Deposits represented 79 per cent of Irish retail banks total funding (€177 billion) at end September 2016. (Central Bank of Ireland Macro Financial Review 2016.II).

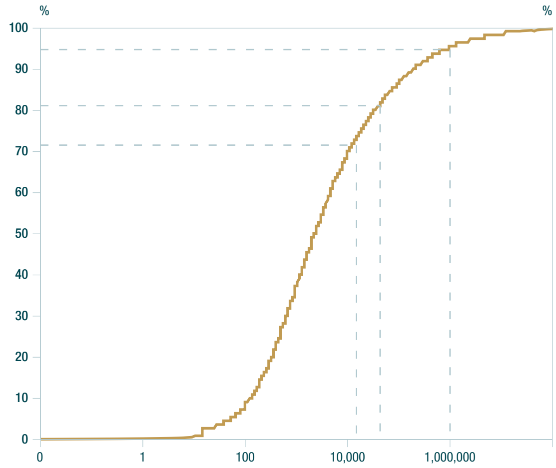
Chart 3: Average Daily Payments per Quarter, Q2 2008 – Q4 2015 – Value (EUR billion)



— Value EUR million (LHS) — Volume (RHS)

Source: Central Bank of Ireland – TARGET2-IE.

Chart 4: Distribution of TARGET2-IE Transactions Across Value Bands in 2015



Source: Central Bank of Ireland – TARGET2-IE.

Note: X-axis is plotted on the log10 scale.
Dashed lines correspond to values of 15,000 (73nd percentile); 50,000 (83rd percentile); and 1,000,000 (95th percentile).

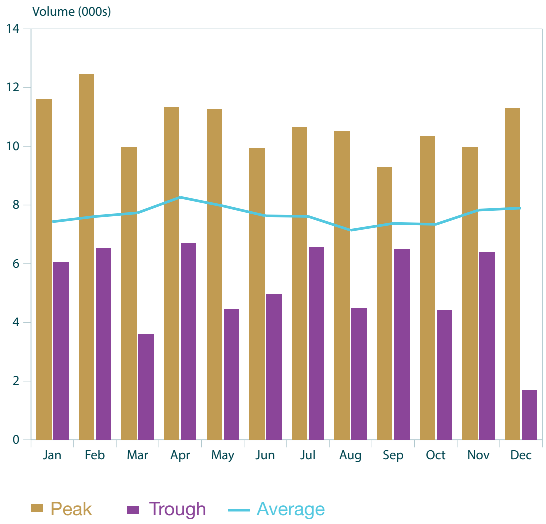
Chart 5: Average Daily Payment Value and Volume per hour of day in 2015

— Interbank (LHS) — Customer (RHS) — Interbank (LHS) — Customer (RHS)

Source: Central Bank of Ireland – TARGET2-IE.

Note: Hour of day is recorded in Central European Time.

Chart 6: Seasonality of TARGET2-IE Transactions Across Months in 2015 (Combined Interbank and Customer)



Source: Central Bank of Ireland – TARGET2-IE.

Table 2: TARGET2 – IE Value and Volume of Payments 2015 by Payment Type.

		Average	Median	Min	Max
Daily Value (EUR million)	Interbank	9,527	8,805	397	28,004
	Customer	2,069	1,855	327	6,260
Daily Volume	Interbank	731	684	322	1,620
	Customer	6,912	6,736	1,384	11,398

Source: Central Bank of Ireland – TARGET2-IE

In 2015, the day with the largest value of interbank payments settling was 20 March 2015 when €28bn was settled (over three times the daily average for 2015). The peak interbank trading day in terms of volume was 13 May 2015 when 1,620 payment transactions took place. The 28 December 2015 was the day on which the minimum interbank and customer transactions took place.

An interesting feature noted by the ECB in its annual report on TARGET2 is that more than two thirds of all transactions in TARGET2 were for values lower than €50,000 and payments in excess of €1 million account for 12 per cent of traffic.[10] A similar feature is present in TARGET2-IE. We find that over four fifths of all payments settled in TARGET2-IE are for amounts less than €50,000 while less than 10 per cent of payments are for amounts in excess of €1 million (Chart 4). Furthermore, the scheme (Instant Credit Transfer scheme) to introduce instant payments in euro by November 2017[11] has set a maximum amount an originator can transfer via a single instruction as €15,000. Over 70 per cent of payments in TARGET2-IE in 2015 were for amounts below this threshold and would hence be potentially eligible for instant payments.

TARGET2-IE is open from 07.00 to 18.00 Central European Time (CET) on each of its working days, with a cut-off time of 17.00 CET for customer payments.[12] The first hour in the morning is the busiest in terms of settlement values for interbank transactions. After a peak at morning opening, the hourly average value of transactions fluctuates throughout the day and reaches a second peak between 11.00 and 12.00 CET for interbank transactions and a peak between 12.00 and 13.00 CET for customer transactions. In terms of volume of payments, early in the morning and late in the day, near 16.00 CET are the busiest times (Chart 5).

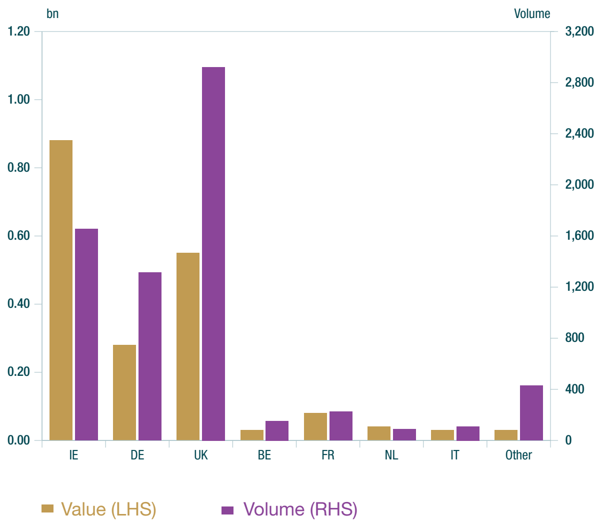
In terms of peak times in the year for payments, some seasonality patterns are observed (Chart 6). The months of April and December had peak average volumes in 2015. A fall in payments volumes is observed in the summer months before picking up again at end year. The month of December had some of the highest (peak) trading days of the year as well as the lowest (trough).

10 ECB TARGET2 Annual Report, 2015.

11 See speech "2017-a decisive year for innovative retail payment services" by Yves Mersch, ECB Executive Board member, 06 January 2017, for further details on euro instant payments introduction.

12 TARGET 2 also has a night-time window facility available between the hours of 19.30 and 07.00 CET the next day to facilitate the settlement of different ancillary systems.

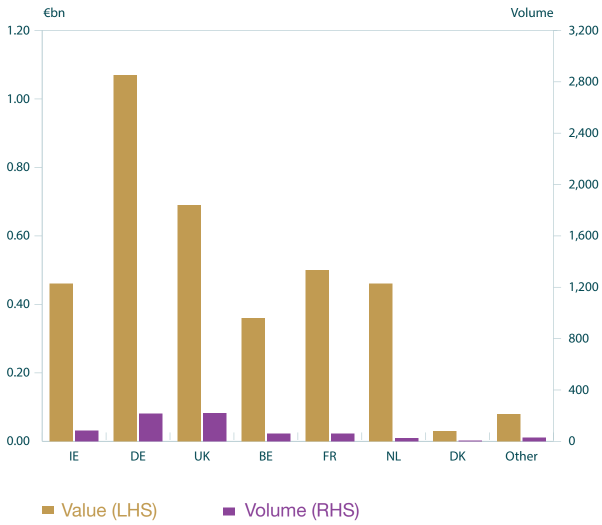
Chart 7: Average Daily Customer Payment Activity Between Ireland Direct Participants and Participants in Other Countries in 2015



Source: Central Bank of Ireland – TARGET2-IE.

Note: LHS = value (€ billion) and RHS = Volume (number of payments). Direct participants as listed in Table 1 but excludes Central Bank of Ireland, NTMA and IPCC. Participants identified via two letter ISO code in their Bank Identifier Code (BIC).

Chart 8: Average Daily Interbank Payment Activity Between Ireland Participants and Participants in Other Countries in 2015



Source: Central Bank of Ireland – TARGET2-IE.

Note: LHS = value (€ billion) and RHS = Volume (number of payments)

Finally, we display the activity of the Irish direct participants with participants in other countries during 2015 (Chart 7 and Chart 8).

From Chart 7 we observe that, on average, there were 1,654 daily customer payment transfers between Irish banks and other Irish banks in 2015. This represented a daily average value of €0.9 billion. Meanwhile, the largest number of customer transfers took place between Irish banks and UK banks with a daily average number of 2,922. Payment volumes between Irish banks and German banks were the next highest with 1,313 payments on average each day during 2015.

Chart 8 displays similar connections for the interbank market, excluding activity with the Central Bank and NTMA. Both value and volume are lower than customer payments reflecting the aforementioned reduced composition of interbank funding in Irish banks total funding sources. In terms of value, interbank daily average activity in 2015 was largest between Irish banks and those in Germany (€1.1 billion daily average) and UK (€0.7 billion daily average).

5. Ireland's Payment Network

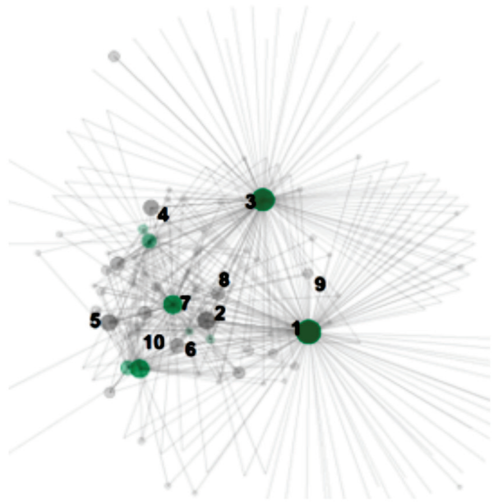
Payment systems have a structure that can be analysed and described using tools from graph theory or network analysis.[13] In recent years, graph theory has found favour in a diverse number of studies such as social networking in social sciences; transportation network studies; the spread of diseases in biological sciences and payment systems in finance.

For payment systems, banks can be considered the nodes of the graph while payments are the links between the nodes. Thinking about payment systems in this manner allows a framework for analysing the Irish payment system as a whole. The importance of such analysis is underscored by ESRB recommendations calling on macroprudential authorities such as the Central Bank of Ireland to develop tools for identifying the degree of connectivity between different sectors in the economy.[14] A topology of the Irish payment system allows for greater understanding of any weaknesses or dependences in the Irish system.

13 Graph Theory has its origins in 1736, when the mathematician Euler first considered the problem of traversing the seven bridges in the city of Konigsberg without going over any bridge more than once and ending back at the same start location.

14 ESRB/2013/1 on intermediate objectives and instruments of macroprudential policy.

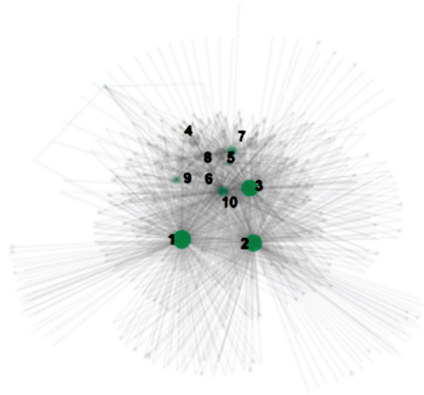
Chart 9: Ireland's Interbank Payment Network March 2015



Source: Central Bank of Ireland – TARGET2-IE

Note: Green nodes denote direct participants in TARGET2-IE. Node sizes correspond to the sum of the value all payments associated with that node (sent or received). Numbers are the ranks of the nodes according to an importance statistic (eigenvector centrality, discussed in Section 6). Transparency of links corresponds to the sum of the value of payments transferred between two nodes. The nodes associated with the bottom 20 percentile are removed to ease visualisation.

Chart 10: Ireland's Customer Payment Network March 2015



Source: Central Bank of Ireland – TARGET2-IE

Note: Green nodes denote direct participants in TARGET2-IE. Node sizes correspond to the sum of the value all payments associated with that node (sent or received). Numbers are the ranks of the nodes according to an importance statistic (eigenvector centrality, discussed in Section 6). Transparency of links corresponds to the sum of the value of payments transferred between two nodes. The nodes associated with the bottom 20 percentile are removed to ease visualisation.

Firstly, in Chart 9, we display the TARGET2-IE interbank payment network for one representative month in 2015, March 2015.[15] In terms of importance, a relatively small number of Irish direct participants listed in Table 1 feature most predominantly in the network (e.g. numbers 1, 3, 7 and 10 in the visualisation). Further, a small number of non TARGET2-IE direct participants (i.e. international banks) also feature (e.g. numbers 2, 4 and 5). In this sense, interbank payment flows were mainly between these Irish banks and with a select few international banks. From a systemic risk viewpoint, monitoring this mapping and connections over time allows sight of the relative importance of any one bank in the system. Further, it facilitates monitoring of interbank market trends between Irish banks with both domestic and foreign banks. The importance of this is underscored by the well documented reduction in interbank lending by international banks to Irish banks during the GFC.

Likewise, Chart 10 displays the network for the TARGET2-IE customer network. There are observably more participants and links present in this network than in the interbank network displayed in Chart 9. A distinct triangle of TARGET2-IE direct participants dominates the network (numbered 1, 2 and 3 respectively). Payment flows are frequent between these three banks and from these three banks to other banks. The customer network is further characterised by these three banks having many connections with each other and with other banks, while there are numerous banks in the network that have very few connections.

While the interbank network provides information on the sources and needs of interbank borrowing of Irish banks, the customer network provides insights to the relative importance to economic activity of individual Irish banks (by virtue of reflecting payments with corporates and individuals).

In terms of network statistics (Table 3), the customer network is larger than the interbank in terms of number of nodes (banks) and edges (connections), while the interbank

15 A similar network map is observable for other months in 2015, indicating that the topology for any one month is fairly representative, although the ranking of importance does change month-by-month in the interbank network. The customer network ranking of banks is observed to be more stable in terms of individual bank ranking over time.

network is larger in terms of the total value of payments. In March 2015, there were, on average, 598 edges in the customer network, composed of 200 banks. This is compared to a daily average of 212 edges and 73 banks in the interbank network. However, in total, approximately €126 billion was transferred in the interbank network compared with €33 billion in the customer network in March 2015.

Table 3: Network Summary Statistics – March 2015

		Average	SD	Min	Max
Edge count	Interbank	212.05	22.56	130	247
	Customer	597.86	70.02	302	654
Node count	Interbank	72.82	5.62	62	88
	Customer	199.64	17.72	128	222
Total Transferred	Value	Total(bn)			
	Interbank	126.131			
	Customer	33.205			

SD = standard deviation while Min and Max represent the minimum and maximum respectively over all days in March.

6. Systemic Risk Applications

Systemic financial risk can be defined as the risk of disruption to financial services that results from an impairment of the financial system, with the potential to harm the real economy. It can arise anywhere in the financial system and may be amplified as market participants overreact to incomplete or incorrect information. How this risk is distributed across entities and sectors depends on the structure of balance sheet linkages, which can be complex.

Policymakers who monitor systemic risk therefore need an analytical framework to capture this complexity. This requires multiple indicators, based on a range of data (Ryan, 2017). The indicators should provide a broad view of the financial system, ideally from several vantage points.

One promising source of these indicators comes from payments data. In the subsections that follow, we present three possible indicators that offer potential for systemic risk monitoring. The three indicators are chosen for illustration purposes and is not an exhaustive list of possible indicators available.

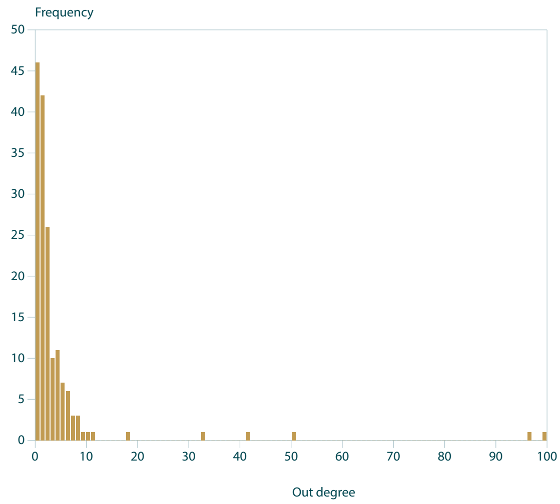
6.1 DEGREE CENTRALITY

In a payments network, one question of interest is how to identify 'important' banks in the network. In network theory, the concept of centrality is frequently used for this purpose. There are multiple centrality measures. We focus on two in this section.

The first, and perhaps the simplest centrality measure in a payments network is the degree of a node (bank) which is defined as the number of edges (payments) connected to it. In payment networks, banks typically have both an in-degree and an out-degree where in-degree represents the number of in-coming payments to the bank and out-degree represents the number of out-going payments from the bank. A strength of the in (out)-degree centrality measure is that it offers a simple, yet informative metric for ranking the relative importance of a bank in the network at any one point in time or over a period of time, based on its incoming (outgoing) payments.

For TARGET2-IE, we find that the distribution of both in and out degrees is highly skewed, with most banks having few connections and only a small number having many connections (Chart 11).

Chart 11: Out-degree Distribution of TARGET2-IE Interbank Payment Banks for March 2015



Source: Central Bank of Ireland – TARGET2-IE.

Note: Out-degree distribution shows the number of unique out-going interbank payments (aggregated per banking pair) emanating from each bank in March 2015.

6.2 EIGENVECTOR CENTRALITY

A more useful extension of degree centrality is the concept of eigenvector centrality. Pioneered by Katz (1953), Bonacich (1972) and Bonacich (1987), eigenvector centrality captures better the relative importance of banks in the TARGET2-IE payments networks. It does so by capturing risk by association, which the simple degree centrality measures do not capture. Chart 9 and Chart 10 use eigenvector centrality to rank each banks' importance in the interbank and customer networks respectively. The top-10 banks by eigenvector centrality are labelled 1 to 10.

A bank's importance in a network may be increased by virtue of the fact that it has connections with other banks which are themselves important. This is the concept behind eigenvector centrality. It assigns a large score to banks that are well connected (in this case by payment flows) or connected to banks that are well connected. In this manner, eigenvector centrality has the nice property that it can be large either because a bank has many neighbours or because it has important neighbours (or both).

Bonacich (1972) states that: eigenvector centrality takes into account direct connections as well as indirect ones, hence, this measure considers "the entire pattern of the network" in a weighted sum.

Mathematically, eigenvector centrality is defined as:

$$e_i = \frac{1}{\lambda} \sum_{j:j \neq i} A_{i,j} e_j$$

where e_i is the eigenvector centrality measure for node i (or bank i in this case) and A_{ij} is the associated adjacency matrix capturing the payments between bank i and all other banks in the network. The elements of the matrix, a_{ij}, equals 1 if there is a payment link between bank i and bank j and a_{ij} equals 0 otherwise.

The eigenvector centrality, e_i, is proportional to the sum of the centralities of i's neighbours. In other words, the measure takes into consideration the centrality of the neighbours to compute the centrality of a node. The exact computation of eigenvectors for each bank is achieved by solving the above equation iteratively.

Similar to out- and in- degree centrality, in directed networks, there exists the concepts of both left and right eigenvector centrality respectively.

Right eigenvector centrality for a bank is larger if more banks are making payments to the bank, i.e. other banks in the network bestow importance on a bank by virtue of sending more payments to it. A useful analogy in thinking about right eigenvector centrality is from the World Wide Web. The number and importance of webpages that point to a page gives an indication of how important that page is. For payments networks, we could interpret this as borrowing centrality, in the sense that it could represent a bank's borrowings from numerous other banks. The failure of a node with high borrowing centrality would result in defaults on large obligations (failure to pay back borrowings) and could set off a default cascade.

Left eigenvector centrality, on the other hand, captures the importance that one bank bestows on others by sending payments. We may interpret this as funding centrality. The failure of a node with high funding centrality could create a liquidity shock at other nodes through the withdrawal of funding.

Table 4 displays the ranking of 15 banks in TARGET2-IE in March 2015 according to payment value weighted versions of the centrality measures introduced above. The lower the ranking score in the table, the relatively more important the bank is in the network according to the ranking. In many instances, both degree measures and eigenvector centrality rank similarly. However, there are some notable cases where the metrics offer different ranking perspectives. For example, Bank C ranks higher according to degree centrality than its ranking under eigenvector centrality measures. Furthermore, rankings for some banks can vary considerably based on whether they are ranked relatively more important due to their role in sending payments to other banks or vice-versa due to their role in receiving payments. Bank K, for example, is a bank identified as having low importance ranking for in-coming payments yet higher importance ranking for out-going payments. Ranking banks in the network in this manner allows an intuitive and metric based approach for identifying banks that form key connections in the Irish payment network. In this manner, network based rankings facilitate a broad understanding of the importance of individual banks in the network.

Table 4: Importance Ranking of Irish Banks in Interbank Network – March 2015

	Degree		Eigenvector centrality	
bank	Out	In	Left	Right
A	1	1	1	1
B	2	2	3	3
C	3	4	16	12
D	4	3	9	5
E	5	6	6	4
F	6	5	2	2
G	7	8	4	7
H	8	12	17	14
I	9	13	5	8
J	10	10	15	15
K	12	153	7	153
L	13	9	12	10
M	15	27	8	18
N	16	7	13	6
O	23	16	10	9

6.3 TIME SERIES PROPERTIES

From a financial stability perspective, it is useful to monitor the trend of TARGET2 payments over periods of time. Large spikes in payment values or large falls may indicate stress in the payment system. The problem is how best to extract a signal from the data so analysis of TARGET2 would highlight abnormal values.

A simple method is to construct a time series of daily average values of payments settled in the TARGET2 system. Large deviations from a trend could constitute a warning signal that the payment system is behaving differently from its historical average. To achieve this, we consider a test statistic that closely resembles a standard t-statistic, which we call 'standard deviation distance (SDD)'. The formula is as follows:

$$SDD_t = \frac{P_t - \bar{P}}{\sigma_P}$$

where P_t is today's payment value, $\bar{P}$ is the series average and σ_p is the series standard deviation. The statistic calculates the "distance" of today's value from the average daily payment amount, taking into account volatility in the series.

For illustrative purposes, we choose a numerical value of 3 as the critical value that must be breached before a warning is issued by the test statistic.[16] Since this method may also produce negative values, we also allow -3 to be the lower bound of the acceptable range.

One issue is that the payment system is constantly changing, i.e. payments networks are dynamic over time. A daily value of €10 billion may look like an anomaly today but may not have been last year. Therefore we also construct measures of the mean and standard deviations of the series over a 90-day rolling window.[17]

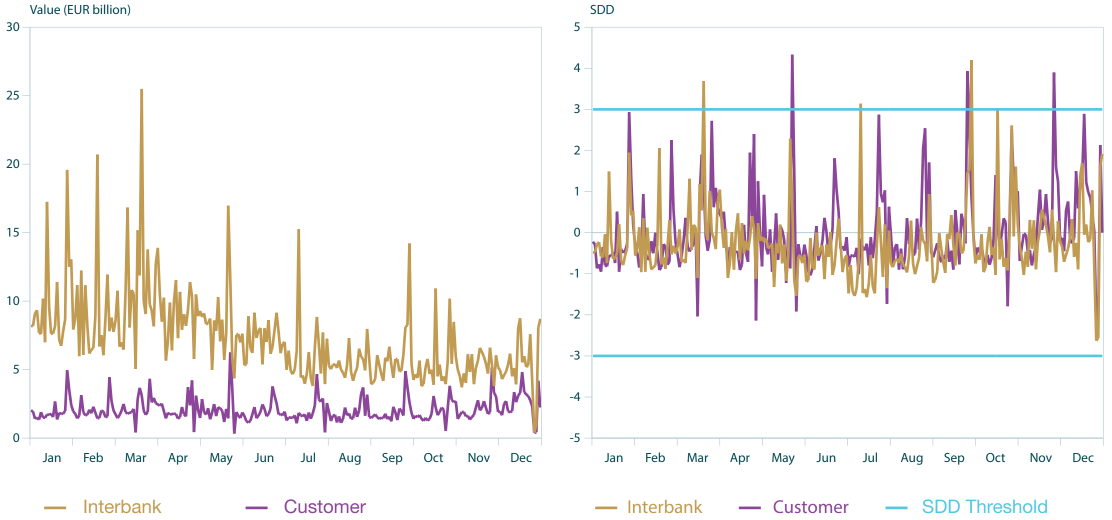
We examine payments for each payment type in 2015 and plot both the raw time series and the SDD metric below.

The [-3,3] interval which we set as the acceptable range is breached 7 times over the course of the year: three times for customer payments and four for the interbank series. There are, however, somewhat predictable spikes in the statistic as evidenced by equal

16 While the threshold 3 is used for illustrative purposes in this article the choice of this threshold can be informed by historical trends.

17 Including weekends and TARGET2 bank holidays.

Chart 12: Time Series Properties of 2015 TARGET2 Payments



Source: Central Bank of Ireland – TARGET2-IE.
Left panel shows raw data of TARGET2 payment amounts for 2015 customer and interbank transactions.
Right panel shows results from the SDD test statistic procedure. Also shown is the [-3, 3] threshold interval.

distances between spikes in the line. A more involved analysis would be to use univariate time series methods to further extract signal from the noisy series. In this manner, extracting trends by smoothing the noise and fitting a statistical model would allow another means to look at payment behaviour. An autoregressive integrated moving-average (ARIMA) model[18] could be used to control for the predictable parts of the series, e.g. higher turnovers at month-end/maintenance period end or during certain days of the week. Deviations from the daily prediction would then become the time series we use to produce our test statistics. These time series indicators will be further developed but offer advantages for looking at salient trends in Irish payments over time.

7. Conclusion

A clear lesson from the GFC, is the need for central banks and other policy makers to have a suite of indicators to better understand the key connections within the financial system. This is underscored by ESRB recommendations to macroprudential authorities to develop indicators for systemic risk monitoring. In this article, we introduce the Irish component of TARGET2. We show how visualisations of the data coupled with a number of carefully chosen indicators can offer benefits for monitoring the key features of both the network of Irish customer payments and the network of Irish interbank payments. The article presents, for the first time, a topological view of these payment networks. Additionally, the article introduces practical indicators for operationalising the close monitoring of payments data to extract salient features for financial stability and payment system oversight. These include network based measures based on degree and eigenvector centrality, as well as more novel time-series measures (SDD). Combined with previously developed indicators for Irish interbank lending (Gaffney, forthcoming), these indicators provide a means for intensive scrutiny of Irish payment connections – thus conferring a deeper understanding of the components that contribute to the smooth functioning of the Irish economy and a stable financial system.

18 In statistics, ARIMA models are fitted to non-stationary time series data either to better understand the data or to predict future points in the series (forecasting).

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