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National accounting from the bottom up using large-scale financial transactions data:
An application to input-output tables

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Abstract

Technical advances enabled real-time data collection at a large scale, but lacking standards hamper their economic interpretation. Here, we benchmark a new monthly time series of inter-industrial flows of funds, constructed from aggregated and anonymised real-time payments between UK businesses, covering 5-digit SIC codes industries for the period 08/2015 to 12/2023, against established economic indicators, including GDP, input-output tables (IOTs), and stylised facts of granular firm- and industry-level production networks. We supplement the quantitative analyses with conceptual discussions, explaining the caveats of bottom-up collected payment data and their differences to national account tables. The results reveal strong GDP correlations, some qualitative consistency with official IOTs and stylised facts. We guide on the interpretation of the data and areas that require special attention for reliable quantitative research.

JEL codes: C67, C8, D57, E01

Keywords: National accounts, real-time data, payment data, economic networks, input-output table

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Disclaimer

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1 Introduction

The grand policy challenges of today can require a granular understanding of our economy, ideally in real time. Examples include supply chain disruptions caused by pandemics, climatic shocks and regional conflicts, or transition policies for net-zero and economic resilience. New and large-scale data can help tackle these challenges, and statistical offices are currently exploring how such data can be developed (ONS, 2023f; ONS, 2023a; The White House, 2023; Woloszko, 2023). New data come with new challenges, and it is unclear how the data sets can be interpreted in the terminology of national accounts (NAs).

In this work, we use monthly experimental data on inter-industrial payments compiled from anonymised and aggregated data from the Bankers' Automated Clearing Services (Bacs) payments system and provided to the Office for National Statistics (ONS). Bacs system is one of the major payment systems used by businesses in the UK (ONS, 2023e; Pay.UK, 2023a; Mantziou et al., 2023). This data embeds in a series of other real-time indicators explored by the ONS (ONS, 2023a; ONS, 2023h) and offers an unprecedented view on the UK economy and supply chains. The data include a monthly network time series of industry-to-industry payments at 5-digit Standard Industry Classification (SIC) level and cover the period August 2015 to December 2023, and bears the potential to be sourced in real-time. Such granular real-time data on industry to industry flows had never been available before: official inter-industry input-output tables (IOTs) are much more aggregate, published with time lags and only available at an annual frequency.

However, indicators developed using inter-industry payments are new, and their usefulness in real-world economic analyses is still to be proven. Also, the interpretation of observed time trends, short-term responses to shocks, and static properties and their relationship to established economic indicators is not necessarily clear. For example, trends of payment aggregates can reflect true economic dynamics or changes in payment preferences and behaviours. Also, cash transactions declined over the past decade, accelerated by Covid-19 (UK Finance, 2022), while cashless payments have been steadily increasing (Bodley and Brice, 2022). Such behavioural changes are independent of the underlying trends in "real" economic activity.

Other challenges are posed by financial intermediation, which may be responsive to innovation and regulation in payment systems. Financial intermediaries often execute transactions on behalf of their clients. Intermediation activities may inform about financial liquidity in the real economy (which is valuable information itself), but they hide the actual production activities and input-output linkages between trading industries.

Despite these and other challenges, the new data offers an unprecedented potential to advance research: beyond the timeliness and lower aggregation, our Payment data offers entirely new data types, such as differentiations between the counts and values of transactions, entailing distinct kinds of economic information. On the downside, the inter-industrial Payment data do not reveal the full picture: depending on the purpose and type of transaction, businesses rely on multiple payment systems next to Bacs, such as card payments, high-value-high-security or international systems.

This paper guides on how to read the novel data and offers a validation exercise, showing how real-time Payments relate to official macroeconomic time series and IOTs published by the ONS (2023g). A one-by-one validation is not possible in all dimensions, as monthly or 5-digit IOTs do not exist. Therefore, we rely on monthly macroeconomic indicators, annual IOTs, and stylised facts of granular production network data.

We find that transaction values show strong statistical relationships to nominal economic indicators, while counts (the number of monthly transactions) appear powerful in picking up trends of data in real terms. To date, count data has rarely (if at all) been used in economics, but it can be indicative of business dynamism: variations in the counts can indicate deviations from standing regular payments, such as fees, royalties, and loan repayments. We observe high levels of auto-correlations and promising cross-correlations when comparing our inter-industrial Payments to official IOTs and GDP. We supplement our quantitative analysis with a conceptual discussion of the (likely) major sources of observed differences. These are, for example, the treatment of investments in physical capital, the financial and retail sector, and international trade, along with aspects related to classification and the time of recording.

We also show that the structure of the highly granular 5-digit SIC Payment network matches relevant stylised facts from the literature, such as growth rate fluctuations and centrality distributions (Carvalho, 2014; Mungo and Moran, 2023; Magerman et al., 2016; Bacilieri et al., 2023). This paves the way for applied economic research exploiting the granular network structure. This is a very promising endeavour: long time series of an evolving monthly proxy-IOT at such a granular level has never been used in economic research before (to the best of our knowledge).

This work relates to two major streams of research and advances in data: Firstly, we contribute to recent and ongoing work on real-time but non-standardised data, fuelled by data science and new technology in economic measurement (ONS, 2023a; ONS, 2023h; Bank of England, 2023; Ialongo et al., 2022; Woloszko, 2023). Our research provides an in-depth analysis of research challenges and the relations to official national accounts (NAs). Secondly, our work embeds in current economic research trends relying on highly granular production network data, including networks reconstructed from financial transaction data (Fujiwara et al., 2021; Silva et al., 2022; Barja et al., 2019; Magerman et al., 2016). We contribute by assessing data extracted from the payment system infrastructure, which adds the granular time-series dimension and has never been used before.

The structure of this article is as follows: we provide an introduction to the UK payment systems in Sec. 2. In 3, we assess the data at the macroeconomic level, before diving into the benchmarking in comparison to NAs in Sec. 4. Sec. 5 discusses the conceptual differences to NAs. Sec. 6 shows how the granular network relates to established stylised facts. Sec. 7 concludes.

2 Data

This section gives a short introduction to payment systems (2.1), explains payment routes in the UK (2.2), and discusses the possible impact of regulation and innovations on payment data (2.3).

2.1 Basic concepts

Payments are made in different ways, for example using cash, credit and debit cards, bank transfers, mobile payments, or cheques, and thereby rely on various interconnected *payment systems*. In this work, we focus on anonymised and aggregated electronic payments in £ extracted from the *infrastructure* of the Bankers' Automated Clearing System (Bacs), which is one key systems used by UK businesses for bank transfers. Infrastructure data differs from transaction data obtained from single banks (Buda et al., 2023; Carvalho et al., 2021; Ialongo et al., 2022), as the infrastructure connects different banks and other payment service providers (PSPs) to transfer funds between the accounts of their clients.

Different payment infrastructures co-exist, dependent on the *payment scheme*. Loosely speaking, a payment scheme is a set of rules on how to transfer funds between accounts at different PSPs. The rules cover, for example, technical and security standards, the transaction speed and limit, and define the payment instruments, such as direct debits or credit transfers. PSPs can decide whether they join a scheme, but usually, all major PSP within an economic area use the same schemes.

Transferring funds involves two steps: *clearing* and *settlement*. Roughly spoken, clearing is the exchange of messages about an obligation to be established, sometimes including an inquiry of whether funds on the payer's account are sufficient. Settlement is the realisation of the transfer, which often happens with a time

Table 1: Overview of major UK payment schemes

Name	Type	Main use cases	Characteristics	Operator
Bacs	Retail	Recurrent & bulk payments; B2B payments, salaries, fees, utility bills, state benefits; often, long-term relationship between payer & payee	£20m limit,[a] high security, 3-5 days until clearing & settlement, low fees (£0.05-0.5[b])	Pay.UK
FPS	Retail	One-off low-value payments; often consumers as payee or payer	£1m limit,[a] immediate clearing, moderate fees (£1-5[b])	Pay.UK
CHAPS	Wholesale	Interbank market; high-value one-off purchases & investments	No transaction limit, high security, immediate settlement, high transaction fees (£12-35[b])	Bank of England
ICS	Retail	One-off medium-high value payments; bills, warrants, travel cheques, payable orders	Cheque payments; mostly businesses	Pay.UK
LINK	Retail	Cash withdrawals and operation of ATM infrastructure	Consumer and business users; creates the link between physical cash and electronic book money	
Cards	Retail	One-off payments, dominant in consumer shopping (can be linked to mobile phones), international transactions possible	Systems completely run by single entity; moderate fees (2-6% of transaction value plus additional charges)	private
SWIFT	Retail	International transactions in any currency by businesses and consumers	No legal limit,[a,c] up to 7 days for clearing & settlement; moderate fees vary across banks and transaction types (£20-40[b] or 3-5% of transaction value)	SWIFT
SEPA	Retail	Transactions in EUR by businesses and consumers from and to the EU	Moderate fees (£1-20[b])	ECB
TARGET2	Wholesale	EU analogue to CHAPS; high-value transactions in EUR, mainly by businesses, used for transactions from and to the EU	High fees (£10-35[b])	ECB

Notes: This table shows the major payment schemes used in the UK. It reflects a time snapshot in 2023. A short discussion of ongoing transformations and the expected impact on the data is provided below 2.3. [a] Banks may impose lower limits on their clients. [b] The fees refer to indicative fees charged by banks to their business clients. The numbers shown are approximate values in 2023. These numbers are estimated aggregates for an average transaction. The costs vary across banks, across transaction volumes, values, type of customer, and may change over time, and banks may charge additional costs. Often, PSPs offer schemes that combine fix prices with a percentage fee and a price cap. [c] High-value transactions are also regulated in the context of anti-money laundering and tax policies.

delay in pre-determined settlement cycles and on a net basis. Net settlement means that PSPs only transfer the net of their mutual obligations arising from multiple transactions made within the cycle (BIS, 2016). Unlike other work using payment system data provided by central banks (Aprigliano et al., 2019), our data is collected at the clearing level. This preserves the account-level network structure among businesses, that is otherwise hidden by financial intermediaries.

One can distinguish *wholesale* and *retail* payment systems, whereby wholesale is mostly used for high-value transactions settled in real-time gross settlement. Retail payment systems often settle on a net basis and are mostly used in everyday economic activity (Aprigliano et al., 2019). Bacs is one of the major retail payment systems in the UK. The UK's wholesale payment system is CHAPS, operated by the Bank of England (BoE). Non-financial businesses rarely use it for everyday transactions as it is costly, although they may still choose it for high-value and time-sensitive payments.

2.2 Payments in the UK and our data

Payments in the UK can be made through different systems and payment instruments. Consumers and businesses use various systems depending on the type and purpose of a transaction. UK Finance reports 40.4bn payment counts in the UK in 2021, whereby the majority are consumer payments. Businesses made about 5.5bn payments, with 3bn being business-to-business (B2B) (UK Finance, 2022). Our data covers only a small fraction (2.6%) of all B2B transactions if measured as counts of executed transactions, but a significant amount of the transferred value (£>1.2tn in 2021). As a benchmark, the UK annual GDP in current prices was circa £2.28tn in 2021.[1]

Businesses often use other systems than consumers, depending on the transaction purpose, value, frequency, security level, and costs. Table 1 summarises the major payment schemes for electronic transactions in the UK, their main use cases, characteristics, and operators. The discussion below focuses on the relevant characteristics from a B2B perspective.

The Payment data used in this paper is a subset of Bacs transactions, one of the three major domestic schemes for B2B transactions in £, next to CHAPS and Faster Payment System (FPS). Bacs can only be used by businesses to initiate direct debit (DB) collections and direct credit (DC) transfers. To access Bacs services, businesses need to fulfil certain eligibility criteria.

From a technical perspective, businesses can access Bacs services in three ways: (1) they can register their own Service User Number (SUN) and submit and receive payments themselves; (2) they can indirectly access the system via a so-called Bacs bureau while receiving their own SUN, but the bureau handles the transactions under their SUN; or (3) they rely on a third-party PSP that makes transactions on behalf of its customers using its own single SUN (Bacs, 2023b; Bacs, 2023a).

Compared to other payment options, Bacs transaction fees are very low (£0-0.5) and offer high security standards.[2] Further, Bacs offers a relatively high transaction limit (£20m for businesses). This makes the scheme attractive for frequent and/or regular bulk payments. Bacs offers two payment instruments: Direct Debits (DD) and Direct Credits (DC), which are used for different purposes. Businesses use DC for mainly B2B payments and employment-related payments, such as payroll and pensions. The main use cases of DD in the B2B context are regular B2B collections, commercial billing, leasing, rental, and fee payments. DD provide a high guarantee to be paid in time (Pay.UK, 2023a). Bacs DC and DD are also the major means of payment for governments to pay state benefits and collect taxes and national insurance contributions. In B.1, we provide some statistics and a short discussion about the differences of the economic information embodied in aggregate transactions of different payment instruments.

The Bacs payment data used in this article are derived from an unweighted sample of anonymised and aggregated DD and DC payments between approximately 117,000 Bacs service users and capture roughly 22.1% of the value of Bacs payments in 2023. The data set presents both the industry source and destination of the payments, with industries being assigned to SUNs using a combination of deterministic and probabilistic approaches matching Bacs service users' names to Companies House and other information (ONS, 2023d).

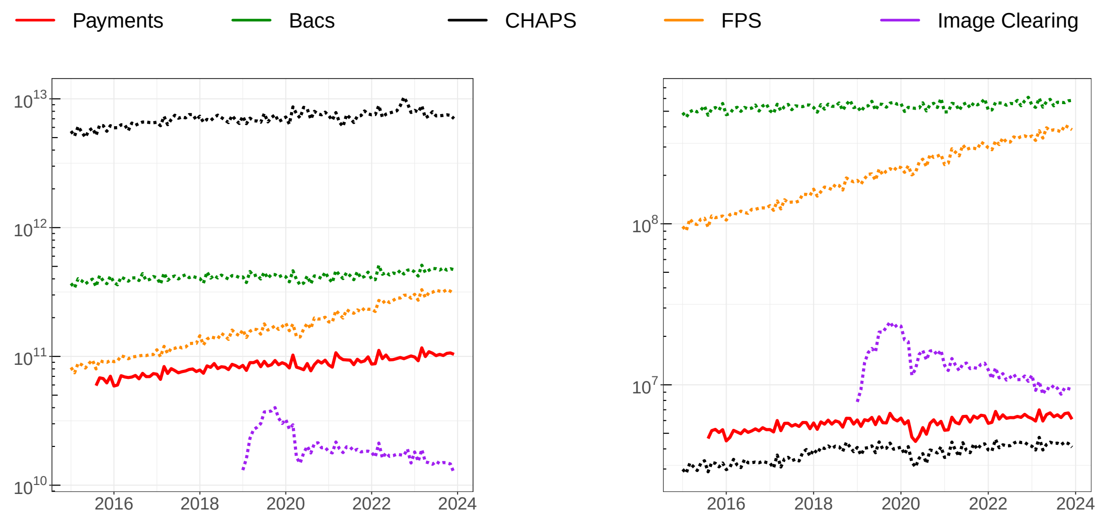
Currently, the major alternatives to Bacs for electronic payments are the Faster Payment System (FPS), Credit and Debit Cards, and the Clearing House Automated Payment System (CHAPS). FPS, introduced in 2008, is the youngest of them and was a major payment innovation globally. It offers near-to-real-time clearing, which provides a high guarantee of being paid. Compared to Bacs, the maximum transaction value for FPS is lower (£1m) and the transaction fee is higher (£1-5).[3] While still accounting for only a

[1] Note that a direct comparison to GDP is not possible as the two variables are conceptually different.

[2] Transaction fees depend on the agreement between the PSP and the business. Fees usually vary across different account types and PSPs offering these services. In addition to fees, businesses also have to pay the set-up costs for obtaining a Bacs account.

[3] The maximum transaction value was lifted from £250k to £1m in early 2023, and it is not yet possible to evaluate the impact of

Figure 1: Monthly time series of our Payment data and major UK schemes



(a) Values

(b) Counts

Notes: The vertical axis is scaled at a log-10 scale. Payments (red) are monthly aggregates of our data. The Bacs, CHAPS, FPS, and Image Clearing System data are downloaded from Pay.UK (2023b).

small share of annual payments by counts and values, the use of FPS has been increasing steadily (see Fig. 1), having reached an aggregate transaction value of almost £2bn in the 2020s.

Card payments are mostly used in consumer-to-business (C2B) transactions, especially in physical and online retail shopping. Transaction fees for card payments tend to be relatively high for businesses, while the exact conditions depend on the account type that businesses have at their PSP. CHAPS transactions are expensive for businesses and tend to be used only in special cases for high-value transactions, that require a high security and eventually exceed the transaction limit in the other schemes.

The other domestic schemes are Image Clearing System (ICS) for cheques and LINK, which connects electronic money to cash through withdrawals and cash deposits. Both are of minor and decreasing relevance, as suggested by the decreasing trends of cash and cheque usage for payments. UK businesses also use the international (SWIFT) and European schemes (SEPA, TARGET2), which tend to be used mostly for international transactions in other currencies.

Fig. 1 shows a time series of monthly aggregate transaction values and counts of our Payments data and the other UK schemes (excluding cards), covering August 2015 to December 2023 using a log-10 scale.

In 2023, the aggregate value of our Payments data was £1.25tn, which corresponds to 22.1% of the aggregate Bacs transaction values and 13% when taking FPS, Bacs, and ICS together.[4] The share of transaction counts is considerably lower (1.13% for Bacs and 0.67% for the aggregate). This can be explained by the exclusion of transactions from and to consumers, which often are most frequent, but with a relatively low value compared to the transactions in our data. The average transaction value in our data was about £16.2k in 2023, which is about 20 times higher than an average Bacs transaction (£830).

The values transferred through the CHAPS system are much higher. This is expected as it is a wholesale system for high-value transactions. CHAPS only indirectly reflects dynamics in the goods market but can

this increase on payment behaviour.

[4]These numbers are calculated using the data after statistical disclosure control (SDC).

be informative about the financial and interbank market.

Over time (Fig. 1), the evolution of the aggregate transaction values in the Payment data, Bacs, and CHAPS have been fairly stable, with minor monthly fluctuations, and a moderate rise. FPS is the only scheme that exhibits a relatively steep rise over time, both by values and counts. ICS shows some fluctuations in the end of 2019, but a slowly decreasing trend reflecting the decreasing use of cheques.

2.3 Innovation and change in payments

One key challenge for using payments data in research is their responsiveness to crises, regulation, attempts for international harmonisation, and innovation. This can affect the businesses' and consumers choice of how to make payments, as exemplified by the decline of cash and cheques, and the rise of card and FPS payments (UK Finance, 2022; Bodley and Brice, 2022; Jackson, 2018). Until now, most innovations were limited to the relationship between PSPs and their customers, such as new payment instruments and services, connecting services, or user interfaces. These innovations were mostly driven by digitalisation and enabled by regulation after the financial crisis. This was aligned with high-level operational changes in the UK payment system, such as the introduction of FPS.

Since 2015, there has been an ongoing transformation that will likely affect all major schemes operated by Pay.UK. The Payment System Regulator (PSR) outlined a strategy to build a "new payments architecture" (NPA) (PSO, 2017). One of the goals of the NPA is the replacement of the existing retail payment systems (Bacs, FPS, ICS) by a uniform scheme and infrastructure, providing a comprehensive technical update, and a higher compatibility with digitalisation, new consumer habits, and international developments (Bodley and Brice, 2022). So far these plans have not yet been realised, and the impact on payments data is hard to evaluate ex-ante. In the best case, a harmonisation of payments under a uniform architecture would improve the coverage, assuming that the matching of accounts with businesses and industries would be still possible.

3 Macroeconomic benchmarking

Before diving into the industry-level network analysis, we assess the economic information embodied in the Payment data at the macroeconomic level through a comparison to GDP and monetary aggregates and compare it to other available payment data (Pay.UK, 2023b). Our results show that trends in the Payment data behave similarly to those of Bacs totals, and most importantly for future economic applications, we find strong correlations with macroeconomic fundamentals, including GDP and monetary aggregates.

Table 2 shows monthly and annual correlations of our Payment data with the other UK payment schemes, real GDP, monetary aggregates (M1) and prices, measured in levels (top rows) and growth rates (bottom rows). Data from the years of the Covid-19 pandemic (proxied by March 2020-December 2022) are excluded.[5] In levels, aggregate Payment values and counts show strong correlations with the other UK payment data, ranging between 80-97%. For transaction values, we find the highest levels for annual Bacs and monthly FPS aggregates, while CHAPS is highly similar by counts.

The growth rates exhibit more heterogeneous patterns: annual aggregates poorly correlate, which may be due to differences in the long-term trends (see also Fig. 2). In contrast, monthly growth calculated as growth in relation to the same month of the preceding year, shows fairly high correlations, especially for the Bacs value data with 88.2%.

[5] Additional results including the period of Covid-19 are available in B.2.

Table 2: Correlations with other payments and macro aggregates

	Bacs	FPS	CHAPS	GDP nsa	GDP sa	M1 nsa	M3 nsa	Prices
Raw data in levels								
Yearly (value)	0.967	0.962	0.926	0.998	0.998	0.996	0.948	0.999
Monthly (value)	0.874	0.926	0.794	0.865	0.915	0.911	0.921	0.898
Yearly (count)	0.972	0.884	0.949	0.988	0.996	0.993	0.969	0.990
Monthly (count)	0.817	0.800	0.934	0.867	0.854	0.783	0.806	0.825
Yearly (avg)	0.948	−0.190	−0.487	0.992	0.978	0.979	0.894	0.991
Monthly (avg)	0.696	−0.095	−0.409	0.632	0.858	0.923	0.919	0.786
Growth rates								
Yearly (value)	0.050	−0.223	0.462	0.682	0.066	0.955	0.787	−0.837
Monthly (value)	0.882	0.695	0.565	0.720	0.365	0.579	0.630	0.189
Yearly (count)	0.047	−0.321	−0.251	0.686	0.071	0.956	0.789	−0.835
Monthly (count)	0.619	0.137	0.382	0.785	0.328	0.067	0.138	0.240
Yearly (avg)	0.957	0.732	0.340	0.415	−0.261	0.856	0.616	−0.905
Monthly (avg)	0.667	0.548	0.138	−0.162	0.132	0.738	0.735	−0.108

Notes: This table shows Pearson correlations between the Payment data with the other UK payment schemes and macroeconomic aggregates (GDP, M1, M3, Prices). The monthly (annual) time series cover the period August 2015-December 2023 (2016-2023), excluding the period of Covid-19, proxied by March 2020-December 2022 (2020-2022). "sa" ("nsa") is short for (non-)seasonally adjusted. All payment data (our data and other aggregates published by Pay.UK) are compared by aggregate values, counts, and average values (short "avg") given by value divided by count. The top panel shows correlations of the aggregates measured in levels, the bottom panel shows a comparison by growth rates. Monthly growth rates are calculated as percentage growth compared to the (same month of the) previous year (for monthly data). Annual growth rates show relative deviations compared to the previous year. The column "Retail" shows the sum of all retail payment schemes, excluding cards. Bacs, FPS, Retail, and CHAPS data are obtained from Pay.UK (2023b). Monthly GDP is proxied by indicative (non-)seasonally adjusted monthly "Total Gross Value Added" index data published by the ONS and serves as a proxy of monthly (non-)deseasonalised GDP (ONS, 2023c; ONS, 2023b). "Prices" is short for Consumer prices index data obtained from the OECD Key Economic Indicators (KEI) dataset (OECD, 2023a). M1 (M3) are narrow (broad) monetary aggregates, and thus nominal indicators, obtained from the OECD Main Economic Indicators (MEI) dataset (OECD, 2023b).

The average transaction values show a high similarity with Bacs, but correlate not or only negatively with the other payment schemes. Negative correlations of average values may indicate that our Payment data captures different types of payments than the those being reflected in the aggregate payment data: for example, low-value payments in everyday expenditures differ from high-value investments or purchases of consumer durables.

However, looking at growth rates, we find higher levels of similarity, indicating that there may be a common underlying pattern of how transaction values evolve. One possible direction of interpretation may be their relationship with prices, here measured as consumer price index. However, while finding strong positive correlations with prices measured in levels, we find a negative one when comparing by growth rates. This may seem counter-intuitive, but differences in the trends may arise from sluggish price adjustments, especially when comparing consumer prices with B2B data.[6]

Turning now to economic fundamentals, we find strong correlations between Payments and real GDP, ranging between 85-92% for monthly data in levels. We analysed both seasonally adjusted ("sa") and non-adjusted ("nsa") data.[7] The correlation performance for both indicators is similar. Looking at growth rates, the difference is more clear: at the monthly level, correlations between values (counts) are about 72% (79%) for non-adjusted data, but only half as high (36% (33%)) for seasonally adjusted GDP. These are very promising signals regarding the value of the data for applied economic research and advancing national statistics.

As a next step, we relate Payments to monetary aggregates, measured as M1 and M3, which can be considered as an indicator of financial liquidity in the real economy.[8] Again, we observe strong statistical relationships for both M1 and M3 with high correlations of >90% for Payment values and around 60% for

[6] We additionally made a comparison to producer price indices for manufacturing, but observe similar patterns.

[7] As monthly non-deseasonalised GDP data is not available, we use indicative Total Gross Value Added (GVA) as a proxy (ONS, 2023c).

[8] M1 and M3 are monetary aggregates used as measures of the quantity of money and assets, while M3 includes assets at low levels of liquidity (OECD, 2023b).

their monthly growth rates. Correlations for Payment counts are lower, with around 80% for the data in levels and 7-14% for growth rates.

These observations confirm the idea of Payment values as a nominal indicator and counts being more strongly related to data in real terms. B2B count data can indicate business dynamism: variations in the counts can indicate deviations from standing regular payments (such as fees, royalties, and loan repayments).

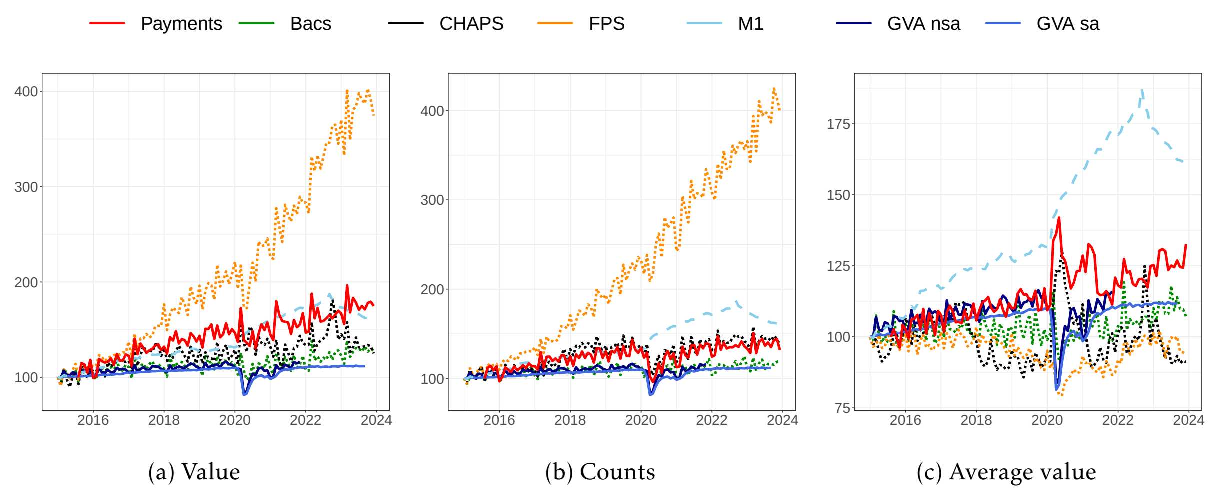


Figure 2: Monthly UK payments, GDP and M1

Notes: These figures show monthly time series of the Payment data, the major UK payment schemes, and indicative non-seasonally adjusted monthly "Total Gross Value Added" data published by the ONS, which serves as a proxy of real GDP (ONS, 2023c). The time series show indexed data with 2015=100. The average value of is only provided for the Payment, Bacs, CHAPS, and FPS data obtained by dividing values by counts, while GDP shows the index.

Fig. 2 illustrates this, showing indexed monthly time series plots of real GDP, M1, Payments, and other UK payment schemes for transaction values, counts, and the average value of transactions. Five key observations can be made: (1) By value, Payments rose relatively more than GDP, CHAPS, and Bacs, and almost perfectly match with the long-term rise in nominal monetary aggregates M1 until 2022, when central banks began to tighten the money supply. By counts, the rise and fluctuations of the Payment data almost perfectly co-evolve with CHAPS counts, and show very similar fluctuations as non-deseasonalised real GDP, but not the same long-term trend. (2) The Covid-19 shock in early 2020 shows ambiguous correlations: it is associated with a drop in GPD and Payment counts, but higher peaking average transaction values and an unclear relationship to Payment values (see also B.2). (3) Average transaction values show the same pattern of growth as real GDP until the Covid-19 shock in 2020 when both time series radically decouple. They re-converge over the following months showing a similar long-term trend. (4) The index series underline the steep rise of FPS. (5) Lastly, the time series show some volatility, but no clear pattern of seasonality, in line with the higher correlations with non-deseasonalised GDP.

4 Comparison to national accounts

Here, we first describe the construction of Payment-based IOTs (Sec. 4.1). Then, we compare the different IOTs by the aggregate network structure (Sec. 4.2), auto- and cross-correlations (Sec. 4.3), and quantify edge-level differences (Sec. 4.4).

4.1 From inter-industrial flow of funds to input-output tables

Payments in our data present both source and destination industries and can be transformed into symmetric matrices of monetary flows, whereby rows are paying industries and columns are those being paid. Transposing the matrices (swapping rows and columns) leads to symmetric matrices of input-output flows, showing the row industries (being paid) as the suppliers of an input and column industries as (paying) customers.

These matrices serve as proxies of IOTs, enabling a benchmarking exercise with the official NAs tables. Here, we look at three different types of symmetric IOTs published by the ONS: (1) intermediate use within the supply and use tables (SUTs), and two analytical IOTs in an (2) industry-by-industry (IxI) and (3) product-by-product (PxP) format. These tables reflect supply-chain linkages between industries within an economy. The classification used for industries in the IOTs is given by SIC codes (ONS, 2009) and for products by the Classification of Product by Activity (CPA) (Eurostat, 2015). These classifications are fully aligned with each other: at each level of aggregation, the CPA shows the principal products of the industries according to the SIC (paragraph 9.2 Eurostat, 2010).[9]

To compare the Payments with the official IOTs, we aggregated monthly transactions into annual aggregates and harmonised the classification between the data sources. To construct the Payment-based IOTs, we used data at the 3-digit level with 265 distinct industries for most sectors, and used 5-digit data with 612 different sectors whenever CPA codes were too granular for a 3-digit level matching. We applied this mixed procedure to maximise the coverage, as the statistical disclosure control (SDC) is more restrictive at the 5-digit level.[10]

We obtain a panel of annual proxy-IOTs covering the years 2016-2023.[11] While our inter-industrial Payment data includes all Bacs payments received (limited by our data coverage), the ONS intermediate demand tables only cover payments received for an industry's primary product (see also Sec. 5). The official IOTs are compiled by the ONS in a step-wise procedure, whereby SUTs are the starting point. The SUTs show the flows of products and services in the economy across industries, products, and institutional sectors and with the rest of the world. The ONS assembles SUTs from a sample of almost 300 different data sources, consisting of business, and consumer surveys conducted annually by the ONS and other public and private datasets.[12] The data assembling follows international standards of balancing and applying national accounting identities (Eurostat, 2010).

The intermediate demand within the SUT framework shows what nationally supplied products and services plus imports are used as an input into the production process of each industry, valued at current prices (Eurostat, 2010, ch. 9), excluding those part of gross fixed capital formation.

The symmetric IxI and PxP tables are derived from the SUTs. They differ in the way how products and production activities are assigned to CPA codes. While intermediate demand within SUTs shows the use of products by industry, the symmetric tables show, either, how products are used to make products (PxP) or how the outputs of one industry are used as intermediate inputs in another industry (IxI) (Eurostat, 2010, par. 9.09). To simplify the language, we refer to the CPAs as industries, being aware that PxP tables and SUTs rely (partially) on products as units of analysis.

PxP tables focus on products that may be produced by various industries as their primary or secondary

[9]The European standards refer to NACE (*"nomenclature statistique des activités économiques dans la Communauté européenne"*) codes used at Eurostat, which are equivalent to the SIC used in the UK.

[10]Appendix A shows the mapping from SIC to CPA codes for each industry. The raw number of industry codes in the data is 705, but some of them were "whitened" due to the SDC.

[11]The year 2015 is dropped due to incomplete coverage.

[12]The list of data sources used for the SUTs is available here: `https://www.ons.gov.uk/economy/nationalaccounts/supplyandusetables/datasets/supplyandusetablesdatasourcescatalogue` [accessed on 2024/01/04]. See also ONS (2023g).

output, while IxI tables focus on industries that supply their primary output to multiple industries. Industries are classified by their primary production activity. The reallocation of non-primary products produced by an industry can be done in different ways, either by assuming that a certain product is always produced by using the same inputs, regardless of the industry producing it, or by assuming that a specific product is always sold to the same set of industries, regardless of the producer. In the UK, the IxI tables rely on the latter assumption. PxP tables are computed using both assumptions (ONS, 2023g).

The Payment-based IOTs differ conceptually: they reflect transactions between multi-product industries, while the payment purpose remains unknown.[13] The industry classification is based on the self-declared business activity indicated as one or multiple 5-digit SIC codes when companies register at Companies House.[14] In this experimental data version, we only rely on the first code indicated by the firms.[15]

Further, when comparing official NAs to the Payment data, some product categories are completely missing in the Payment data, such as "T97 - Activities of households of domestic personnel" or "Imputed rents", which is a natural feature of a dataset based on B2B payments.

We compare the Payment-based IOTs using both transaction counts and values with the SUT, IxI, and PxP tables. The data availability varies: Payments are available for 2016-2023, IxI for 2018-2019, PxP for 2010, 2013-2015, 2017-2019, and SUT for 1998-2021.[16] The availability of the official data reflects the publication delays caused by the complex data collection and compilation procedure when merging and harmonising data from heterogeneous sources.[17] The compilation of the official tables is occasionally revised in response to economic change and methodological improvements. Only the SUTs are revised backwards, thus providing a consistent time series. However, inconsistencies can still arise from improvements and extensions of the data collection process, for example when surveys are amended.

4.2 Aggregate network statistics

We now analyse the IOTs from a network perspective, representing the tables as weighted networks of industries trading goods and services. The network view is relevant as most supply chain and input-output analytics rely on network methods (Carvalho, 2014; Acemoglu et al., 2012; Leontief, 1991). The nodes in the network are given by the industries (CPA codes) and the links are transactions between two industries. The links are weighted by the transaction value (or count) Z_{ij}^{α} between two industries i and j, where j buys inputs from i. As a notation, we use α to indicate the type of IOT with $\alpha = \{\text{Value}, \text{Count}, \text{IxI}, \text{PxP}, \text{SUT}\}$.

We also calculate input (output) shares $\omega_{\alpha,ij}^{\text{in}}$ ($\omega_{\alpha,ij}^{\text{out}}$) by dividing the raw weight of an input (output) link Z_{ij}^{α} (Z_{ji}^{α}) by the sum of inputs purchased (outputs sold) from (to) all other industries, given by

[13] Theoretically, the trade flows in the Payment data could be disambiguated, using a top-down imputation approach, where proportions are informed from other data sources. This was not tried for the existing data, also as there may be unknown issues, for example when primary and non-primary outputs are paid through other payment schemes. Working with the raw data on payment flows between multi-product industries can also be advantageous for certain applications: for example, diversification into new product markets can be an innovation strategy of firms and an indicator of technological and industrial change.

[14] See https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1090526/IN01-V8.0.pdf and https://companieshouse.blog.gov.uk/2021/10/12/choosing-a-standard-industrial-classification-sic-code-for-your- [accessed on 12/10/2023].

[15] Updated versions using a classification approach using all SIC codes are in the process of development. The reliance on the first code only may cause a bias towards an over-representation of SIC codes with a smaller number, as multiple codes tend to be listed in an increasing order. Systematic checks for eventual biases were beyond the scope of this article.

[16] We exclude the PxP from 2016 as they rely on another industry disaggregation and cover only 64 sectors. The SUT series is taken from the ONS Blue Book 2023 (ONS, 2023g). All data has been downloaded from the ONS website in Q1/2024.

[17] In the Blue Book 2023 (ONS, 2023g), the catalogue of data sources used for the SUTs includes 279 different entries, including data from public institutions like the ONS, the BoE, Treasury, Tax and Customs offices, government departments, private sector-specific data providers, international institutions, data from other public institutions and subnational authorities.

$$\omega_{ij}^{\text{in},\alpha} = \frac{Z_{ij}^{\alpha}}{\sum_i Z_{ij}^{\alpha}} \qquad \left(\omega_{ij}^{\text{out},\alpha} = \frac{Z_{ji}^{\alpha}}{\sum_j Z_{ij}^{\alpha}}\right). \tag{1}$$

Using this network interpretation of the IOTs, we calculate aggregate properties of the Payment-based and ONS IOTs, shown in Table 3 using 2019, which is the most recent year for which data for IOTs were available when writing the paper (Q1/2024). The upper part of the tables illustrates the statistics when using raw transactions as weights, the lower parts when using input and output shares.

Table 3: Properties of the Payment and ONS input-output networks in 2019

	Value	Count	PxP	SUT	IxI
Raw transactions					
Density	0.286	0.286	0.723	0.474	0.980
Average degree	28.550	28.550	75.202	49.260	101.885
Average strength	2,783.139	239,906.400	10,563.500	12,741.830	10,593.480
Average weight	97.483	8,403.027	140.468	258.667	103.975
Reciprocity	0.554	0.554	0.793	0.534	0.989
Transitivity	0.648	0.648	0.921	0.787	1
Assortativity by degree	−0.358	−0.358	−0.176	−0.190	−0.005
Input shares					
Average strength	0.885	0.940	0.840	0.741	0.846
Average weight	0.031	0.033	0.011	0.015	0.008
Output shares					
Average strength	0.839	0.864	0.812	0.731	0.828
Average weight	0.029	0.030	0.011	0.015	0.008

Notes: This table shows aggregate network statistics of the IOTs obtained from the Payment data and the ONS. The first column uses transaction values, the second transaction counts as weights. The latter three columns represent the official tables as published by the ONS, whereby PxP is short for Product-by-Product, IxI for Industry-by-Industry, and SUT for Supply-and-Use Table. The aggregation is 105 CPA product codes (see Sec. 4.1). Raw transaction data are shown in £m.

The comparison reveals that the Payment networks are much less densely connected than the ONS SUT, PxP, and IxI networks, reflected in a low density of <30%, compared to 47-98% for the ONS tables. On average, an industry has about 29 Payment links out of 105 theoretically possible links, as reflected by the degree, including loops reflecting within-industry trade. The connectivity is strongest in the IxI network which is almost fully connected, and lowest in the SUT with a density of 47% and 45 links per industry on average.

The density steeply decreases in the ONS-based IOTs if we truncate the network by removing non-significant links: for example, if we remove all links in an IOT α with an input (output) share $\omega_{ij}^{\text{in},\alpha}$ ($\omega_{ij}^{\text{out},\alpha}$) smaller than 1% (5%), the density drops from 47-98% to 16-18% (3-4%). The Payment-based IOTs are less sensitive to such truncation, declining from 29% to 11-14% (4-6%) and become even denser than the ONS IOTs if the truncation is strong (see B.3). This arises from the SDC procedure, where all small and potentially disclosive links between industries have already been removed.[18]

Transitivity and reciprocity range between 55-100%, and are higher the denser the network. This number indicates the share of industries, which are customers and sellers to each other at the same time (reciprocity) or are connected through a third industry, forming a closed triad (transitivity). These values are lowest for the SUT and the Payment-based IOTs.

[18] Note that this report relies on an experimental version of the data, and an expansion of coverage of firms included in the analysis is in development. This will likely contribute to a higher connectivity of the network.

All networks show a negative node-assortativity, telling us that large and well-connected industries tend to trade more with smaller and less connected industries, whereby "well-connected" means a high number of links (degree), and "large" refers to a high level of output or input. The negative assortativity of the raw networks is an often documented property of IOTs (Hötte, 2023), but not surprising given the high density. The assortativity becomes positive if we impose a network truncation of 5% (see Table B.4), meaning that large industries are more frequently connected to other large sectors. This change over truncation thresholds is qualitatively consistent across all IOTs.

Wrapping up, the Payment-based IOT proxies and official IOTs are qualitatively consistent by network properties. We found qualitative consistent responses in almost all indicators when removing links with a small economic weight, but the lowest sensitivity to truncation for the Payment-based IOT, which may be associated with the SDC. At the 5% truncation level (which is often imposed on IOTs before studying spillovers (see Hötte, 2023, and references therein)), the aggregate network properties of IOTs from the different data sources are very similar.

Beyond the impact of the SDC, the quantitative variations and their sensitivity to link removal can be associated with differences in the compilation procedure and data sources. The Payment data captures every financial transfer between two businesses using DD or DC, which can produce multiple products and services, leading to an aggregation into multi-product industries. In contrast, the ONS tables are based on surveys asking businesses to state their major purchases, mostly by product category. The assignment of product categories to industries is associated with several steps of harmonisation and balancing. The SUTs are the "rawest" form, showing which industry used which products as intermediate inputs. The SUTs do not reflect whether the products are the inputs to or outputs of primary or non-primary production.This explains lower connectivity in the SUTs: including non-primary production implies the imputation of additional links, leading to a higher density of the PxP and IxI networks.

Also, the treatment intermediary industries (trade, retail, finance) plays a role, as the Payment data shows the full transfer as a transaction from or to the intermediary and ONS tables only allocate the margin charged on the service provided to the intermediary, but add a new link between the seller and final user of the traded good, leading to a higher density and transitivity of the networks (see also Sec. 5).

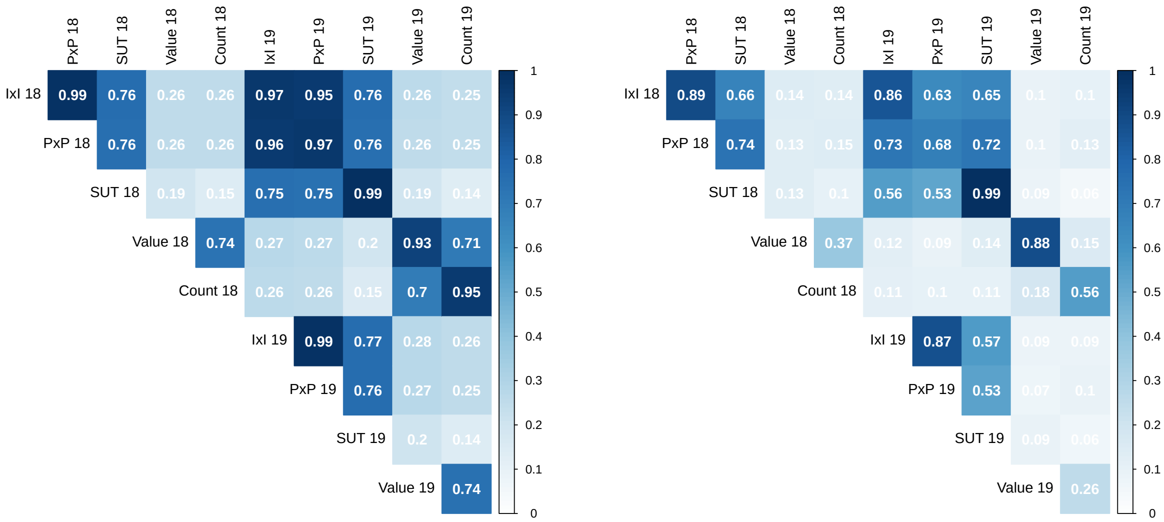
4.3 Auto- and cross-correlations

Next, we analyse auto- and cross-correlations of IOTs at the edge- and industry-level, exploring how inputs and outputs of industries auto-correlate within the same IOT, and cross-correlate across different IOTs. The edge-level results are illustrated by Fig. 3, which shows pairwise auto- and cross-correlations of in- and output shares in the different IOTs from 2018-2019, using the Pearson correlation coefficient. A darker colour indicates stronger correlations.

The similarities of the IOTs across data sources (ONS, Payments) by input shares are about 10-20% higher compared to similarities by output shares, ranging between 14-27% instead of 6-15%. Generally, we observe high within-data source cross-correlations, with coefficients for the input side ranging between 76-99%, and high auto-correlations within the same IOT. Similarities tend to be lower when looking at the output rather than the input side. This decline is strongest for the within-Payment correlations between Values and Counts (declining from 74% to 36-37%), and for the similarity of SUTs to the analytical IxI and PxP tables, going down from >75% to 50-70%. These findings are consistent with an analogous correlation analysis at the industry level, comparing industries by aggregate inputs and outputs. The results are illustrated and discussed in B.4.

The analysis reveals three core insights: (1) Within-ONS and within-Payment similarities are larger than across data sources for any measure and across time. (2) We find very high auto-correlations (up to

Figure 3: Auto- & cross-correlations of input and output shares (2018-2019)



(a) Input shares (b) Output shares

Notes: This figure illustrates auto- and cross-correlations measured by the Pearson correlation coefficient between input- and output-shares in the input-output tables based on Values and Counts of the Payment data and SUT, PxP, and IxI tables, showing only the years 2018-2019 when all tables are available. On the left- (right-)hand side, correlations between input (output) shares are shown. The networks are not truncated, and the data is raw, i.e. without transformation or truncation.

99%). (3) At the edge level, similarities by input links are much higher than by outputs. At the industry level, aggregate inputs in the Payment-based IOTs are most similar to SUTs, but more similar to PxP and IxI by output. This might be explained by the nature of SUTs, reflecting the supply of an industry classified by its primary output. In contrast, the input side of SUTs is based on the correct classification of products used as inputs by multi-product industries.

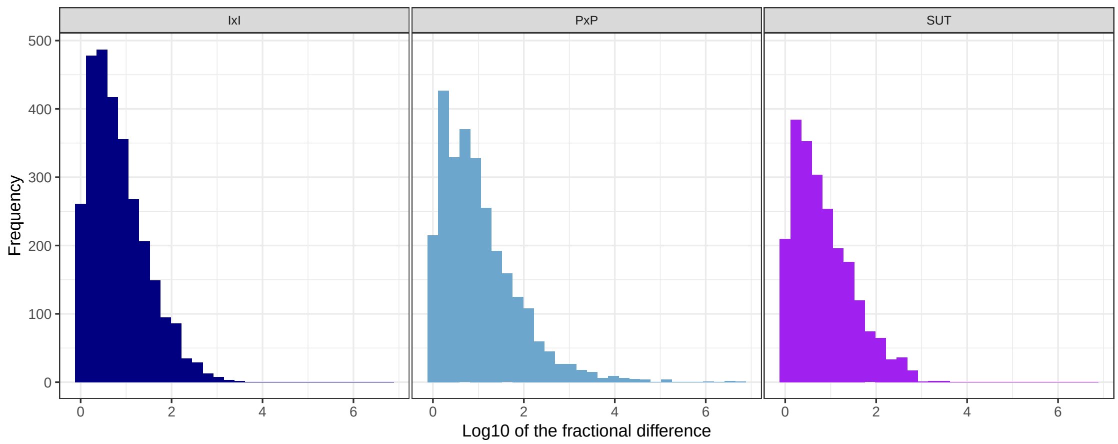
Relatively high similarities of the Payment-based and ONS IOTs at the industry and transaction level, without any pre-processing or statistical data cleaning, are promising signals for using the data in applied economic research at the macro, industry, and network level.

4.4 Quantifying the edge-level difference

After analysing similarities, we now quantify the typical differences. We face three issues: (1) the overall value of transactions is different across datasets, caused by the under- and over-sampling of industries (see also B.5 and C.7). This undermines the direct comparison. To improve the comparability, we rescale the values. (2) Some industry pairs have much higher values of mutual transactions than other pairs. Therefore, the difference between the ONS and Payment data tends to be extremely high for industry pairs with very high transaction values. To solve this issue, we can use measures of relative differences, such as percentages or log10 differences, in absolute value. (3) However, there are cases where one of the two datasets has a value of exactly zero. This prevents us from using log differences or percentage differences, and we only compare those transactions between industries, which are non-zero in both datasets.

We develop a measure, called proportional difference, indicating how many times larger a value is in one dataset compared to the other: a value of 1 means that the two values, measured as a proportion of the total transaction value, are equal (zero error), and a value of 2 means that the value is twice as large in one dataset compared to the other. Details are provided in B.6.

Figure 4: Proportional differences between the ONS and Payment-based IOTs



Notes: The figures illustrate the distribution of the proportional edge-level differences between the Payment-based and ONS IOTs, using 2019 data. The is scaled at a log-10 basis. Industry pairs are removed if the mutual transaction is zero in one of the two datasets. A comparison of the differences between IOTs with and without such link removal in available in B.6, using a scaled percentage difference metric.

Table 4: Quantiles of the proportional differences

	25%	50%	75%	100%
IxI	2.20	5.10	15.24	3851.66
PxP	2.40	6.76	27.74	582092.2
SUT	2.12	5.08	17.01	2911.96

Notes: Quantiles of the proportional differences for the three ONS tables (IxI, PxP, SUT) compared to Payment-based IOTs shown in Fig. 4, using data from 2019. Note that the values shown are not log-scaled, unlike as in Fig. 4.

Fig. 4 shows the histograms of proportional differences, scaled to a log-10 basis. The quartiles of the distributions are summarised in Table 4.

The results show that the differences can be extremely large: the medians range between 5.1-6.8 for all the three IOTs, meaning that for half of the pairs, one value is at least 5-7 times larger than in the Payment-based IOT. The 25% and 75% quantiles range around 2.1-2.4 and 15.2-27.7, indicating a highly skewed distribution with long tails. For most industries, we observe moderate deviations, but for some industry pairs, the differences are extreme. Due to the different coverage of the two data sets and the proportion of data not allocated to any industry in the Payment data (circa 40%), this is not a surprising result.

Further and confirming the earlier results, the differences are largest between the Payments and the PxP table, also with the most extreme outliers. The differences to the IxI and SUT range around similar values, while the distribution for IxI tends to have a thinner tail.

The restriction on quantifying the differences between non-zero transaction links in both datasets may be seen as a distortion. In B.6, we show additional results for an alternative metric that allows keeping the one-sided zero distances. We generally observe that the differences tend to be slightly smaller and less skewed, but the effect is small.

5 Conceptual differences between Payments and National Accounts

Now, we discuss the main conceptual differences between Payment-based and official IOTs, focusing on the (likely) most impactful aspects summarised in Table 5. This section is partly based on Bacilieri et al. (2023, Appendix A), with a similar discussion of firm-level production networks constructed from VAT data. We supplement our discussions with information on Bacs processing statistics (Pay.UK, 2021).

Table 5: Conceptual differences

National accounts element	**SUT Intermediate Use**	**Payments**
Time of recording	Products enter the production process	Payment takes place
Gross fixed capital formation	Excluded	Likely included; debt repayment for financing GFCF also likely included
Financial services	Included	Flow of funds to financial sector likely to include payments from debtor to creditor, including financial services
Goods and services bought for resale	Excluded	Likely included
Distributive transactions	Excluded; taxes are added to basic prices while subsidies are deduced to calculate purchasers' prices	Likely partially included, examples can include dividends and interests, insurance premiums and settlements, taxes and subsidies
International trade	Exports excluded Imports included	Likely excluded
Inventories	Excluded	Likely included
Industrial classification	Reported by firms answering ONS surveys and other data sources	Results of matching exercise from SUNs to Companies House data and other information

Notes: This table summarises the conceptual differences between national accounts, focusing on the intermediate consumption table obtained from the SUTs. Most of the issues discussed are equally valid for the analytical IxI and PxP tables.

Time of recording and inventories NAs, like business accounts, adopt accrual recording (Eurostat, 2010, par. 20.171), that is, NA "*records flows at the time economic value is created, transformed, exchanged, transferred or extinguished.*" For intermediate consumption, products used in the production process are recorded and valued when they enter such process (Eurostat, 2010, par. 3.91).

By contrast, the Payment data shows when the payment was made and received (without delays). As noted in Eurostat (2010), accrual basis "*is different from cash recording and, in principle, from due-for-payment recording, defined as the latest time payments can be made without additional charges or penalties.*" We are also unable to identify whether flows of payments refer to goods and services used in the production process at the time of the transactions. Some transactions may refer to inventories, thus contributing to the observed difference between the two data sources.

The difference in the recording time can be important in some applications, such as real-time supply chain analyses. In many industries, suppliers are paid with a delay, and cash flow financing is an important part of credit activities with financial intermediaries specialising in supply chain financing (Gelsomino et al., 2016).

Investment in physical capital The intermediate use table shows the value of *intermediate* goods and services exchanged between industries, that is, *"goods and services consumed as inputs by a process of production, excluding fixed assets whose consumption is recorded as consumption of fixed capital. The goods and services are either transformed or used up by the production process"* (Eurostat, 2010, par. 3.88). By contrast, Payments between industries are observed for multiple reasons, including payments related to capital investments and debt repayments. The latter occurs when firms finance at least part of their investment via debt and generate credit flows. On the other hand, the Payment data potentially embodies an investment network, that could be separated by distinguishing capital and intermediate goods-producing businesses at the 5-digit SIC level. Such an investment network may be a valuable supplement when connecting short-term business cycles to investment dynamics and long-term growth (Lehn and Winberry, 2022).

Financial services In NAs, the output of financial intermediation services arises from two components (Eurostat, 2008, p.106): first, financial institutions perceive direct fees and commissions explicitly charged. We expect to see such fees in the Payment data. Second, NAs consider that financial intermediaries provide credit services and the value of these services can be estimated by finding the margin taken by financial institutions on the credit they make. This margin is estimated by comparing the interest rate at which banks borrow, and the one at which they make loans. As a result, in NA, the payment between an industry and the financial sector represents the value of financial services provided. In the Payment data, by contrast, we observe the raw flows of funds, rather than the margin. Hence, we expect credit flows in both directions: flows of money from a creditor to a debtor, and, subsequently, reimbursements from a debtor to a creditor. These flows can be large and would not appear in the IOTs, leading to an over-representation of the financial sector in the Payment-based IOTs (see also B.5, C.7).

Trade and transport margins Within the SUTs, the supply table is valued at basic prices, while the use tables are valued at purchasers' prices. The transition from basic to purchaser's prices involves reallocating trade and transport margins. The output of retail and wholesale sectors equals total trade margins and is included in the supply table, while their services appear as an empty row in the intermediate use table (they are included in the purchaser's prices). As a result, when a firm from industry i buys an intermediate good from industry j via a wholesaler k, SUTs record the flow between industry i and j directly, adding another flow from the buyer to the wholesale industry k to account for the payment of trade services (part of the trade margins).

In the Payment data, only direct payments are present. This causes two issues. First, there is a double counting issue. In NAs, the value of goods bought for resale is counted only once – when it flows from industry j to industry i. By contrast, in the Payments, the flows observed likely capture both flows of funds from the wholesaler industry to the producer industry and from the buyer industry to the trade industry. This means that the value of an intermediate good would appear twice in the Payment data (and include trade services). Second, there is a misallocation of flows issue. In the SUTs, we would see a flow between industry i and j, and no flow between the wholesaler and the supplier. By contrast, in the Payment data, we would not see a flow between industries i and j, but observe flows between industries k and j and between industries k and i. Similar issues arise for transport margins.

Distributive transactions Distributive transactions are those where the value added generated by production is redistributed (Eurostat, 2010, par. 4.01). This includes compensation of employees, taxes on production and imports, subsidies, property income, and other current transfers. Within the NAs framework, such elements are outside inter-industry intermediate transaction matrices. Some flows associated with these transfers may appear in our Payment data, for instance, dividends and interests, insurance premia and settlements, or taxes and subsidies. This is likely important in our comparison exercise for some industries, such as public administration. Within the SUTs, the difference between taxes and subsidies is used to move from basic prices to producers' prices. Thus, contributing to the value of the products supplied in the economy as available in the supply table, equalling total use. By contrast, if the flow of funds captures subsidies to and taxes from businesses, we observe the flow of payments from/to public administration to other industries.

International trade In NAs, the Supply table aims to show the total supply of products available within an economy. It thus shows the domestic supply of products by industry, and includes an extra column showing "Imports". Similarly, the Use tables show domestic use and include an extra "Exports" column to account for the use of the total supply made by non-domestic industries, ensuring total supply equals total use. However, the final symmetric IOTs only show exports as a final demand column. Imports are integrated into the inter-industry matrix, to ensure that each column shows meaningful input requirements, as we typically want to know what an industry needs, irrespective of where it sources it from. The Use Tables provided by the ONS include a "combined use" matrix (used as SUT before), which already incorporates imports.

In the Payment data, we do not observe non-domestic payment flows. However, it remains possible that foreign entities have accounts in the UK that they use to pay or get paid. With that caveat in mind, we may think of IOTs and Use Tables as including imports but not exports, while Payment data would exclude the vast majority of imports and exports. However, some international trade flows entering the production process are captured, if they are mediated by domestic wholesale or retail.

Unit of analysis and industrial classification NAs group institutional units either based on their function or on their kind of activity (Eurostat, 2010, par. 1.55-1.56). Institutional units are "economic entities that are capable of owning goods and assets, of incurring liabilities and of engaging in economic activities and transactions with other units in their own right", and are grouped into 5 distinct sectors: financial and non-financial corporations, households, general government, and non-profit institutions serving households (NPISH) (Eurostat, 2010, par 1.57). In our Payments data, anonymised and aggregated Bacs transactions between industries are derived from a sample of organisations that are Bacs service users, which makes them our original unit of analysis.

As a result of this process, two main issues potentially arise. First, there is a "headquarter effect". Payments to/from an enterprise might be captured under the industry classification of its headquarter, although these payments might refer to subsidiaries producing other goods. Second, there is a risk that entities are classified into the incorrect sector (e.g., an NPISH classified as a non-financial corporation). The observed flow of funds between industries might be affected by the different routes available to access Bacs services. Where organisations use an intermediary, the payment flows might be attributed to the intermediaries rather than directly between the organisations paying or receiving funds (ONS, 2023d). Analytical IOTs are built from surveys that attempt to consider the multi-product nature of firms. Here, instead, entities are classified into a single industry.

Second, issues arise with the classification of activities, particularly public services.

Informal sector NA should in principle estimate the output and income from the informal sector. It is not necessarily clear whether this output appears in the Payment data. Likely, such transactions would be made with cash or card payments rather than electronic transactions. To the extent that informal activities are accurately represented in IOTs, and are absent from data based on electronic payments, we expect industries with high informal activities to be under-represented in Payment data, compared to NAs. However, neither of the assumptions can be verified or appear plausible a priori.

6 Stylised facts of the granular data

Now, we study the most granular 5-digit data. A direct comparison to official statistics is infeasible, as such granular data does not (yet) exist at a macroeconomic scale.[19] To benchmark the data, we evaluate the data by its ability to reproduce two stylised facts documented in the literature on economic networks:

1. The average correlation of growth rates at a given network distance apart decreases with network distance (see Sec. 6.1).
2. The CCDF of the so-called Katz-Bonacich centrality exhibits a power law-like behaviour with a tail exponent $1 < \gamma < 2$ (see Sec. 6.2), implying that shocks at the industry level can lead to aggregate fluctuations, for example in GDP.

Consistency with these stylised facts suggests that the granular Payment data is valuable for economic network research.

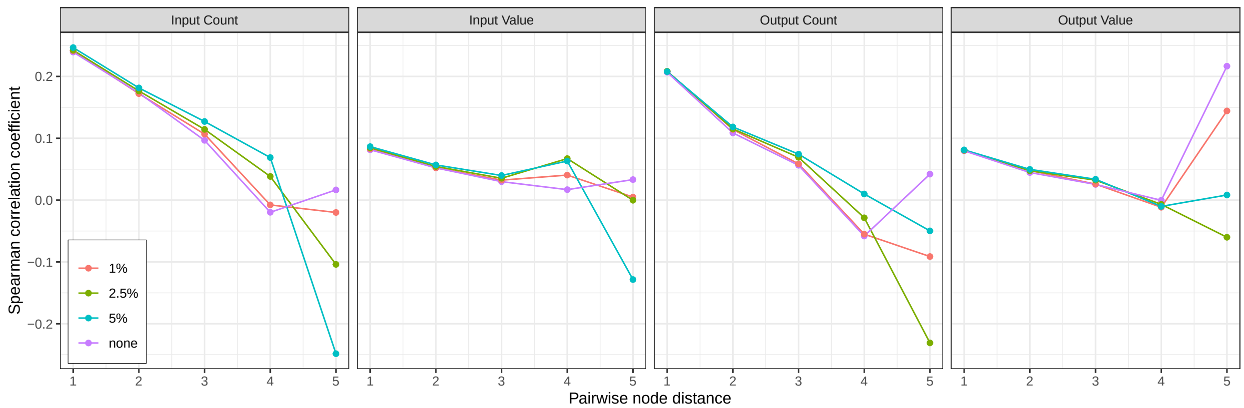
6.1 Correlation of growth rates

Carvalho (2014) and Mungo and Moran (2023) documented for industry- and firm-level data that the correlation of rates between a pair of industries (firms) decreases with their distance in the network, where the distance refers to the shortest path of input linkages in the network that connects the two sectors. Here, we test whether this holds in the granular 5-digit network data of 601 distinct industries, and correlate industry-level growth rates of the selling and buying industry, whereby growth rates are given by the change in industry-level outputs (inputs) from a given month to the month in the subsequent year. We calculate correlations for input and output growth using count and value data and plot the correlations against the distance. The network distances are obtained from annual aggregate input networks for the corresponding year. The colours indicate different truncation thresholds imposed on the network, to remove noisy links.[20]

Fig. 5 illustrates the results, with the vertical axis showing the Spearman correlation coefficient and the horizontal axis showing different distance levels. We use the Spearman correlation due to its lower sensitivity against outliers compared to Pearson correlations used above (see 4). The results generally confirm that growth rate correlations decrease in the network distance. The results become noisy and even negative at large distances, which is not surprising given the sparsity and incomplete coverage of the data. The results are consistent across the different data types (inputs, outputs, counts, and values) with steeper curves for count data.

[19] An exception are the granular IOTs available for the US, which, however, are only available at a quinquennial basis (Hötte, 2023).
[20] The truncation procedure is the same as discussed before (Sec. 4.2).

Figure 5: Correlations of growth rates



Notes: These figures illustrate the correlations of growth rates of directly and indirectly connected pairs of industries, using data from 2016-2019 and 2023, excluding the period of Covid-19. Growth rates are given by the growth from one month in a given year to the same months in the next year and are calculated for inputs and outputs using counts and values. The vertical axis shows the Spearman correlation coefficient. The horizontal axis shows the distance of the industry pairs, using annual aggregates of the network data. The distances are the shortest path (lowest number of steps) that connects the pair of industries in the network. A value of one indicates a direct link (one step) between the pair. The colours indicate different percentage truncation thresholds imposed on the annual network data before calculating the distances. Links whose weight, given by the input share, is below the threshold are removed (see also Sec. 4.2).

6.2 Centrality distribution

Previous research has shown that the impact of firm- and industry-level shocks on aggregate economic fluctuations depends on the network position of the firm or industry (e.g. Acemoglu et al., 2012; Carvalho, 2014). Negative and positive shocks occurring in an industry that plays a central role in the network of supply and demand linkages tend to have larger spillover effects on other industries. Such supply chain spillover effects are a key reason for studying economic networks.

The "right" way of measuring the centrality of an industry depends on the assumption of the underlying model to study aggregate volatility and on the nature of available data. For some established centrality metrics, one needs to know the whole IOT, including value-added and final demand components next to intermediate trade as captured by our Payment data.

Because we do not have final demand and value-added equivalents in our data, we compute a centrality metric that can be computed solely from the industry-industry flows. We use the *influence vector*, also known as Katz-Bonacich centrality, which quantifies the impact of industry-level productivity shocks in a standard equilibrium input-output analysis with Cobb-Douglas production functions, no capital, and uniform final demand shares (Acemoglu et al., 2012; Magerman et al., 2016). It is given by

$$v \equiv \frac{\alpha_L}{n}\left[\mathbf{I} - (1-\alpha_L)\mathbf{W}'\right]^{-1}\mathbf{1}, \tag{2}$$

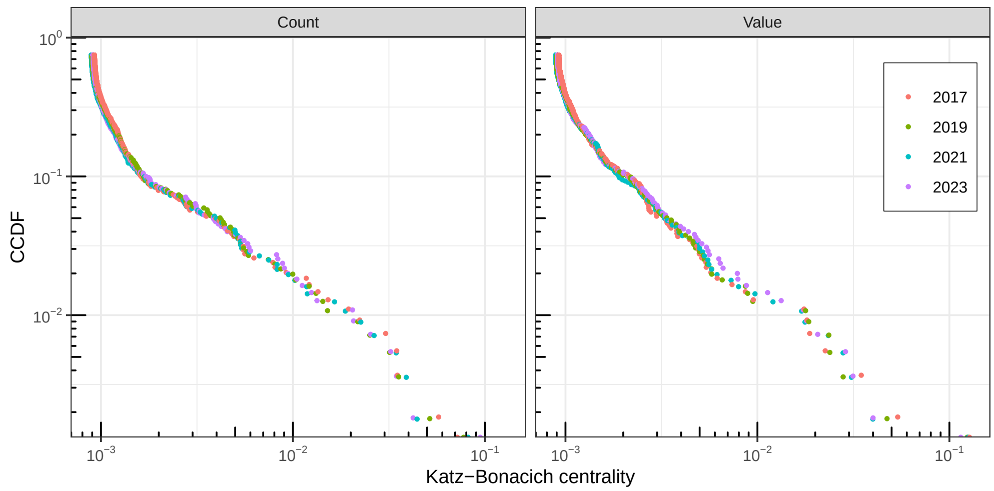
where $\alpha_L \in (0,1]$ is the labour share of gross output, n is the number of industries, $\mathbf{I}$ is an identity matrix, $\mathbf{1}$ is a vector of ones and $\mathbf{W}'$ is the (column-stochastic) matrix of input shares, $\omega_{ij}^{in,\alpha}$ computed according to Eq. (1). The influence vector v is a micro-level measure of the importance of a certain industry in the production network. An interesting theoretical result (Acemoglu et al., 2012) is that its distribution is related to aggregate fluctuations as

$$\text{std}(\log(\text{GDP})) \sim n^{-(1-1/\gamma)}, \tag{3}$$

where $1 < \gamma \leq 2$ is the power law exponent of the distribution of the influence vector, and n is the number of firms or industries. In other words, if centralities are highly unequally distributed, micro-shocks to industries do not average out in the aggregate.

Previous studies have measured γ on existing input-output data, providing us with benchmark results to compare our data with. As a first step, we analyse whether the influence vector in the Payment data follows a power law.

Figure 6: CCDF of the Katz-Bonacich centrality



Notes: These figures illustrate the CCDF of the Katz-Bonacich centrality as introduced in Eq. (2) for different years, using a labour share parameter of $\alpha_L = 0.5$ (see Magerman et al., 2016) and both types of Payment-based input-share matrices that can be constructed (Count- and Value-based).

Fig. 6 shows a complementary cumulative distribution (CCDF) at a log-log scale, for the input-share networks from different years. The CCDF supports the idea of a heavy-tailed distribution, with most sectors scoring at low values and some sectors being extremely central. In C.7, we list the top-10 sectors scoring extremely high, and find public administration to take the top rank, consistently across years and datasets, and the other ranks being mostly taken by retail and finance, and at lower levels transport and electricity. The Count data generally appears to exhibit a slightly more equal distribution, with less extreme deviations among sectors.

The close-to-linear shape of the tail of the log-log CCDF indicates a power law. To test whether the data can be well-fitted by a power law distribution and to obtain the tail exponent γ, we use a Hill estimator (Clauset et al., 2009). Results and test statistics of this fitting exercise are provided in the C.2. We find tail exponents, ranging between 1.34-1.69 for the Value and 1.98-2.21 for the Count data. The values for the Value data are similar to those reported in the literature using firm- and industry-level data. For example, Carvalho (2014) reported $\gamma = 1.44$ for industry-level US data, and Magerman et al. (2016) and Bacilieri et al. (2023) found $\gamma \in [1.12, 1.44]$, using firm-level VAT data from Belgium, Ecuador, and Hungary.[21]. However, the significance tests suggest that the power law hypothesis can be only supported for some years, but more often when using count data.

[21] VAT data reports supplier-customer relationships amongst firms within a country. Just like our payment data, they represent flows of money and usually record transactions above a certain threshold. For instance, for Belgium, the threshold is 250€. For more details on the description of the VAT datasets from Ecuador and Hungary see Bacilieri et al. (2023).

6.3 Discussion

In the previous two subsections, we have made connections to two stylised facts in the literature on economic networks:

- The average correlation of growth rates of industries at a given network distance apart decreases with distance.
- The CCDF of the Katz-Bonacich centrality has a power law tail of $1 < \gamma < 2$.

Our results confirm an alignment with the literature (Bacilieri et al., 2023; Magerman et al., 2016), suggesting that the network structure of the granular Payment data resembles the structure of other large-scale economic networks, that have been successfully used in applied economic research, reliant on network methods.

The decrease in the correlation of growth rates with the network distance indicates network effects: industries grow when their neighbours (suppliers and customers) grow. This can be informative for clusters of industrial growth, and cross-industrial spillover effects (Hötte, 2023; Carvalho, 2014), telling policymakers about which industries to nurture to promote growth in particular sectors or regions (Oosterhaven and Hewings, 2021; Dietzenbacher, 2002; Kitsos et al., 2023).

Further, we obtain values around 1.5 for the tail exponents of the CCDF of the Katz-Bonacich centrality in agreement with exponents found in previous studies. Tail-exponents of $1 < \gamma < 2$ indicate that micro-level fluctuations can be drivers of large aggregate fluctuations, suggesting a need to monitor the economy at a granular level to understand aggregate outcomes.

The analysis of centrality has also revealed some “biases” towards the public sector, finance, and retail compared to the NA perspective (see Sec. 5). Some of them are also present in other firm-level data sets (see Bacilieri et al., 2023). This does not hamper the usefulness of this data for applied economic research but may affect the validity of assumptions made in theoretical and empirical models applied to the data.

7 Conclusion and outlook

This paper provided a first economic validation of a monthly time series of granular financial transactions, showing monetary flows between industries in the UK. The granularity and monthly availability offer an unprecedented potential to advance economic research, national statistics, and to deliver targeted policy advice in real time. However, the lack of standardisation and the innovative nature of payment data hamper the straightforward interpretation in the terminology established in NAs and economic research.

The results of our benchmarking exercises show strong correlation between monthly aggregate payment values and monetary aggregates, while the number of transactions appears to be more strongly related to real indicators. Strong linkages between Payment counts and real GDP indicate counts to be related to business dynamism: variations in the counts can reflect deviations from standing regular payments (such as fees, royalties, and loan repayments). Count data have, to the best of our knowledge, not been used before in economic analyses. Our analysis suggests them to be a valuable new economic indicator, especially when distinguishing real from nominal dynamics.

Aggregate network statics from Payment networks and official IOTs indicate that Payment networks are less densely connected than networks derived from the official tables. This potentially arises from the SDC, and we find almost identical aggregate network properties when focusing on the most significant links. However, there are large transaction-level differences in values between Payments data and IOTs. We provided a detailed list of conceptual aspects driving these results; including industry classification, the role of intermediaries, time of recording, and more. The observed differences mean that inter-industrial flows of funds from the Payments data would need to be apportioned, informed from other available data sources, before further NAs applications in the IOT space. In certain instances, the apportionment method could still not lead to valid results, as it might not be possible to overcome the conceptual differences and businesses might use different payment methods.

On the other hand, raw payments provide an alternative, complementary perspective on inter-industrial trade, capturing "realised" monetary flows between multi-product industries. This can be valuable for specific research questions, including granular industrial input and output diversification strategies in response to technological change, policy and shocks, which may not be observable in NAs due to accounting rules. Our granular validation exercise with the 5-digit level data confirms the consistency of the data with other economic network data, being a promising signal for its use in applied work.

We hope we guided through the challenges associated with this new data source, paving the way to cutting-edge applied economic research. Key areas of application are economic now-casting at different levels of aggregation; dynamics in granular production networks and the development of early warning indicators of supply chain pressure. The data source also offers the potential to derive regional versions of the data. This would enable disaggregate analyses of the impact of Brexit, recent supply chain disruptions, and policy studies for levelling-up and net-zero transition.

This work relies on an experimental version of the data (see also ONS, 2023e; ONS, 2023d), and improvements in terms of coverage and industrial classification are underway. We hope to have given a primer on that, what can be expected soon.

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A Concordance table

Table A.1 shows how industries classified by 5-digit SIC codes are re-allocated to CPA codes used in the official ONS IOT and NA data (ONS, 2009; Eurostat, 2015). The 5-digit SIC codes are more disaggregate and aggregated into 105 CPA classes. The codes in the first column (SIC) are short for the first 2-4 digits of the 5-digit codes. All industries with these digits as leading digits are aggregated into the respective CPA category. The "·"s in the columns of the table indicate which SIC codes belong to a more aggregate CPA category.

SIC	SIC names	CPA	CPA names
01	Crop and animal production, hunting and related service activities	A01	Products of agriculture, hunting and related services
02	Forestry and logging	A02	Products of forestry, logging and related services
03	Fishing and aquaculture	A03	Fish and other fishing products; aquaculture products; support services to fishing
05	Mining of coal and lignite	B05	Coal and lignite
06	Extraction of crude petroleum and natural gas	B06-F7	Extraction Of Crude Petroleum And Natural Gas & Mining Of Metal Ores
07	Mining of metal ores	·	·
08	Other mining and quarrying	B08	Other mining and quarrying products
09	Mining support service activities	B09	Mining support services
101	Preserved meat and meat products	C101	Preserved meat and meat products
102	Processing and preserving of fish, crustaceans and molluscs	C102-3	Processed and preserved fish, crustaceans, molluscs, fruit and vegetables
103	Processing and preserving of fruit and vegetables	·	·
104	Vegetable and animal oils and fats	C104	Vegetable and animal oils and fats
105	Dairy products	C105	Dairy products
106	Grain mill products, starches and starch products	C106	Grain mill products, starches and starch products
107	Bakery and farinaceous products	C107	Bakery and farinaceous products
108	Other food products	C108	Other food products
109	Prepared animal feeds	C109	Prepared animal feeds
1101	Distilling, rectifying and blending of spirits	C11.01-6 & C12	Alcoholic beverages & Tobacco products
1102	Manufacture of wine from grape	·	·
1103	Manufacture of cider and other fruit wines	·	·
1104	Manufacture of other non-distilled fermented beverages	·	·
1105	Manufacture of beer	·	·
1106	Manufacture of malt	·	·
1107	Manufacture of soft drinks	C1107	Soft drinks
12	Manufacture of tobacco products	·	·
13	Manufacture of textiles	C13	Textiles
14	Manufacture of wearing apparel	C14	Wearing apparel
15	Manufacture of leather and related products	C15	Leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	C16	Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials
17	Manufacture of paper and paper products	C17	Paper and paper products
18	Printing and reproduction of recorded media	C18	Printing and recording services
19	Manufacture of coke and refined petroleum products	C19	Coke and refined petroleum products
2011	Manufacture of industrial gases	C20A	Industrial gases, inorganics and fertilisers (all inorganic chemicals) - 20.11/13/15
2012	Manufacture of dyes and pigments	C20C	Dyestuffs, agro-chemicals - 20.12/20
2013	Manufacture of other inorganic basic chemicals	·	·
2014	Manufacture of other organic basic chemicals	C20B	Petrochemicals - 20.14/16/17/60
2015	Manufacture of fertilisers and nitrogen compounds	·	·
2016	Manufacture of plastics in primary forms	·	·
2017	Manufacture of synthetic rubber in primary forms	·	·
2020	Manufacture of pesticides and other agrochemical products	·	·
203	Paints, varnishes and similar coatings, printing ink and mastics	C203	Paints, varnishes and similar coatings, printing ink and mastics
204	Soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations	C204	Soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations
205	Other chemical products	C205	Other chemical products
2060	Manufacture of man-made fibres	·	·
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	C21	Basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products	C22	Rubber and plastic products
231	Manufacture of glass and glass products	C23 other	Glass, refractory, clay, other porcelain and ceramic, stone and abrasive products - 23.1-4/7-9
232	Manufacture of refractory products	·	·
233	Manufacture of clay building materials	·	·
234	Manufacture of other porcelain and ceramic products	·	·
235	Manufacture of cement, lime and plaster	C235-6	Cement, lime, plaster and articles of concrete, cement and plaster
236	Manufacture of articles of concrete, cement and plaster	·	·
237	Cutting, shaping and finishing of stone	·	·
239	Manufacture of abrasive products and non-metallic mineral products n.e.c.	·	·
241	Manufacture of basic iron and steel and of ferro-alloys	C241-3	Basic iron and steel
242	Manufacture of tubes, pipes, hollow profiles and related fittings, of steel	·	·
243	Manufacture of other products of first processing of steel	·	·
244	Manufacture of basic precious and other non-ferrous metals	C244-5	Other basic metals and casting
245	Casting of metals	·	·
251	Manufacture of structural metal products	C25 other	Fabricated metal products, excl. machinery and equipment and weapons & ammunition - 25.1-3/25.5-9
252	Manufacture of tanks, reservoirs and containers of metal	·	·
253	Manufacture of steam generators, except central heating hot water boilers	·	·
254	Weapons and ammunition	C254	Weapons and ammunition
255	Forging, pressing, stamping and roll-forming of metal; powder metallurgy	·	·

SIC	SIC names	CPA	CPA names
256	Treatment and coating of metals; machining	·	·
257	Manufacture of cutlery, tools and general hardware	·	·
259	Manufacture of other fabricated metal products	·	·
26	Manufacture of computer, electronic and optical products	C26	Computer, electronic and optical products
27	Manufacture of electrical equipment	C27	Electrical equipment
28	Manufacture of machinery and equipment n.e.c.	C28	Machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers and semi-trailers	C29	Motor vehicles, trailers and semi-trailers
301	Ships and boats	C301	Ships and boats
302	Manufacture of railway locomotives and rolling stock	C30 other	Other transport equipment - 30.2/4/9
303	Air and spacecraft and related machinery	C303	Air and spacecraft and related machinery
304	Manufacture of military fighting vehicles	·	·
309	Manufacture of transport equipment n.e.c.	·	·
31	Manufacture of furniture	C31	Furniture
32	Other manufacturing	C32	Other manufactured goods
3311	Repair of fabricated metal products	C33 other	Rest of repair; Installation - 33.11-14/17/19/20
3312	Repair of machinery	·	·
3313	Repair of electronic and optical equipment	·	·
3314	Repair of electrical equipment	·	·
3315	·	C3315	Repair and maintenance of ships and boats
3316	·	C3316	Repair and maintenance of aircraft and spacecraft
3317	Repair and maintenance of other transport equipment	·	·
3319	Repair of other equipment	·	·
332	Installation of industrial machinery and equipment	·	·
351	Electricity, transmission and distribution	D351	Electricity, transmission and distribution
352	Manufacture of gas; distribution of gaseous fuels through mains	D352-3	Gas; distribution of gaseous fuels through mains; steam and air conditioning supply
353	Steam and air conditioning supply	·	·
36	Water collection, treatment and supply	E36	Natural water; water treatment and supply services
37	Sewerage	E37	Sewerage services; sewage sludge
38	Waste collection, treatment and disposal activities; materials recovery	E38	Waste collection, treatment and disposal services; materials recovery services
39	Remediation activities and other waste management services.	E39	Remediation services and other waste management services
41	Construction of buildings	F41-43	Construction
42	Civil engineering	·	·
43	Specialised construction activities	·	·
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	G45	Wholesale and retail trade and repair services of motor vehicles and motorcycles
46	Wholesale trade, except of motor vehicles and motorcycles	G46	Wholesale trade services, except of motor vehicles and motorcycles
47	Retail trade, except of motor vehicles and motorcycles	G47	Retail trade services, except of motor vehicles and motorcycles
491	Passenger rail transport, interurban	H491-2	Rail transport services
492	Freight rail transport	·	·
493	Other passenger land transport	H493-5	Land transport services and transport services via pipelines, excluding rail transport
494	Freight transport by road and removal services	·	·
495	Transport via pipeline	·	·
50	Water transport	H50	Water transport services
51	Air transport	H51	Air transport services
52	Warehousing and support activities for transportation	H52	Warehousing and support services for transportation
53	Postal and courier activities	H53	Postal and courier services
55	Accommodation	I55	Accommodation services
56	Food and beverage service activities	I56	Food and beverage serving services
58	Publishing activities	J58	Publishing services
59	Motion picture, video and television programme production, sound recording and music publishing activities	J59-60	Motion Picture, Video & TV Programme Production, Sound Recording & Music Publishing Activities & Programming And Broadcasting Activities
60	Programming and broadcasting activities	·	·
61	Telecommunications	J61	Telecommunications services
62	Computer programming, consultancy and related activities	J62	Computer programming, consultancy and related services
63	Information service activities	J63	Information services
64	Financial service activities, except insurance and pension funding	K64	Financial services, except insurance and pension funding
651	Insurance	K65.1-3	Insurance, reinsurance and pension funding services, except compulsory social security
652	Reinsurance	·	·
653	Pension funding	·	·
66	Activities auxiliary to financial services and insurance activities	K66	Services auxiliary to financial services and insurance services
681	Buying and selling of own real estate	L68 BX L683	Real estate services, excluding on a fee or contract basis and imputed rent
682	Owner-Occupiers' Housing Services	L68A	Owner-Occupiers' Housing Services
·	Renting and operating of own or leased real estate	·	·
683	Real estate services on a fee or contract basis	L683	Real estate services on a fee or contract basis
691	Legal services	M691	Legal services
692	Accounting, bookkeeping and auditing services; tax consulting services	M692	Accounting, bookkeeping and auditing services; tax consulting services
70	Activities of head offices; management consultancy activities	M70	Services of head offices; management consulting services
71	Architectural and engineering activities; technical testing and analysis	M71	Architectural and engineering services; technical testing and analysis services
72	Scientific research and development	M72	Scientific research and development services
73	Advertising and market research	M73	Advertising and market research services
74	Other professional, scientific and technical activities	M74	Other professional, scientific and technical services
75	Veterinary activities	M75	Veterinary services
77	Rental and leasing activities	N77	Rental and leasing services
78	Employment activities	N78	Employment services
79	Travel agency, tour operator and other reservation service and related activities	N79	Travel agency, tour operator and other reservation services and related services
80	Security and investigation activities	N80	Security and investigation services
81	Services to buildings and landscape activities	N81	Services to buildings and landscape
82	Office administrative, office support and other business support activities	N82	Office administrative, office support and other business support services
84	Public administration and defence; compulsory social security	O84	Public administration and defence services; compulsory social security services
85	Education	P85	Education services
86	Human health activities	Q86	Human health services
87	Residential care activities	Q87-88	Residential Care & Social Work Activities
88	Social work activities without accommodation	·	·
90	Creative, arts and entertainment activities	R90	Creative, arts and entertainment services
91	Libraries, archives, museums and other cultural activities	R91	Libraries, archives, museums and other cultural services

SIC	SIC names	CPA	CPA names
92	Gambling and betting activities	R92	Gambling and betting services
93	Sports activities and amusement and recreation activities	R93	Sports services and amusement and recreation services
94	Activities of membership organisations	S94	Services furnished by membership organisations
95	Repair of computers and personal and household goods	S95	Repair services of computers and personal and household goods
96	Other personal service activities	S96	Other personal services
97	Activities of households as employers of domestic personnel	T97	Services of households as employers of domestic personnel

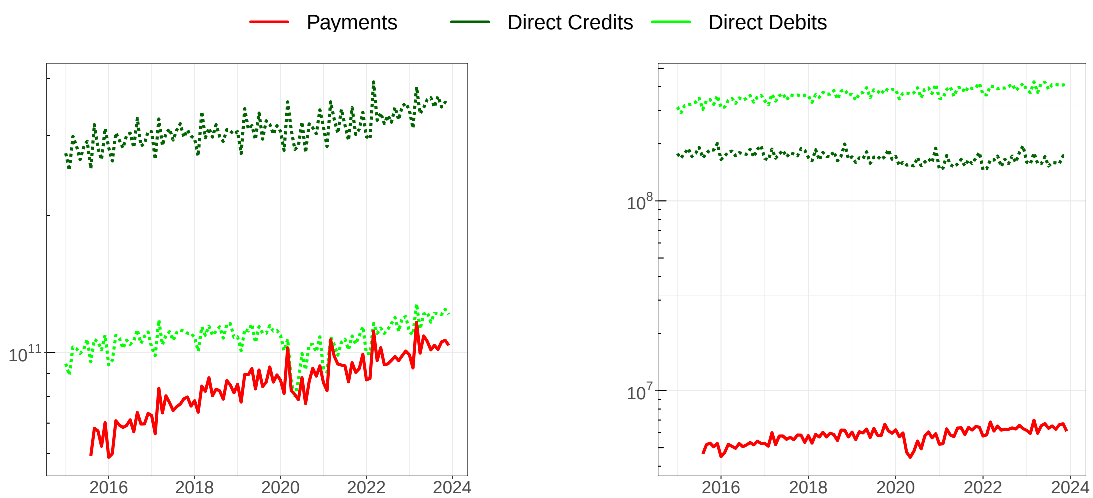
Table A.1: Concordance table from SIC to CPA codes.

B Additional material: comparison to existing data

B.1 Direct debits and credits

Bacs DD and DC contain different kinds of economic information.

Figure B.1: Monthly Payments data, direct debits and direct credits



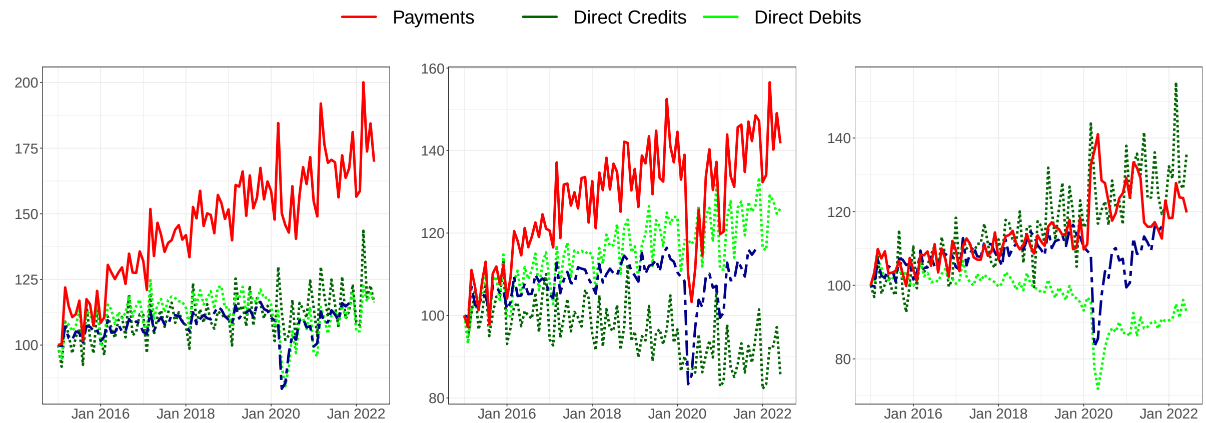
(a) Values

(b) Counts

Notes: The vertical axis is scaled at a log-10 scale. Payments (red) are monthly aggregates of our data. The Bacs Direct Debit and Direct Credit data is downloaded from Pay.UK (2023b).

Fig. B.1 shows a time series of monthly data of the Payment data and Bacs DB and DC by nominal values in log £m (Fig. B.1a) and counts in log 1,000s (Fig. B.1b). The time series indicates a persistent rise in transaction values for DC and our Payment data. Bacs DB exhibit a steep downward kink during the first Covid-19 lock down and a monotonous recovery thereafter, back to the pre-Covid level. Compared to DC and the Payments data, the overall growth in DB values from 2015-2023 was modest. Since the start of the Covid-19 pandemic, the aggregate value of the Payment data has risen to almost the same aggregate value as DDs. DCs are the largest share of values processed through Bacs, despite corresponding to a smaller share of counts compared to DD. As shortly discussed in B.1, Bacs DB and DC tend to differ by patterns over time, responses to Covid-19, and similarities to our Payments, indicating that the disaggregation by payment instruments can be valuable when using payment data for economic research.

The Fig. 2 shows a disambiguation of Bacs DD and DC in comparison to the trends in the Payment data. While the Bacs aggregates grow only moderately by value at a similar pace as GDP despite GDP being in real and Bacs in nominal terms, the Payment data shows a much steeper increase. While DC and DD evolve



(a) Value (b) Counts (c) Average value

Figure B.2: Monthly Payments, Direct Debits and Credits

Notes: These figures show monthly time series of the Payment data, and Bacs transactions disaggregated by Direct Debits and Credits. The time series show indexed data with 2015=100. The average value of is only provided for the Payment, Bacs, CHAPS, and FPS data obtained by dividing values by counts, while GDP shows the index.

similarly by value, they differ by counts and average value. The number of Bacs DC decreased over time, but their average transaction value increased similarly as the average value in the Payment data. This may be indicative of shifts in the utilisation of the Bacs system.[22]

B.2 Macroeconomic benchmarking

Table B.2 shows the results of the macro-level correlation analysis introduced in Sec. 3 when the period of Covid-19 is not removed from the data. While all correlations are lower, we observe still high values for the count data for almost all indicators except M1 and M3, suggesting that payment counts are more robust in capturing dynamics of real economic indicators during the exceptional period of Covid-19.

[22]Possible reasons for changes in Bacs utilisation are the rise of FPS, increasing use of Cards, and digital payment innovation (UK Finance, 2022), but answering this question is beyond the scope of this paper.

Table B.2: Correlations with other payments and macro aggregates

	Bacs	FPS	CHAPS	GDP nsa	GDP sa	M1 nsa	M3 nsa	Prices
Share in 2019	0.207	0.540	0.013	0.469	0.469	0.578	0.363	
Share in 2021	0.221	0.431	0.013	0.490	0.514	0.471	0.321	
Raw data in levels								
Yearly (value)	0.885	0.964	0.797	0.159	−0.380	0.887	0.916	0.988
Monthly (value)	0.824	0.907	0.696	0.394	0.484	0.832	0.868	0.816
Yearly (count)	0.941	0.842	0.948	0.733	−0.168	0.629	0.697	0.756
Monthly (count)	0.768	0.739	0.928	0.799	0.747	0.636	0.674	0.645
Yearly (avg)	0.476	−0.525	−0.024	−0.472	−0.507	0.926	0.904	0.900
Monthly (avg)	0.371	−0.439	0.098	−0.326	−0.072	0.752	0.773	0.625
Growth rates								
Yearly (value)	0.226	−0.197	0.288	0.352	0.160	0.196	0.354	−0.526
Monthly (value)	0.773	0.613	0.008	0.709	0.589	−0.212	−0.111	0.010
Yearly (count)	0.429	−0.361	0.066	0.391	0.207	0.154	0.324	−0.480
Monthly (count)	0.567	0.526	0.751	0.893	0.863	−0.165	−0.124	0.199
Yearly (avg)	−0.626	−0.737	0.582	−0.947	−0.656	0.693	0.533	−0.771
Monthly (avg)	−0.131	−0.445	0.590	−0.813	−0.823	0.121	0.141	−0.343

Notes: The panel on top of the panel shows the aggregate value of payments as a share of the respective indicator in the column. The panels below show Pearson correlations between the Payment data with the other UK payment schemes and macroeconomic aggregates (GDP, M1, M3, Prices). The monthly (annual) time series cover the period August 2015-December 2023 (2016-2023), without removing the period of Covid-19. "sa" ("nsa") is short for (non-)seasonally adjusted. All payment data (our data and other aggregates published by Pay.UK) are compared by aggregate values, counts, and average values (short "avg") given by value divided by count. The top panel shows correlations of the aggregates measured in levels, the bottom panel shows a comparison by growth rates. Monthly growth rates are calculated as percentage growth compared to the (same month of the) previous year (for monthly data). Annual growth rates show relative deviations compared to the previous year. The column "Retail" shows the sum of all retail payment schemes, excluding cards. Bacs, FPS, Retail, and CHAPS data are obtained from Pay.UK (2023b). Monthly GDP is proxied by indicative (non-)seasonally adjusted monthly "Total Gross Value Added" index data published by the ONS and serves as a proxy of monthly (non-)deseasonalised GDP (ONS, 2023c; ONS, 2023b). "Prices" is short for Consumer prices index data obtained from the OECD Key Economic Indicators (KEI) dataset (OECD, 2023a). M1 (M3) are narrow (broad) monetary aggregates, and thus nominal indicators, obtained from the OECD Main Economic Indicators (MEI) dataset (OECD, 2023b).

B.3 Aggregate network statistics

Fig. B.3 illustrates how the density in the input (left) and output (right) networks decreases if all links are removed if the weight of connecting input (output) links $\omega_{ij}^{\text{in},\alpha}$ ($\omega_{ij}^{\text{out},\alpha}$) falls below a given percentage threshold level shown at the x-axis. Note that the x-axis is quadratically scaled. The Tables B.3 and B.4 summarise network statistics analogous to those in Table 3 for networks truncated at a 1% and 5% threshold level. The figure and the tables include the results for both truncation by input and output share. The density in all networks decreases in all networks but with a much steeper slope for the ONS IOTs, which is due to the forestalled truncation caused by the SDC. The decrease is slightly faster in the output network, suggesting a higher concentration by outputs. The truncation also affects other properties of the networks, but qualitative homogeneously across the different IOTs, except for assortativity.

Table B.3: Properties of the payment and ONS-based IOTs in 2019, truncated with a 1% threshold

Variable	Value	Count	PxP	SUT	IxI
Raw transactions – truncation by input-share					
Density	0.157	0.198	0.181	0.164	0.186
Average degree	16.214	20.417	17.546	15.897	18.072
Average strength	5,808.344	425,637.300	8,567.096	10,369.400	8,344.459
Average weight	358.239	20,846.710	488.254	652.291	461.730
Reciprocity	0.212	0.185	0.224	0.217	0.235
Transitivity	0.428	0.488	0.466	0.433	0.471
Assortativity by degree	−0.310	−0.429	−0.266	−0.216	−0.248
Raw transactions – truncation by output-share					
Density	0.115	0.131	0.129	0.112	0.139
Average degree	11.796	13.476	12.536	10.887	13.505
Average strength	5,963.682	426,890.600	8,009.429	9,876.381	7,888.582
Average weight	505.563	31,678.480	638.910	907.205	584.116
Reciprocity	0.170	0.144	0.214	0.169	0.232
Transitivity	0.367	0.394	0.432	0.393	0.441
Assortativity by degree	−0.308	−0.364	−0.096	−0.054	−0.154
Input shares – truncation by input-share					
Average strength	0.805	0.815	0.740	0.643	0.708
Average weight	0.050	0.040	0.042	0.040	0.039
Input shares – truncation by output-share					
Average strength	0.261	0.204	0.422	0.427	0.405
Average weight	0.022	0.015	0.034	0.039	0.030
Output shares – truncation by input-share					
Average strength	0.351	0.270	0.530	0.529	0.507
Average weight	0.022	0.013	0.030	0.033	0.028
Input shares – truncation by output-share					
Average strength	0.830	0.814	0.705	0.642	0.678
Average weight	0.070	0.060	0.056	0.059	0.050

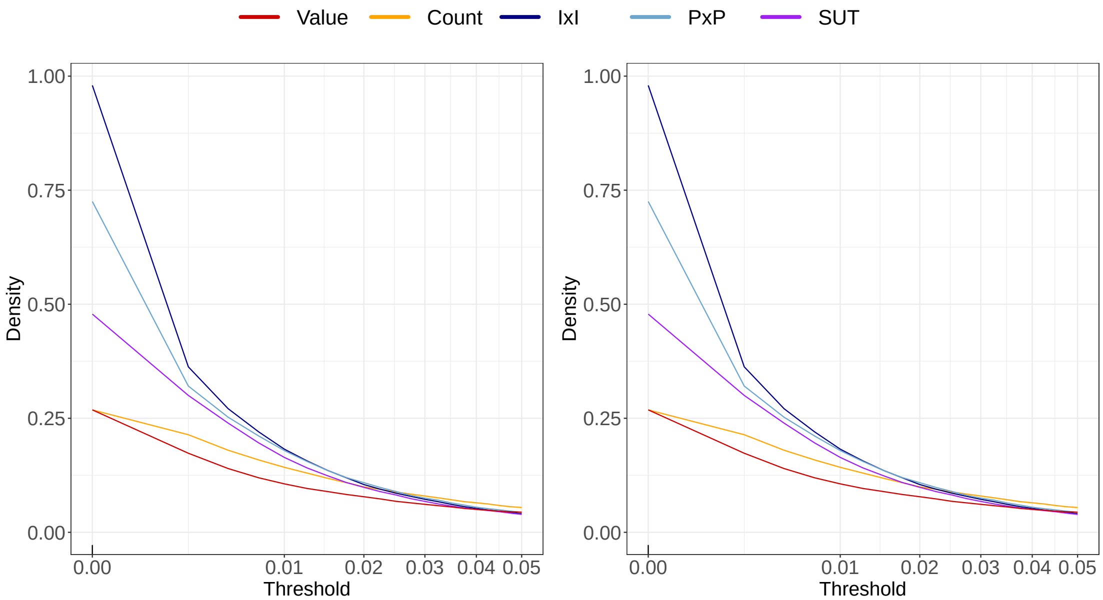
Notes: This table shows aggregate network statistics of the IOTs obtained from the Payment data and the ONS. The networks are truncated networks at a 1% threshold: a link between two industries is removed if the connecting weight measured by the input (output) share is below 1%. The first column uses transaction values, the second transaction counts as weights. The latter three columns represent the official tables published by the ONS, whereby PxP is short for Product-by-Product, IxI for Industry-by-Industry, and SUT for Supply-and-Use Table. The aggregation is 105 CPA product codes (see Sec. 4.1). Raw transaction data are shown in £m.

Table B.4: Properties of the payment and ONS-based IOTs in 2019, truncated with a 5% threshold

Variable	Value	Count	PxP	SUT	IxI
Raw transactions – truncation by input-share					
Density	0.040	0.045	0.041	0.034	0.037
Average degree	4.107	4.650	3.969	3.299	3.598
Average strength	3,053.352	236,213.000	4,356.415	5,378.907	3,862.778
Average weight	743.488	50,793.190	1,097.590	1,630.481	1,073.609
Reciprocity	0.043	0.063	0.036	0.075	0.046
Transitivity	0.136	0.131	0.156	0.168	0.133
Assortativity by degree	0.400	0.634	0.245	0.140	0.248
Raw transactions – truncation by output-share					
Density	0.040	0.033	0.033	0.031	0.032
Average degree	4.155	3.447	3.186	2.990	3.124
Average strength	4,055.909	278,181.800	4,491.696	5,933.608	4,277.842
Average weight	976.072	80,711.900	1,410.014	1,984.690	1,369.474
Reciprocity	0.047	0.028	0.039	0.041	0.040
Transitivity	0.134	0.114	0.137	0.118	0.118
Assortativity by degree	0.470	0.541	0.246	0.306	0.304
Input shares – truncation by input-share					
Average strength	0.530	0.465	0.437	0.366	0.391
Average weight	0.129	0.100	0.110	0.111	0.109
Input shares – truncation by output-share					
Average strength	0.086	0.048	0.169	0.210	0.164
Average weight	0.021	0.014	0.053	0.070	0.052
Output shares – truncation by input-share					
Average strength	0.086	0.065	0.217	0.238	0.187
Average weight	0.021	0.014	0.055	0.072	0.052
Output shares – truncation by output-share					
Average strength	0.660	0.595	0.505	0.468	0.456
Average weight	0.159	0.173	0.158	0.157	0.146

Notes: This table shows aggregate network statistics of the IOTs obtained from the Payment data and the ONS. The networks are truncated networks at a 5% threshold: a link between two industries is removed if the connecting weight measured by the input (output) share is below 5%. The first column uses transaction values, the second transaction counts as weights. The latter three columns represent the official tables published by the ONS, whereby PxP is short for Product-by-Product, IxI for Industry-by-Industry, and SUT for Supply-and-Use Table. The aggregation is 105 CPA product codes (see Sec. 4.1). Raw transaction data are shown in £m.

Figure B.3: Network density at different truncation thresholds



(a) Input network

(b) Output network

Notes: This figure illustrates how the network density decreases with the truncation threshold imposed on linkages. In the left (right) figure, a link in the IOT is removed if the input (output) share in the respective network (Value, Count (Payments), IxI, PxP, SUT (ONS)) is smaller than the threshold value shown at the x-axis. The y-axis shows the value of the aggregate network density.

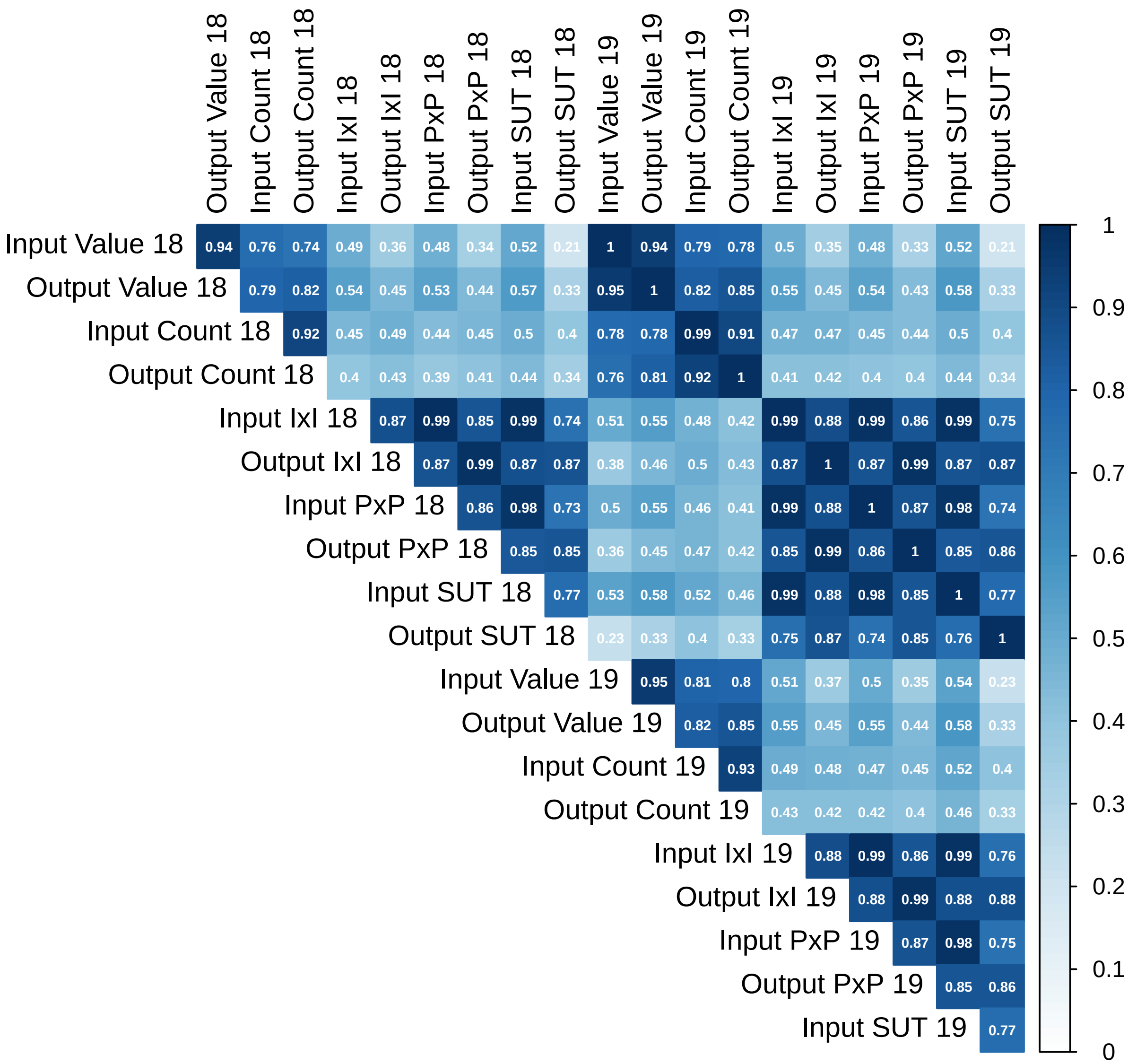
B.4 Auto- and cross-correlations

Fig. B.4 shows the pairwise Pearson correlation coefficients for industry-level inputs and outputs derived from the Payment and ONS tables from 2018-2019, which can be seen as an indicator of industry size. As above, a darker colour indicates stronger correlations. An analogous figure for input and output growth rates is shown in Fig. B.5.

The analyses of growth rate correlations broadly confirm these relationships but with much lower correlation rates and discrepancies between in- and output growth, with output growth being much less or even negatively auto-correlated. Note that these correlations do not provide any information about statistical significance.

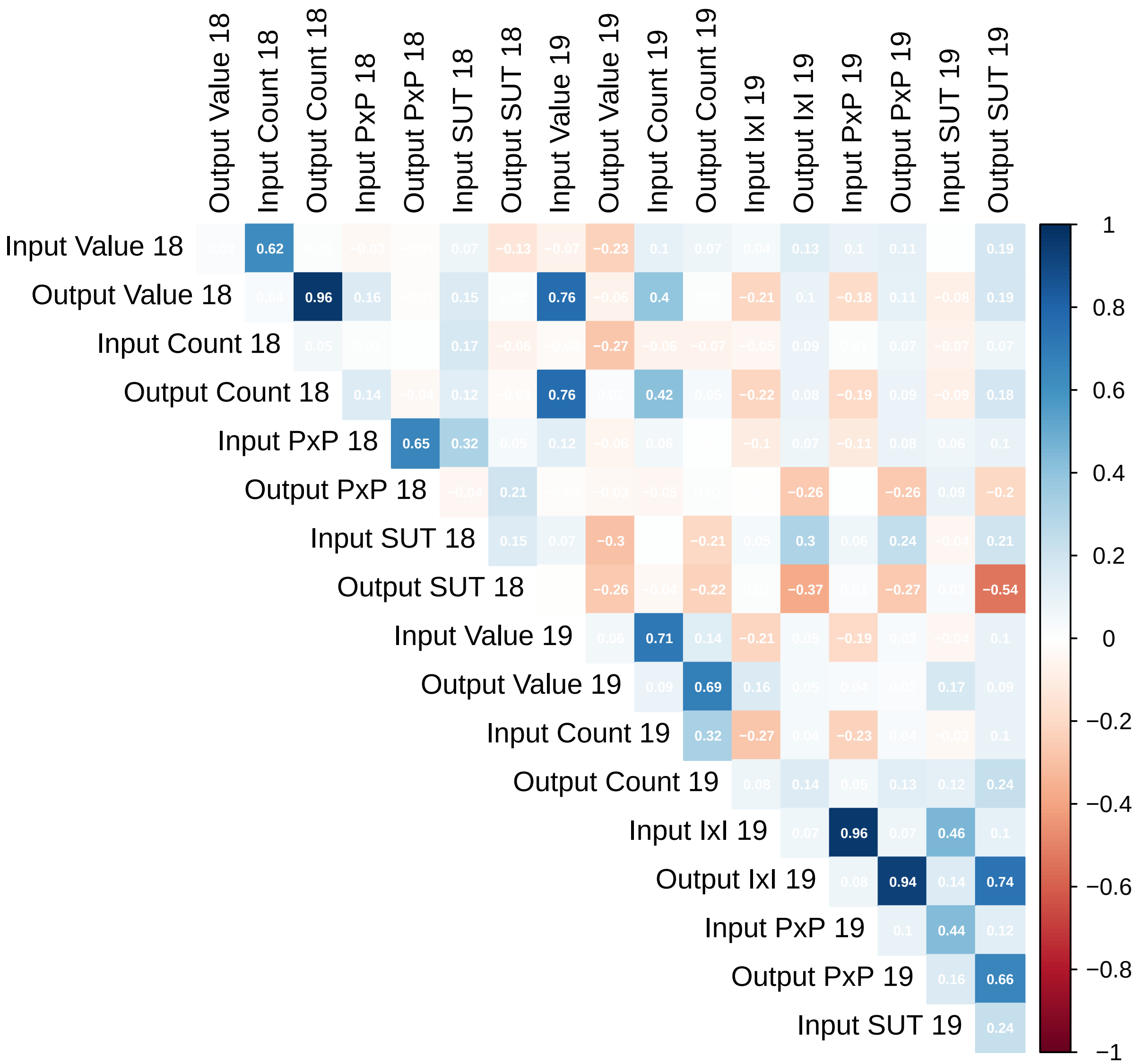
At the industry level, we also correlated aggregate inputs and outputs in the Payment data with other economic performance indicators, such as labour compensation and value added. As a broad takeaway, these analyses confirm that the Payment data shows strong statistical relationships with these indicators. The correlations are weaker compared to those of ONS analogues, but there remains a promising statistical signal confirming the value of the data for economic analyses.

Figure B.4: Auto- and cross-correlations of inputs & outputs



Notes: This figure illustrates auto- and cross-correlations measured by the Pearson correlation coefficient between industry-level annual outputs and inputs in 2018-19 calculated by using raw transaction Values and Counts of the Payment data and the row- and column sums of ONS IxI, PxP, and SUTs.

Figure B.5: Auto- and cross-correlations of input & output growth



Notes: This figure illustrates auto- and cross-correlations measured by the Pearson correlation coefficient between industry-level annual growth rates of outputs and inputs in 2018-19 calculated by using raw transaction Values and Counts of the Payment data and the row- and column sums of ONS IxI, PxP, and SUTs.

B.5 Scale differences across datasets

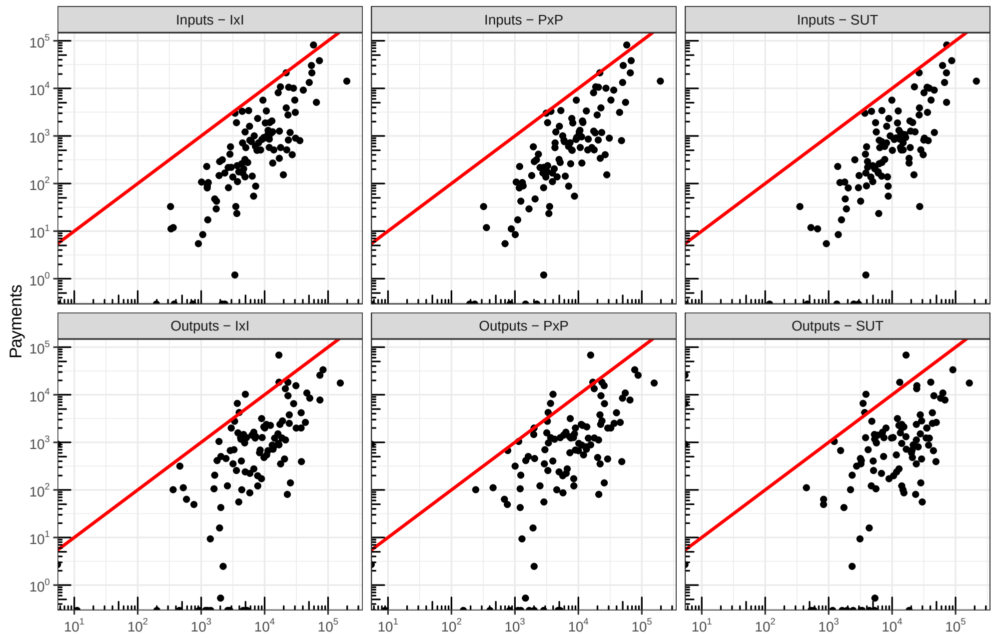


Figure B.6: Comparison of industry sizes

Notes: This figure shows the differences in the transaction values, separately for industry level aggregate inputs and outputs, captured by the different datasets. The values in the Payment data are shown at the vertical axis, and those for different ONS IOTs (IxI, PxP, SUT) at the horizontal. The red line is a 45 degree line, where the transaction captured by the Payment data would be equal to those in the ONS table.

The differences of the scale of aggregate input purchases and output sales, as captured by the different data sources, is illustrated in Fig. B.6. Each dot in the figure reflects the data for one of the 105 different industries. The red 45 degree line illustrates of how the dots would be allocated if transaction values were equal. The figure shows that for the majority of sectors, we find much lower values in the Payment data compared to the ONS datasets, with few exceptions.

B.6 Difference quantification

In this section, we provide additional analyses and details related to the difference analysis performed in Sec. 4.4. The proportional difference between the Payment-based and the ONS IOTs, illustrated in Fig. 4 is defined as

$$\log_{10} \varepsilon_{ij}^{\mathrm{ONS}} = \left| \log_{10}\left(\frac{Z_{ij}^{\mathrm{Value}}}{\sum_{i,j} Z_{ij}^{\mathrm{Value}}} \right) - \log_{10}\left(\frac{Z_{ij}^{\mathrm{ONS}}}{\sum_{i,j} Z_{ij}^{\mathrm{ONS}}} \right) \right|, \tag{B.4}$$

where ONS $\in \{\mathrm{IxI}, \mathrm{PxP}, \mathrm{SUT}\}$ and Value corresponds to the Payment-based table in values.

We consider pairwise transactions that are non-zero in both datasets. To adjust for major differences in the scale and coverage, we normalise the transaction values between a pair of industries i and j by the aggregate value of all transactions in the respective IOT, excluding those between industry pairs that have no linkages in the other dataset.

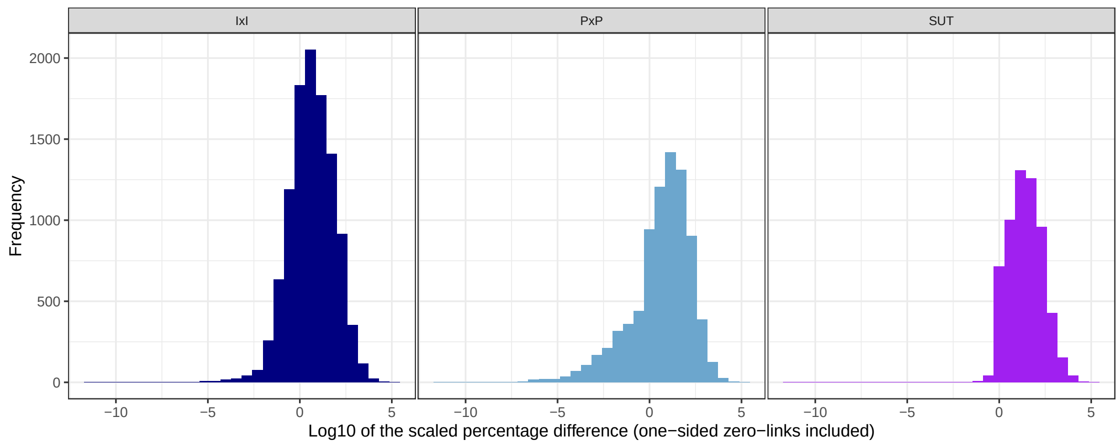
As an additional measure of difference, we also compile a scaled percentage difference measure, that allows keeping those links, that are non-zero in at least one of the data sets, using the formula

$$\hat{\varepsilon}_{ij}^{\text{ONS}} = \log_{10}\left(\left|\frac{Z_{ij}^{\text{Value}}}{\sum_{i,j} Z_{ij}^{\text{Value}}} - \frac{Z_{ij}^{\text{ONS}}}{\sum_{i,j} Z_{ij}^{\text{ONS}}}\right| \cdot \frac{\sum_{i,j}(Z_{ij}^{\text{Value}} + Z_{ij}^{\text{ONS}})}{2}\right), \tag{B.4}$$

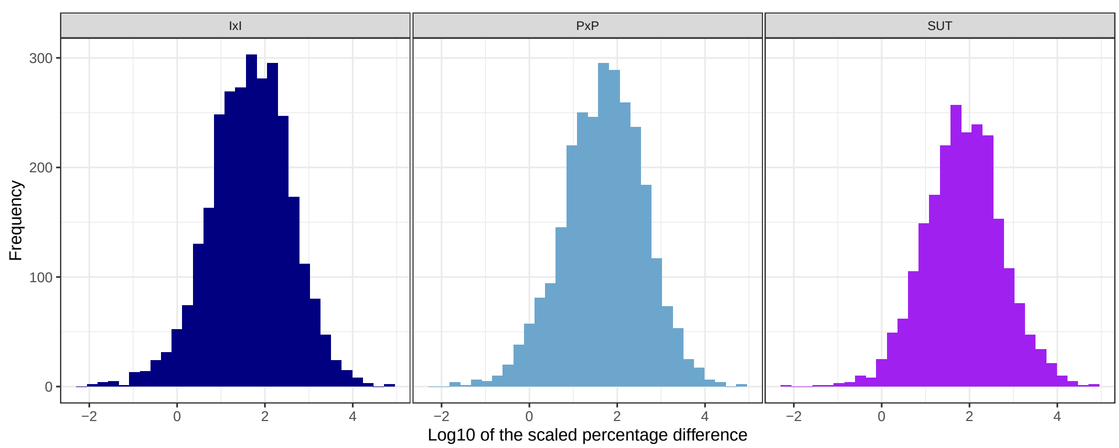
which compiles the absolute value of the difference of transactions measured as the percentage of total transactions in the respective dataset. We scale it by the average of total of transactions and take the log to deal with the highly skewed nature of the data.

Figure B.7: Scaled percentage difference

(a) One-sided zero-links included



(b) One-sided zero-links excluded



This modified measure is illustrated in Fig. B.7 and summarised by quartiles in Table B.5. We find the differences to be much smaller when keeping the one-sided zero links in the data. Note that the scale of the indicator is not comparable to the difference metric used in the main text (Sec. 4.4). In contrast to the proportional difference, the scaled percentage differences lack a clear quantitative interpretation but are used to illustrate the qualitative impact of removing one-sided zero-links.

Table B.5: Quartiles of the scaled percentage differences

	25%	50%	75%	100%
IxI	11.30	47.81	192.86	62,674.01
including zero	0.72	4.34	30.52	73,521.71
PxP	12.31	53.50	213.27	63,817.68
including zero	0.72	8.05	54.46	73,543.50
SUT	18.85	72.75	268.92	81,455.65
including zero	5.36	24.42	113.21	88,906.08

Notes: Quantiles of the scaled percentage differences for the three ONS tables (IxI, PxP, SUT) compared to Payment-based IOTs shown in Fig. 4, using data from 2019. Note that the scale of the scaled percentage difference is not comparable to the proportional difference used in the main text.

C Additional material: stylised facts of the granular network

C.1 Correlation of growth rates

In Sec. 6.1 we have studied the correlation of growth rates between different SIC-5 industries in our Payment dataset and their dependence on network distance. To perform that analysis, we have truncated our network by imposing a threshold on the input-shares[23]. We truncate the network using an industry-specific approach by removing links that fall below a certain input-share threshold, similar to above (see Fig. B.3). In detail, this implies:

- Aggregate all monthly transactions in a given year at a given level of industry-aggregation to obtain a network of yearly transactions.
- Impose a threshold below which to remove links. The threshold is specified through the input-shares of a given industry, in line with the prescription used by Carvalho, 2014 for a similar analysis.

We do this for each year in 2016-2023 and use the truncated annual network to calculate the distances. We transform the network into an edgelist and match the annual growth rate of the selling and buying industry to the respective pairwise distance in the network from the same year. For example, growth rates from 2019 are attributed to the distances calculated from the network in 2019.

C.2 Influence vector and power law

Table C.6 summarises the test statistics and fitted coefficients, when fitting a power law function to the influence vector for both the Payment network of Values and Counts, and for the years illustrated in Fig. 6. The bottom panel of the table shows the result for truncated data. We observe γ-values ranging between 1.34-1.69 (0.98-2.21) for the network of Payments in Values (Counts). Generally, we find that the power law hypothesis is not significant for the Value data, but holds for some years when using the Count data. Truncating the data does not have any relevant effect. Also made additional robustness checks considering all available years and compiled the influence vector using slightly different but plausible assumptions of the labour share $\alpha_L = \{0.3, 0.7\}$, and do not find any qualitative change compared to the results shown here.

Table C.7 additionally shows the industries that would be ranked as most central for the years 2017 and 2023. Consistently with earlier results and the conceptual discussion, we find the public sector, finance, trade and retail sectors to be highly central, which is different from centrality in IOTs following the NA standards.

[23] A qualitatively similar result is also found when imposing a threshold on the output-shares.

Table C.6: Power law fitting statistics

	Value					Count				
Year	γ	xmin	logLik	KS.stat	p-value	γ	xmin	logLik	KS.stat	p-value
2017	1.362	0.001	530.532	0.06	0.855	2.082	0.001	1570.413	0.167	0
2019	1.429	0.001	713.972	0.087	0.267	1.141	0.003	133.594	0.072	0.995
2021	1.615	0.001	1057.93	0.088	0.117	1.974	0.001	1539.515	0.17	0
2023	1.382	0.001	767.922	0.111	0.061	0.982	0.001	295.351	0.062	0.964
	Data truncated at 10% quantile of transaction value									
2017	1.343	0.001	474.976	0.054	0.952	2.207	0.001	1646.743	0.172	0
2019	1.455	0.001	677.768	0.086	0.305	1.882	0.001	1345.955	0.167	0
2021	1.689	0.001	1098.346	0.086	0.117	1.022	0.001	319.632	0.062	0.95
2023	1.49	0.001	857.5	0.117	0.03	1.022	0.001	309.591	0.058	0.977

Notes: This table shows the power law fitting statistics, where γ is the fitted exponent, xmin is the minimum level of the influence vector beyond which a power law can be reasonably fitted (see Clauset et al. (2009)), logLik shows the log-Likelihood, and KS is short for the Kolmogorov-Smirnov test statistic for significance. The p-value indicates the probability of rejecting the hypothesis that the distribution of the influence vector could have been drawn from a power law distribution. A p-value <0.05 would be considered as confirming the power law hypothesis.

Table C.7: Top 10 industries by influence vector

SIC		Industry description	SIC		Industry description
2017					
		Value			Count
84110	0.1273	General public administration	84110	0.0719	General public administration
82990	0.0538	Other business support services n.e.c.	82990	0.0574	Other business support services n.e.c.
64999	0.0347	Financial intermediation n.e.c.	64910	0.035	Financial leasing
64910	0.0226	Financial leasing	61900	0.0347	Other telecommunications
65110	0.0187	Life insurance	64999	0.0304	Financial intermediation n.e.c.
61900	0.0181	Other telecommunications	45111	0.0223	Sale of new & motor vehicles
45111	0.0175	Sale of new & motor vehicles	64191	0.0195	Banks
70100	0.0095	of head offices	65110	0.0152	Life insurance
62090	0.0087	Other information technology services	64921	0.0135	Credit granting by non-deposit finance
49410	0.0074	Freight transport by road	62090	0.0121	Other information technology services
2023					
		Value			Count
84110	0.1146	General public administration	84110	0.0946	General public administration
82990	0.04	Other business support services n.e.c.	82990	0.0423	Other business support services n.e.c.
65110	0.0315	Life insurance	64910	0.0346	Financial leasing
64999	0.0287	Financial intermediation n.e.c.	61900	0.0323	Other telecommunications
64910	0.0206	Financial leasing	45111	0.0254	Sale of new & motor vehicles
61900	0.018	Other telecommunications	64999	0.0207	Financial intermediation n.e.c.
45111	0.0173	Sale of new & motor vehicles	62090	0.0204	Other information technology services
62090	0.0133	Other information technology services	65110	0.0133	Life insurance
35130	0.0113	Distribution of electricity	64921	0.0125	Credit granting by non-deposit finance
49410	0.0088	Freight transport by road	35130	0.0112	Distribution of electricity