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Abstract

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

JEL classification: C67, C8, D57, E01

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Revisiting Hötte (2025): A Companion Analysis with Extended Evidence from UK Inter-Industry Payment Data, 2017–2024

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In 2025, the UK Office for National Statistics released a novel dataset of monthly inter-industry payment flows during January 2017 to November 2024 at the 5-digit SIC level (ONS, 2025a), covering >3.1 million UK organizations. Annual aggregates amount to 490 million transactions with an aggregate value of over £3.1 trillion in 2023. Such publicly available data are unprecedented by their granularity and timeliness, providing a rich basis for economic research and real-time policy advice. Hötte (2025) provided an empirical validation supplemented with conceptual discussions for using such bottom-up collected data in macroeconomic, industry-level, and economic network studies based on an earlier non-public and smaller version of the data. The novel data features much greater coverage, along with several methodological improvements. This paper gives an update on the earlier empirical results. It summarizes the major methodological changes of data construction, discusses key empirical observations, and their differences and consistencies relative to Hötte (2025). It concludes by discussing the implications for using payment data and outlining remaining challenges and expected future developments.

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1 Introduction

In 2025, the UK Office for National Statistics released a novel dataset of monthly inter-industry payment flows covering the period January 2017 to November 2024 at the 5-digit SIC level (ONS, 2025a; ONS, 2025b), spanning more than 3.1 million UK organizations. Annual aggregates amount to 490 million transactions with a total value exceeding £3.1 trillion in 2023. This kind of publicly available data is unprecedented in its granularity and timeliness, offering a rich foundation for economic research and real-time policy advice. Hötte (2025) provided an empirical validation, supplemented with conceptual discussions, of using such bottom-up data in macroeconomic, industry-level, and economic-network studies, based on an earlier non-public, smaller version of the dataset.[1] Since then, ONS has achieved major improvements, expanding coverage and addressing several conceptual challenges related to classification.

This paper updates the earlier empirical results. It summarizes the main methodological changes in data construction, discusses key empirical observations, and highlights their differences and consistencies relative to the earlier release.

The paper follows the structure of Hötte (2025), beginning with benchmarking against UK payment statistics (Sec. 2) and key macroeconomic variables including GDP, monetary aggregates, and inflation (Sec. 3). Sec. 4 continues with a systematic comparison to national accounts, focusing on input–output tables (IOTs) at both the network and industry levels. To assess the validity of empirical patterns at the 5-digit network level, Sec. 5 evaluates the consistency of the new data with established stylized facts from the network-economics literature. Most empirical figures and tables are reproduced from Hötte (2025), supplemented with additional descriptive statistics. For technical details, conceptual discussions, and a deeper understanding of the indicators presented, readers are referred to the original article.

Overall, the empirical evidence confirms significant improvements in data coverage and shows high levels of consistency between the new and earlier datasets. The new release often displays greater conceptual alignment with established national-accounts indicators and stylized facts. The paper concludes by outlining implications for the use of the dataset in economic measurement and applied research, as well as expected future developments.

This paper is not intended to be self-contained. Rather, it is designed as a companion to Hötte (2025), focusing on key updates and novel empirical and conceptual insights. For further detail and the broader conceptual background, readers are referred to the original article.

2 Data

The dataset is derived from the infrastructure of two major UK payment systems, enabling real-time monitoring of transactions. An introduction to payment system data and business payments (with a focus on the UK) is provided in Hötte (2025).

The key differences of the 2025 data release compared to the previous version are the following:

[1] At the time of writing Hötte (2025), a public version, released in December 2023, was available. This version had been much more aggregated, covering only about 40 industries and containing many missing entries due to Statistical Disclosure Control (SDC).

- **Greater coverage for two major reasons:** (1) The algorithm for business classification has improved. In the previous version, about 118,000 business accounts could be matched to Companies House (CH). The 2025 dataset includes 3.142 million organizations, more than half of all organizations registered in the UK in 2023 (5.656 million, of which about 5.1 million were coded as 'active').[2] (2) Transactions made through the Faster Payment System (FPS) have been added. The earlier version only covered the Bankers' Automated Clearing System (Bacs). The dataset now includes both major payment systems used by UK businesses for domestic payments. Unlike Bacs, which includes Direct Debit (DD) collections, FPS can only be used for payments initiated by the payer. It is similar to Bacs Direct Credits but also supports standing payments for regular transactions.[3]

- **Qualitative changes in the classifiers:** businesses with multiple SIC codes were classified using the first SIC code listed in the CH register (typically the lowest-numbered code). Transactions are now classified using all 5-digit SIC codes listed in a business's CH entry, with each code given equal weight.

- **Different time period covered:** The new dataset covers monthly transactions from January 2017 to November 2024. The previous non-public dataset covered August 2015 to December 2023, while the earlier public release covered January 2016 to October 2023.[4]

- **Disaggregation by industry:** The 2025 data are available at the 5-digit level, distinguishing 712 different sectors. The earlier non-public data had the same level of disaggregation, but the publicly available version distinguished only about 40 sectors. The broader coverage of businesses in the new release has enabled publication of highly disaggregated data without breaching Statistical Disclosure Control (SDC) requirements.[5]

Supplementary discussions of the data changes and the underlying methodology are provided in ONS (2025a), ONS (2025b), and Hötte (2025).

Figure 1 benchmarks aggregate payment values, volumes, and average transaction values of the dataset against other major UK payment schemes. Analogous figures for the previous release are provided in A.1. Unlike the results in Hötte (2025), the new figures show two distinct time series: 'cleaned' and 'raw' data. The cleaned data exclude all payment flows where the payer or payee could not be matched to CH or where the SIC code could not be mapped to any of the 104 CPA codes used in the official national accounts IOTs (ONS, 2024). The raw data include all transactions.[6] Results in Hötte (2025) reported only aggregates of the raw data.

The key empirical observations are the following:

[2] https://www.gov.uk/government/statistics/companies-register-activities-statistical-release-2022-to-2023/companies-register-activities-2022-to-2023#other-statistics-in-this-release [accessed in August 2025]

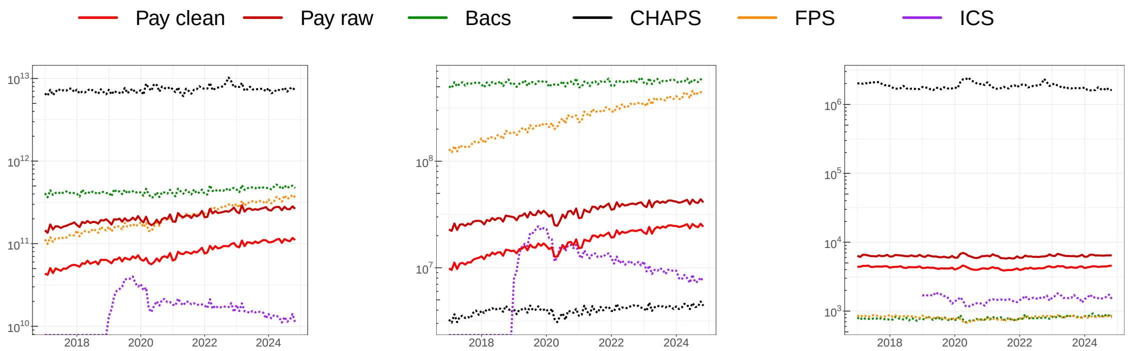
[3] In addition to the CH-matched data with a valid SIC code, the raw dataset also contains transactions identified as B2B payments that either could not be matched to CH or are missing SIC information. These residual payments are assigned a dummy code '0'.

[4] Publishing agreements with the data owner do not allow ONS to extract longer time periods from the data for publication. However, future research can construct longer time series by combining subsequent releases on a rolling basis.

[5] The non-public data used in Hötte (2025) had been subject to less restrictive SDC compared to the publicly available versions, yet the impact of different SDC procedures on the qualitative composition of firms and transactions covered is expected to be negligible.

[6] Non-identified payers/payees are assigned to '0' in the data. Non-matchable codes include, for example, activities of extra-territorial organizations or non-trading and dormant companies, which are tagged as '74990' and '99999' in CH, respectively.

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



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

Notes: The vertical axis is on 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 (2023).

- **Unmatchable payment flows:** A large share (about 60%) of the transaction network remains unclassified or assigned to codes that cannot be matched to CPA codes, with the payer and/or payee assigned to a non-CPA matchable code.

- **Coverage in numbers:** Coverage by aggregate value and transaction counts is significantly higher than in the previous dataset. In 2023, the raw data recorded an annual aggregate value of £3.131 trillion and 490 million transactions. The cleaned data show £1.227 trillion and 281 million transactions. Average transaction values were £6,394 (raw) and £4,366 (cleaned). By comparison, the previous dataset recorded £1.25 trillion, 77 million transactions, and an average transaction value of £16,200. Monthly averages in 2023 were £261 billion (raw) and £102 billion (cleaned) for values, and 41 million (raw) and 23 million (cleaned) for counts.

- **Lower average transaction values and types of payments:** The lower average transaction value (about £4,400) compared to the earlier dataset (£16,200) may reflect the inclusion of more smaller businesses in the new release. It may also be related to the integration of FPS payments, which are capped at £1 million since 2022 (and £250,000 before that), whereas Bacs allows up to £20 million. The two systems also differ in accessibility, and businesses may use FPS and Bacs for different purposes (see Hötte, 2025). Average transaction values are relatively stable across schemes. Notably, the average value is higher in the raw data than in the cleaned data, suggesting that many high-value transactions are associated with non-matchable accounts. This is unexpected, as large organizations with high transaction values would typically be easier to identify. A possible explanation is that international trade and foreign organizations with UK Bacs accounts execute many high-value transfers. These potential explanations warrant further investigation in future research.

- **Qualitative consistency:** The new and earlier data show qualitative similarity in several respects: (1) Both capture transactions with relatively high values. This is unsurprising, as most payments by count in Bacs and FPS are from or to consumers, while the dataset only captures B2B transfers. (2)

As before, the drop during Covid-19 is more pronounced for counts. (3) An upward overall trend is observed, which appears stronger in the new dataset.

3 Macroeconomic benchmarking

This section repeats the macroeconomic benchmarking exercise presented in Hötte (2025), but extends it with additional results. These include the distinction between raw and cleaned data, correlations with producer price inflation (PPI), and correlations with the OECD Composite Leading Indicator (CLI). The CLI captures business and consumer confidence and serves as a real-time indicator often used in economic nowcasting.

Table 1: Correlations with other payments and macro aggregates (including Covid-19 period)

	Pay	Bacs	FPS	CHAPS	GDP nsa	GDP sa	M1	M3	CPI	PPI	CLI
Raw payment data including non-classified payment flows											
Share in 2023	2.550	0.556	0.836	0.034	1.234						
Yearly (value)	0.999	0.916	0.994	0.695	−0.074	0.605	0.894	0.941	0.969	0.962	−0.325
Monthly (value)	0.986	0.854	0.959	0.432	0.390	0.570	0.793	0.880	0.924	0.916	0.011
Yearly (count)	0.998	0.968	0.984	0.829	−0.044	0.591	0.919	0.953	0.938	0.937	−0.323
Monthly (count)	0.990	0.686	0.956	0.813	0.467	0.618	0.828	0.897	0.899	0.901	0.059
Yearly (avg)	0.917	0.314	0.657	0.134	−0.113	0.061	−0.336	−0.231	0.142	0.098	0.052
Monthly (avg)	0.817	0.361	0.256	0.108	−0.453	−0.273	−0.113	−0.031	0.153	0.107	−0.283
Cleaned payment data excluding payments that could not be matched to CPA codes											
Share in 2023	0.392	0.218	0.328	0.013	0.484						
Yearly (value)	0.999	0.924	0.997	0.691	−0.127	0.600	0.889	0.939	0.977	0.965	−0.312
Monthly (value)	0.986	0.810	0.986	0.379	0.311	0.570	0.796	0.897	0.966	0.947	0.037
Yearly (count)	0.998	0.967	0.991	0.811	−0.174	0.561	0.924	0.960	0.947	0.938	−0.326
Monthly (count)	0.990	0.624	0.982	0.761	0.318	0.574	0.844	0.924	0.938	0.929	0.044
Yearly (avg)	0.917	0.296	0.827	0.052	0.321	0.208	−0.494	−0.406	−0.026	−0.032	0.286
Monthly (avg)	0.817	0.290	0.480	−0.020	−0.266	−0.055	−0.279	−0.149	0.190	0.137	−0.046
Growth rates											
Raw payment data including non-classified payment flows											
Yearly (value)	0.993	0.737	0.943	−0.286	0.917	0.902	−0.198	−0.185	0.435	0.630	0.108
Monthly (value)	0.977	0.767	0.899	0.038	0.860	0.746	−0.033	−0.058	0.334	0.472	0.209
Yearly (count)	0.965	0.667	0.565	0.840	0.984	0.921	−0.016	−0.082	0.094	0.410	0.231
Monthly (count)	0.976	0.560	0.713	0.820	0.934	0.856	0.010	−0.061	0.073	0.281	0.416
Yearly (avg)	0.874	0.054	0.224	0.365	−0.811	−0.433	−0.357	−0.168	0.646	0.259	−0.324
Monthly (avg)	0.892	0.043	0.141	0.514	−0.816	−0.625	−0.028	0.085	0.384	0.167	−0.557
Cleaned payment data excluding payments that could not be matched to CPA codes											
Yearly (value)	0.993	0.708	0.933	−0.330	0.868	0.863	−0.224	−0.202	0.420	0.581	0.140
Monthly (value)	0.977	0.716	0.879	−0.032	0.833	0.758	−0.083	−0.095	0.342	0.467	0.244
Yearly (count)	0.965	0.613	0.703	0.937	0.910	0.812	−0.020	−0.082	0.009	0.316	0.193
Monthly (count)	0.976	0.513	0.721	0.861	0.889	0.804	0.024	−0.041	0.024	0.246	0.386
Yearly (avg)	0.874	0.511	0.555	0.171	−0.926	−0.017	−0.456	−0.264	0.895	0.516	−0.130
Monthly (avg)	0.892	0.162	0.350	0.363	−0.750	−0.382	−0.208	−0.076	0.624	0.345	−0.423

Notes: This table shows Pearson correlations between annual (monthly) payments and other UK payment schemes and macroeconomic aggregates (GDP, M1, M3, Prices) during 2017 and 2024 (01/2017 and 11/2024), excluding the Covid-19 period, proxied by 2020 to 2022 (03/2020 to 12/2022). 'sa' ('nsa') is short for (non-) seasonally adjusted in all other rows. Our payment data and other payment aggregates are compared by aggregate values, counts, and average values (short 'avg') given by value divided by count. Growth rates are calculated as percentage growth compared to the (same month of the) previous year (for monthly data). Bacs, FPS, and CHAPS data are obtained from Pay.UK (2023). Monthly GDP is proxied by indicative (non-)seasonally adjusted monthly 'Total Gross Value Added' index data published by the ONS (ONS, 2023b; ONS, 2023a). GDP nsa data end in 2021, rendering the calculation of annual correlations when removing the Covid-19 period meaningless. Consumer price inflation (CPI) and producer price inflation (PPI) data are obtained from ONS (PDID: D7BT and GB7S). M1, M3 and composite leading indicator (CLI) data are obtained from the OECD Key Economic Indicators (KEI) and Main Economic Indicators (MEI) dataset (OECD, 2023b; OECD, 2023a).

Table 1 shows an analysis of raw correlations between monthly and annual payments (raw and cleaned data), other UK payment schemes (Bacs, FPS, CHAPS) and various macroeconomic indicators (GDP, infla-

Table 2: Correlations with other payments and macro aggregates (excluding Covid-19 period)

	Pay	Bacs	FPS	CHAPS	GDP nsa	GDP sa	M1	M3	CPI	PPI	CLI
Raw payment data including non-classified payment flows											
Yearly (value)	0.999	0.984	0.993	0.921	0.985	0.976	0.986	0.985	0.984	0.984	−0.571
Monthly (value)	0.991	0.901	0.971	0.533	0.781	0.940	0.939	0.955	0.961	0.957	−0.018
Yearly (count)	0.999	0.999	0.991	0.824	0.997	0.989	0.973	0.971	0.970	0.969	−0.625
Monthly (count)	0.995	0.714	0.976	0.821	0.743	0.959	0.934	0.949	0.955	0.950	−0.055
Yearly (avg)	0.884	0.430	0.931	0.459	−0.925	0.001	0.360	0.372	0.368	0.378	0.628
Monthly (avg)	0.777	0.471	0.438	0.064	−0.094	0.069	0.262	0.276	0.275	0.279	0.274
Cleaned payment data excluding payments that could not be matched to CPA codes											
Yearly (value)	0.999	0.989	0.997	0.934	0.982	0.968	0.992	0.991	0.989	0.989	−0.541
Monthly (value)	0.991	0.876	0.988	0.486	0.716	0.949	0.949	0.971	0.983	0.976	0.043
Yearly (count)	0.999	1.000	0.995	0.812	0.991	0.982	0.982	0.980	0.979	0.978	−0.593
Monthly (count)	0.995	0.666	0.990	0.786	0.691	0.963	0.947	0.967	0.976	0.971	−0.004
Yearly (avg)	0.884	0.127	0.965	0.800	−0.999	−0.373	−0.008	0.002	0.006	0.010	0.905
Monthly (avg)	0.777	0.255	0.415	0.234	−0.378	−0.136	0.152	0.186	0.211	0.194	0.577
Growth rates											
Raw payment data including non-classified payment flows											
Yearly (value)	1.000	0.956	0.996	0.972		0.869	0.992	0.995	0.987	0.994	0.988
Monthly (value)	0.976	0.799	0.909	0.679	0.473	0.551	0.820	0.847	0.851	0.863	0.036
Yearly (count)	0.994	1.000	0.997	−0.100		0.899	0.998	0.999	0.995	0.999	0.996
Monthly (count)	0.977	0.603	0.902	0.361	0.574	0.603	0.802	0.812	0.801	0.827	−0.052
Yearly (avg)	0.961	0.816	1.000	0.353		0.745	0.943	0.951	0.932	0.948	0.932
Monthly (avg)	0.881	0.561	0.667	0.222	−0.029	0.251	0.562	0.621	0.655	0.630	0.235
Cleaned payment data excluding payments that could not be matched to CPA codes											
Yearly (value)	1.000	0.952	0.994	0.968		0.862	0.990	0.993	0.985	0.992	0.985
Monthly (value)	0.976	0.738	0.947	0.608	0.335	0.544	0.868	0.908	0.923	0.931	0.106
Yearly (count)	0.994	0.996	0.983	0.012		0.844	0.985	0.989	0.979	0.987	0.979
Monthly (count)	0.977	0.504	0.934	0.338	0.334	0.586	0.851	0.877	0.872	0.898	0.002
Yearly (avg)	0.961	0.944	0.956	0.598		0.901	0.998	0.999	0.996	0.999	0.996
Monthly (avg)	0.881	0.530	0.586	0.338	0.101	0.208	0.552	0.623	0.691	0.636	0.430

Notes: This table shows Pearson correlations between annual (monthly) payments and other UK payment schemes and macroeconomic aggregates (GDP, M1, M3, Prices) during 2017 and 2024 (01/2017 and 11/2024), excluding the Covid-19 period, proxied by 2020 to 2022 (03/2020 to 12/2022). 'sa' ('nsa') is short for (non-)seasonally adjusted in all other rows. Our payment data and other payment aggregates are compared by aggregate values, counts, and average values (short 'avg') given by value divided by count. Growth rates are calculated as percentage growth compared to the (same month of the) previous year (for monthly data). Bacs, FPS, and CHAPS data are obtained from Pay.UK (2023). Monthly GDP is proxied by indicative (non-)seasonally adjusted monthly 'Total Gross Value Added' index data published by the ONS (ONS, 2023b; ONS, 2023a). GDP nsa data end in 2021, rendering the calculation of correlations among annual growth rates meaningless. Consumer price inflation (CPI) and producer price inflation (PPI) data are obtained from ONS (PDID: D7BT and GB7S). M1, M3 and composite leading indicator (CLI) data are obtained from the OECD Key Economic Indicators (KEI) and Main Economic Indicators (MEI) dataset (OECD, 2023b; OECD, 2023a).

tion and others). The upper (bottom) two panels in the table show correlations of data in levels (transformed into year-on-year growth rates) using raw and clean payment aggregates. The first rows in the upper two panels relate the aggregate annual value of the raw and cleaned payment data to annual aggregates from other payment schemes and GDP. The first column in the table correlates the raw and clean payment data.

Analogous results excluding the Covid-19 period are shown in Table 2 and results from Hötte (2025) are provided in A.2 to ease the comparison.

Table 1 and 2 reveal the following:

- **Relative values:** In 2023, the aggregate value of the raw data was about 2.55 times that of the cleaned data, and about 1.23 times nominal GDP. The cleaned data amounted to roughly 50% of GDP.[7] In the previous raw dataset, annual aggregates corresponded to roughly 40% of GDP. In general, raw and cleaned data correlate almost perfectly by values and counts (>97–99%), but slightly less by average transaction value (82–89%), as seen in column 1.

- **GDP correlations:** For monthly growth rates (bottom panels), correlations range between 75–86% for deseasonalized GDP and 83–93% for non-deseasonalized GDP, with typically higher values for (1) payment count data and (2) the raw data. These correlations are stronger than in the previous dataset, where they ranged between 65–86% and 71–89%. Consistent with the earlier data, correlations with non-deseasonalized GDP are higher when including the Covid-19 years. Excluding the Covid-19 period (Table 2), correlations are lower, ranging between 54–60% for deseasonalized GDP and 33–57% for non-deseasonalized GDP. This decline may partly reflect the shorter sample, especially for the non-deseasonalized series, which is only available until the end of 2021. Average transaction values show inconsistent correlation patterns and appear less meaningful for drawing conclusions about GDP.

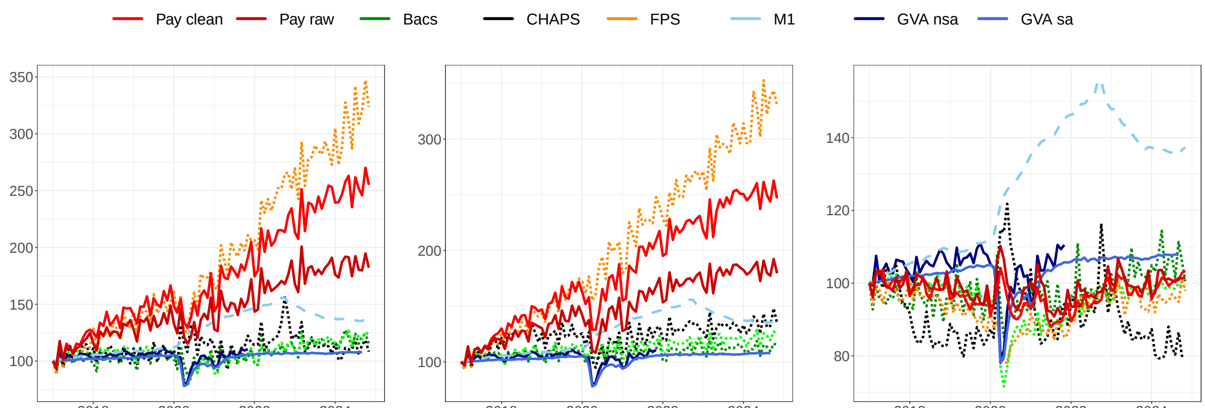
- **Inflation and monetary aggregates:** The inclusion or exclusion of the Covid-19 period has a large effect on observed correlations between monetary indicators and payment data. Excluding Covid-19, correlations between monthly growth rates of payments (values and counts) and consumer and producer price inflation (CPI and PPI) are high, at 85–93%. Including the Covid-19 period, correlations fall sharply, to around 33–47% for payment values. Correlations between payment counts and PPI are 25–28%, while correlations with CPI are almost absent. In all settings, correlations are (1) higher for PPI than for CPI and (2) weaker for counts than for values.

  The relationship with monetary aggregates (M1, M3) helps explain these differences. Excluding Covid-19, there is a clear statistical relationship, with correlations above 80% (see also Fig. 2). Including Covid-19, correlations become slightly negative or vanish. The Covid-19 period was characterized by massive counter-cyclical monetary and fiscal interventions, leading to sharp increases in monetary supply captured by M1 and M3.

  Interestingly, the relationship between average payment values in the cleaned data and CPI appears robust, with correlations of about 62–69% both with and without Covid-19. PPI shows similar correlations when Covid-19 is excluded, but the relationship is much weaker otherwise.

[7] Payments are conceptually not comparable to GDP, which only capture value added, whereas payments are gross transaction values. The comparison is made purely to gauge the scale of the dataset.

- **Payments and business/consumer confidence:** Payments also show positive correlations (stronger for counts) with the OECD Composite Leading Indicator (CLI), which measures business and consumer confidence. This relationship, however, is absent when excluding the Covid-19 period. Since the CLI is widely used in economic nowcasting and forecasting as a measure of expectations about future activity, these results suggest that realized transactions can be an indicator of expectations during times of crisis.



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

Figure 2: Monthly UK payments, GDP and M1

Notes: These figures show monthly time series (indexed to 01/2017 = 100) for payments, the major UK payment schemes, and indicative (non-)seasonally adjusted monthly 'Total Gross Value Added' (GVA) data published by the ONS (ONS, 2023a; ONS, 2023b). Average values are obtained by dividing total values by counts. 'Pay raw' refers to payment data that include non-classified payment flows. 'Pay clean' excludes all payments that could not be matched to CPA codes.

Fig. 2 illustrates fluctuations and trends in the monthly aggregates of payments, other UK payment schemes, M1, and GDP. The data are indexed to January 2017 = 100. Analogous figures for the previous data release are shown in A.2. The key observations are as follows:

- **Rising payments:** Payments in our sample show a stronger increase than aggregates of Bacs, CHAPS, M1, and GDP. Only FPS exhibits a stronger rise.[8] The rise also appears stronger compared to the previous version of the data, partly due to the inclusion of FPS transactions. This pattern holds for both values and counts, while average transaction values of most payment series appear relatively stable in the long run, with strong fluctuations during Covid-19. In the previous version, average transaction values rose noticeably. Several factors may explain this stability: financial innovations in payment interfaces have lowered access barriers to FPS and Bacs for small firms, and may also encourage firms to execute more frequent, small-value real-time transactions rather than bundling them.

- **Steeper rise of cleaned than raw data:** The observed rise is stronger for the cleaned than for the raw data, though both series behave similarly in long-term trends of average value and in monthly fluctuations of counts and values. This may reflect a selection bias from relying on a current snapshot of

[8]FPS is a relatively young scheme, introduced in 2008 and subject to changes. In 2022, its transaction limit was raised from £250,000 to £1 million, which may have contributed to its wider diffusion.

the UK business register (CH). The register includes CPA-matchable codes for active businesses, while inactive firms are tagged as 'non-trading' or 'dormant' with SIC codes '74990' and '99999'. Firms that went bankrupt between 2017 and 2024 would be classified as dormant and excluded from the cleaned dataset, even if they were active with valid SIC codes earlier. Newly founded firms, by contrast, would be added. This issue could be addressed in future versions by using annual snapshots of CH.[9] The CH file also lists 'foreign entities' without SIC codes. A deeper investigation of the discrepancy between cleaned and raw data is beyond the scope of this paper.

- **Seasonality:** While no strong seasonal patterns are evident, payment series (including FPS, CHAPS, Bacs) show greater monthly fluctuations than deseasonalized GDP, similar to non-deseasonalized GDP. This is consistent with the earlier data and highlights the potential need for deseasonalization when working with payment data.

4 Comparison to national accounts

This section benchmarks input-output tables (IOTs) constructed from the payment data against three types of official IOTs from the UK national accounts (ONS, 2024): the intermediate consumption table from the Supply and Use Tables (SUT), and the analytical product-by-product (PxP) and industry-by-industry (IxI) IOTs. Technical and conceptual details of this exercise are provided in Hötte (2025). By design, the results presented here focus on the cleaned data, as the analysis only includes payment flows where both the payer and payee can be mapped to CPA codes.

Several minor changes compared to the analyses in Hötte (2025) should be noted: (1) The time coverage differs, and the analysis is extended through 2022. In addition, the availability of analytical PxP and IxI data has improved, as these tables are now published annually after 2018.[10] (2) The aggregation now includes 104 sectors instead of 105, because sector C254 was merged with the aggregate category C25OTHER in the 2024 release of ONS (2024).[11] (3) This section also presents several additional descriptive statistics, which are not available in Hötte (2025) and therefore cannot be benchmarked against the earlier data.

4.1 Aggregate network statistics

Table 3 summarizes the aggregate network properties of the payment-based (for counts and values) and the three ONS IOTs (SUT, IxI, PxP), using an annual snapshot from 2022, which is the last date for which ONS IOTs are available in the 2024 Blue Book (ONS, 2024). Supplementary descriptives using 2019 data and a network density plot are provided in Table A.4 and Fig. 3. Analogous results from the previous data release are shown in A.3.

The key observations from this exercise are the following:

- **Network density:** The improved coverage of the novel data is associated with a higher density compared to the previous release. The density informs about the existence of transaction links. With

[9] Backdating is not possible due to the lack of historical snapshots.

[10] Note that the analytical IOTs are not backward revised, in contrast to the SUT, and their use as a time series comes with conceptual limitations (ONS, 2024).

[11] This may lead to minor deviations from Hötte (2025) when presenting results on ONS tables, for example in Fig. A.4.

Table 3: Properties of the payment and ONS-based input-output networks in 2022

Variable	Value	Count	SUT	PxP	IxI
Raw transactions					
Density	0.552	0.404	0.474	0.718	0.978
Average degree	57.423	41.650	48.343	73.275	99.735
Average strength	8,872.127	2,314,359.000	15,643.100	12,790.050	12,809.820
Average weight	154.505	55,566.200	323.585	174.550	128.438
Reciprocity	0.783	0.753	0.535	0.788	0.987
Transitivity	0.757	0.682	0.750	0.860	0.990
Assortativity by degree	−0.324	−0.416	−0.192	−0.183	−0.006
Input shares					
Average strength	0.867	0.943	0.733	0.829	0.834
Average weight	0.015	0.023	0.015	0.011	0.008
Output shares					
Average strength	0.877	0.922	0.724	0.791	0.817
Average weight	0.015	0.022	0.015	0.011	0.008

Notes: The first (second) column uses payment values (counts) as weights. The other columns represent official IOTs published by the ONS, where PxP is short for Product-by-Product, IxI for Industry-by-Industry, and SUT for Supply-and-Use Table. The data are aggregated into 104 distinct CPA codes (see Hötte, 2025, Sec. 4.1). Raw transaction data are shown in £ million.

55% it scores still lower than the observed density of IxI and PxP tables (71.18% and 97.8%), but higher than the density of SUTs (47.4%). The count-based network has a lower density, which arises from the SDC procedure.[12].

Similarly to the previous data, the network density across datasets converges with network truncation (Fig. 3), i.e., removing IO links if their weight given by the input or output share falls below a percentage threshold. Thresholds of <2.5% are sufficient to achieve almost identical levels of density. The previous data has been less sensitive to truncation. This suggests that the improved coverage led to the addition of many small-weight transaction linkages, which is in line with the earlier observation of lower average transaction values and the interpretation of many more small firms having been integrated into the sample. Notably, SDC can operate in a similar way as network truncation.

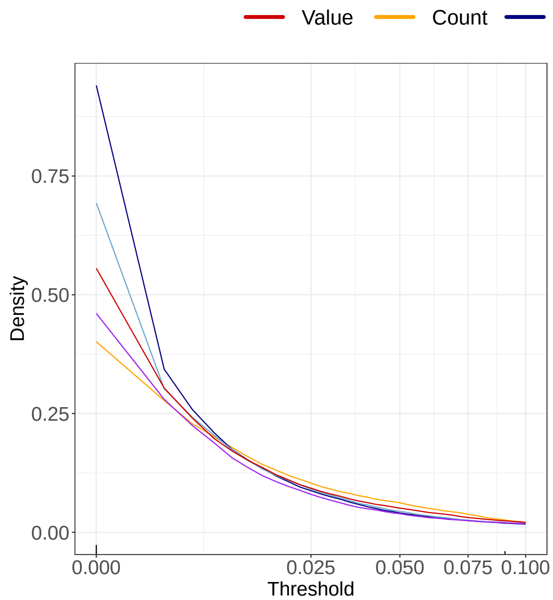
- **Coverage by transaction values:** By value, the payment data capture lower volumes compared to the official IOTs, as indicated by a relatively lower average strength. The average value of transactions traded by an industry is about £8.87 million, as measured by the strength. This is about two thirds of the value observed for the PxP and the IxI tables but 3 times higher than the value observed in the previous data release. Normalizing the links in the IOTs into shares, the strength tends to be slightly higher compared to IxI and PxP.

  The average weight indicates the value of an average transaction link in the network. This indicator is sensitive to the number of links being included in the network and varies across the IxI and PxP IOTs.

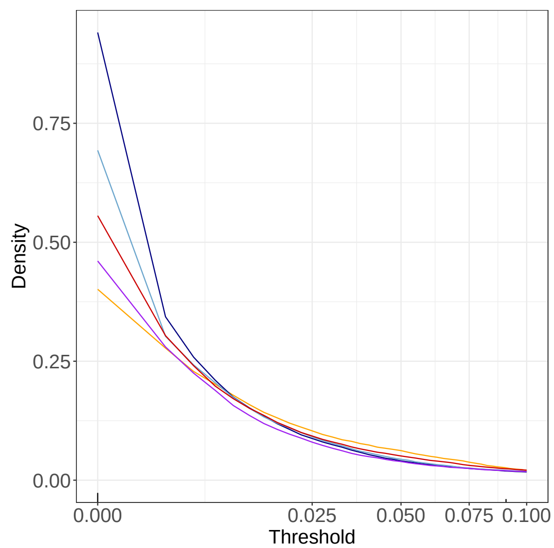
- **Structure of mutual connections:** The payment-based IOTs have slightly lower transitivity, reciprocity and degree assortativity. This may indicate that there are fewer or different hub and clustering structures compared to the official tables. However, this has not been tested here.

[12] A bilateral transaction link can be non-zero by value but zero by counts if the number of counts is <50 (see ONS, 2025a)

Figure 3: Network density at different truncation thresholds



(a) Input network



(b) Output network

Notes: This figure shows the effect of network truncation thresholds (x-axis) on the network density (y-axis). In the left (right) figure, a link is removed if the input (output) share is smaller than the threshold value. Figure uses 2022 data.

- **Stability:** The topological properties of the payment network and their qualitative relation to the official IOTs are relatively stable over time, as a comparison of the 2022 to 2019 tables reveals (see A.4). However, all IOTs show a rise of nominally weighted indicators (strength and weight), which is not surprising as all data types (excluding the counts) are nominal measures and subject to inflation.

4.2 Auto- and cross-correlations

The preceding subsection informs about the topological properties of the aggregate network, while being agnostic about the identity of sectors.[13] This subsection explores auto- and cross-correlation patterns of indicators constructed from the payment-based and national accounts IOTs. The correlation patterns are indicative of transaction- and industry-level similarities across the data sets.

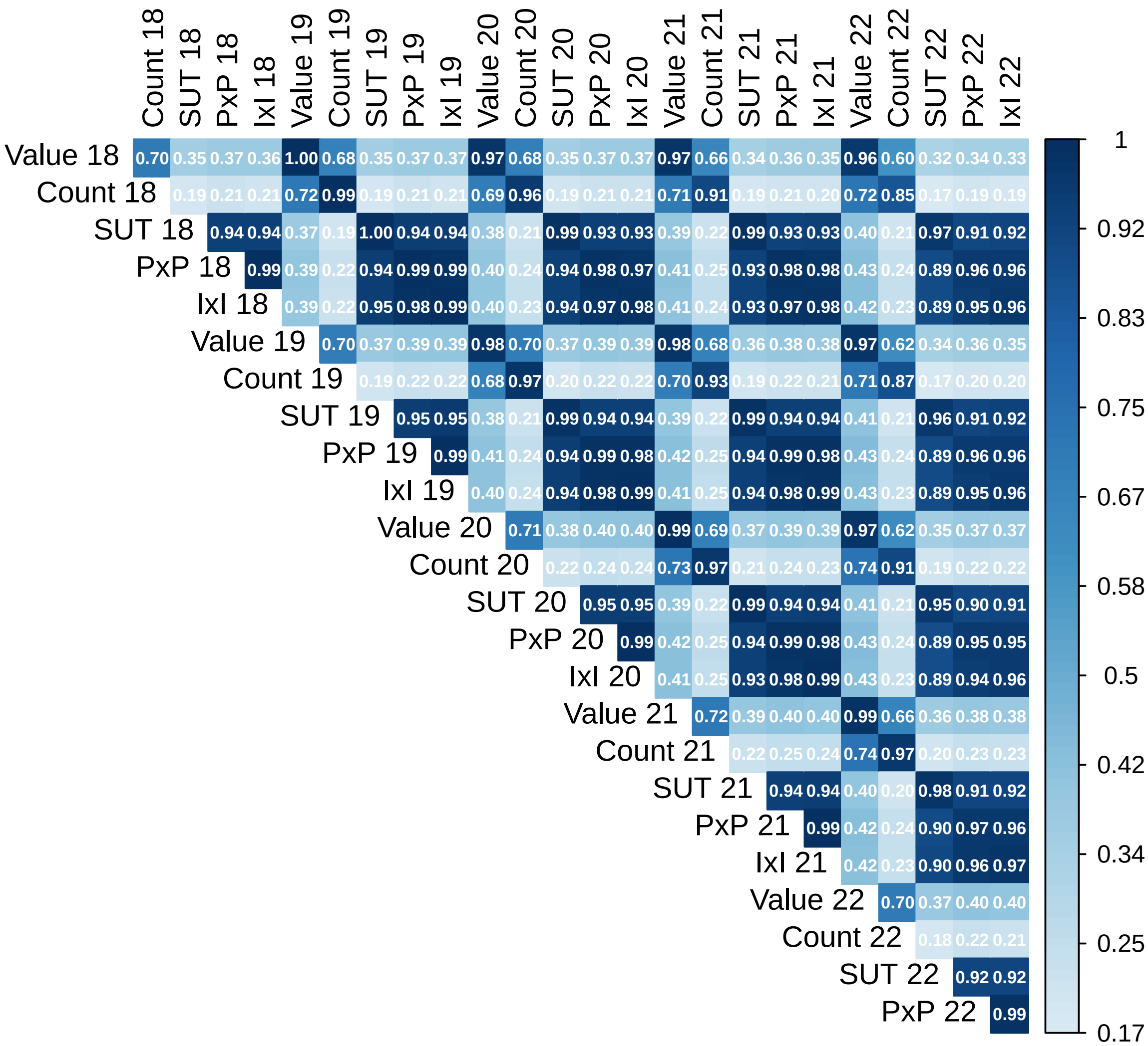
4.2.1 Transaction-level correlations

Fig. 4 and 5 illustrate correlations of IO links across the different network and across time. The former shows the correlations of links normalized as input- and output-shares, the latter uses raw transaction values without any data transformation such as taking logs, normalization or truncation. Results from the previous data release are provided in A.3.2.

The key observations are as follows:

[13]For example, two economic networks can have an identical topology from an aggregate view but for policy it makes a difference whether a critical industry as identified by the topology is, for example, financial services or machinery manufacturing.

Figure 4: Auto- & cross-correlations at the edge level (2018-2022)

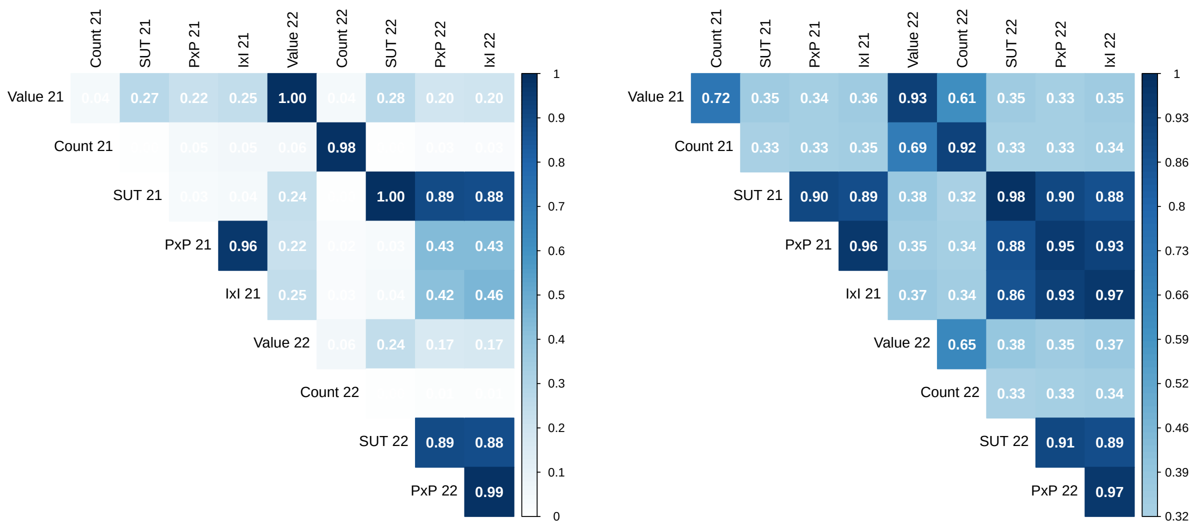


Notes: The correlations are measured by the Pearson correlation coefficient between raw transactions in the payment-based IOTs (values and counts) and the IxI, PxP, and SUTs.

- **Promising link-level similarity:** Cross-correlations between transaction links in the payment-value-based IOTs and the ONS IOTs score between 35-42%, with slightly higher values for the analytical PxP and IxI tables than for SUTs (Fig. 4). These values are even higher when log-transforming the data, indicating skewness.

  The cross-correlations are relatively stable when using lagged data, indicating the potential of using

Figure 5: Auto- & cross-correlations at the edge level (2021-2022)



(a) Input shares

(b) Output shares

Notes: The correlations are measured by the Pearson correlation coefficient between raw transactions, input and output shares in the payment-based IOTs (values and counts) and the IxI, PxP, and SUTs.

the real-time payment network to nowcast IOTs.

- **Higher similarities on the output side:** Normalizing the data into input and output shares (Fig. 5) reveals stronger cross-correlations for output shares than for input shares (34-35% versus 20-28%). This contrasts with the observations from the previous version of the data (A.7), although overall correlation levels are higher than before. Cross-correlations for input shares are weaker when using pre-Covid-19 data, while correlation patterns for output shares appear stable across time periods (A.8).

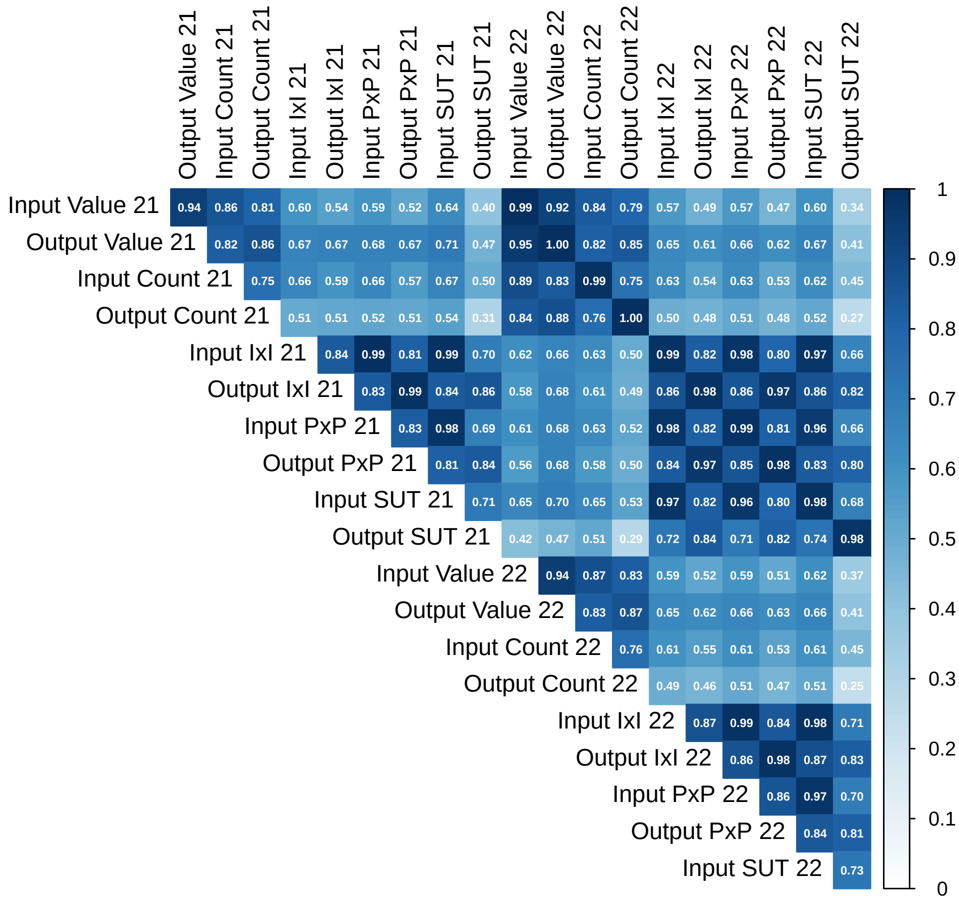
  Input-output shares provide an indication of the relative importance of industries as input suppliers or downstream customers. In the case of the payment data, they may be more informative about downstream linkages, possibly due to the underrepresentation of primary inputs from agriculture, mining, and energy in the data (see Fig. 7 below).

- **Payment counts and IOTs:** Payment counts poorly correlate with input shares, but show persistent correlations with output shares, at slightly lower but similar levels compared to payment value-based tables. They also reveal weaker correlations when comparing IOTs by raw transactions. In the previous data version, the correlations between counts and values were very similar (A.7).

4.2.2 Industry-level similarities

This subsection explores industry-level similarities showing correlations between payment-based and official IOTs using industry-level aggregates of input and output flows (Fig. 6) and the relation of payments to other industry-level indicators, such as value added, salaries, final demand, and exports (Fig. A.12). Additional results for data in growth rates are available in A.3. Fig. 7, 8 and A.14, A.16, A.17 illustrate the relative extent to which aggregate payment values cover the transaction values in the official tables and their evolution over time.

Figure 6: Auto- and cross-correlations of inputs & outputs at the node level



Notes: The correlations are measured by the Pearson correlation coefficient between industry-level annual outputs and inputs in 2021-2022 calculated by using raw transaction values and counts of the payment data and the row- and column sums of ONS IxI, PxP, and SUTs.

The key observations are as follows:

- **Inputs versus outputs:** Comparing how payment-based input and output aggregates correlate with those in the official IOTs, we observe stronger correlations for payments with inputs rather than outputs obtained from the IxI, PxP and SUTs (Fig. 6) with correlations ranging between 51-71% and 42-50% for growth rates from 2021-22 (Fig. A.10). Growth rates during Covid-19 from 2020-2021 show no meaningful relationship.

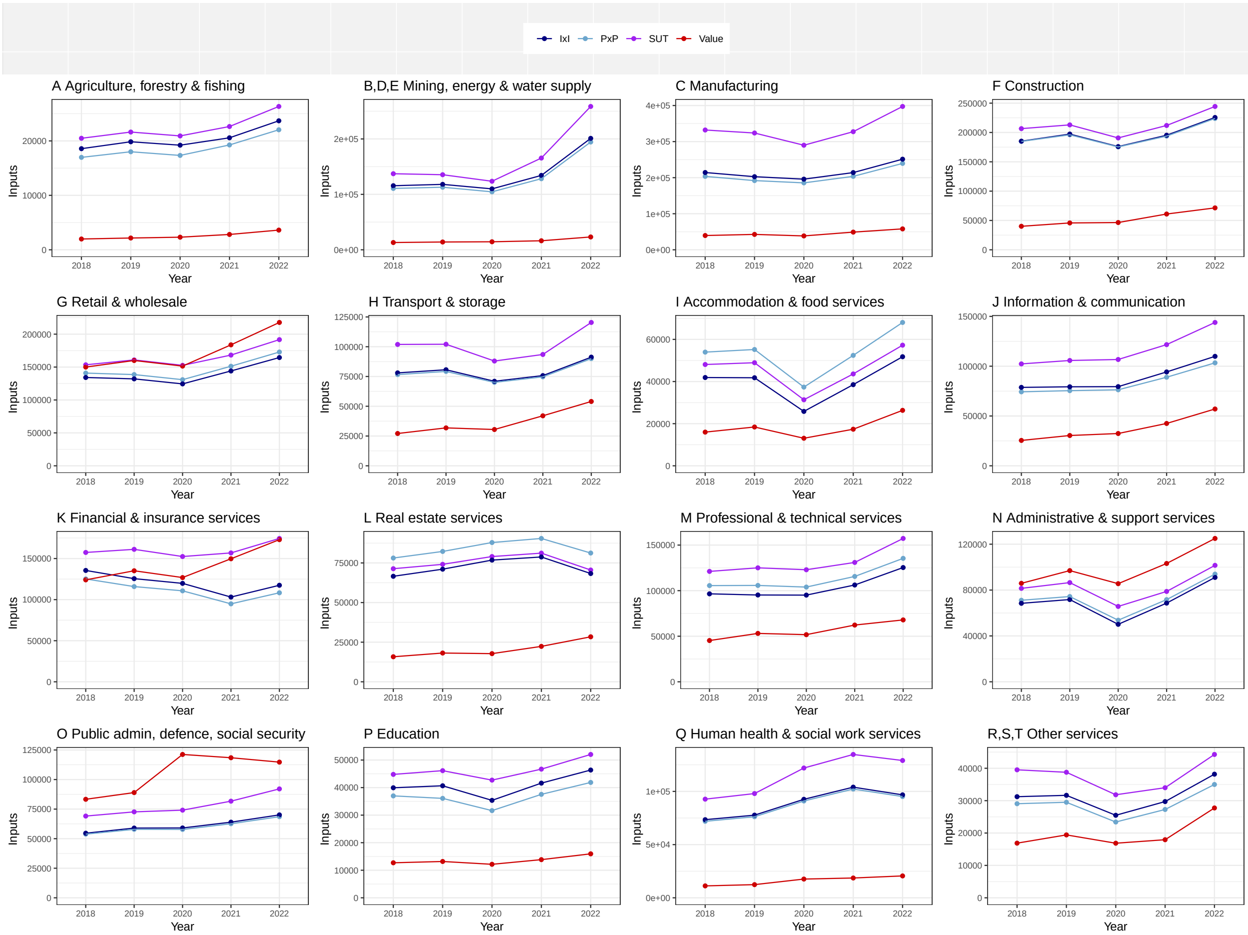


Figure 7: Comparison of aggregate industry sizes by sum of inputs over time

Notes: The figure shows how industry level aggregates evolved over time for different data sets. Industries are grouped into sectors. Aggregates are calculated as sum over all input links for an industry group. Scales of the y-axes differ across plots.

The opposite tends to hold for cross-correlations of payment value-based input and output aggregates: Payment-based output values correlate more strongly with most of the IxI, PxP and SUT aggregates than payment-based inputs. In some cases, payment outputs more strongly correlate with PxP and IxI inputs rather than payment inputs, which indicates that input purchases tend to be incompletely captured by the payment data. Payment counts tend to behave oppositely, with input counts being more strongly related to IOT aggregates than output counts.

- **Relative coverage by sector:** Compared to the previous version of the data (Fig. A.14 and A.15), coverage improved across all datasets: various industries that have been almost absent by value in the previous data are relatively well captured in the novel data, with few exceptions. Overall, the relative coverage appears more equally distributed than before. We also observe that a larger number of sector entries now overreports values in comparison to national accounts.

Supplementing the coverage analysis, Fig. 7 and 8 use a 16-sector aggregation and illustrate how the

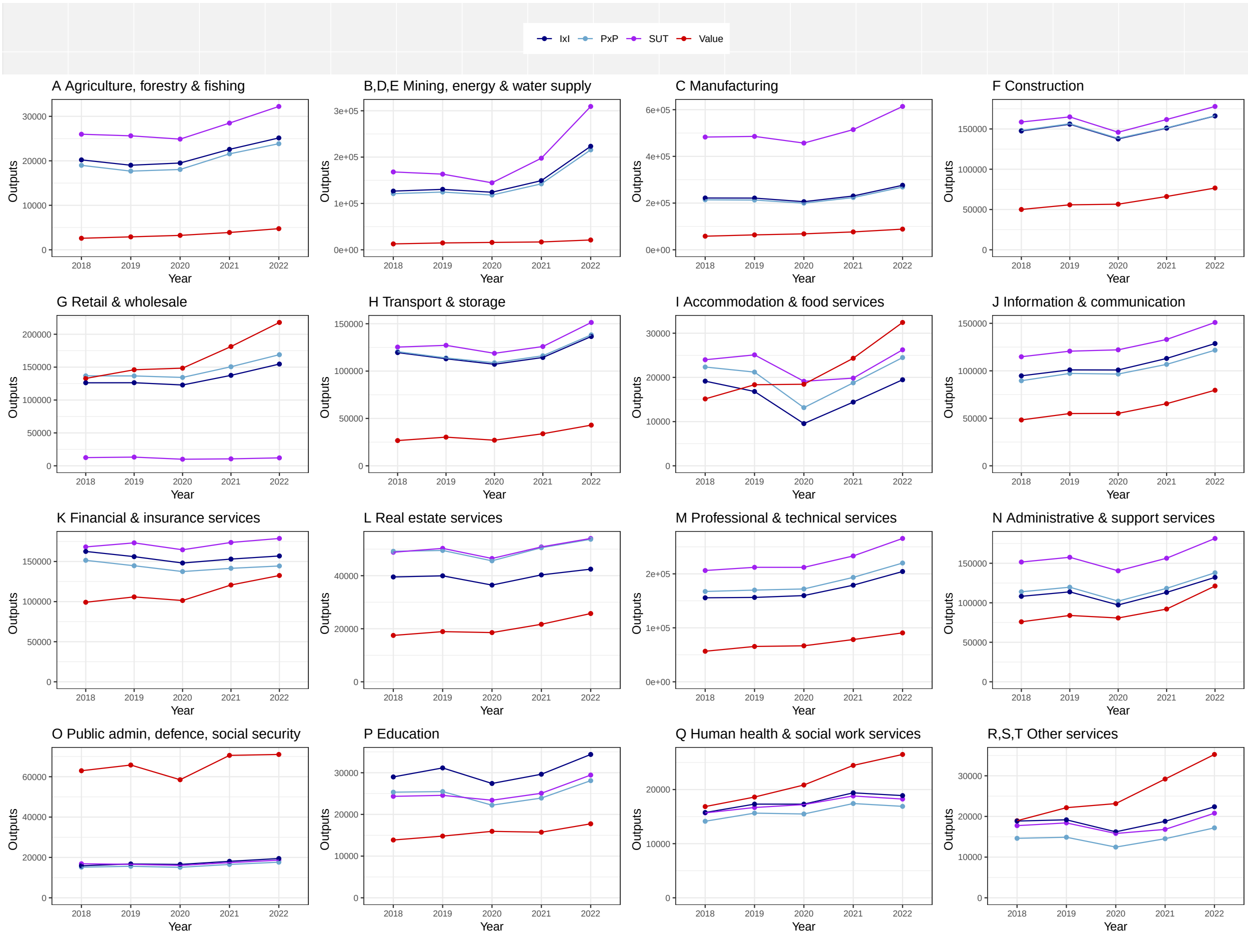


Figure 8: Comparison of aggregate industry sizes by sum of outputs over time

Notes: The figure shows how industry level aggregates evolved over time for different data sets. Industries are grouped into sectors. Aggregates are calculated as sum over all output links for an industry group. Scales of the y-axes differ across plots.

relative coverage of input and output transactions differs across sectors and time. Underreporting (on the input and output side) of the payment data appears to be strongest for agriculture, mining and energy, manufacturing and construction, which are typically more upstream in the supply chain. Despite their low coverage and as discussed below, some of these sectors show high levels of network centrality (Table A.16) despite their relatively weak coverage.

We also observe significant underreporting in various service sectors, including transport and storage, real estate, communication and professional services. Some sectors show significant underreporting on the input side but have a good or even excessive coverage on the output side, such as accommodation and food services and health and social services. Notably, the concern of an excessive overrepresentation of intermediary industries like retail and wholesale as well as financial services appears to be weakly justified at the 16-sector aggregation, as these show rather similar aggregate values as observed in national accounts.[14] Only public administration remains as an extreme outlier with significant over-

[14]Fig. A.16 and A.17 show additional time series figures at the granular level of 104 distinct CPA codes, illustrating

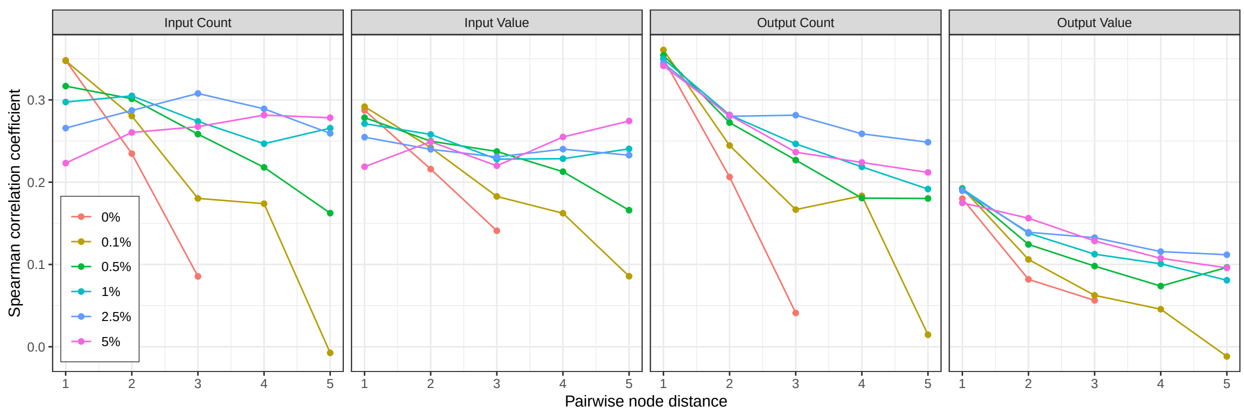
reporting at the output side. This likely arises from a conceptual issue as public administration entities receive payments by collecting fees and tax payments which would be excluded from the official IOTs.

5 Stylized facts of the granular data

This section investigates the consistency of payment data at the most disaggregated 5-digit SIC level with stylized facts on highly granular production networks that have been documented in the literature. More details on the background of these analyses are provided in Hötte (2025).

5.1 Correlation of growth rates

Figure 9: Correlations of growth rates



Notes: These figures illustrate the Spearman correlation coefficients between monthly (year-on-year) growth rates of directly and indirectly connected pairs of industries, using data from 2016 to 2018 and 2024. The x-axis shows the distance of the industry pairs in annual network aggregates.[15] The colors indicate truncation thresholds imposed on the network before calculating the distances. Links with a weight (input share) below the threshold are removed (see also Section 4.1).

Fig. 9 shows correlations of year-on-year growth rates of a pair of industries at different stages of distance in the network and for different levels of network truncation. Additional results for the old data and figures excluding intermediary industries or using Pearson instead of Spearman correlations are provided in the Appendix A.4. The key observations are the following:

- **Correlations decrease with distance:** Growth rates correlate less when industries are more distant in the network, supporting a stylized fact from the literature. This pattern is robust when truncating the network at moderate levels and holds for growth rates of inputs and outputs measured as counts or values. The levels of correlation are higher compared to the previous version of the data (Fig. A.22) and robust when removing intermediary industries (retail and wholesale (G45, G46, G4), financial and insurance services (K64, K65, K66), public administration (O84)) (Fig. A.23).
- **Effects of network truncation:** When strongly truncating the network by removing small links, correlations are not meaningful and we observe in some cases and a u-shaped pattern of correlations.

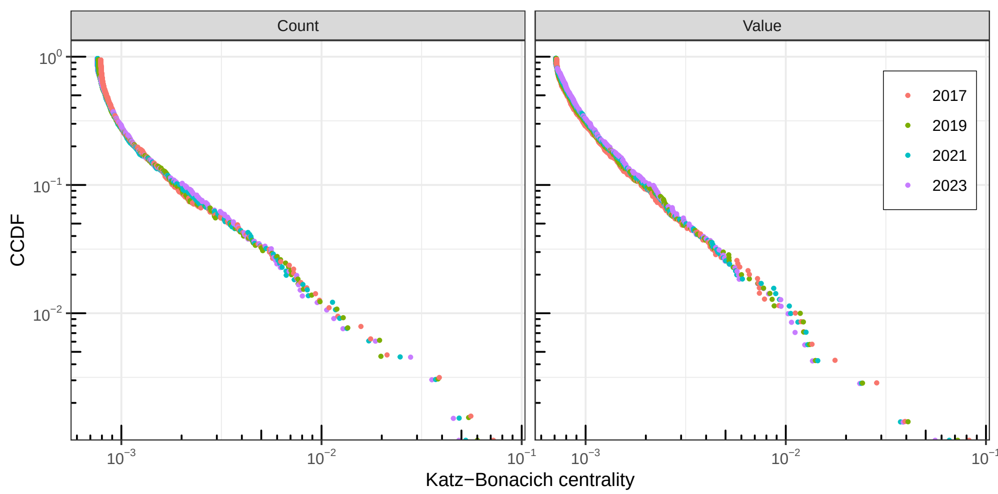
heterogeneity at the granular level in coverage.

This effect is stronger when removing intermediaries (Fig. A.23) or using the Pearson correlation coefficient (Fig. A.24), which is more sensitive to outliers. Compared to the earlier version of the data, the pattern of a negative relationship between growth and distance is more robust against different approaches to data pre-processing. Yet it remains true that when too many links are removed, the network may no longer be a meaningful representation of the supply chain and thus any truncation based on threshold values must be carefully be thought through.

5.2 Centrality distribution

Fig. 10 and A.25 show the complementary cumulative distribution function (CCDF) of the Katz-Bonacich centrality of the 5-digit industries. Robustness checks evaluate the impact of network truncation, and potential role of outliers by removing intermediary sectors (Fig. A.27) and services (Fig. A.28). Table 4 shows a ranking of the top-10 sectors that rank highest by their influence vector and would be expected –according to theory– to be the drivers of aggregate fluctuations. The upper (bottom) panel shows the ranking in the raw network data (for data where service sectors have been removed before centrality scores are calculated). Additional ranking tables for other years and samples excluding intermediaries and service sectors are shown in Table A.14, A.15, A.16).

Figure 10: CCDF of the Katz-Bonacich centrality



Notes: These figures illustrate the CCDF of the Katz-Bonacich centrality (see Hötte, 2025) for different years, using a labor share parameter of $\alpha_L = 0.5$ (Magerman et al., 2016) and payment-based input share matrices based on counts and values.

The key observations are as follows:

- **Power law-like cumulative distribution:** The CCDF exhibits a nearly log-linear shape beyond a tiny threshold value (<0.001). This indicates consistency with stylized facts from the literature. The near-linearity is visually stronger for data measured in values and stronger in comparison to the previous data (Fig. 10 and A.25). This pattern is consistent across years and robust against network truncation (Fig. A.26), the exclusion of intermediaries (Fig. A.27), and service sectors (Fig. A.28).

Table 4: Top 10 industries by influence vector in 2023

SIC		Industry description	SIC		Industry description
Raw network data					
	Value			Count	
84110	0.0823	General public administration	61900	0.0722	Other telecommunications activities
82990	0.0394	Other business support services n.e.c.	82990	0.0557	Other business support services n.e.c.
64999	0.0285	Financial intermediation n.e.c.	84110	0.0388	General public administration
61900	0.0176	Other telecommunications activities	64999	0.0212	Financial intermediation n.e.c.
65110	0.0135	Life insurance	65110	0.0176	Life insurance
62090	0.0123	Other information technology services	62090	0.0157	Other information technology services
49410	0.0119	Freight transport by road	96090	0.0121	Other service activities n.e.c.
70100	0.0112	Activities of head offices	64910	0.0109	Financial leasing
62020	0.0092	Information technology consultancy	65120	0.0098	Non-life insurance
96090	0.0078	Other service activities n.e.c.	49410	0.0093	Freight transport by road
Excluding services					
	Value			Count	
32990	0.033	Other manufacturing n.e.c.	32990	0.0535	Other manufacturing n.e.c.
43999	0.0304	Other specialised construction n.e.c.	43999	0.0252	Other specialised construction n.e.c.
35140	0.023	Trade of electricity	36000	0.0219	Water collection, treatment and supply
35130	0.0198	Distribution of electricity	33200	0.0207	Industrial machinery installation
25990	0.0174	Metal products manufacture n.e.c.	35140	0.0204	Trade of electricity
35110	0.0154	Production of electricity	35220	0.0168	Gas fuels distribution through mains
35220	0.0146	Gas fuels distribution through mains	35130	0.0168	Distribution of electricity
43210	0.0142	Electrical installation	43210	0.0156	Electrical installation
22290	0.0117	Manufacture of other plastic products	25990	0.0139	Metal products manufacture n.e.c.
42990	0.0109	Civil engineering construction n.e.c.	43220	0.0122	Plumbing/heat/air-condition installation

Notes: Transaction links to service-related sectors (G45-Q88, S94-U99) have been removed from the data before the centrality scores are calculated.

However, for most data configurations, significance tests on whether the centrality distribution truly follows a power law do not confirm this to be significant against null models (see A.4.2).

- **Power law coefficients in alignment with the literature:** For the baseline case, the fitted power law coefficients range between 1.3-1.6 (A.4.2), which is consistent with stylized facts reported by the literature and indicates greater consistency with other empirically described production networks compared to the values observed in the previous data.

- **Ranking of sectors by influence:** Investigating the top ranks of industries by centrality points to potential issues with the payment data. Public administration, telecommunications, financial intermediation, and business service support activities dominate the top ranks by centrality (Table 4). The top rank by public administration arises from the data construction, connecting this sector to almost any business in the UK that pays fees to public authorities or receives public benefits. Such transactions are differently treated in national accounts (see Sec. 4.2.2 and Hötte (2025)). In addition, various top ranks are taken by sectors attached with an 'not elsewhere classified' (n.e.c.) residual classification code, which might be used by a very heterogeneous range of businesses connected to diverse customers and input suppliers, depending on the good being produced and traded. However, this does not imply that an individual good being traded represents an essential input to the full range of customers. At higher levels of aggregation, this issue disappears when 'n.e.c' subclasses are merged with aggregates.[16]

  When removing services from the data, we observed that energy, construction, and machinery manufacturing score high. This can be relevant for applied research on supply chain disruptions as these sectors are often considered origins of macro-level fluctuations. It seems that the payment network captures their influential role, despite their relative underreporting by scale in relation to national accounts (Sec. 4.2.2).

6 Concluding remarks and remaining challenges

6.1 Wrapping up

This study provides a systematic empirical update on the 2025 public release of the UK inter-industry payment dataset, building on and extending earlier work and methodology (Hötte, 2025). For conceptual discussions and methodological detail, the reader is referred to the original article.

The key advances of the updated data include (1) the broader inclusion of organizations (>3.1 million, exceeding 50% of all registered UK businesses), (2) the integration of transactions made through the FPS, and (3) improvements in industry classification. Further, the increased scale of the data enabled the public release of a highly disaggregated 5-digit version of the data, without breaching SDC. These updates have significantly increased the dataset's representativeness, analytical utility, and consistency with official national accounts.

The empirical validation exercises in this paper demonstrate that the data exhibit strong correlations with key macroeconomic aggregates, including GDP, monetary aggregates, and inflation. Compared to the previous version, these raw correlations are stronger, indicating an increased usefulness of the data in macro-

[16] Other research on industry classification has shown that n.e.c.s are often associated with emerging technologies. See https://escoe-website.s3.amazonaws.com/wp-content/uploads/2022/06/13151521/SS-E-Russell.pdf

and industry-level economic forecasting and modeling. Observations such as a lower average transaction value suggest an increased coverage of SMEs, which represent >99% of businesses registered in the UK. Benchmarking against industry-level national accounts data reveals an improved coverage and consistency of the data in relation to official IOTs, while issues of underreporting and conceptual challenges remain. At the most granular 5-digit level, the data align well with documented stylized facts from the production network literature, suggesting the potential future use of the data in a real-time tracing of the granular origins of aggregate fluctuations (Acemoglu et al., 2012). Overall, the novel data mark a major step forward in constructing real-time economic indicators from bottom-up collected naturally occurring data (Buda et al., 2023). The novel data release offers a promising base for highly granular, real-time applied economic research, developing novel empirical methodologies and advancing economic theory.

6.2 Remaining Challenges

Despite these advances, various challenges and conceptual considerations remain. First, a considerable share of transactions (approximately 60%) are linked to bank accounts which either remain unclassified or where associated SIC codes cannot be mapped to CPA codes used in official national accounts IOTs. This reduces the effective coverage of the cleaned data for national accounts benchmarking and introduces potential biases in empirical applications and theoretical models that rely on the assumption of a closed economic cycle and full classification. Additional biases arise from potential industry- and firm-specific payment behaviors as discussed in Hötte (2025).

Second and relatedly, the presence of high-value transactions among non-identifiable entities is a puzzle. These payments may stem from foreign organizations, dormant and non-trading companies, or other institutions not registered in CH or registered with placeholder SIC codes (e.g., '74990' '99000', '99999'). Some of these entities might be involved in international trade, yet their structural roles in the economy remain unclear due to classification gaps. Future work might investigate their role systematically by analyzing the distribution of payment flows for which only one side (payer or payee) remains unclassified. Since input and output patterns are idiosyncratic across industries, insights could be gained into the nature of these semi-unclassified payments. As an interim solution, applied econometric modeling at the sector- and macro-level might consider including such semi-unclassified payment flows as control variables in the analyses.

Third, another open challenge relates to the 'time of recording' (see Hötte, 2025). The real-time nature of the data opens a window into real-time economic measurement, yet little is known about the exact timing of firms' payment behavior and the role of industrial heterogeneity and financial intermediation in this process. This issue might be hard to address systematically during data processing. However, it is plausible to expect businesses that run into economic difficulties to be no longer able to pay their bills, which would be statistically reflected in the data, given the data's scale and coverage. It will be up to applied economic research to demonstrate the capacity of the data to provide real-time economic insights.

Fourth, a related issue arises from adjustments in prices and rigidities in this process. The relationship of payments to inflationary patterns is to be investigated in future work, whereby the high level of granularity and the availability of payment counts as a novel indicator may open entirely new opportunities for economic research.

Various other conceptual considerations discussed in Hötte (2023) remain valid for the novel data. Researchers using payment data need to keep these in mind when developing theoretical models and drawing empirical inference based on the data.

6.3 Outlook

Some of the issues listed above are on the agenda of ongoing research and ONS continues its efforts of further developing, improving and extending the data and its portfolio of related data publications, including a regional breakdown. This paper gives an update on recent achievements and should serve as a primer on what can be expected soon.

References

Acemoglu, Daron, Vasco M Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi (2012). "The network origins of aggregate fluctuations". In: *Econometrica* 80.5, pp. 1977–2016. DOI: 10.3982/ECTA9623.

Buda, Gergely, Stephen Hansen, Tomasa Rodrigo, Vasco M Carvalho, Álvaro Ortiz, and José V Rodríguez Mora (2023). "National accounts in a world of naturally occurring data: A proof of concept for consumption". In: DOI: 10.2139/ssrn.4552219.

Clauset, Aaron, Cosma Rohilla Shalizi, and M. E. J. Newman (2009). "Power-Law Distributions in Empirical Data". In: *Society for Industrial and Applied Mathematics Review* 51.4, pp. 661–703. DOI: 10.1137/070710111.

Eurostat (2015). *CPA Ver. 2.1 – Structure and explanatory notes*. Tech. rep. Eurostat – Unit B5, Central Data and Metadata Services. URL: http://www.ons.gov.uk/ons/guide-method/classifications/other-classifications-used-within-national-statistics/other-national-and-international-classifications/cpa-ver--2-1-structure-and-explanatory-notes.pdf (visited on 07/25/2023).

Hötte, Kerstin (2023). "Demand-pull, technology-push, and the direction of technological change". In: *Research Policy* 52.5, p. 104740. DOI: 10.1016/j.respol.2023.104740.

— (2025). "Mapping the disaggregated economy in real-time: Using granular payment network data to complement national accounts". In: *Economic Systems Research*. DOI: 10.1080/09535314.2025.2518944.

Magerman, Glenn, Karolien De Bruyne, Emmanuel Dhyne, and Jan Van Hove (2016). *Heterogeneous firms and the micro origins of aggregate fluctuations*. Working Paper Research 312. National Bank of Belgium. URL: https://hdl.handle.net/10419/173768 (visited on 04/14/2024).

OECD (2023a). *Key Short-term Economic Indicators*. URL: https://stats.oecd.org//Index.aspx?QueryId=118961.

— (2023b). *Main Economic Indicators - complete database*. DOI: 10.1787/mei-data-en. URL: https://stats.oecd.org//Index.aspx?QueryId=119000.

ONS (2009). *UK Standard Industrial Classification of Economic Activities 2007 (SIC 2007) – UK Standard Industrial Classification of Economic Activities 2007 (SIC 2007)*. Tech. rep. Office for National Statistics. URL: https://www.ons.gov.uk/file?uri=/methodology/classificationsandstandards/ukstandardindustrialclassificationofeconomicactivities/uksic2007/uksic2007webamend8531.pdf (visited on 03/28/2024).

— (2023a). *Indicative monthly GDP – consistent with quarterly national accounts*. URL: https://www.ons.gov.uk/economy/grossdomesticproductgdp/datasets/indicativemonthlygdpconsistentwithquarterlynationalaccounts (visited on 03/26/2024).

— (2023b). *Indicative monthly non-seasonally adjusted GDP*. URL: https://www.ons.gov.uk/economy/grossdomesticproductgdp/adhocs/14197indicativemonthlynonseasonallyadjustedgdp (visited on 10/16/2023).

— (2024). *UK National Accounts, The Blue Book 2024 – National accounts statistics including national and sector accounts, industrial analysis and environmental accounts*. Tech. rep. Office for National Statistics. URL: https://www.ons.gov.uk/releases/uknationalaccountsthebluebook2024 (visited on 06/25/2025).

ONS (2025a). *Industry-to-industry monthly payments, UK Quality and Methodology Information*. ONS website, methodology, last revised: 13 January 2025. Office for National Statistics. URL: https://www.ons.gov.uk/economy/economicoutputandproductivity/output/methodologies/industrytoindustrymonthlypaymentsukqmi (visited on 06/02/2025).

— (2025b). *Industry-to-industry payment flows, UK: 2017 to 2024, experimental data*. ONS website, article. Office for National Statistics. URL: https://www.ons.gov.uk/economy/economicoutputandproductivity/output/articles/industrytoindustrypaymentflowsuk/2017to2024experimentaldata (visited on 06/02/2025).

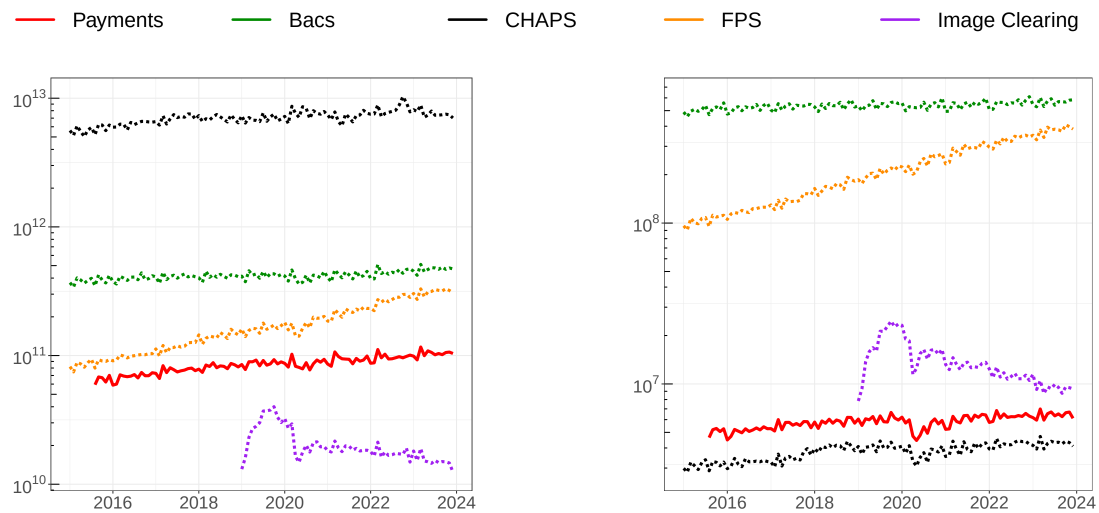
Pay.UK (2023). *Historical monthly payment statistics*. URL: https://newseventsinsights.wearepay.uk/media/oejmhupa/historical-monthly-payment-statistics-1990-to-may-2023.xls (visited on 10/17/2023).

A Supplementary statistics and previous results

This appendix provides additional descriptive statistics and shows figures and tables from Hötte (2025) to supplement the comparison.

A.1 Benchmarking UK payments

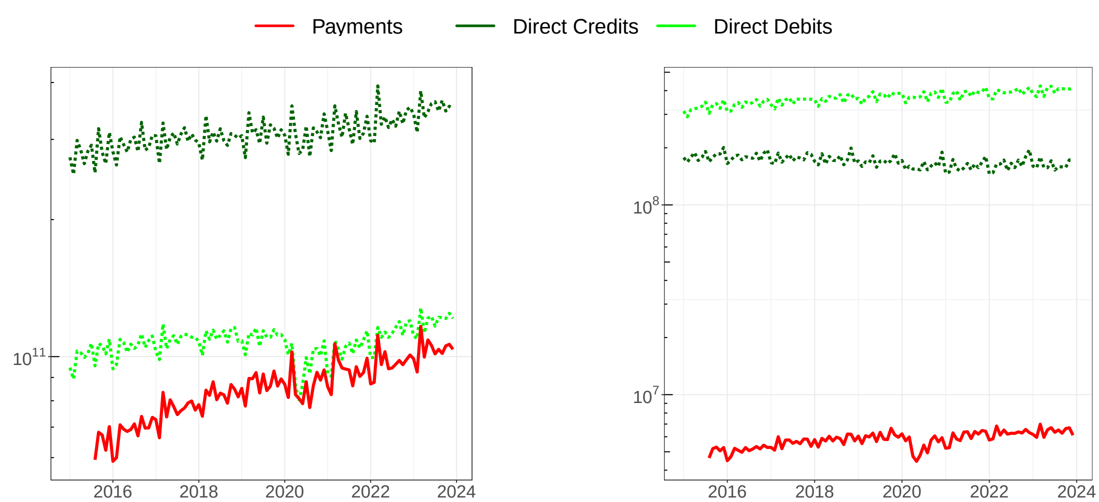
Figure A.1: OLD DATA: Monthly time series of payment data and major UK schemes



(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 (2023).

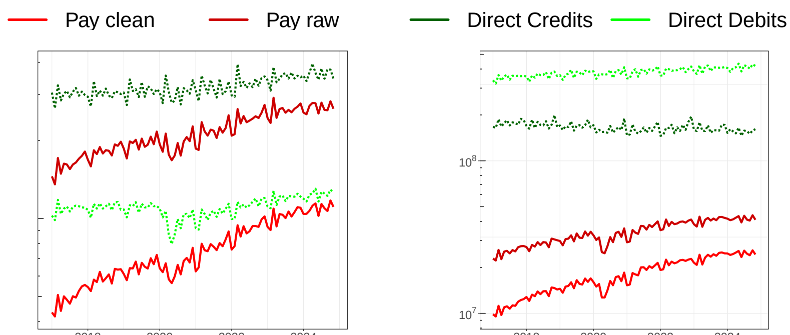
Figure A.2: OLD DATA: Monthly payment data, direct debits and direct credits



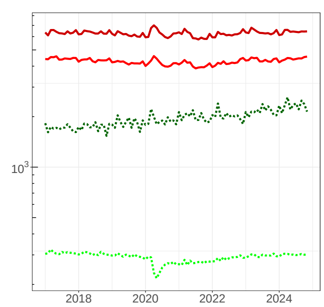
(a) Values (b) Counts

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

Figure A.3: Monthly payment data, direct debits and direct credits



(a) Values (b) Counts



(c) Average

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

A.2 Macroeconomic benchmarking

Table A.1: OLD DATA: Correlations with other payments and macro aggregates (excluding Covid-19 period)

	Bacs	FPS	CHAPS	GVA nsa	GVA 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 annual (monthly) payments and other UK payment schemes and macroeconomic aggregates (GDP, M1, M3, Prices) during 2016 and 2023 (08/2015 and 12/2023), excluding the Covid-19 period, proxied by 2020 to 2022 (03/2020 to 12/2022). 'sa' ('nsa') is short for (non-)seasonally adjusted. Our payment data and other payment aggregates are compared by aggregate values, counts, and average values (short 'avg') given by value divided by count. Growth rates are calculated as percentage growth compared to the (same month of the) previous year (for monthly data).[17]

Table A.2: OLD DATA: Correlations with other payments and macro aggregates (including Covid-19 period)

	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: This table shows Pearson correlations between annual (monthly) payments and other UK payment schemes and macroeconomic aggregates (GDP, M1, M3, Prices) during 2016 and 2023 (08/2015 and 12/2023), including the Covid-19 period. 'sa' ('nsa') is short for (non-)seasonally adjusted. Our payment data and other payment aggregates are compared by aggregate values, counts, and average values (short 'avg') given by value divided by count. Growth rates are calculated as percentage growth compared to the (same month of the) previous year (for monthly data). Bacs, FPS, and CHAPS data are obtained from Pay.UK (2023). Monthly GDP is proxied by indicative (non-)seasonally adjusted monthly 'Total Gross Value Added' index data published by the ONS (ONS, 2023b; ONS, 2023a). '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).

A.3 Comparison to national accounts

A.3.1 Aggregate network statistics

Table A.3: OLD DATA: Properties of the payment and ONS input-output networks in 2019

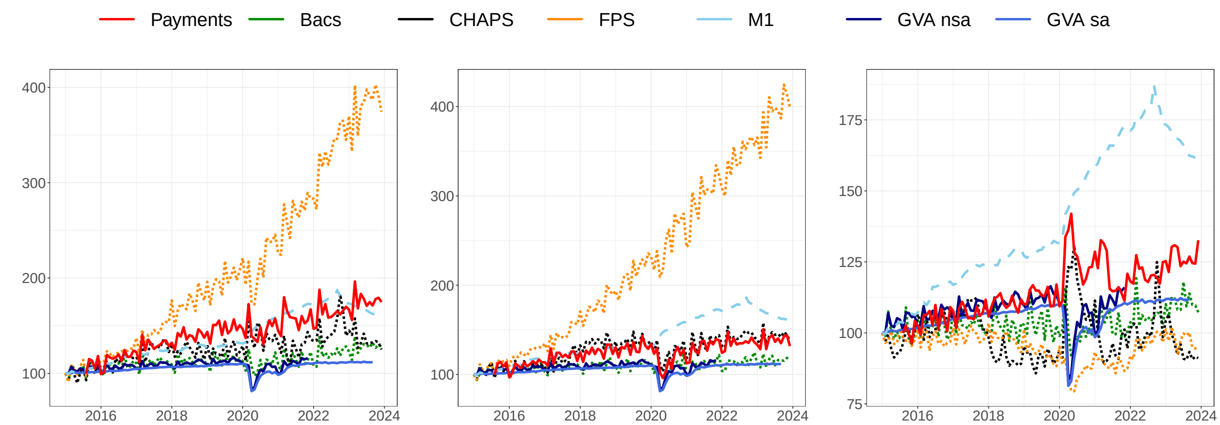
	Value	Count	PxP	SUT	IxI
Raw transactions					
Density	0.286	0.286	0.723	0.474	0.980
Average degree	28.550	28.550	75.202	49.260	101.885
Average strength	2,783.139	239,906.400	10,563.500	12,741.830	10,593.480
Average weight	97.483	8,403.027	140.468	258.667	103.975
Reciprocity	0.554	0.554	0.793	0.534	0.989
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: The first (second) column uses payment values (counts) as weights. The other columns represent official IOTs published by the ONS, where PxP is short for Product-by-Product, IxI for Industry-by-Industry, and SUT for Supply-and-Use Table. The data are aggregated into 105 distinct CPA codes (see Hötte, 2025, Sec. 4.1). Raw transaction data are shown in £ million.

Table A.4: Properties of the payment and ONS-based input-output networks in 2019

Variable	Value	Count	SUT	PxP	IxI
Raw transactions					
Density	0.534	0.383	0.475	0.727	0.979
Average degree	55.538	39.476	48.471	74.157	99.882
Average strength	6,529.642	1,687,796.000	12,526.810	10,495.810	10,500.010
Average weight	117.570	42,755.290	258.442	141.535	105.124
Reciprocity	0.783	0.749	0.534	0.799	0.989
Transitivity	0.747	0.671	0.750	0.861	0.991
Assortativity by degree	−0.338	−0.436	−0.189	−0.180	−0.005
Input shares					
Average strength	0.890	0.956	0.736	0.837	0.843
Average weight	0.016	0.024	0.015	0.011	0.008
Output shares					
Average strength	0.893	0.941	0.727	0.808	0.824
Average weight	0.016	0.024	0.015	0.011	0.008

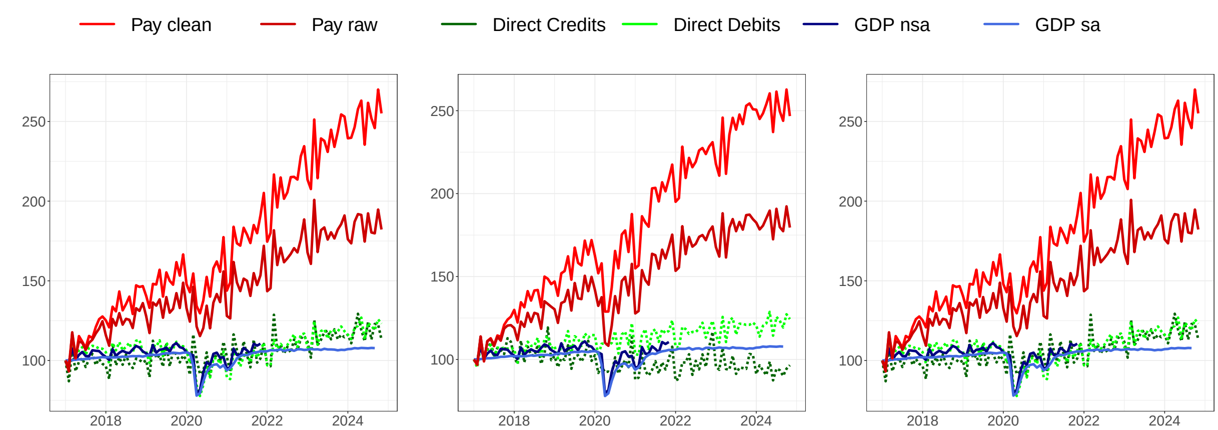
Notes: The first (second) column uses payment values (counts) as weights. The other columns represent official IOTs published by the ONS, where PxP is short for Product-by-Product, IxI for Industry-by-Industry, and SUT for Supply-and-Use Table. The data are aggregated into 104 distinct CPA codes (see Hötte, 2025, Sec. 4.1). Raw transaction data are shown in £ million.



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

Figure A.4: OLD DATA: Monthly UK payments, GDP and M1

Notes: These figures show monthly time series (indexed to 08/2015 = 100) for payments, the major UK payment schemes, and indicative (non-)seasonally adjusted monthly 'Total Gross Value Added' (GVA) data published by the ONS (ONS, 2023a; ONS, 2023b). Average values are obtained by dividing total values by counts.

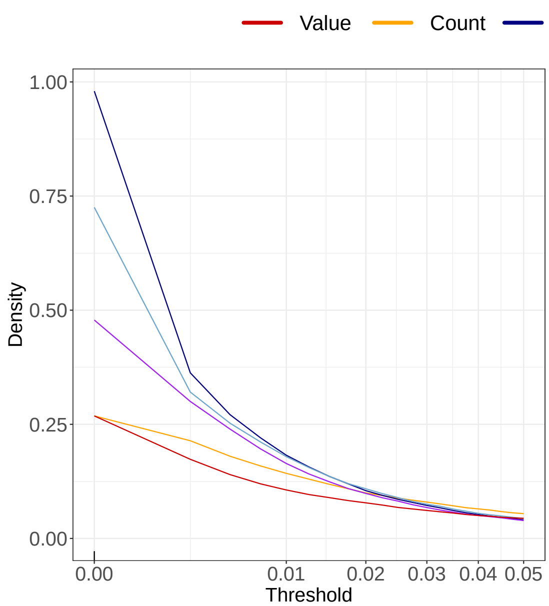


(a) Value (b) Counts (c) Average value

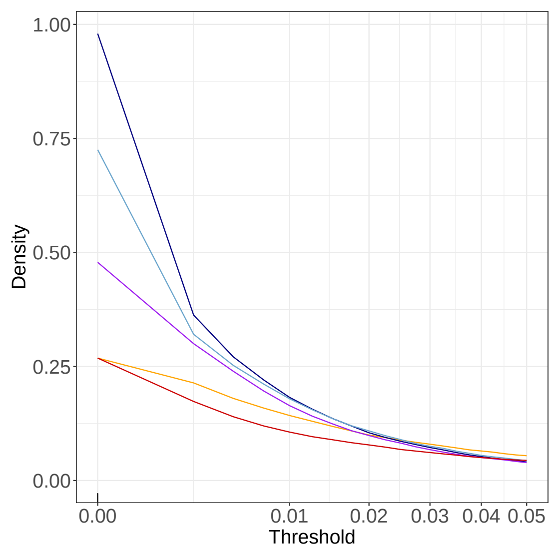
Figure A.5: Monthly payments, Direct Debits and Credits

Notes: These figures show monthly time series of the payment data, and Bacs transactions disaggregated by Direct Debits and Credits, indexed by 2019 = 100. The average value is calculated by dividing values by counts. The dark blue dashed line shows monthly deseasonalized GVA as a benchmark.

Figure A.6: OLD DATA: Network density at different truncation thresholds



(a) Input network

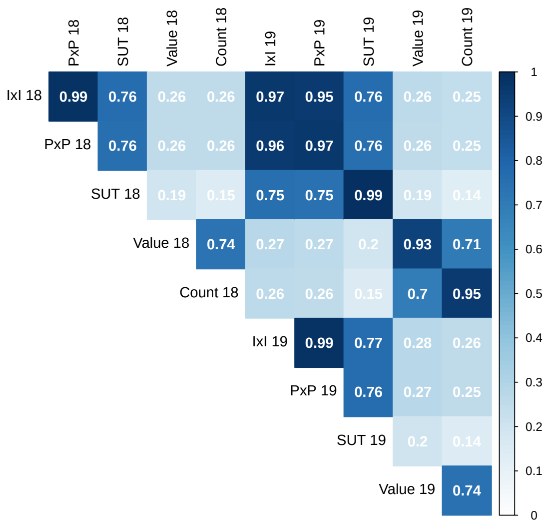


(b) Output network

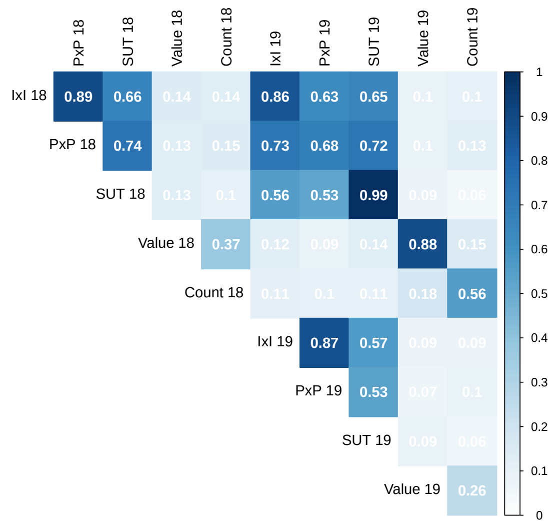
Notes: This figure shows the effect of network truncation thresholds (x-axis) on the network density (y-axix). In the left (right) figure, a link is removed if the input (output) share is smaller than the threshold value.

A.3.2 Edge-level correlations

Figure A.7: OLD DATA: Auto- & cross-correlations of input and output shares (2018-2019)



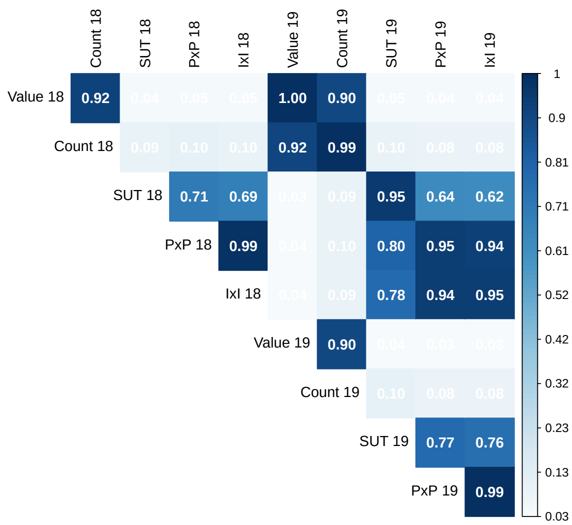
(a) Input shares



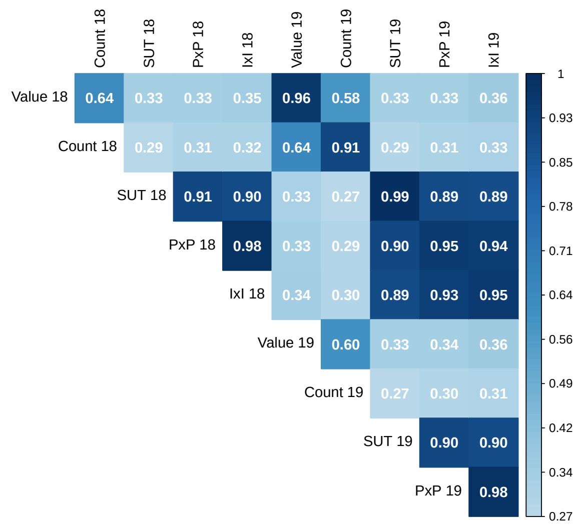
(b) Output shares

Notes: The correlations are measured by the Pearson correlation coefficient between input and output shares in the payment-based IOTs (values and counts) and the IxI, PxP, and SUTs.

Figure A.8: Auto- & cross-correlations at the edge level (2018-2019)



(a) Input shares

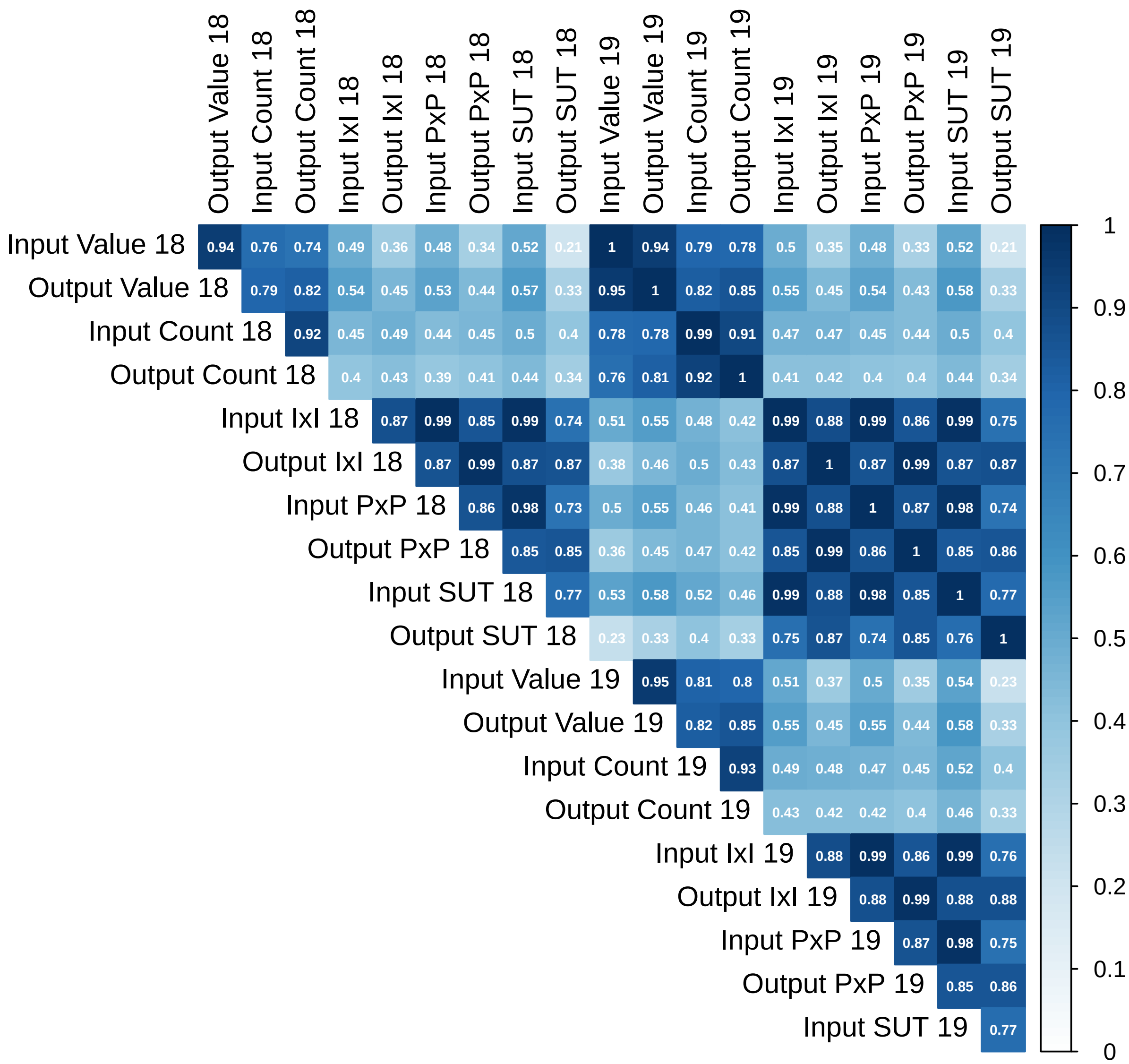


(b) Output shares

Notes: The correlations are measured by the Pearson correlation coefficient between raw transactions, input and output shares in the payment-based IOTs (values and counts) and the IxI, PxP, and SUTs.

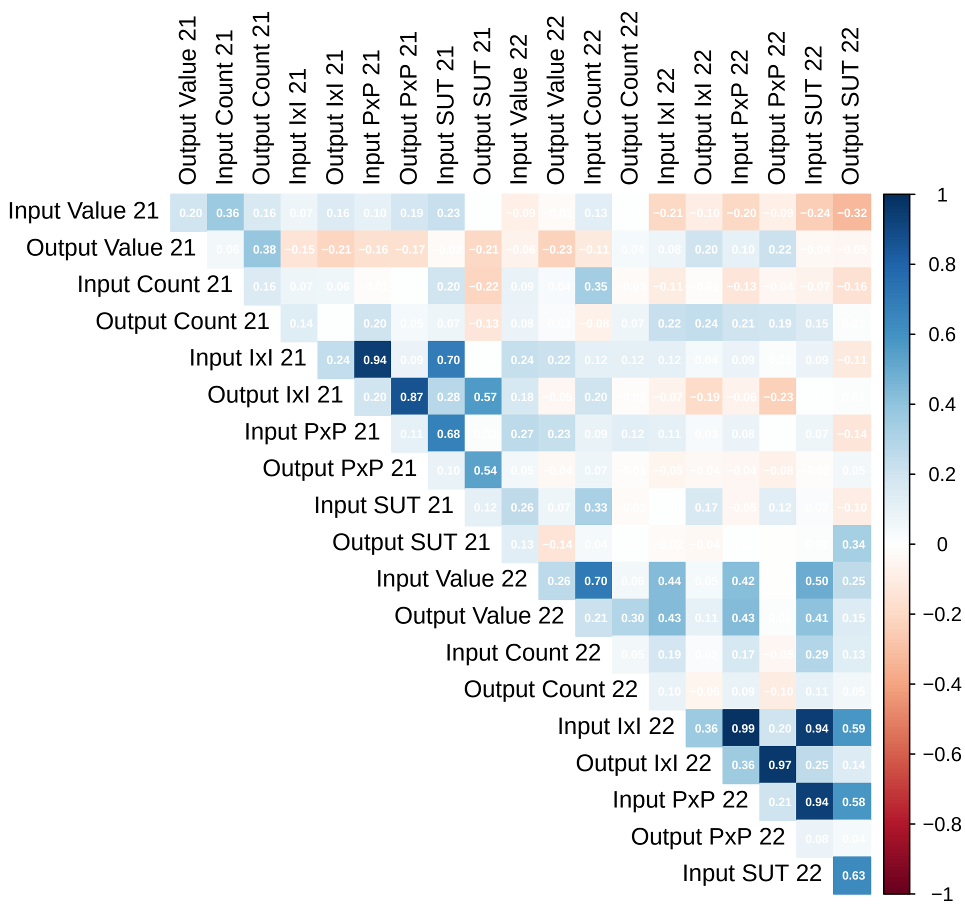
A.3.3 Industry-level similarities

Figure A.9: OLD DATA: Auto- and cross-correlations of inputs & outputs



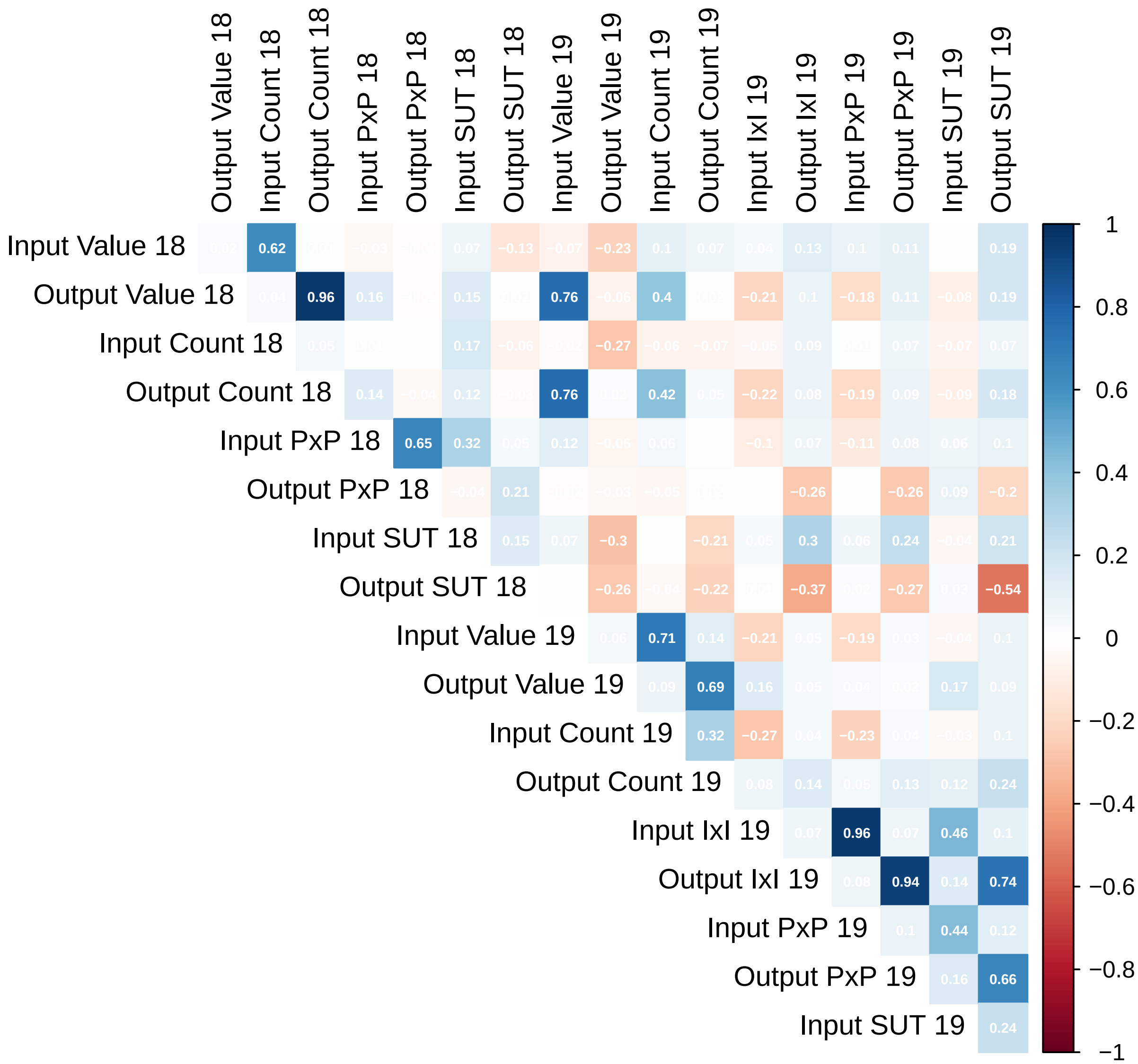
Notes: The correlations are measured by the Pearson correlation coefficient between industry-level annual outputs and inputs in 2018-19 calculated by using raw transaction values and counts of the payment data and the row- and column sums of ONS IxI, PxP, and SUTs.

Figure A.10: Auto- and cross-correlations of inputs & outputs growth rates



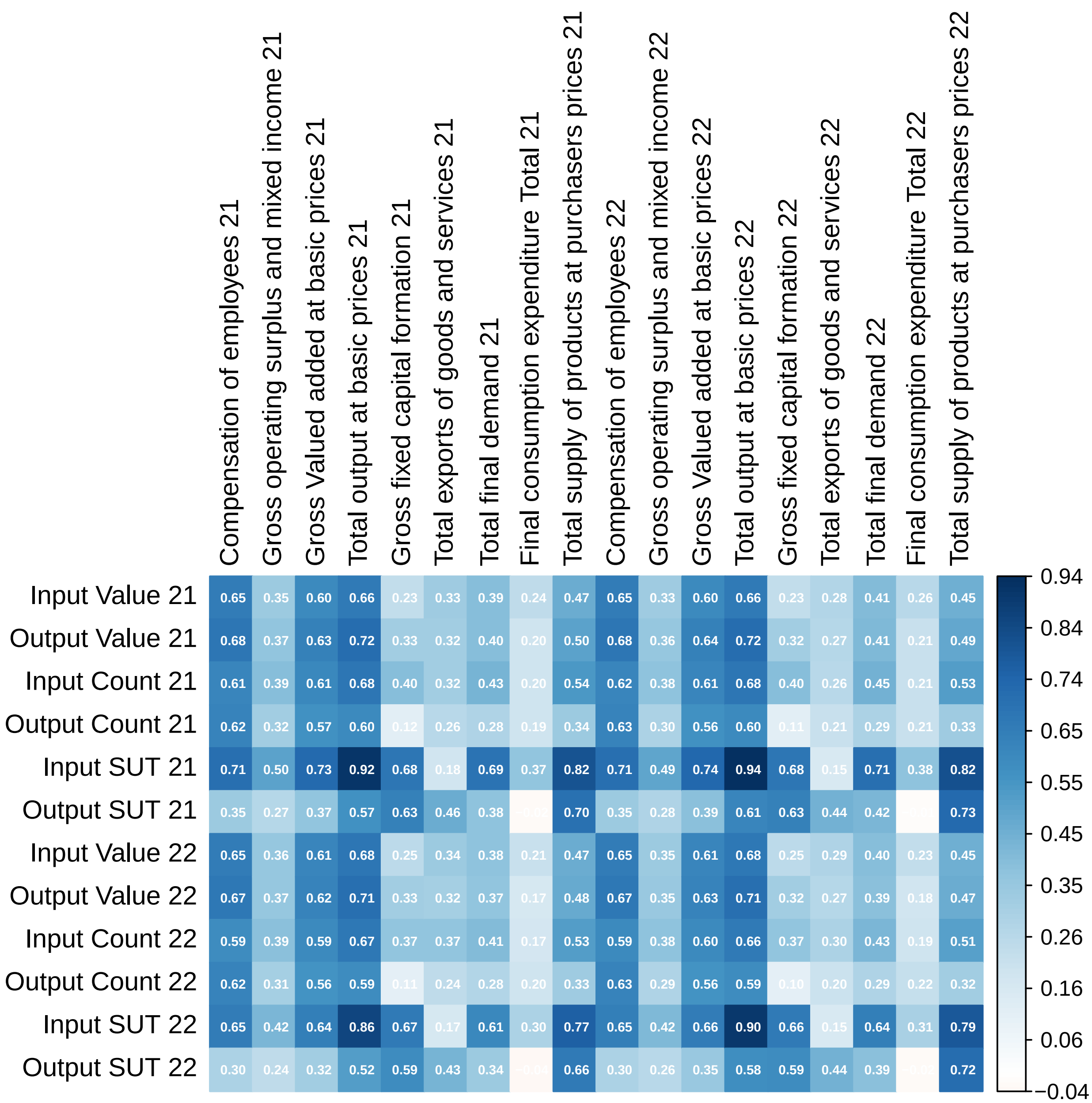
Notes: The correlations are measured by the Pearson correlation coefficient between industry-level annual outputs and inputs in 2021-22 calculated by using raw transaction values and counts of the payment data and the row- and column sums of ONS IxI, PxP, and SUTs.

Figure A.11: OLD DATA: Auto- and cross-correlations of input & output growth



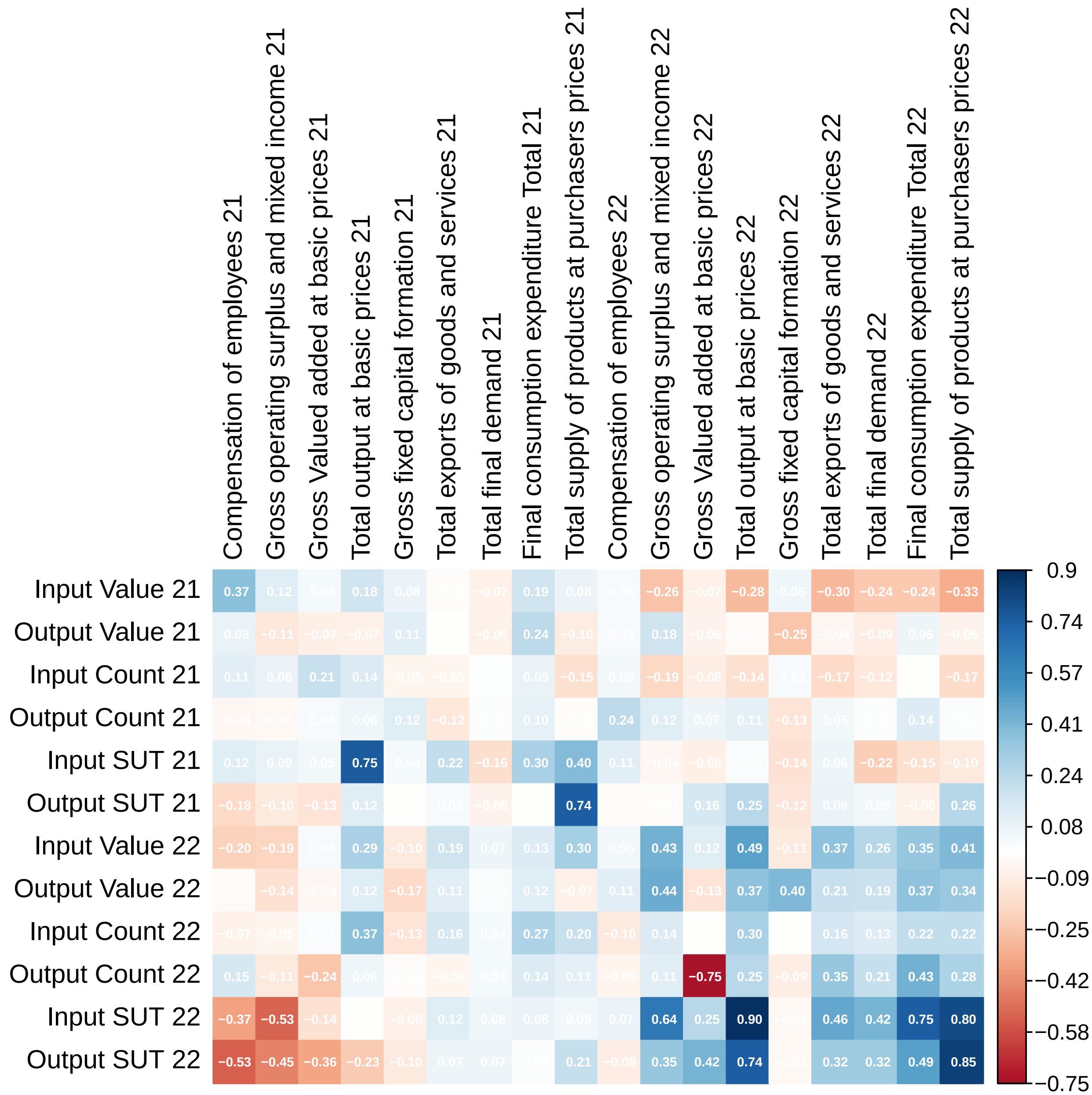
Notes: The correlations are measured by the Pearson correlation coefficient between industry-level annual growth rates of outputs and inputs in 2018 and 2019 calculated by using raw transaction values and counts of the payment data and the row- and column sums of ONS IxI, PxP, and SUTs.

Figure A.12: Correlations with other national accounts variables



Notes: The correlations are measured by the Pearson correlation coefficient between industry-level annual outputs and inputs in 2021-2022 calculated by using raw transaction values and counts of the payment data and various macro account data obtained from SUT.

Figure A.13: Correlations with other national accounts variables (growth rates)



Notes: The correlations are measured by the Pearson correlation coefficient between industry-level annual outputs and inputs in 2021-22 calculated by using raw transaction values and counts of the payment data and various macro account data obtained from SUT.

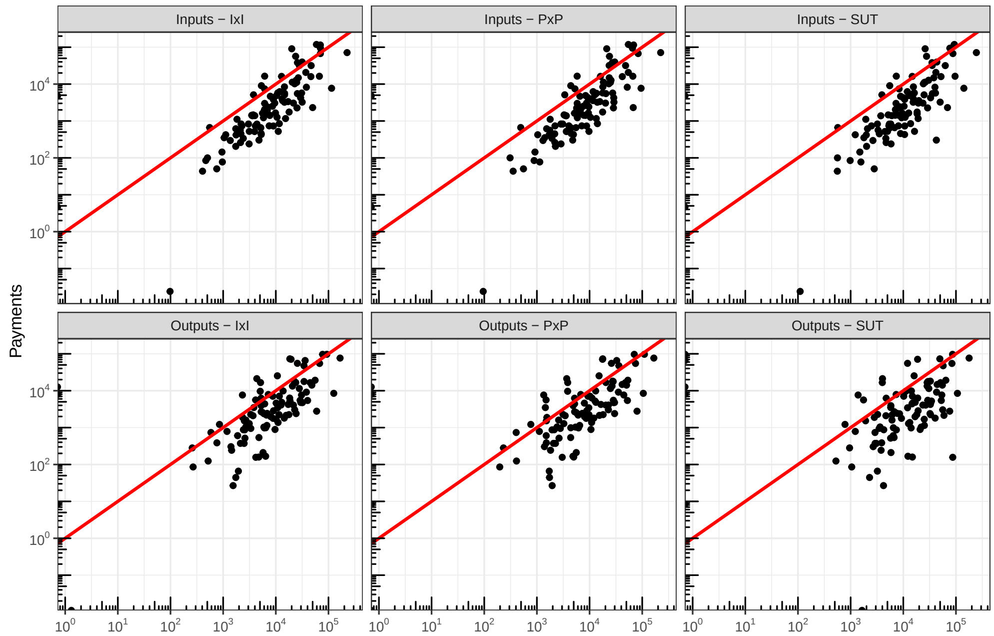


Figure A.14: Comparison of industry sizes in 2022

Notes: This figure shows the differences of industry-level aggregate inputs and outputs. Payment data values are shown at the vertical axis, and those for different ONS IOTs (IxI, PxP, SUT) at the horizontal. The red line shows at which the values in the payment data would be equal to those in the ONS table.

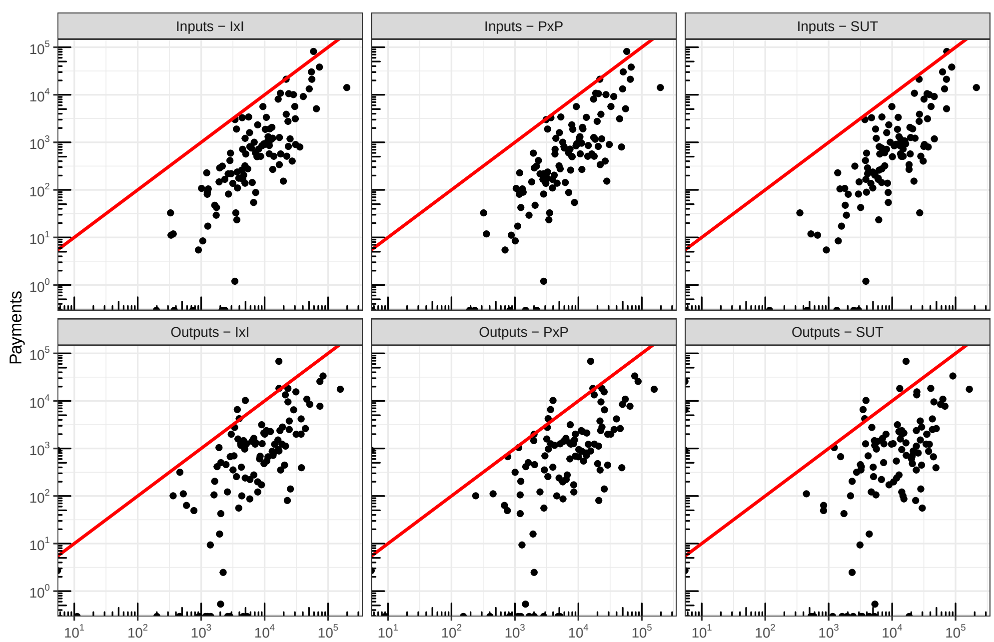


Figure A.15: OLD DATA: Comparison of industry sizes in 2019

Notes: This figure shows the differences of industry-level aggregate inputs and outputs. Payment data values are shown at the vertical axis, and those for different ONS IOTs (IxI, PxP, SUT) at the horizontal. The red line shows at which the values in the payment data would be equal to those in the ONS table.

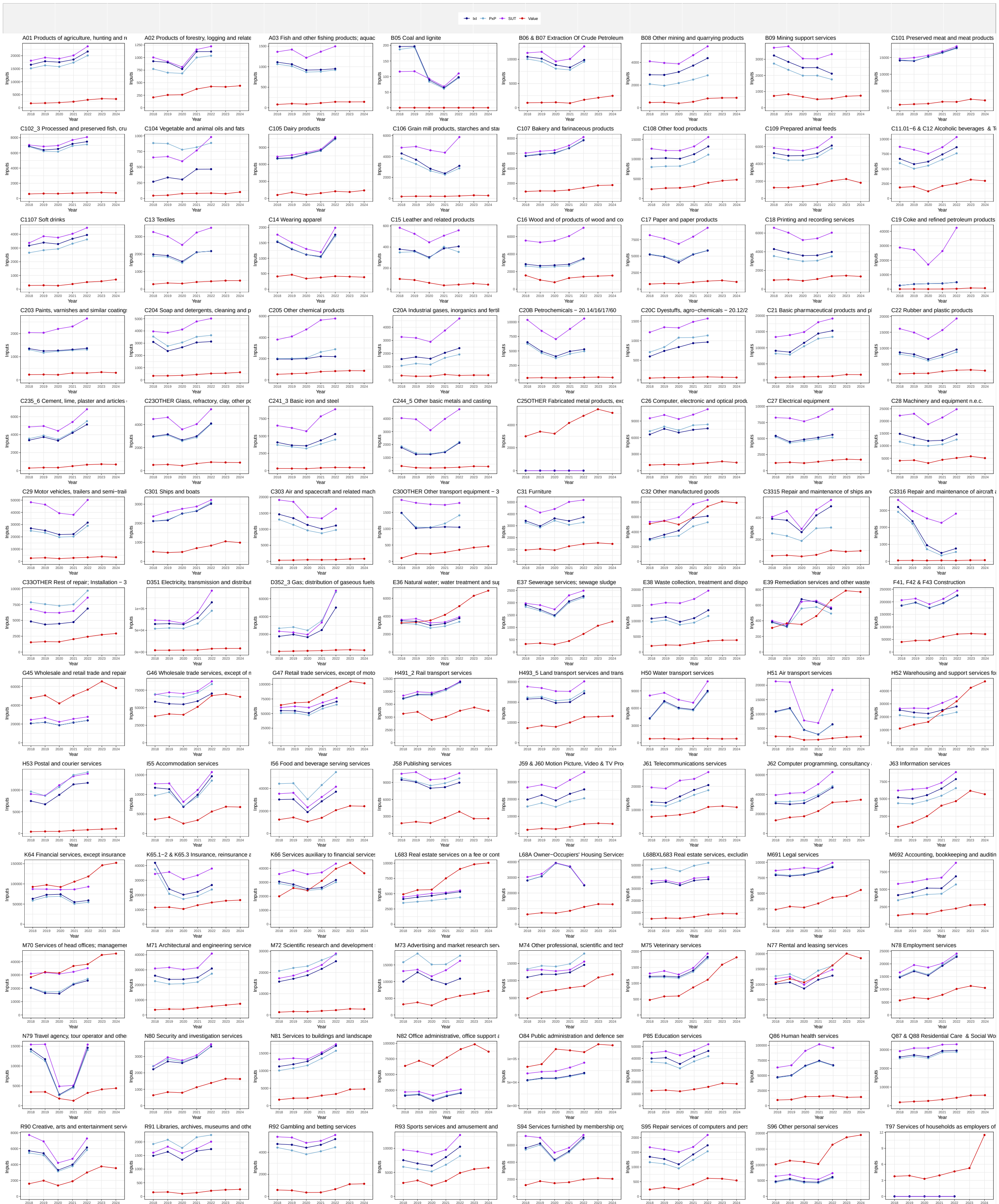


Figure A.16: Comparison of aggregate industry sizes by sum of inputs over time

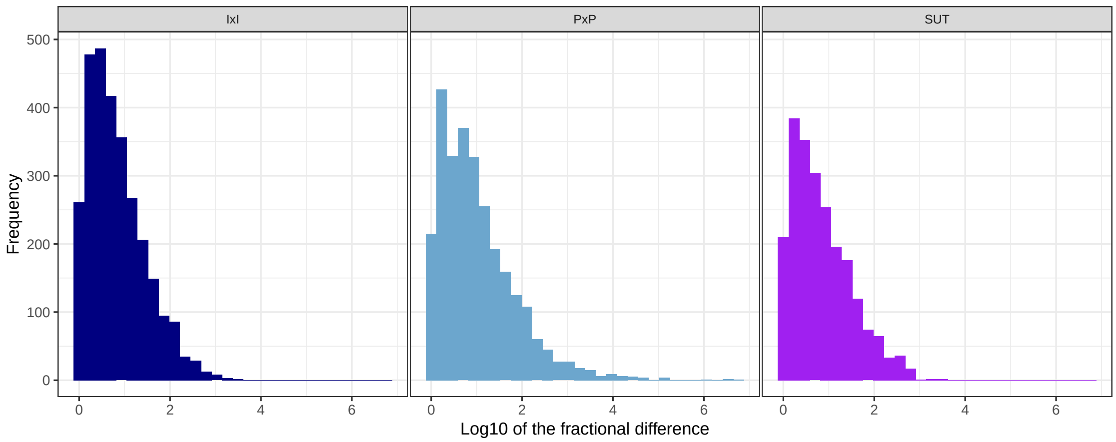
Notes: The figure shows how industry level aggregates evolved over time for different data sets. Industries are grouped into sectors. Aggregates are calculated as sum over all input links for an industry group. Scales of the y-axes differ across plots.

Figure A.17: Comparison of aggregate industry sizes by sum of outputs over time

Notes: The figure shows how industry level aggregates evolved over time for different data sets. Industries are grouped into sectors. Aggregates are calculated as sum over all output links for an industry group. Scales of the y-axes differ across plots.

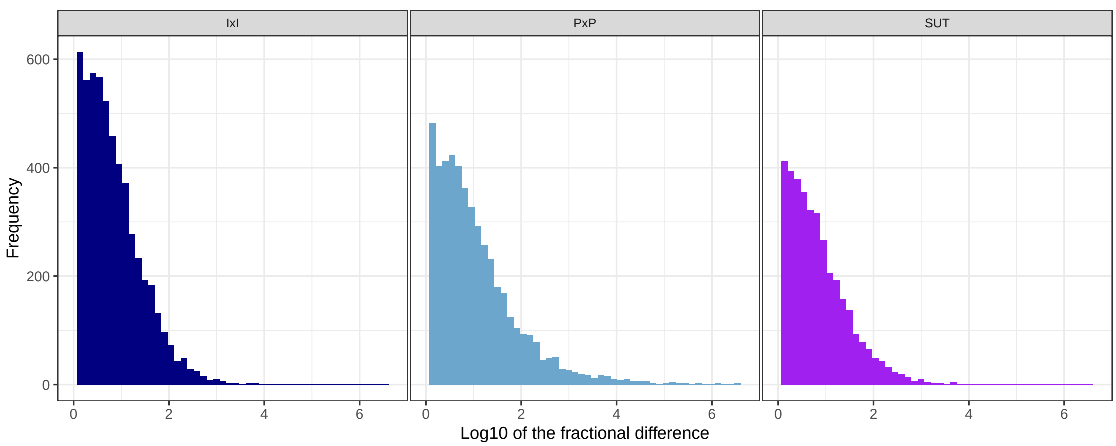
A.3.4 Quantifying the edge-level difference

Figure A.18: OLD DATA: Proportional differences between the ONS and payment-based IOTs



Notes: The figures show the distribution of the proportional edge-level differences (scaled at a log-10 basis) between the payment-based and ONS IOTs, using 2019 data. Industry pairs are removed if the transaction value is zero in one of the two datasets.[18]

Figure A.19: Proportional differences between the ONS and payment-based IOTs (2022 data)



Notes: The figures show the distribution of the proportional edge-level differences (scaled at a log-10 basis) between the payment-based and ONS IOTs, using 2022 data. Industry pairs are removed if the transaction value is zero in one of the two datasets.[19]

This subsection illustrates a quantification of edge-level differences and their distribution following the approach in Hötte (2025). The key observations are:

- **Scale:** Edge-level differences can be still significant (Fig. A.19 and A.21) but they tend to be smaller by scale in relation to the previous version of the data (A.21).
- **Distribution:** The distribution of edge-level differences indicates that there are more edges with small differences for all ONS IOTs. However, it also seems that there also more outliers, with transaction values between a pair of sectors being large in one data set and extremely tiny in the other. For

Table A.5: OLD DATA: 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 between the IxI, PxP, SUTs and the payment-based IOT in 2019. Unlike as in Fig. A.19, the values are not log-scaled.

Table A.6: Quantiles of the proportional differences

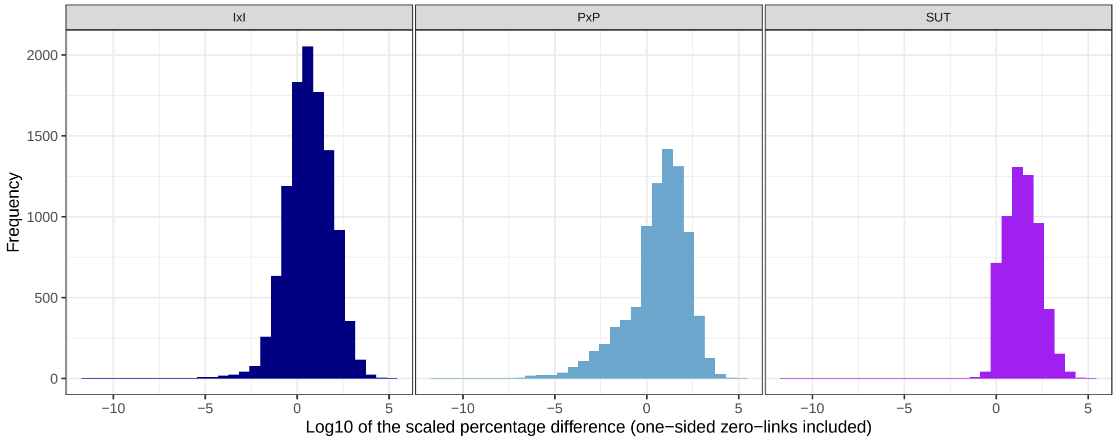
	25%	50%	75%	100%
IxI	2.414	6.420	25.614	$3,365,800,927,989$
IxI (incl zero)	1.000	1.000	1.000	1.041
PxP	2.414	6.420	25.614	$3,365,800,927,989$
PxP (incl zero)	1.000	1.000	1.000	1.041
SUT	2.085	4.773	13.963	$4,749.393$
SUT (incl zero)	1.000	1.000	1.000	1.031

Notes: Quantiles of the proportional differences between the IxI, PxP, SUTs and the payment-based IOT in 2022. Unlike as in Fig. A.19, the values are not log-scaled.

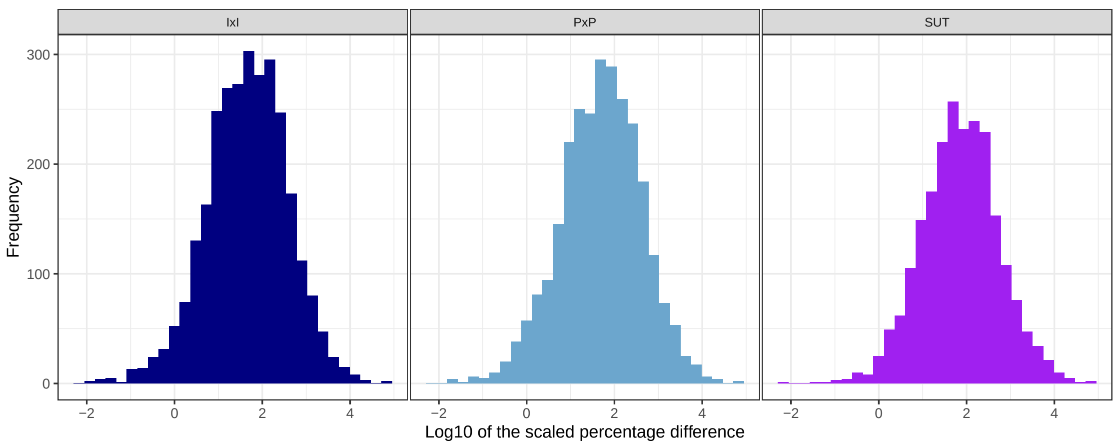
plotting the data, a handful of very extreme outliers have been removed. Potentially, this arises from a lower number of one-sided zero links in the novel data, which has not been tested here but might be indicated by the overall higher density of the payment network compared to the previous data version (see Sec. 4.1).

Figure A.20: OLD DATA: Scaled percentage difference

(a) One-sided zero-links included



(b) One-sided zero-links excluded



Notes: The figures show a comparison between the distribution of the scaled percentage edge-level differences (scaled at a log-10 basis) between the payment-based and ONS IOTs from 2019, when including or excluding links with a zero value in one of the two datasets.

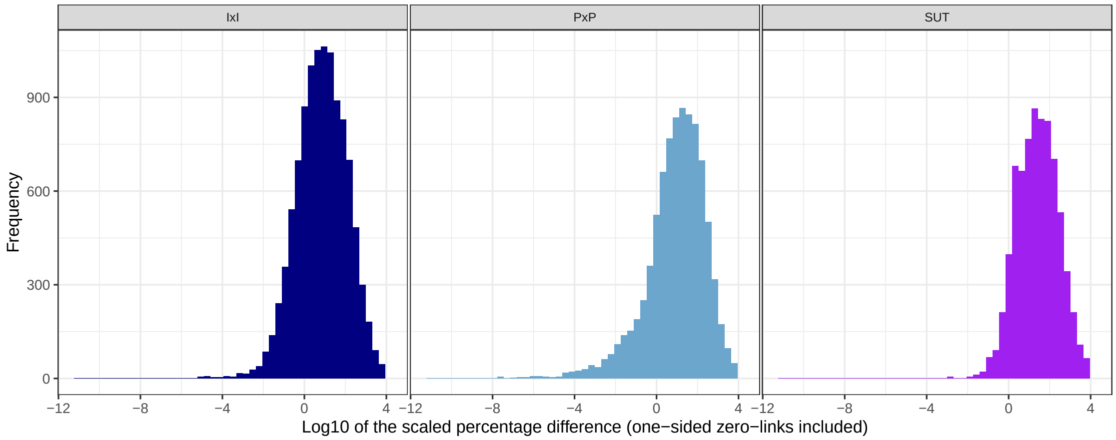
Table A.7: OLD DATA: Quartiles of the scaled percentage differences

	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

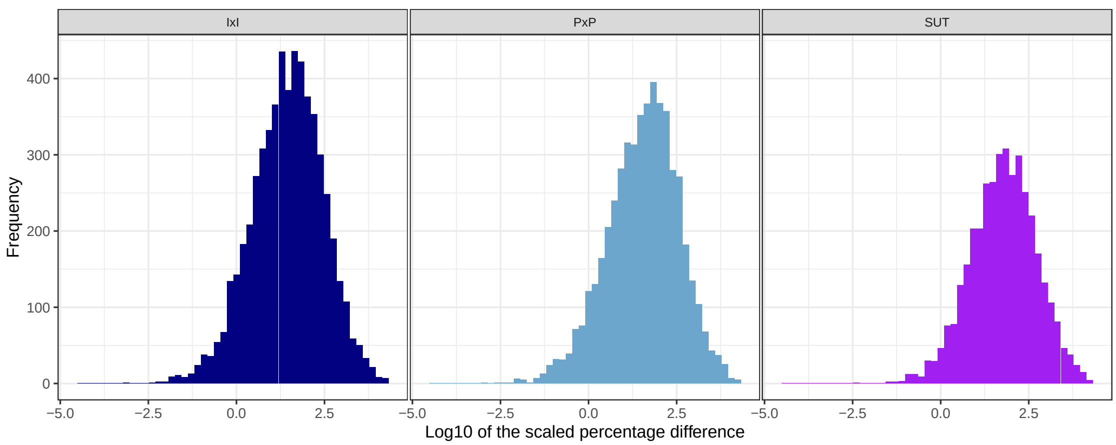
Notes: Quantiles of the scaled percentage differences between the IxI, PxP, SUTs and the payment-based IOT in 2019. Unlike as in Fig. A.21, the values are not log-scaled. The scale of the scaled percentage difference is not comparable to the proportional difference used in the main text.

Figure A.21: Scaled percentage difference

(a) One-sided zero-links included



(b) One-sided zero-links excluded



Notes: The figures show a comparison between the distribution of the scaled percentage edge-level differences (scaled at a log-10 basis) between the payment-based and ONS IOTs from 2022, when including or excluding links with a zero value in one of the two datasets.

Table A.8: Quartiles of the scaled percentage differences

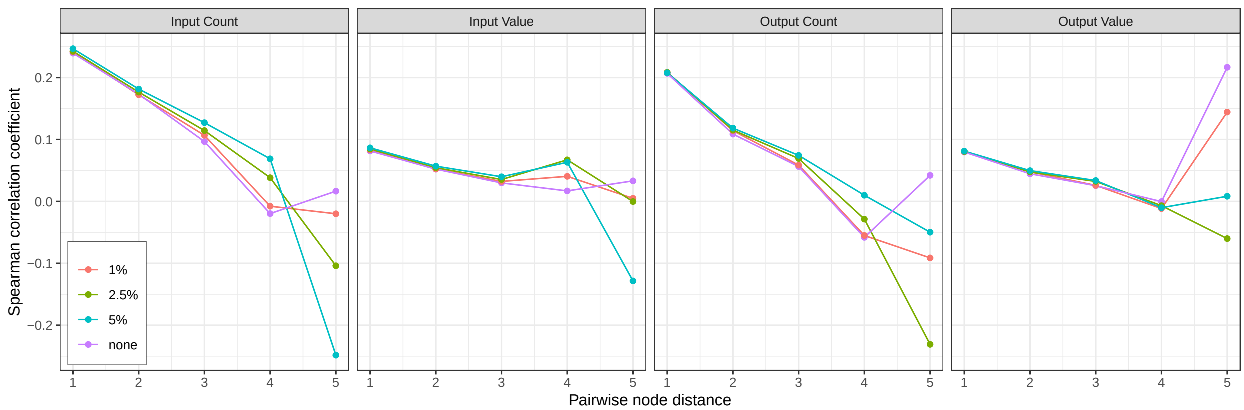
	25%	50%	75%	100%
IxI	7.867	41.837	171.152	59,823.480
IxI	1.599	12.901	84.852	59,595.450
PxP	7.867	41.837	171.152	59,823.480
PxP	1.599	12.901	84.852	59,595.450
SUT	14.375	62.388	254.859	47,126.070
SUT	4.464	25.256	132.529	53,446.630

Notes: Quantiles of the scaled percentage differences between the IxI, PxP, SUTs and the payment-based IOT in 2019. Unlike as in Fig. A.21, the values are not log-scaled. The scale of the scaled percentage difference is not comparable to the proportional difference used in the main text.

A.4 Stylized facts of granular networks

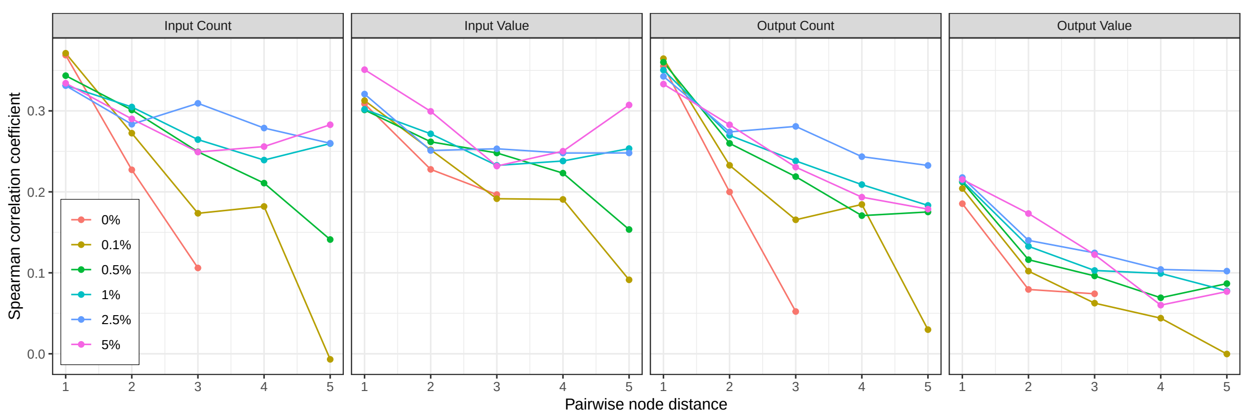
A.4.1 Correlations of growth rates

Figure A.22: OLD DATA: Correlations of growth rates



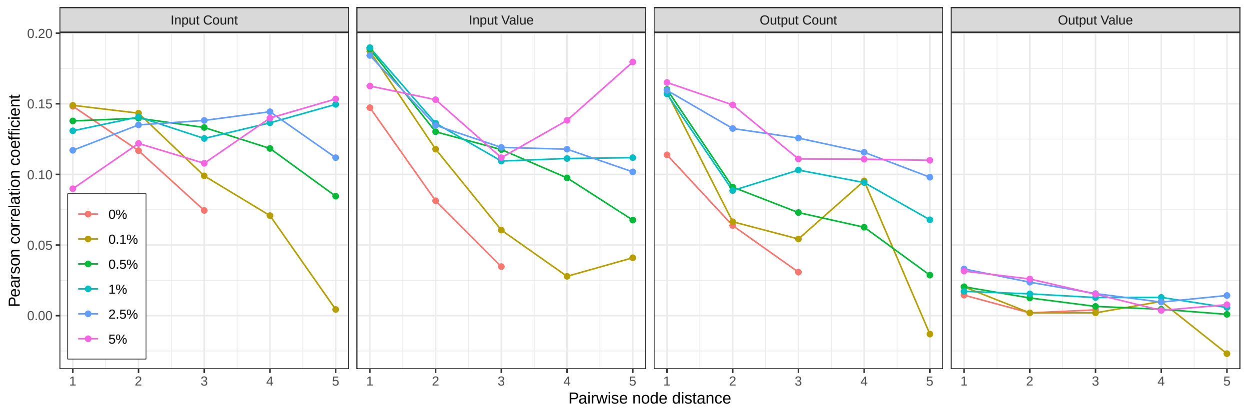
Notes: These figures illustrate the Spearman correlation coefficients between monthly (year-on-year) growth rates of directly and indirectly connected pairs of industries, using data from 2016 to 2019, excluding the Covid-19 period. The x-axis shows the distance of the industry pairs in annual network aggregates.[20] The colours indicate truncation thresholds imposed on the network before calculating the distances. Links with a weight (input share) below the threshold are removed (see also Section 4.1).

Figure A.23: Correlations of growth rates (intermediaries excluded)



Notes: These figures illustrate the Spearman correlation coefficients between monthly (year-on-year) growth rates of directly and indirectly connected pairs of industries, using data from 2016 to 2024. The x-axis shows the distance of the industry pairs in annual network aggregates.[21] The colours indicate truncation thresholds imposed on the network before calculating the distances. Links with a weight (input share) below the threshold are removed (see also Section 4.1).

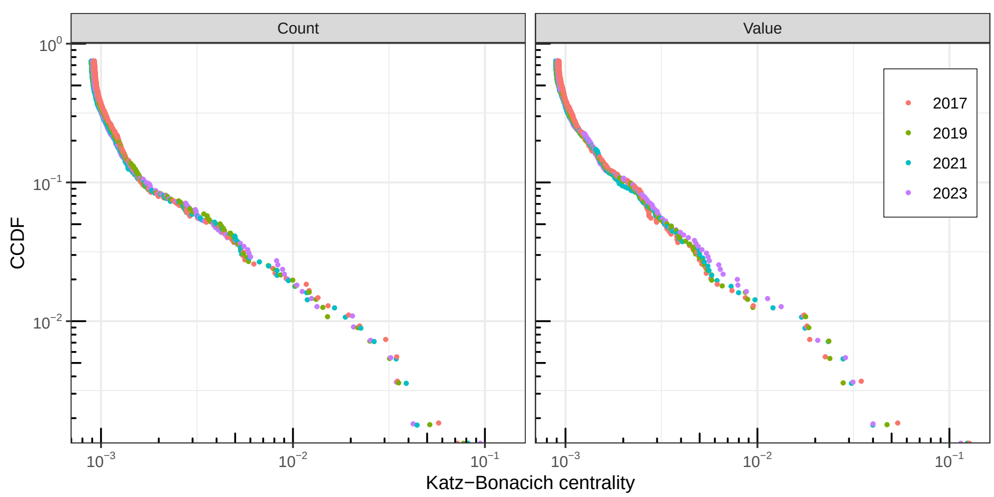
Figure A.24: Pearson correlations of growth rates



Notes: These figures illustrate the Pearson correlation coefficients between monthly (year-on-year) growth rates of directly and indirectly connected pairs of industries, using data from 2016 to 2018 and 2024. The x-axis shows the distance of the industry pairs in annual network aggregates.[22] The colors indicate truncation thresholds imposed on the network before calculating the distances. Links with a weight (input share) below the threshold are removed (see also Section 4.1).

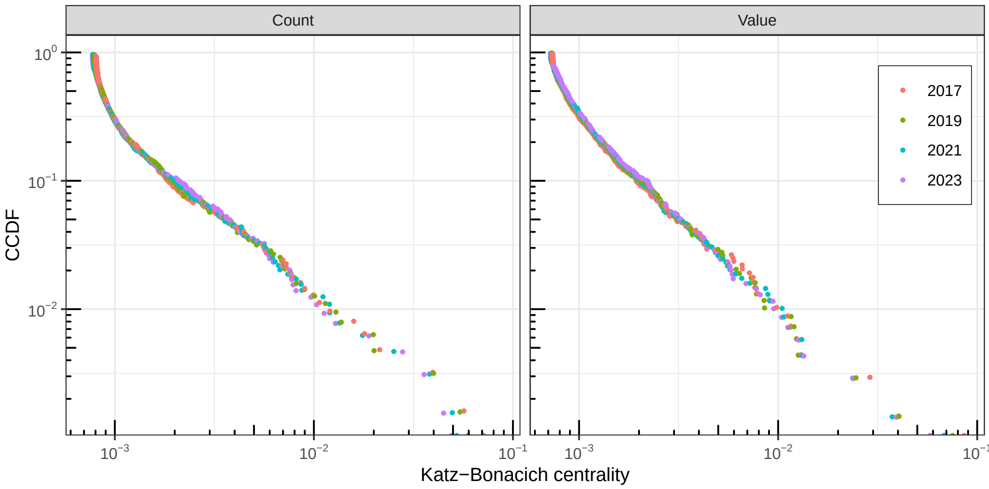
A.4.2 Centrality and power law

Figure A.25: OLD DATA: CCDF of the Katz-Bonacich centrality



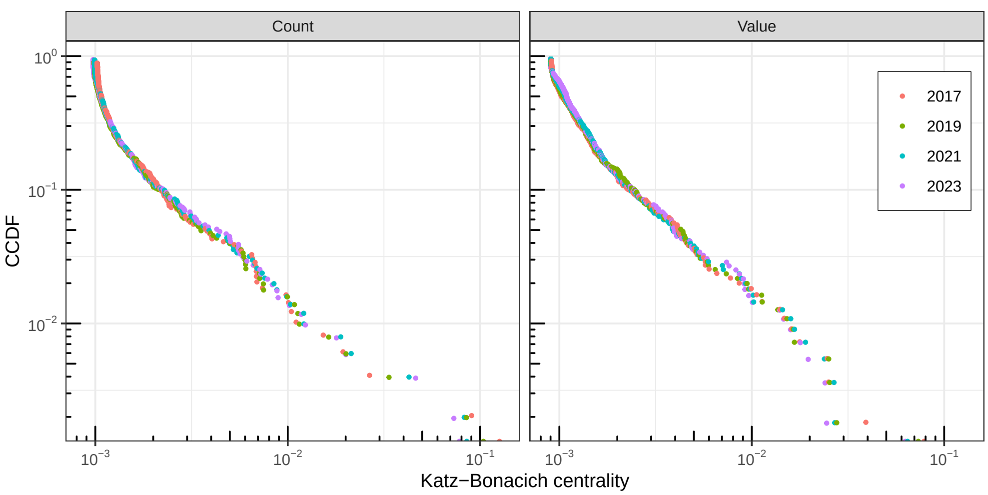
Notes: These figures illustrate the CCDF of the Katz-Bonacich centrality (see Hötte, 2025) for different years, using a labour share parameter of $\alpha_L = 0.5$ (Magerman et al., 2016) and payment-based input share matrices based on counts and values.

Figure A.26: CCDF of the Katz-Bonacich centrality (truncated data)



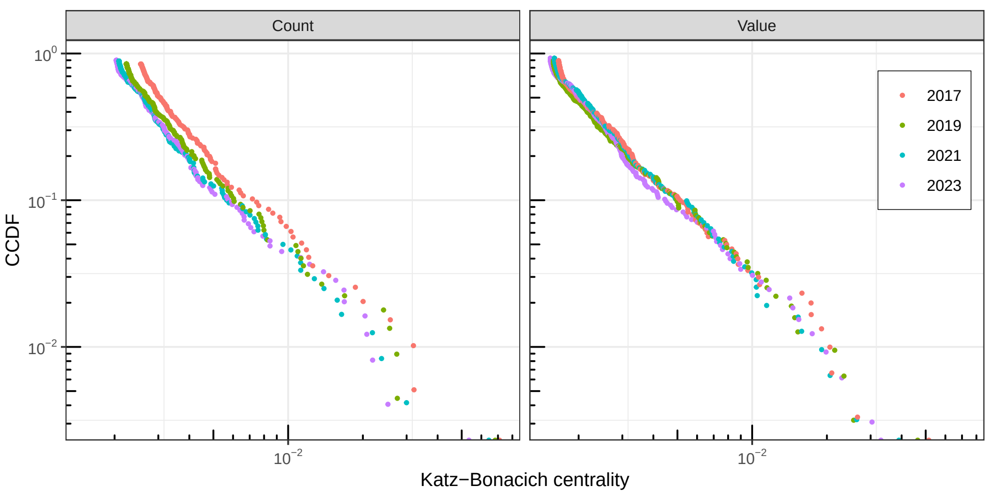
Notes: These figures illustrate the CCDF of the Katz-Bonacich centrality (see Hötte, 2025) for different years, using a labour share parameter of $\alpha_L = 0.5$ (Magerman et al., 2016) and payment-based input share matrices based on counts and values.

Figure A.27: CCDF of the Katz-Bonacich centrality (excluding intermediary sectors)



Notes: These figures illustrate the CCDF of the Katz-Bonacich centrality (see Hötte, 2025) for different years, using a labour share parameter of $\alpha_L = 0.5$ (Magerman et al., 2016) and payment-based input share matrices based on counts and values. Transaction links to intermediary sectors and public administration (G45, G46, G47, K64, K65, K66, O84) have been removed from the data.

Figure A.28: CCDF of the Katz-Bonacich centrality (excluding services)



Notes: These figures illustrate the CCDF of the Katz-Bonacich centrality (see Hötte, 2025) for different years, using a labour share parameter of $\alpha_L = 0.5$ (Magerman et al., 2016) and payment-based input share matrices based on counts and values. Transaction links to service-related sectors (G45-Q88, S94-U99) have been removed from the data.

Table A.9: OLD DATA: 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 supports the power law hypothesis.

Table A.10: Power law fitting statistics

	Value					Count				
Year	γ	xmin	logLik	KS.stat	p-value	γ	xmin	logLik	KS.stat	p-value
2017	1.356	0.002	486.138	0.033	0.94	1.394	0.001	890.361	0.06	0.105
2019	1.395	0.001	545.22	0.041	0.635	1.376	0.001	817.888	0.053	0.17
2021	1.573	0.001	1154.403	0.043	0.3	1.237	0.001	602.754	0.033	0.927
2023	1.483	0.001	890.667	0.035	0.733	1.243	0.001	606.849	0.034	0.93
	Data truncated at 10% quantile of transaction value									
2017	1.388	0.002	499.739	0.04	0.74	1.302	0.004	130.61	0.057	0.787
2019	1.43	0.001	560.129	0.039	0.713	1.368	0.001	766.544	0.054	0.162
2021	1.5	0.001	750.067	0.038	0.652	1.244	0.001	596.473	0.034	0.907
2023	1.543	0.001	952.907	0.036	0.662	1.269	0.001	668.004	0.032	0.95

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 supports the power law hypothesis.

Table A.11: Power law fitting statistics (intermediary sectors removed)

	Value					Count				
Year	γ	xmin	logLik	KS.stat	p-value	γ	xmin	logLik	KS.stat	p-value
2017	1.334	0.003	207.251	0.054	0.755	1.551	0.001	752.531	0.074	0.018
2019	1.335	0.002	330.213	0.04	0.958	1.167	0.002	243.483	0.064	0.49
2021	1.326	0.002	419.443	0.044	0.85	1.173	0.002	290.15	0.049	0.833
2023	1.318	0.002	423.306	0.046	0.73	1.219	0.002	368.96	0.054	0.642
	Data truncated at 10% quantile of transaction value									
2017	1.316	0.002	346.369	0.047	0.723	1.567	0.001	740.562	0.074	0.015
2019	1.401	0.002	537.185	0.041	0.855	1.177	0.002	243.556	0.069	0.4
2021	1.322	0.002	374.95	0.047	0.8	1.185	0.002	290.887	0.048	0.833
2023	1.351	0.002	437.322	0.048	0.7	1.218	0.002	362.8	0.054	0.615

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 supports the power law hypothesis. Transaction links to intermediary sectors and public administration (G45, G46, G47, K64, K65, K66, O84) have been removed from the data.

Table A.12: Power law fitting statistics (services removed)

	Value					Count				
Year	γ	xmin	logLik	KS.stat	p-value	γ	xmin	logLik	KS.stat	p-value
2017	1.777	0.002	1061.934	0.032	0.833	1.879	0.003	511.369	0.055	0.325
2019	1.592	0.002	492.461	0.04	0.708	1.892	0.002	668.283	0.048	0.392
2021	1.823	0.002	1254.179	0.039	0.388	2.115	0.002	1037.558	0.065	0.01
2023	1.887	0.002	1429.422	0.046	0.11	2.041	0.002	1059.163	0.043	0.322
	Data truncated at 10% quantile of transaction value									
2017	1.83	0.002	1088.138	0.028	0.902	1.94	0.003	482.776	0.058	0.275
2019	1.815	0.002	1070.375	0.043	0.31	1.848	0.003	451.254	0.049	0.51
2021	1.939	0.002	953.091	0.035	0.695	2.191	0.002	1055.467	0.07	0
2023	1.935	0.002	1429.714	0.044	0.168	2.186	0.002	1095.388	0.069	0.005

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 supports the power law hypothesis. Transaction links to service-related sectors (G45-Q88, S94-U99) have been removed from the data.

Table A.13: OLD DATA: 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

Table A.14: Top 10 industries by influence vector

SIC		Industry description	SIC		Industry description
2017					
		Value			Count
84110	0.0823	General public administration	61900	0.0722	Other telecommunications activities
82990	0.0394	Other business support services n.e.c.	82990	0.0557	Other business support services n.e.c.
64999	0.0285	Financial intermediation n.e.c.	84110	0.0388	General public administration
61900	0.0176	Other telecommunications activities	64999	0.0212	Financial intermediation n.e.c.
65110	0.0135	Life insurance	65110	0.0176	Life insurance
62090	0.0123	Other information technology services	62090	0.0157	Other information technology services
49410	0.0119	Freight transport by road	96090	0.0121	Other service activities n.e.c.
70100	0.0112	Activities of head offices	64910	0.0109	Financial leasing
62020	0.0092	Information technology consultancy	65120	0.0098	Non-life insurance
96090	0.0078	Other service activities n.e.c.	49410	0.0093	Freight transport by road
2023					
		Value			Count
84110	0.0557	General public administration	82990	0.0486	Other business support services n.e.c.
82990	0.0386	Other business support services n.e.c.	61900	0.0456	Other telecommunications activities
64999	0.0234	Financial intermediation n.e.c.	84110	0.0356	General public administration
62090	0.0136	Other information technology services	62090	0.0279	Other information technology services
49410	0.0124	Freight transport by road	64999	0.0186	Financial intermediation n.e.c.
70100	0.0111	Activities of head offices	96090	0.0128	Other service activities n.e.c.
61900	0.0107	Other telecommunications activities	64910	0.0115	Financial leasing
96090	0.0103	Other service activities n.e.c.	49410	0.0106	Freight transport by road
62020	0.0095	Information technology consultancy	65110	0.0095	Life insurance
65110	0.0094	Life insurance	46900	0.008	Non-specialised wholesale trade

Table A.15: Top 10 industries by influence vector (intermediary sectors removed)

SIC		Industry description	SIC		Industry description
2017					
		Value			Count
82990	0.0786	Other business support services n.e.c.	61900	0.126	Other telecommunications activities
61900	0.0392	Other telecommunications activities	82990	0.0903	Other business support services n.e.c.
49410	0.0251	Freight transport by road	62090	0.0266	Other information technology services
62090	0.0246	Other information technology services	96090	0.0194	Other service activities n.e.c.
62020	0.0177	Information technology consultancy	49410	0.0153	Freight transport by road
70100	0.0161	Activities of head offices	70229	0.0111	Non-financial management consultancy
96090	0.0148	Other service activities n.e.c.	62020	0.0104	Information technology consultancy
70229	0.014	Non-financial management consultancy	70100	0.0101	Activities of head offices
32990	0.0113	Other manufacturing n.e.c.	77110	0.0098	Renting & leasing of cars
77110	0.0106	Renting & leasing of cars	69201	0.0074	Accounting and auditing activities
2023					
		Value			Count
82990	0.0628	Other business support services n.e.c.	61900	0.078	Other telecommunications activities
49410	0.0245	Freight transport by road	82990	0.073	Other business support services n.e.c.
62090	0.024	Other information technology services	62090	0.0462	Other information technology services
61900	0.0196	Other telecommunications activities	96090	0.0201	Other service activities n.e.c.
96090	0.0179	Other service activities n.e.c.	49410	0.0179	Freight transport by road
62020	0.0159	Information technology consultancy	62020	0.0124	Information technology consultancy
70100	0.0146	Activities of head offices	70229	0.0118	Non-financial management consultancy
70229	0.014	Non-financial management consultancy	77110	0.0102	Renting & leasing of cars
32990	0.0101	Other manufacturing n.e.c.	69201	0.0089	Accounting and auditing activities
43999	0.0096	Other specialised construction n.e.c.	70100	0.0088	Activities of head offices

Notes: Transaction links to intermediary sectors and public administration (G45, G46, G47, K64, K65, K66, O84) have been removed from the data.

Table A.16: Top 10 industries by influence vector (service sectors removed)

SIC		Industry description	SIC		Industry description
2017					
		Value			Count
32990	0.0515	Other manufacturing n.e.c.	32990	0.071	Other manufacturing n.e.c.
43999	0.0266	Other specialised construction n.e.c.	35140	0.0321	Trade of electricity
35140	0.0209	Trade of electricity	33200	0.032	Industrial machinery installation
25990	0.0206	Metal products manufacture n.e.c.	43999	0.0258	Other specialised construction n.e.c.
35110	0.019	Production of electricity	36000	0.02	Water collection, treatment and supply
33200	0.0173	Industrial machinery installation	25990	0.0187	Metal products manufacture n.e.c.
22290	0.0173	Manufacture of other plastic products	43210	0.0146	Electrical installation
43210	0.0159	Electrical installation	35110	0.0126	Production of electricity
35130	0.0107	Distribution of electricity	29100	0.0121	Manufacture of motor vehicles
10910	0.0106	Manufacture of feeds for farm animals	22290	0.0118	Manufacture of other plastic products
2023					
		Value			Count
32990	0.033	Other manufacturing n.e.c.	32990	0.0535	Other manufacturing n.e.c.
43999	0.0304	Other specialised construction n.e.c.	43999	0.0252	Other specialised construction n.e.c.
35140	0.023	Trade of electricity	36000	0.0219	Water collection, treatment and supply
35130	0.0198	Distribution of electricity	33200	0.0207	Industrial machinery installation
25990	0.0174	Metal products manufacture n.e.c.	35140	0.0204	Trade of electricity
35110	0.0154	Production of electricity	35220	0.0168	Gas fuels distribution through mains
35220	0.0146	Gas fuels distribution through mains	35130	0.0168	Distribution of electricity
43210	0.0142	Electrical installation	43210	0.0156	Electrical installation
22290	0.0117	Manufacture of other plastic products	25990	0.0139	Metal products manufacture n.e.c.
42990	0.0109	Civil engineering construction n.e.c.	43220	0.0122	Plumbing/heat/air-condition installation

Notes: Transaction links to service-related sectors (G45-Q88, S94-U99) have been removed from the data.

B Concordance table

Table B.17 shows how industries classified by 5-digit SIC codes are re-allocated to CPA codes used in the official ONS IOT and national accounts data (ONS, 2009; Eurostat, 2015). The 5-digit SIC codes are aggregated into 104 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	·	·

SIC	SIC names	CPA	CPA names
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, incl. machinery and equipment and weapons & ammunition - 25.1-9
252	Manufacture of tanks, reservoirs and containers of metal	·	·
253	Manufacture of steam generators, except central heating hot water boilers	·	·
254	Weapons and ammunition	·	·
255	Forging, pressing, stamping and roll-forming of metal; powder metallurgy	·	·
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

SIC	SIC names	CPA	CPA names
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
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 B.17: Concordance table from SIC to CPA codes.