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Abstract

This study utilizes novel bank transaction data from business accounts to analyze inter-industry money flows and their relation to the input-output table. Results reveal a strong correlation between money flows in the bank data and physical flows in the input-output table. Further, lagged money flows from a destination industry significantly predict current money flows, highlighting the role of supply chain connections in shaping money flow dynamics.

JEL Classification Number: D57, E01, E23, E51

Keywords: input-output table, supply chain, money multipliers

*Waseda University (E-mail: kozo.ueda@waseda.jp, Address: 1-6-1 Nishi-Waseda Shinjuku-ku, Tokyo, JAPAN). The data were made available through a strict contract between Mizuho Bank and Waseda University, and were analyzed in a setting where measures such as masking and other anonymous processing were taken to prevent the identification of individuals. The author would like to thank the staff of Mizuho Bank, and seminar participants at the Canon Institute for Global Studies and the University of Osaka. The author is also grateful for the financial support from the JSPS (23H00046, 25K00622). The views and opinions expressed in this paper are solely those of the author and do not reflect those of Mizuho Bank.

1 Introduction

Empirical studies on business networks have typically relied on either firm-level data or input-output tables. These data sources are generally based on physical transactions of goods and services and are available only at low frequencies—annually for firm-level data and every five years for input-output tables. Networks depicted by firm-level data are often qualitative in nature, indicating whether a trade connection exists or not, and typically depend on self-reported information. Recent advances, such as the use of bank transaction data and value-added tax records, have begun to offer new perspectives on inter-firm networks.

This study contributes to this literature by using novel bank transaction data to shed light on business networks. Unlike earlier studies that use bank transaction data for individual accounts, our data are based on business accounts and capture actual monetary transactions at a high monthly frequency. To preserve anonymity, the data are aggregated at the industry level—similar to input-output tables but unlike standard firm-level data. The data are provided by Mizuho Bank, one of the three major banks in Japan, and are highly comprehensive. They cover the period from January 2019 to December 2023 (60 months), including both the number and amount of monetary flows among 447 sectors, which we aggregate into 144 industries to align with the industry classification in the input-output table.

Using this novel data, I undertake three main analyses. First, I document stylized facts about the business network, including time-series developments and measures of centrality, while also checking the representativeness of the data. I find that financial services and wholesale trade are the two most central industries in the network.

Second, I examine the relationship between the bank transaction data and the input-output table by comparing inter-industry flows. Since physical flows captured in the input-output table should move in the opposite direction to money flows in the bank transaction data, I assess the similarity between the two matrices after transposing one of them. The results show that the two are significantly positively correlated. This positive correlation is robust to various specifications, including the inclusion of industry fixed effects and limiting the analysis to manufacturing sectors. However, the estimated slope coefficient is approximately 0.5, which is significantly less than one, indicating the presence of measurement error in both data sources.

Third, I explore the dynamics of money flows. Thanks to the high monthly frequency of the data, I analyze how a shock in one month affects money flows from one sector to another in the following month, allowing an assessment of spillovers or multipliers. Specifically, using a balanced panel of monthly inter-industry money flows, I regress current money flows from industry i to j on lagged money flows to i and from j, as well as industry-pair and time fixed effects. The results indicate that lagged money flows from j are significantly positive, highlighting the role of upstream industries in driving spillovers through supply chains.[1] In contrast, lagged money flows to i are insignificant, suggesting that increased inflows to a sector do not necessarily translate into higher outflows to other sectors. In other words, supply shocks originating from upstream industries appear to be more important in shaping money flow dynamics than demand shocks from downstream industries.

To the best of my knowledge, no prior study has directly compared money flows derived from bank transaction or value-adde tax data with the input-output table. Even studies that use business accounts from bank transaction data remain rare, and those that do exist mainly adopt network science perspectives rather than economic analyses (e.g., Sokolov et al. 2012; Fujiwara et al. 2021; Saxena et al. 2021).[2] Constructing the input-output table is a costly task, involving the integration of various data sources and complex computations, and is still prone to measurement errors (see Copeland 1949; Klein 2003). By contrast, constructing an input-output table using bank transaction data is far less costly and more straightforward. In this respect, this study contributes to the advancement of input-output table construction.[3]

This study also deepens our understanding of shock propagation within supply chain networks. While numerous empirical studies have explored this topic using firm-level data (e.g., Inoue and Todo 2019; Carvalho et al. 2021; Arata and Miyakawa 2024 for studies related to Japan), this study is unique in leveraging high-frequency (monthly)

[1] In this study, upstream and downstream refer to suppliers and clients, respectively, in the context of physical flows within supply chains. Note that these directions are reversed in money flows, as suppliers receive payments from their clients.

[2] See Baker and Kueng (2022), Kubota, Onishi, and Toyama (2023), Ueda (2024, 2025) for studies that use individual accounts from bank transaction data. For the studies that use value-adde tax records, see, for example, Dyne, Magerman, and Rubínova (2015) and Diem et al. (2022).

[3] Although the field of ecological economics distinguishes between the monetary input-output table (MIOT) and the physical input-output table (PIOT), these concepts differ from what is analyzed in this study. In that literature, the MIOT corresponds to the standard input-output table, while the PIOT captures material flows in physical units, such as kilograms.

data on actual monetary transactions. Regarding the relative importance of demand versus supply shocks, this study provides fresh insights by examining whether shocks to money senders or money receivers drive changes in money flows in subsequent months.

The remainder of this paper is structured as follows. Section 2 describes the data. Sections 3 and 4 present the results on the relationship with the input-output table and the dynamics of money flows, respectively. Section 5 concludes.

2 Data

2.1 Data Descriptions

I use industry-by-industry panel data at the monthly frequency, constructed from actual transaction records involving Mizuho Bank. As one of Japan's three mega banks, Mizuho serves approximately 24 million individual accounts (equivalent to one in five people) and 420,000 business accounts (about one in seven firms), making the data highly comprehensive. Access to the data was granted through a formal agreement between Mizuho Bank and Waseda University. To protect privacy, all analyses were conducted under strict confidentiality protocols, including anonymization and masking. Furthermore, to prevent the identification of individual firms—particularly in industries with a small number of businesses—the data are aggregated at the industry level, similar to the structure of input-output tables, in contrast to standard firm-level datasets.

The main variables are the number and amount (in Japanese yen) of money flows from industry i to industry j in month t, calculated from transactions where either the payer (origin) or payee (destination) holds an account with Mizuho Bank. It is important to note that flows are double-counted when both parties use Mizuho Bank, which may introduce bias, particularly if firms within the Mizuho client base behave differently from those outside it. Unfortunately, no information is available regarding the purpose of the transactions, which may include procurement payments, trade credit, loan disbursements, or repayments. However, at the industry level, some aggregate firm characteristics, such as sales, profits, and outstanding bank borrowings as of 2022, are also available for firms that conduct transactions through their business accounts at Mizuho Bank.

The dataset spans January 2019 to December 2023 (60 months) and includes the number and total amount of monthly monetary flows between 447 sectors, which are further aggregated to 144 industries to match the classification used in the input-output table. Notably, the dataset includes a unique category labeled "households," which captures transactions between firms and individual household accounts.

While Mizuho Bank is considered highly comprehensive, it is nevertheless important to assess the representativeness of the data. Japan's three mega banks, including Mizuho, are generally more concentrated in urban areas such as Tokyo and tend to have stronger ties with larger firms. As a result, the number of money flows is likely to be underrepresented in the data compared to the total amount of money flows. In Appendix A.1, I examine the representativeness of the Mizuho data by comparing Financial Statements Statistics of Corporations by Industry provided by the Ministry of Finance, which is a fundamental statistical survey based on the Statistics Law in Japan. I confirm the significant positive correlations between the two data across industries, with regression slopes close to 45 degrees. This suggests that the Mizuho data are broadly representative, capturing most of the nationwide firm sales and bank borrowings without significant industry-level skew.

2.2 Observing the Data

Appendix A.1 presents basic statistics on money flows. It also includes a scatter plot comparing firm sales based on accounting data with money inflows by industry, given the close relationship between industry-level sales and inflows. The results show a strong positive correlation between the two variables.

Next, I investigate time-series changes in money flows from January 2019 to December 2023 by plotting Figures 1 and 2. Figure 1 illustrates the aggregate changes in both the number and amount of money flows. Four key observations emerge. First, the number of records is lower in the early months of 2019. This is due to a major system update around July 2019, which rendered data prior to that period incomplete. Second, there is clear seasonality, with the largest peak occurring in December each year. Third, the COVID-19 pandemic led to a noticeable decline in money flows during 2020–2021. Fourth, in 2022–2023, the amount of money flows rose sharply, while the number of transactions remained relatively stable. This likely reflects the global surge in inflation during that period.

Since the COVID-19 pandemic affected industries unevenly, Figure 2 examines money outflows from and inflows to four specific industries: accommodations, eating and drinking services, financial services, and wholesale trade. The first two industries were particularly impacted by the pandemic, while the latter two are the industries with the highest centrality (see below). The figure shows that the accommodation industry was hit hardest, with both money inflows and outflows plummeting during 2020–2021. As expected, the eating and drinking services industry also saw a significant decline. Interestingly, financial services experienced a comparable drop, especially in money inflows. In contrast, wholesale trade remained relatively stable. During the pandemic, the central and local governments introduced various support measures for affected industries—for example, subsidies for infection prevention in restaurants and compensations for employee work absences. However, such support is not clearly visible in the Mizuho data. This suggests two possibilities. First, transactions involving government entities may not be fully captured in the data. Second, government support may have been directed primarily toward individuals rather than businesses. For instance, compensation for work absences was typically paid directly to individuals.

In Appendix A.1, I further examine the characteristics of money flows using standard network analysis methods. I compute several centrality measures, including degree, PageRank, and eigenvector centrality, and find that they are highly correlated with one another. Industries such as financial services and wholesale trade stand out with high values for both PageRank and degree centrality.

3 Relationship with the Input-Output Table

In this section, I compare money flows based on the Mizuho data with the input-output table. To enable a meaningful comparison, I harmonize the industry classifications to 144 categories. Since the input-output table is for the year 2020, I aggregate monthly money flows over the same year to obtain annual totals. Importantly, because money flows move in the opposite direction to goods and services flows, I transpose the coefficients in the input-output table.

Figure 3 presents the main result of this section, showing a clear and statistically significant positive correlation between money flows and goods/services flows. This relationship remains robust across multiple specifications, as demonstrated in Table 1 and Figure 4. Specifically, I estimate the following regression:

$$\log_{10}(Money_{ij}) = \beta \log_{10}(IO_{ij}) + \alpha_i + \alpha_j + \varepsilon_{ij}, \tag{1}$$

where $Money_{ij}$ and IO_{ij} denote the monetary and goods/services flows between industry i and j, and α_i and α_j are industry fixed effects. The estimated coefficient β is consistently and significantly positive, around 0.5, regardless of whether I include fixed effects, a same-industry dummy (for $i = j$), or a quadratic term. The top panel of Figure 4 further supports this robustness by restricting the sample to manufacturing industries only.

Theoretically, the coefficient β should be one; however, the estimated value is approximately 0.5—significantly lower. One potential explanation is measurement error in the explanatory variable, namely the input-output table. Constructing an input-output table involves combining diverse data sources through a complex and labor-intensive process, making measurement error inevitable. Such error biases the estimated β downward. This issue may be particularly pronounced in certain sectors, such as finance and wholesale trade, which are difficult to measure accurately. Nevertheless, I confirm that the estimated coefficient remains below one even when the analysis is restricted to manufacturing industries. A second explanation is the potential lack of representativeness in the Mizuho Bank data. Although I demonstrated a high degree of representativeness in the previous section, this does not imply that the data fully capture all monetary flows across industries. Third, the two measures—physical flows in the input-output table and monetary flows in the bank data—may be intrinsically different. The input-output table primarily captures trade in intermediate goods, while monetary flows may include components of final demand, such as consumption, investment, and exports. Moreover, some monetary flows may reflect transactions not directly related to goods and services, such as financial transfers.[4]

Since the Mizuho Bank data include transactions involving the household sector, I compare these with consumption and compensation of employees recorded in the input-output table, which are components of final demand and value added, respectively. The bottom panels of Figure 4 present the results. The left panel relates to consumption and the right panel to compensation (i.e., wages). Both show significantly positive correlations. Notably, money flows from the household sector are strongly correlated with industry-level consumption. In contrast, money flows to the household sector are also significantly correlated with wages by industry, though the correlation is somewhat

[4]In Appendix A.2, I examine which industries exhibit large discrepancies between monetary and physical flows. The results reveal no clear pattern regarding the types of industries or the direction of flows that tend to diverge systematically.

weaker, possibly because such flows include payments to home businesses and certified professionals (e.g., lawyers and tax accountants).

Overall, these results suggest that money flows based on bank transaction data provide a valuable resource for constructing input-output tables. Given the substantial effort and complexity involved in compiling traditional input-output tables, the use of bank data offers a cost-efficient alternative. Moreover, bank data allow for the timely tracking of money flows, whereas traditional input-output tables are typically updated only every five years. While bank data may not fully substitute for the conventional compilation process, they can serve as a powerful complement, enhancing both efficiency, accuracy, and timeliness.

4 Dynamics of Money Flows

4.1 Method

While the previous section examined money flows at a given point in time, this section focuses on their dynamics. A key concern is the presence of spillovers or multipliers, that is, how shocks to one sector propagate to others and affect the aggregate economy. To investigate this, I estimate the following equation:

$$y_{ijt} = \beta_1 FROM_{it-1} + \beta_2 TO_{jt-1} + \rho y_{ijt-1} + \alpha_{ij} + \alpha_t + \varepsilon_{ijt}, \tag{2}$$

where y_{ijt} denotes the logarithm of money flows from industry i to j in month t, with a small constant (10^{-9}) added to accommodate zero flows.

Figure 5 visually illustrates the underlying intuition. The two key explanatory variables are (i) $FROM_{it-1}$: the total money inflows to industry i in month $t-1$. If firms tend to reallocate incoming funds to other partners, we expect a positive coefficient β_1. Another is (ii) TO_{jt-1}; the total money outflows from industry j in month $t-1$. This captures the idea that physical goods and services delivered to j (i.e., money flows from j) in the past may induce an increase in physical supply from j to i (i.e., money flows from i to j) in the current month. A positive coefficient β_1 would support this mechanism. More specifically, $FROM_{it}$ and TO_{jt} are defined as the logarithm of 10^{-9} plus the sum of money flows to i in month t, $\sum_k y_{kit}$, and 10^{-9} plus the sum of money flows from j in month t, $\sum_k y_{jkt}$, respectively. The equation also includes pair fixed effects α_{ij} to control time-invariant heterogeneity between industry pairs, time fixed effects α_t to account for common time-varying shocks, such as the COVID-19 pandemic, and the lag of the dependent variable to capture persistence. The standard errors are clustered by industry i and j.

The estimation uses a balanced panel of industry pairs (i, j) observed over 59 months. An industry pair is included if it recorded a positive money flow at least once during the sample period. The household sector and uncategorized industries are excluded. This results in a panel comprising 15,428 industry pairs.

Two points are worth noting. First, regarding endogeneity, the equation is specified as a reduced form and should not be interpreted as establishing causal effects of $FROM_{it-1}$ and TO_{jt-1} on y_{ijt}. Nonetheless, it provides useful insights into how these lagged aggregate flows are associated with current bilateral money flows. I deliberately exclude contemporaneous values of $FROM_{it}$ and TO_{jt} to avoid clear endogeneity bias, even though many transactions may occur within the same month. As such, the baseline specification captures only a partial picture of money flow dynamics.

Second, the inclusion of a lagged dependent variable and fixed effects raises the possibility of Nickell bias. While this is a well-known concern in short panels, the relatively long time span of our data, monthly observations over nearly five years, helps mitigate the severity of this bias.

4.2 Degree of Spillover

To interpret the estimated coefficients in equation (2), β_1 captures the effect of incoming money flows to the origin industry (industry i) on bilateral transactions, β_2 captures the effect of outgoing flows from the destination industry (industry j), and ρ reflects the persistence of bilateral flows through an autoregressive component.

To assess the implications of these coefficients, consider a simplified setting: a complete symmetric network with N nodes and unit density, where each pair of industries is connected by bidirectional unit money flows, totaling N^2 flows (within-industry flows included). Suppose a unit positive shock is applied at time $t = 0$, such that the total inflow to industry A increases by $1/N$, and assume $\beta_2 = 0$ for simplicity. In period $t = 1$, the increase in inflow to industry A leads to a rise in outflows from A by β_1/N per edge, multiplied across N edges, resulting in a total increase of β_1. In period $t = 2$, this effect propagates through both inertia ($\rho\beta_1$) and second-round flows. The second-round flows come from each of N nodes from A at $t = 1$, which sends $(\beta_1/N)/N \cdot \beta_1$

per edge. Aggregating across all N nodes and N edges, this yields a contribution of β_1^2. Iterating this process, the total impact of the initial shock accumulates geometrically as $\beta_1 + \beta_1(\rho + \beta_1) + \cdots = \beta_1/(1 - \rho - \beta_1)$. This expression quantifies the spillover effect of a one-time increase in money inflow to a node under the assumption that $\beta_2 = 0$.

Similarly, under the assumption that $\beta_1 = 0$, a unit positive shock originating from industry A (i.e., an increase in its outgoing flows) yields a total impact of $\beta_2/(1-\rho-\beta_2)$.

4.3 Estimation Results

Table 2 presents the main estimation results. Column (1) provides the baseline specification, indicating that the coefficient on TO_{jt-1}, representing physical flows to the destination industry in the previous month, is significantly positive at 0.056. In contrast, the coefficient on $FROM_{it-1}$, which captures lagged money inflows to the origin industry, is positive but statistically insignificant. The lagged dependent variable, y_{ijt-1}, enters significantly at 0.198. These findings suggest that physical flows contribute to subsequent transaction activity, consistent with the notion of input-output propagation, whereas monetary receipts do not exhibit a statistically significant effect.

Using the formula derived in the previous subsection, the implied propagation effect of a shock to physical flows is calculated as $\beta_2/(1 - \rho - \beta_2)$, which equals 7.5%.

Table 2 and Appendix A.3 show the robustness of the results. Excluding intra-industry flows (i.e., money flows where origin and destination industries are the same) has little effect on the results, as shown in column (2). Column (3) replaces the lagged variables $FROM_{it-1}$ and TO_{jt-1} with their contemporaneous counterparts. In this specification, both coefficients are significantly positive, though the estimates are likely biased due to endogeneity. In column (4), omitting the lagged dependent variable leads to increases in the coefficients on both $FROM_{it-1}$ and TO_{jt-1}, and both become statistically significant.[5]

In Table 3, I explore which types of industries play a key role as origins or destinations in the propagation of money flow spillovers. To this end, I estimate the following extended

[5]Appendix A.3 presents additional robustness checks. In particular, the results indicate that the estimated spillover effect of physical flows becomes more pronounced when financial transactions are excluded from the sample.

specification:

$$
\begin{aligned}
y_{ijt} = &\beta_1 FROM_{it-1} + \beta_2 TO_{jt-1} + \rho y_{ijt-1} + \alpha_{ij} + \alpha_t + \varepsilon_{ijt} \\
&+ \gamma_1 FROM_{it-1} \cdot X_i + \beta_2 TO_{jt-1} \cdot X_j,
\end{aligned} \tag{3}
$$

where X_i represents the firm characteristics of industry i. As industry characteristics X_i, I consider the borrowing ratio (defined as outstanding bank borrowings divided by sales), the logarithm of sales, the profit ratio (profits divided by sales), and several measures of network centrality.

The first to third columns of the table indicate that the coefficient on TO_{jt-1} is larger when the destination industry j exhibits a lower bank borrowing ratio or higher sales. This suggests that physical flows generate greater spillover effects when directed toward larger or less financially constrained industries. In contrast, the first column shows that the coefficient on $FROM_{it-1}$ increases with the bank borrowing ratio of the origin industry i, although the coefficient loses statistical significance in the subsequent specifications. This result suggests that money flow spillovers are more likely to originate from financially constrained industries. In other words, such industries may act as bottlenecks in the network, and the injection of funds into these sectors can alleviate the constraint, thereby facilitating spillovers.[6]

5 Concluding Remarks

This study utilizes novel bank transaction data from business accounts to examine their relationship with the input-output table and the dynamics of inter-industry money flows. The findings demonstrate the considerable potential of such data for future research, particularly in enhancing our understanding of economic linkages and sectoral interdependencies.

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Table 1: Relation with the Input-Output Table

	$\log10(Money_{ij})$					
	(1)	(2)	(3)	(4)	(5)	(6)
	All				Manufacturing	
$\log10(IO_{ij})$	0.665^{***}	0.555^{***}	0.426^{***}	0.389^{***}	0.685^{***}	0.631^{***}
	(0.013)	(0.017)	(0.016)	(0.022)	(0.031)	(0.032)
Same industry dummy			2.829^{***}	2.804^{***}		
			(0.089)	(0.090)		
$\log10(IO_{ij})^2$				0.015^{**}		
				(0.007)		
Constant	-1.831^{***}				-1.894^{***}	
	(0.022)				(0.038)	
Observations	6,527	6,527	6,527	6,527	1,790	1,790
Fixed effects	N	Y	Y	Y	N	Y
Adjusted R^2	0.285	0.594	0.650	0.651	0.219	0.487

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2: Money Flow Dynamics

	y_{ijt}			
	(1)	(2)	(3)	(4)
Lag	0.198***	0.198***	0.198***	
	(0.011)	(0.011)	(0.011)	
Lag FROM	0.047	0.047	−0.003	0.092***
	(0.029)	(0.029)	(0.024)	(0.011)
Lag TO	0.056**	0.057**	0.012	0.085***
	(0.024)	(0.024)	(0.020)	(0.009)
FROM			0.196***	
			(0.041)	
TO			0.123***	
			(0.030)	
Observations	899,632	891,372	899,632	899,632
Adjusted R^2	0.827	0.823	0.827	0.820

Note: Column (2) excludes money flows in the same industry.

Table 3: Heterogneity in Money Flow Dyanmics

	y_{ijt}		
	(1)	(2)	(3)
Lag	0.200^{***}	0.200^{***}	0.200^{***}
	(0.011)	(0.011)	(0.011)
Lag FROM	0.059^{*}	-0.091	0.024
	(0.034)	(0.529)	(0.549)
Lag TO	0.061^{**}	-0.667^{**}	-0.506^{*}
	(0.030)	(0.310)	(0.286)
Lag FROM × borrow	12.456^{***}	16.180	-34.244
	(3.278)	(13.135)	(48.952)
Lag TO × borrow	-16.028^{***}	1.738	-126.836^{**}
	(3.892)	(6.625)	(53.471)
Lag FROM × sales		0.006	0.002
		(0.019)	(0.019)
Lag TO × sales		0.027^{**}	0.024^{**}
		(0.012)	(0.011)
Lag FROM × profit			-0.309
			(0.275)
Lag TO × profit			-0.805^{**}
			(0.341)
Observations	861,341	861,341	861,341
Adjusted R^2	0.824	0.824	0.824

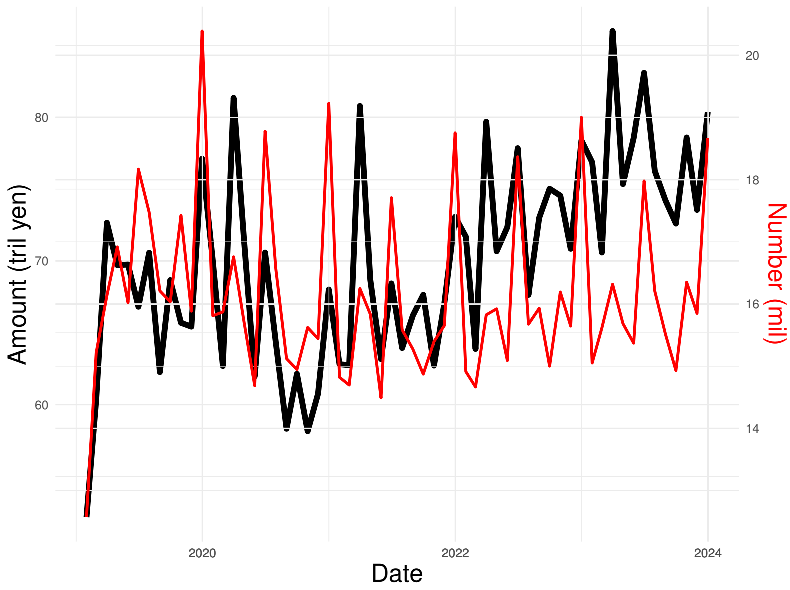

Figure 1: Time-series Changes in Money Flows

Figure 2: Time-series Changes in Money Flows by Industry

Note: Each line is normalized to one based on the average value from July to December 2019.

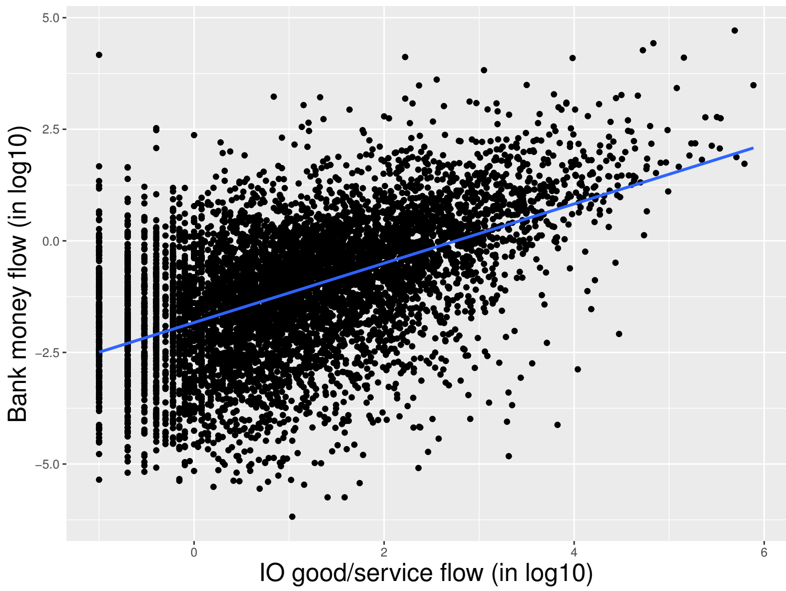

Figure 3: Relations with the Input-Output Table

Note: The horizontal axis represents the flow of goods and services from industry i to industry j, as recorded in the 2020 input-output table. The vertical axis represents the corresponding monetary flow from industry j to i, based on the Mizuho Bank data for the same year. Both axes use the common logarithm of values measured in billions of yen, excluding observations with zero values. The solid line indicates the fitted regression line.

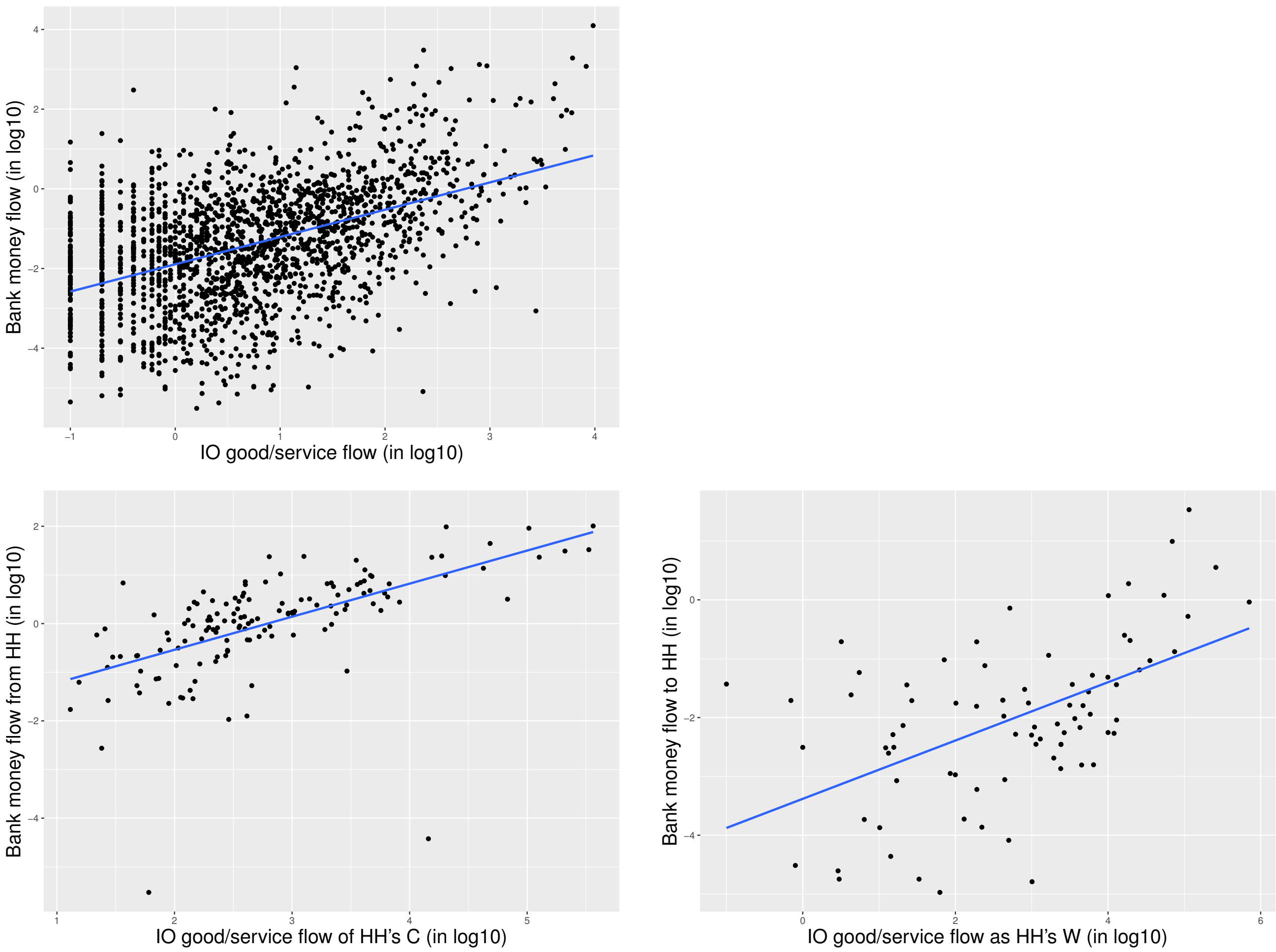

Figure 4: Further Relations with the Input-Output Table

Note: The top panel displays results restricted to manufacturing industries only. The two bottom panels pertain to the household (HH) sector.

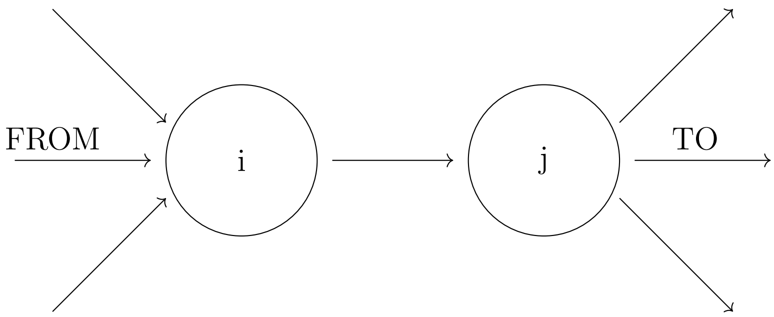

Figure 5: Money Flow Dyanmics

Note: The arrows represent the direction of money flows, which typically run counter to the physical flows of goods and services.

A Further Results

A.1 Observing the Data

Representativeness While Mizuho Bank is considered highly comprehensive, it is nevertheless important to assess the representativeness of the data. Japan's three mega banks, including Mizuho, are generally more concentrated in urban areas such as Tokyo and tend to have stronger ties with larger firms. As a result, the number of money flows is likely to be underrepresented in the data compared to the total amount of money flows.

In Figure 6, I examine the representativeness of the Mizuho data by comparing Financial Statements Statistics of Corporations by Industry provided by the Ministry of Finance, which is a fundamental statistical survey based on the Statistics Law in Japan. Specifically, I compare firm sales and outstanding bank borrowings at the industry level, which are shown in the left and right panels, respectively, where the values as of 2022 are expressed in the logarithm for the unit of one million yen. Each dot represents an industry, and the solid line is the fitted one. The dashed line is the 45 degree line, which represents that the Mizuho data and Financial Statements Statistics yield the same value.

The fitted solid line shows the significant positive correlations between the two data, further exhibiting the slope of nearly 45 degree. One reason why bank borrowings based on the Mizuho data lie above those based on Financial Statements Statistics in the right panel is that the former may capture consolidated accounting, while the latter is based on non-consolidated accounting. These two figures suggest that the Mizuho data are fairly comprehensive, capturing almost all nationwide firm sales and bank borrowings, with unskewed industry distribution.

Basic Observations I examine some basic characteristics of money flows in the Mizuho data. First, since money inflows to an industry are closely related to firm sales in that industry, I present Figure 7, which shows a scatter plot of firm sales (the variable plotted on the vertical axis in the left panel of Figure) against money inflows by industry. The values, as of 2022, are expressed in logarithms, with units in one billion yen. The results reveal a strong positive correlation between the two variables. The fitted slope is close to 45 degrees, and most dots lie near the dashed line. While some industries, such as tobacco, public administration, and financial services, deviate from this one-to-one

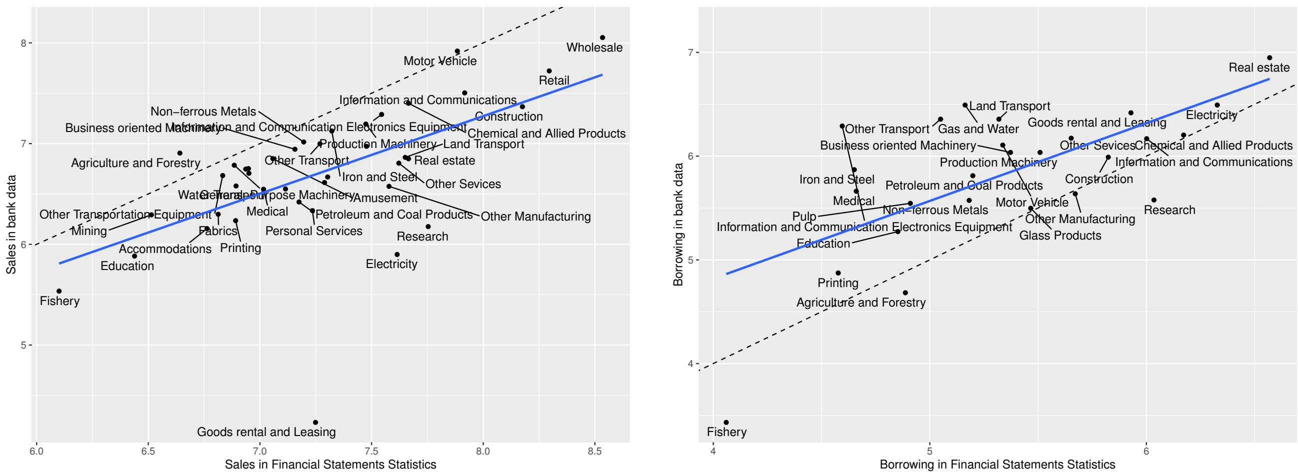

Figure 6: Checking Representativeness: Comparison with Financial Statements Statistics of Corporations by Industry

Note: The values as of 2022 are expressed in the logarithm for the unit of one million yen.

relationship, the figure overall suggests that money inflows can serve as a reliable proxy for firm sales.

Table 4 and Figure 8 present summary statistics for money flows as of December 2023. The money flows are represented as a 144 × 144 matrix, in which 9,196 out of 20,736 possible industry pairs record zero transactions. According to the table, the average number of money flows per non-zero industry pair is 93, and the average transaction amount is 2 billion yen (approximately 14 million USD at an exchange rate of 140 yen per dollar). The figure indicates that the distribution of the number of money flows is right-skewed, whereas the distribution of the transaction amounts appears more symmetric, resembling a log-normal distribution.

Table 4: Money Flows between 144×144 Industries

Variable	N	N of zero	mean	p25	median	p75	SD
Number	20,736	9,196	51.86	0.00	1.00	8.00	693.75
Amount (bil yen)	20,736	9,196	1.16	0.00	0.00	0.01	44.52
Number	11,540	0	93.18	2.00	7.00	24.00	927.90
Amount (bil yen)	11,540	0	2.09	0.00	0.01	0.05	59.66

Note: as of December 2023.

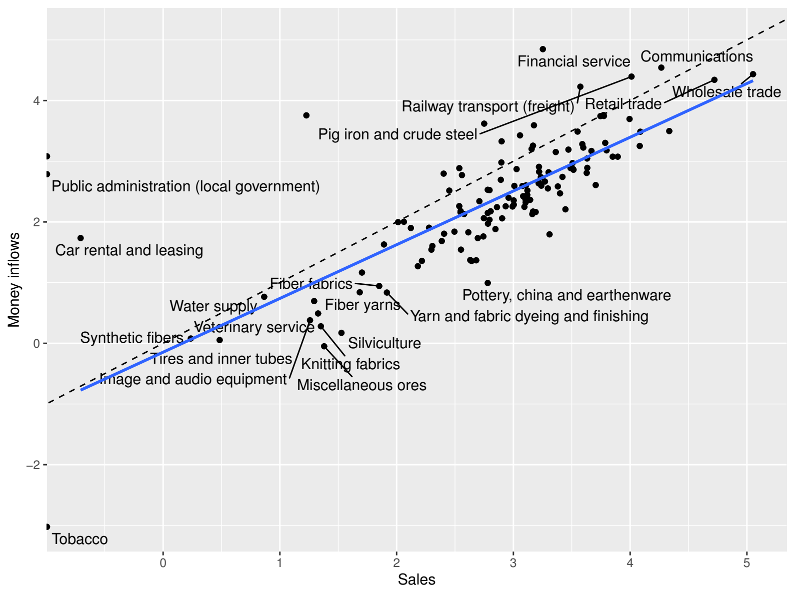

Figure 7: Comparison between Sales and Money Inflows

Note: The values as of 2022 are expressed in the logarithm for the unit of one billion yen.

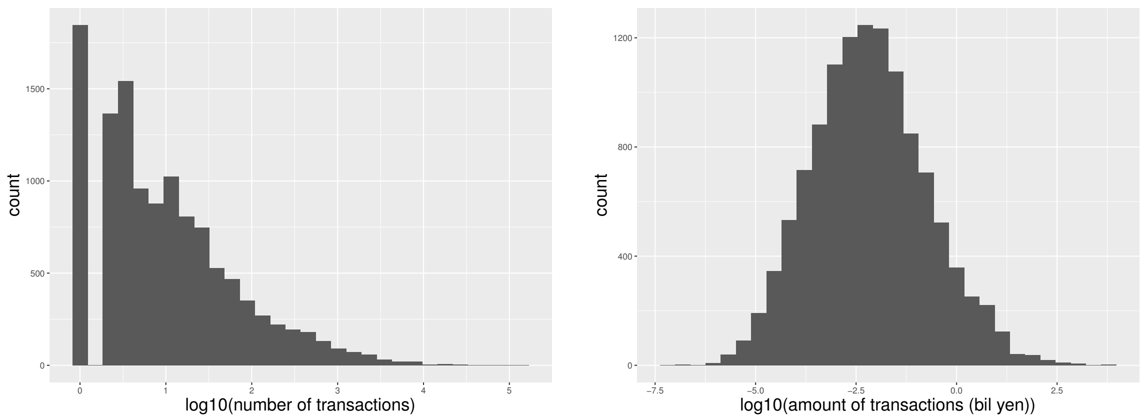

Figure 8: Histogram for the Number and Amount of Money Flows

Note: as of December 2023. Zero transactions are excluded.

Centrality I examine the characteristics of money flows using standard methods from network analysis. Figure 9 illustrates the network structure, where each node represents an industry, and each directed edge corresponds to the amount of money flows from one industry to another as of December 2023.

I compute several centrality measures for this money flow network, including degree, PageRank, and eigenvector centrality. Both PageRank and eigenvector centrality are calculated using unweighted and weighted ones, with the latter based on the money flow amounts. The degree centrality is defined as the simple average of in-degree and out-degree. Table 5 reports the pairwise correlations across the five centrality measures, showing that they are highly correlated with one another. Figure 10 presents a scatter plot of two selected centrality measures: degree and weighted PageRank. The correlation coefficient between them is relatively high at 0.72. However, the figure highlights that financial services and wholesale trade stand out with exceptionally high PageRank values, even though they also rank highest in degree centrality.

Table 5: Correlations among the Five Measures of Centrality

	Degree	Pagerank (unweighted)	Eigenvalue (unweighted)	Pagerank (weighted)	Eigenvalue (weighted)
Degree	1.00	0.95	0.95	0.72	0.78
Pagerank (un)	0.95	1.00	1.00	0.67	0.72
Eigenvalue (un)	0.95	1.00	1.00	0.67	0.72
Pagerank (w)	0.72	0.67	0.67	1.00	0.75
Eigenvalue (w)	0.78	0.72	0.72	0.75	1.00

Note: as of December 2023.

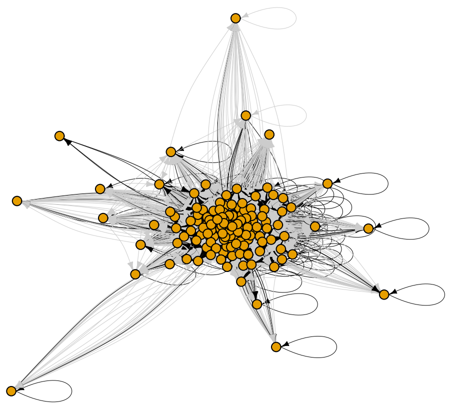

Figure 9: Money Flow Network

Note: as of December 2023. Edge width is calculated based on the amount of money flows.

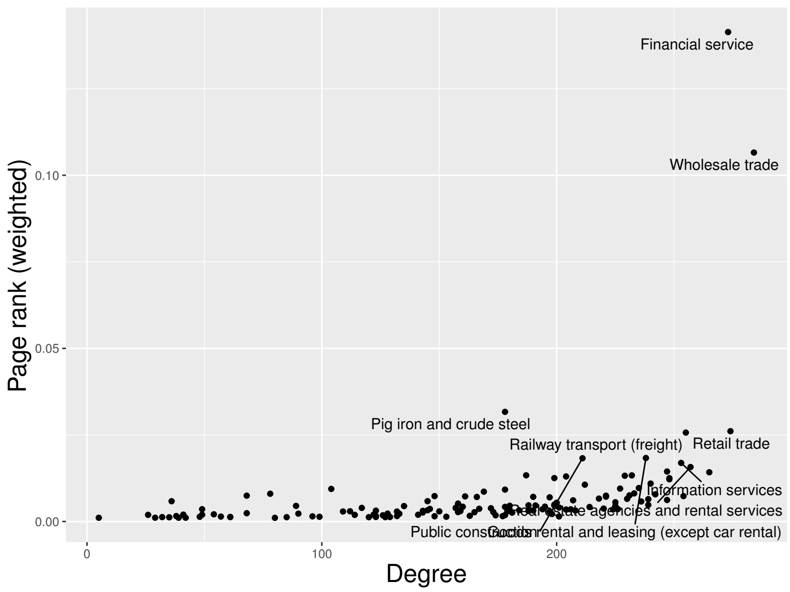

Figure 10: Relations of Two Centrality Measures

Note: as of December 2023.

A.2 Relation with the Input-Output Table

To examine which industries exhibit large discrepancies between monetary and physical flows, I present Table6. This table reports the top and bottom 10 industries based on the estimated values of the industry fixed effects α_i and α_j in equation (1), where the fixed effect α_j for the wholesale trade industry is normalized to zero. The results reveal no clear pattern regarding the types of industries or the direction of flows that tend to diverge systematically. If anything, the estimates suggest that money outflows are generally larger than those implied by the input-output table, compared to money inflows.

Table 6: Top/bottom 10 Industries for Fixed Effects

Industries	Fixed Effects	Money Flow From/To
Railway transport (freight)	1.012	From
Financial service	0.850	From
Agricultural services	0.711	From
Railway transport (freight)	0.634	To
Wholesale trade	0.597	From
Packing service	0.448	From
Pig iron and crude steel	0.443	From
Advertising services	0.364	From
Motor cars	0.286	From
Wholesale trade	0	To
Silviculture	-2.375	From
Fishery	-2.488	From
Railway transport (passengers)	-2.509	To
Miscellaneous processed paper products	-2.680	To
Water supply	-2.695	From
Image and audio equipment	-2.793	From
Tires and inner tubes	-2.873	From
Electricity	-3.199	To
Water supply	-3.283	To
Petroleum refinery products	-3.287	To

Note: The values represent the coefficients of the industry fixed effects for i and j.

A.3 Further Results on Money Flow Dynamics

Tables 7 and 8 provide additional robustness checks on the estimation of money flow dynamics. In the second column of Table 7, the lagged dependent variable is excluded to mitigate concerns about the Nickell bias in dynamic panel estimation. As an alternative to exclusion, the third column includes second lags of the main explanatory variables, $FROM_{it-2}$ and TO_{jt-2}, to account for dynamic effects without introducing potential bias from the lagged dependent variable. The results show that these coefficients are significant. The fourth column reports results after excluding industries related to wholesale trade and financial services, which are highly central in the network and could disproportionately influence the dynamics. The estimation results remain almost unchanged.

In Table 8, I focus specifically on money flows involving the financial services industry. These flows are more likely to reflect financial transactions, such as lending and repayments, rather than physical flows associated with supply chain activities. To account for this distinction, I introduce a dummy variable, finance, which equals one when a money flow involves the financial sector either as origin or destination. Interaction terms between this dummy and both $FROM_{it-1}$ and TO_{jt-1} are included in the regression. The results show that the interaction term with TO_{jt-1} is significantly negative, while the coefficient on TO_{jt-1} itself increases relative to the baseline specification. This suggests that the estimated spillover effect of physical flows is attenuated when financial transactions are included, reinforcing the view that physical (non-financial) flows are the key drivers of propagation in money flow dynamics.

Table 9 presents additional results on heterogeneity by incorporating various measures of network centrality. The coefficients on the interaction terms between centrality and either $FROM_{it-1}$ or TO_{jt-1} are insignificant, suggesting that network centrality does not play a significant role in determining the degree of spillover effects.

Table 7: Further Results on Money Flow Dynamics

Lag	0.198***			0.198***
	(0.011)			(0.011)
Lag FROM	0.047	0.092***	0.073***	0.048
	(0.029)	(0.011)	(0.011)	(0.029)
Lag TO	0.056**	0.085***	0.065***	0.057**
	(0.024)	(0.009)	(0.010)	(0.025)
Lag2 FROM			0.082***	
			(0.011)	
Lag2 TO			0.057***	
			(0.010)	
Observations	899,632	899,632	884,384	866,592
Adjusted R^2	0.827	0.820	0.820	0.817

Note: The fourth column excludes wholelsale trade and financial service sectors.

Table 8: Further Results on Money Flow Dynamics 2

Lag	0.197***	0.198***	0.197***
	(0.011)	(0.011)	(0.011)
Lag FROM	0.055		0.053
	(0.034)		(0.034)
Lag TO	0.068**		0.059**
	(0.030)		(0.030)
Lag FROM finance	0.001	0.002	
	(0.005)	(0.005)	
Lag TO finance	−0.010***	−0.008**	
	(0.003)	(0.003)	
FROM finance			0.005
			(0.006)
TO finance			−0.00003
			(0.004)
Observations	897,862	897,862	897,862
Adjusted R^2	0.826	0.826	0.826

Table 9: Money Flow Dynamics: Heterogeneity

	Degree	Pagerank	Eigenvalue	Pagerank (weighted)	Eigenvalue (weighted)
	(1)	(2)	(3)	(4)	(5)
Lag	0.200***	0.200***	0.200***	0.200***	0.200***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Lag FROM	0.010	0.012	0.011	0.081*	0.063*
	(0.084)	(0.076)	(0.072)	(0.046)	(0.036)
Lag TO	−0.090	−0.083	−0.077	0.058**	0.058*
	(0.079)	(0.078)	(0.073)	(0.029)	(0.030)
Lag FROM × centrality	0.0003	7.523	0.083	−3.667	−2.145
	(0.0004)	(9.172)	(0.094)	(3.609)	(4.062)
Lag TO × centrality	0.001*	21.880	0.226	0.208	1.320
	(0.001)	(13.675)	(0.137)	(2.006)	(2.793)
Observations	861,341	861,341	861,341	861,341	861,341
Adjusted R^2	0.824	0.824	0.824	0.824	0.824