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# A Social Network for Trade and Inventories of Stock during the South Sea Bubble\*

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## ABSTRACT

A social network of stock trading is defined for the notorious South Sea Bubble of 1720. It is a flow network defined in terms of pass-through and core pass-through, which have convenient properties with respect to inventories. These are all useful concepts when examining a liquidity crisis, financial intermediation and the changing social structure of trade. We find that there may have been a liquidity crisis suffered by goldsmith bankers before the Bubble, a gradual path towards dis-intermediation after the Bubble and a switch from intermediation based upon brokerage to intermediation based upon dealership.

**JEL Classification:** G13, N23.

**Keywords:** East India Company; South Sea Company; Bank of England; social networks; financial intermediation; inventories; liquidity.

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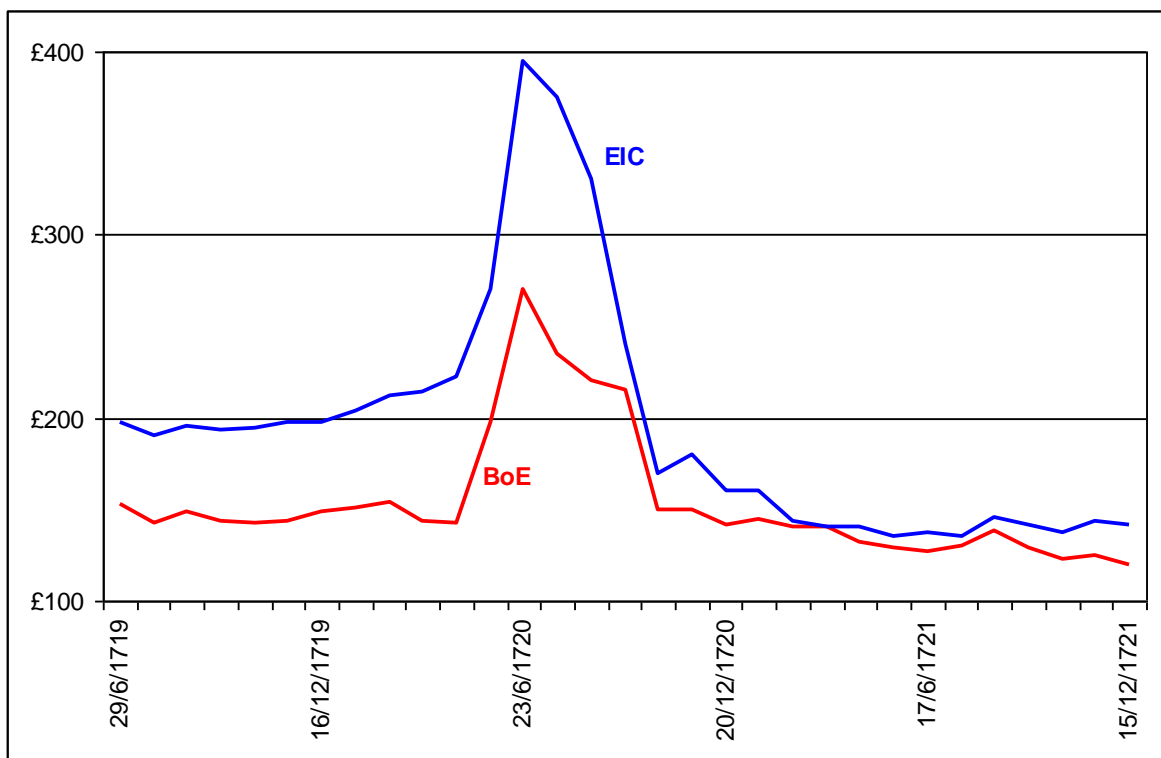
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## 1. Introduction

If an investor today wished to buy a share in a prominently traded stock of a public joint-stock corporation, how likely is it that he or she would know, or even have to know, who was the previous owner of the share? The answer is that in the impersonal and highly intermediated financial markets of today there is almost no likelihood that buyers would have or require such knowledge. Yet in early 18<sup>th</sup> century Britain trade in shares of even the most important public firms could easily be carried out face-to-face between buyer and seller. Historians have described how Britain developed secondary trade in the markets for shares in which investors interacted directly with financial intermediaries and other investors, largely in the City of London, and were much more likely than today to personally know each other and to deal directly with each other (Dickson, 1967; Neal, 1990; Carlos and Neal, 2006, 2008; Carruthers, 1994; Murphy, 2009; Neal and Quinn, 2001). London had even started to differentiate itself from the financial systems of the Low Countries in such ways that it was attracting overseas investors who could also personally interact with British investors and intermediaries in the City (Carlos and Neal, 2011). Face-to-face stock market trading was feasible throughout the 18<sup>th</sup> Century and indeed one of the best-selling financial how-to books of the century (Mortimer, 1761) was published in more than a dozen editions and gave detailed instructions to investors about how to avoid middlemen and thus reduce their personal costs of transactions by seeking out buyers and sellers directly.

As different as early stock markets of Britain were from modern stock markets, they still managed to produce financial crises that resonate today. The South Sea Bubble remains today unarguably the most notorious of the historical financial bubble episodes (Garber, 2000). The Bubble refers to the events in the year 1720 associated

with a scheme to convert much of the British national debt into equity shares of the South Sea Company (Scott, 1910; Dickson, 1967; Carswell, 1993; Neal, 1990). There was an attendant stock market boom and crash that took place in a very short time - in about the six months between April and October 1720. The stock market events that affected South Sea share values affected the value of a wide range of stocks, Bank of England and East India Company shares included (Fig. 1). But the South Sea Bubble is very remote in time and there is very little in the way of data that are of a good standard so as to be useful to a financial economist who wishes to study the Bubble. The purpose of this paper is to demonstrate that a description of a time-series of social networks of stock trading during the South Sea Bubble produces important clues as to how the financial economist might want to model the asset bubble of 1720.



**Fig. 1.** End-of-month share values for Bank of England (BoE) and East India Company (EIC) stocks (Freke, 1719-21).

Network theory can help explain asset bubbles in several ways. The connections between financial models of information cascades and networks are the operable links that make the study of networks potentially fruitful. Some asset pricing models that naturally generate frenzies and crashes have been based upon auction theory. The essence of an auction is that it is a market in which buyers and sellers choose when to participate. Persons' decisions to arrive at a market and to depart from a market can be modelled as a purely random process (Bulow and Klemperer, 1994), but can also be influenced by information, such as in financial "herding" models (Welch, 1992), which describe the coalescence of persons' opinions towards a common valuation of a good. Such herding can be modelled on a network (Golub and Jackson, 2010) in which convergence to beliefs is determined by the influence (trust) wielded by individuals, such as financial intermediaries. Networks also provide a framework for the discovery and understanding of the intermediation that such persons perform. For a homogenous good, such as a corporate share, there is no need for intermediaries to certify the quality of the goods bought and sold, yet intermediaries may stand ready to provide liquidity services in trade and they may also otherwise offer the lowest cost mechanisms for bringing buyers and sellers together. The role of intermediaries' inventories has been of interest in recent studies of liquidity and financial crises (Brunnermeier and Pedersen, 2009; Comerton-Forde, Hendershott et. al., 2010). Repeated transactions through intermediaries may also create trust that builds bridges to other networks that are not directly observable, such as networks for trade in foreign exchange, physical goods and payments clearances (Rauch, 2001).

The plan of this paper is first to define a flow network for stock trading in which the importance of trading nodes is related to frequency of trade, size of trades

and accumulated stock inventories (Section 3). The paper depends upon some results from a parallel paper that has a different expositional emphasis (Mays and Shea, 2011). In that paper is a much more detailed discussion than is contained in Section 2 that follows here about the data sources and descriptive statistics of stock trading during the South Sea Bubble. The emphasis in this paper will be to describe the global characteristics of the trading networks and then to relate them to social affiliations. In our other paper more attention is devoted to analysing the social affiliations that are most useful in defining network partitions. In both papers we document a number of changes in the global and local nature of trading networks that coincide with major events of the Bubble. Although we cannot yet definitively link these changes to the kinds of information cascades of interest to financial economists, some of them do bear a resemblance to phenomena we would expect to see in a liquidity crisis.

## **2. Data**

Our data consist of all trade in shares for the East India Company and the Bank of England in the years 1719-21. What we shall call the South Sea Bubble period is the six months from the end of April to the end of October 1720. This effectively encompasses the stock market boom and collapse (Fig. 1). Unfortunately the data do not record stock trade in actual value terms, but they only record the number of shares passing between stock account owners. Although the data can show volumes of trade passing through a network, they cannot show how shareholder returns were distributed on those same networks. A minority of the records will also include some trade between family members and between business partners that we cannot consider to be purely market transactions. Additionally the trade data in stocks does not show the extent to which stocks were frequently used as security in other financial contracts,

such as forward loan or forward foreign exchange agreements (Neal and Quinn, 2001). There was probably an unobservable network of indirect ownership and trade in shares that is only imperfectly reflected in our data and some of the ownership that appears in the company ledgers that we use may actually represent ownership in trust for other persons. But for the most part the trade recorded in our sources would have reflected the interest in trade in society as that interest ebbed and waned through the Bubble period.

At any time in the years 1719-21 there were about 1800 persons or institutions who held stock in the East India Company (hereafter, the EIC) and for the entire period there were more than 3600 such stock accounts to be found in the EIC records (India Office Records L/A/G/14/5/4, 1719-23). Records covering the years 1720-25 contain the ownership and trade for nearly 8000 stock account holders for the Bank of England (Carlos and Neal, 2006). We have melded the EIC data with the Carlos and Neal Bank of England (hereafter, the BoE) data and restructured all data into a multidigraph. Directed edges represent sales of stocks from one account holder to another and the edge weights correspond to the nominal size of the sale. Edges in the graphs have other attributes, which are changeable through time. Each edge, of course, has a date that corresponds to date of sale. The type of stock (EIC or BoE) transacted is also an edge-attribute. We have also been able to calculate the size of stock inventories held by each buyer and seller. Socio-economic characteristics of stock account holders are coded as [0-1]-binary data, which are treated as node attributes. They include gender, professional class, social class, political class, residence, and nationality.

A device we use throughout this paper is the time-series analysis of subgraphs defined by edge-dates that span a 3-month range. A monthly series of such graphs and

their characteristics are used to create what amounts to moving-average trends in network characteristics. The entire dataset contains more than 20,000 trades (edges) and more than 10,000 nodes. From this graph we create our monthly quarterly subgraphs which contain from 2500 to 3000 BoE nodes and about 1500 to 2000 EIC nodes in each quarter. The largest connected components in these subgraphs are a few hundred nodes for each company's stock trade in the years 1719 and 1721 and up to 1000 BoE nodes and 800 EIC nodes during the Bubble episode of 1720.

### 3. A flow network with pass-through, core pass-through and inventories

We define an enclosed flow network for stocks. It has neither an exterior source of flows nor has it an exterior sink to receive flows, yet every node can be a stopping place for flows. The accumulated flows at any node (inventories) can reside at the node indefinitely and are limited in size only by the total amount of stock contained within the network. Consider a multidigraph defined on a set of nodes  $\{V\}$ . Stock sales and purchases are the flows that pass between persons whom we represent as nodes. The  $i$ -th instance of a flow between two nodes  $\{u,w\}$  is denoted  $f_i(u,w)$ , with  $f_i(u,w) \geq 0$ ,  $u, w \in V$ . Over a period of time there might be a number of such flows,

$N_{uw}$ . Let  $I_{uw} = \{1, \dots, N_{uw}\}$  and define  $f(u, w) = \sum_{i \in I_{uw}} f_i(u, w)$ . For the same period we

define net flows from  $u$  to  $w$  to be  $F(u,w) = f(u,w) - f(w,u)$ . It follows naturally that  $F(u,w) = -F(w,u)$ . The sum of all net flows towards node  $w$  is the change in  $w$ 's stock inventory,  $\Delta_w = \sum_{u \in V} F(u, w)$ . For networks, such as ours, in which the sum of all

inventories is fixed,  $\sum_{w \in V} \Delta_w = 0$ .

Closely related to inventory changes is the concept of pass-through. Pass-through measures the extent to which a node facilitates flows through a network. Pass-through will be proportional to the number of flows (degree) and the sizes (edge weights) of individual flows that pass through a node. Whether a node is important or not, in either a sociological or economic sense, will most certainly be determined by pass-through and inventories together. The resulting measures of node importance will be related to, but distinct from other measures of centrality in a weighted network that have been discussed previously (Opsahla, Agneessensb and Skvoretzc, 2010).

Formally we define pass-through (PT) to be the portion of flows into a node that does not positively contribute to the node's inventories:

$$PT_w = \min \left[ \sum_{u \in V} f(w, u), \sum_{u \in V} f(u, w) \right] = \sum_{u \in V} f(w, u) + \min[0, \Delta_w]. \quad (1)$$

Unlike in a pneumatic flow network, whose network edges will generally have capacity constraints upon them, there is no intrinsic limit to PT through any node or in the network as a whole, except that total PT cannot exceed total flows or, in other words, total sales. This we can readily confirm from (1) by summing over all nodes' pass-through:

$$\sum_{w \in V} PT_w = \underbrace{\sum_{w \in V} \sum_{u \in V} f(w, u)}_{\text{Total Sales}} + \sum_{w \in V} \min[0, \Delta_w]. \quad (2)$$

Total Sales will thus be the natural choice as a normalisation factor for pass-through.

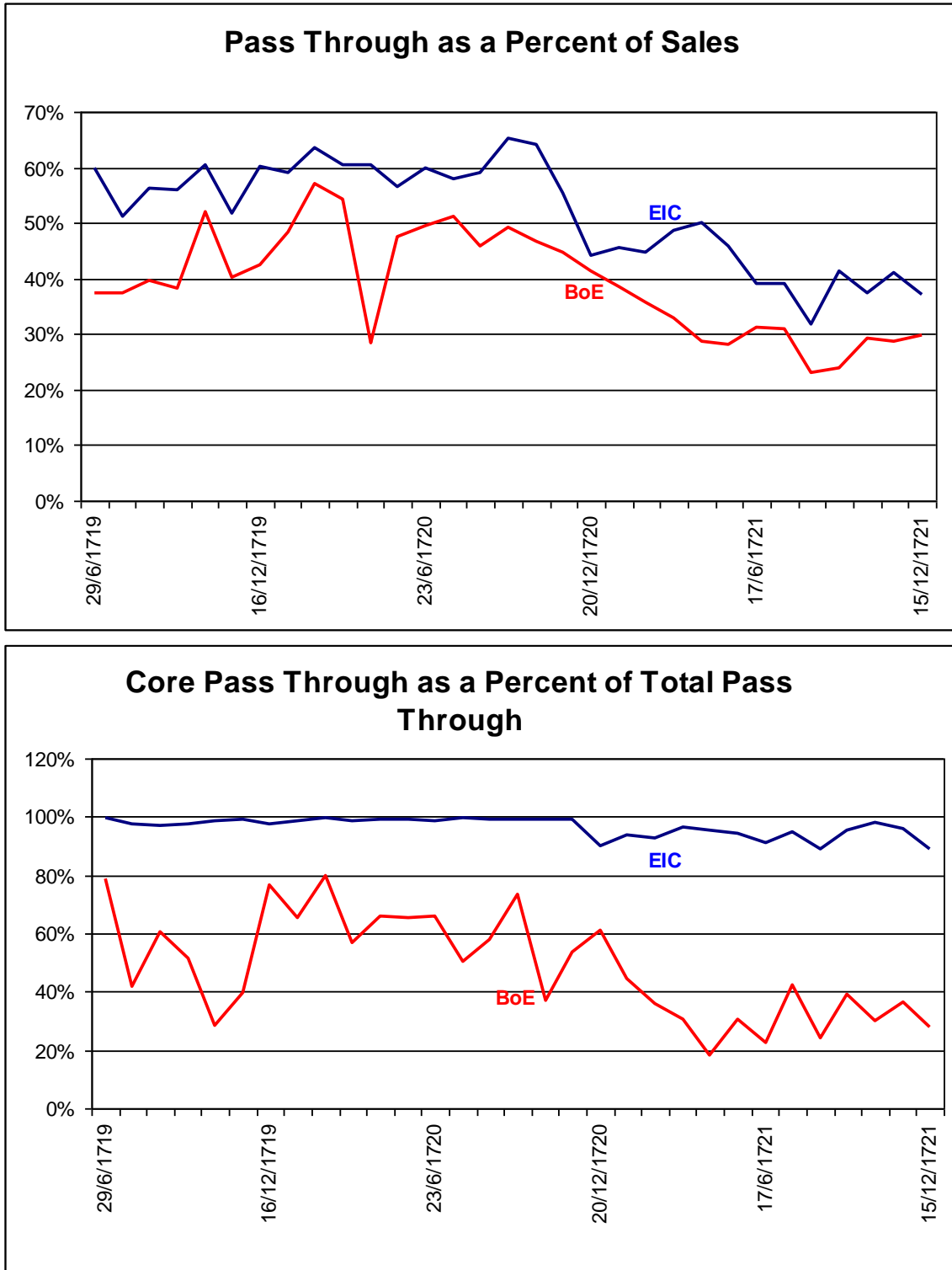


Similar to the World Wide Web, we would expect that our network would have a central densely-connected component and other less-densely connected components (Broder, A., Kumar, R., et. al., 2000). At any time there were many nodes, including some with very large inventories of stock, who did not trade, but when people did happen to trade, they did so largely within a densely connected giant component. The reasons why this was so are connected to the activities of professional financial dealers and brokers in these markets. We emphasize that this is an unremarkable statement only when writing in terms of modern stock markets, but in the early 18<sup>th</sup> Century the development of modern stock market structures, dominated by professional financial intermediaries, was just in its infancy. The stock markets of 1720 possessed every potential of being purely face-to-face markets, markets in which every buyer and seller could actively seek out counterparties directly within networks of social affiliations as readily as counterparties could be brought together by professional intermediaries.

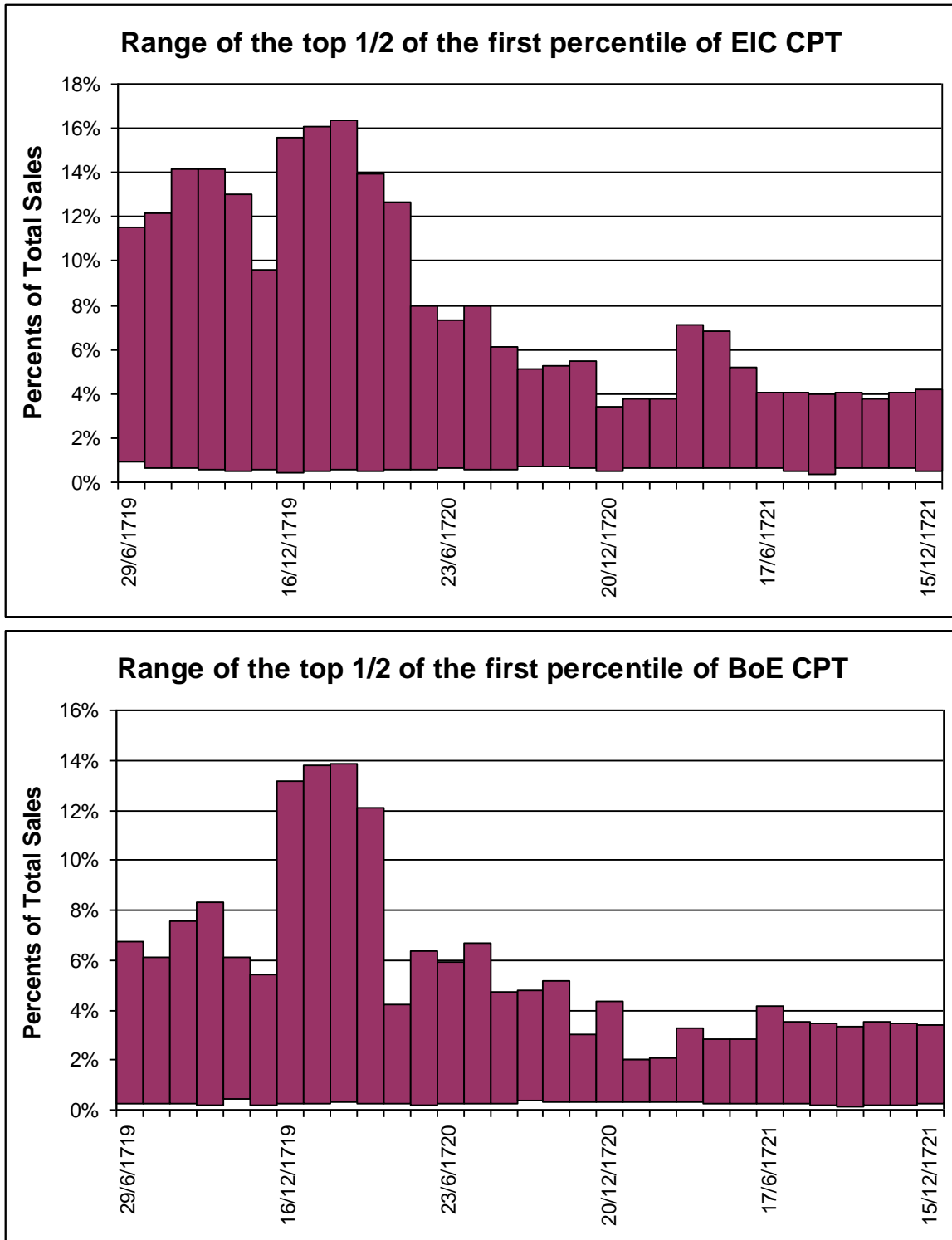
Isolated nodes experience no pass-through, of course, but even very small trading components might contain some pass-through. A node that facilitates pass-through is hardly likely, however, to represent a specialist financial intermediary unless it is connected to other similar nodes that facilitate pass-through. Thus we come to a notion of what we term core pass-through (CPT). A node facilitates CPT if it has pass-through and it is connected (via pass-through) with other nodes that also facilitate pass-through. Formally the set of nodes that reside in this core is defined  $\{w \in V : PT_w > 0, F(w, u) \neq 0, u \in V \text{ s.t. } PT_u > 0\}$ . It is within this core that we expect to find the nodes that are most closely associated with financial intermediaries of interest to us. The size of this core relative to the other trading components in our network indicates the importance of specialist intermediaries during the South Sea

Bubble. In Fig. 2 is illustrated the substantive differences between the networks for BoE and EIC stock trade in terms of PT and CPT. The giant connected components for BoE and EIC are respectively quite different, EIC PT being a larger percentage of trade and taking place within a much more densely connected core network than is the case for BoE PT. Over time, as well, there occurred a change in these large-scale properties of our networks. After 1720, pass-through declines as a percentage of total sales and core pass-through declines as a percentage of pass-through.

Distributions of PT also exhibit considerable skewness. At any time a very small number of nodes command very large percentages of PT and CPT and, by extension, large percentages of total sales. We have to look in the highest  $\frac{1}{2}$  of the first percentile of such distributions to see interesting differences in the respective EIC and BoE CPT. Outside of the top first percentile there were no traders whose CPT would amount to any more than the tiniest fraction of a percent of total sales. Within the top  $\frac{1}{2}$  of the first percentile, however, we can discover some traders whose CPT could account for substantial portions of total sales. In Fig. 3 it is clear that the heyday of the top CPT-trader occurred before the South Sea Bubble. These top traders were generally members of a professional financier class, the goldsmith bankers along with a smaller number of professional brokers. We have applied the label GSBs to such people and in our data they number in all about 240 individuals, acting singly or in partnerships. In EIC trade in particular the heyday of the top CPT trader, the trader who could be a core intermediary of at least 10 percent of a total sales over a quarter, occurred prior to the South Sea Bubble. In the case of BoE trade such



**Fig. 2.** Pass through and core pass through for Bank of England (BoE) and East India Company (EIC) stock trade.



intermediaries existed only briefly in the first quarter of 1720. Once the Bubble period commenced, this type of intermediary simply disappeared, largely due to the demise of the GSBs (Section 6, Mays and Shea, 2011).

Fig. 2 and Fig. 3 together present evidence that the stock markets to some extent experienced disintermediation during and after 1720. Fig. 3 shows that the very largest of the most highly connected intermediaries had their heyday before the stock market boom of 1720 began, while Fig. 2 shows that the prominence of PT in total sales and the prominence of CPT within PT both declined after 1720.

To what extent can the features of Fig. 2 be related to the more fundamental characteristics of the networks? To answer this we have undertaken the simulation of some random networks. PT and CPT are obviously positive functions of trade frequency. The frequency with which persons trade is expressed as the number of flows that enter and leave a node. A node's joint in-degree and out-degree is defined

(for node  $u$ ) by the  $\left\{ \sum_{w \in V} N_{wu}, \sum_{w \in V} N_{uw} \right\}$ -tuple and its degree sum is defined as

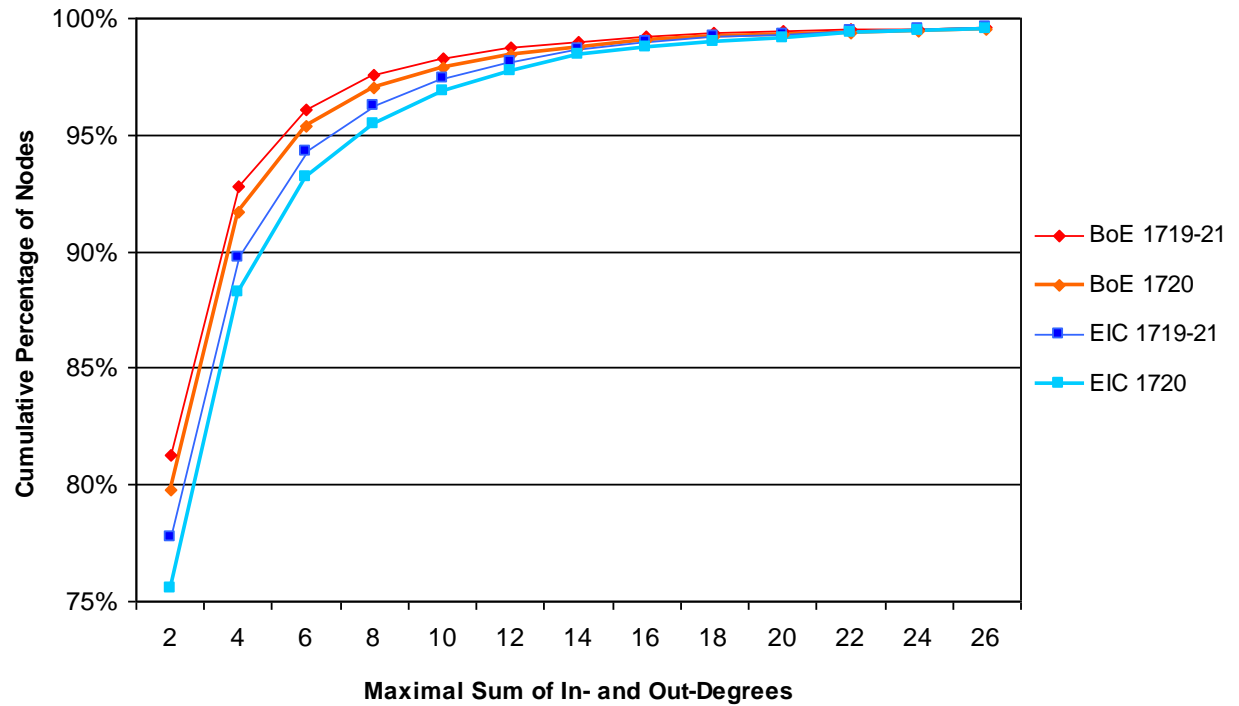
$DS_u = \sum_{w \in V} N_{wu} + \sum_{w \in V} N_{uw}$ . The set of all nodes with a stated maximum (MAX) of

degree sums is  $\{u \in V : DS_u \leq MAX\}$  and from the simple cardinality (#) of this set

relative to the cardinality of  $V$  itself we can build a cumulative distribution of degree

sums over any range of MAX of interest to us. In Fig. 4 we plot for the two stocks

and different periods the ratio  $\#\{u \in V : DS_u \leq MAX\} / \#V$  for  $2 \leq MAX \leq 26$ ,



**Fig. 4.** Cumulative distribution of node degree sums for networks of Bank of England (BoE) and East India Company (EIC) stock trades in the periods 1719-21 and 1720, separately.

The trade in EIC shares was more frequent than trade in BoE shares and trade in both companies' shares was more intense in 1720 than it was in the years surrounding 1720. EIC stock trade was not only more frequent, but also it tended to be larger on a per-trade basis than was BoE stock trade.<sup>2</sup> But the extent to which frequency of trade and size of trades can jointly explain some of the features of Fig. 2 are not apparent. We attempt to explore this issue in simulation of random networks. We start by building two-dimensional empirical histograms of in- and out-degrees and randomly re-sample (100 times) from these histograms to create in-degree and out-

<sup>2</sup> Both facts that are established also by direct enumeration of trades (Mays and Shea, 2011, Section 4).

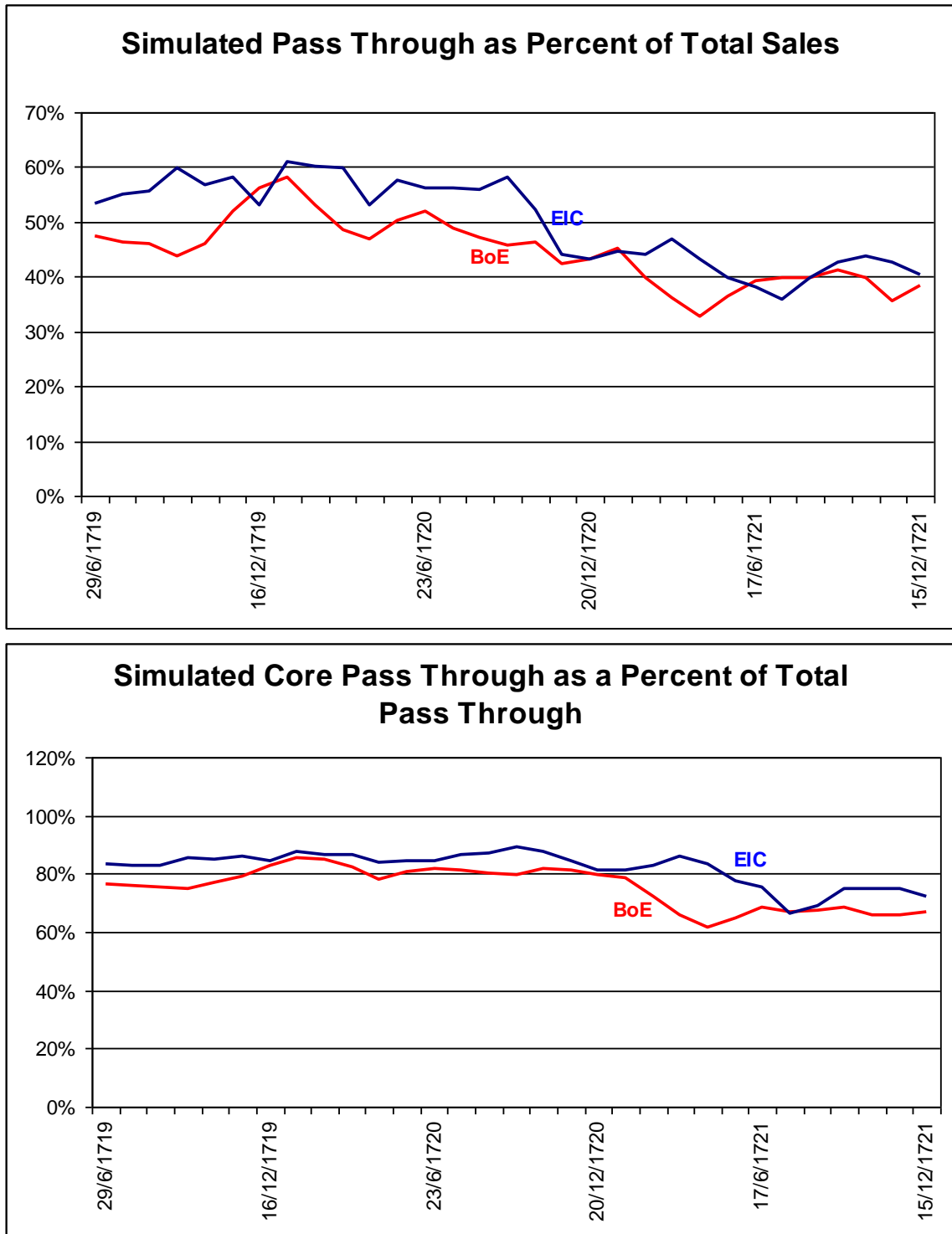
degree tuples. From these we generate randomly configured directed multigraphs.<sup>3</sup> The graphs' edge weights are independently and uniformly distributed randomly generated numbers on the [0,1]-line. The averages of each of the 100 monthly simulations are pictured in Fig. 5.

It is clear that the higher frequencies of trade for EIC stocks can account only for some of the features of Fig. 2. Pass-through as a percentage of sales is accounted for in terms of order of magnitude; these are simulated to be between 60 percent and 40 percent for both EIC and BoE trade before 1721, which roughly corresponds to what we see in Fig. 2, but the clear separation between these percents for EIC and BoE trade that we see in Fig. 2 is not clearly mimicked in Fig. 5. The comparison of simulated CPT as a percentage of PT is less satisfactory. That percentage is greater for the EIC data than it is for the BoE data, but the size of EIC CPT relative to BoE CPT is clearly not nearly as great as it is in Fig. 2. The inter-period variability of BoE CPT is also not well captured in Fig. 5.

We extend our simulation analysis by trying to capture the effects of edge weights. We now construct 4-dimensional histograms of nodes' in- and out-degrees, joint with in-edge weights and out-edge weights. Again we randomly sample from these histograms (100 times) per quarter. Joint distributions of edge weights with node degrees clearly play a role in the relative extent to which CPT is a percentage of PT. The lower panel of Fig. 6 shows a clear separation between EIC and BoE CPT very similar to that displayed in Fig. 2. This verisimilitude however comes at some cost in the upper panel of Fig 6. In that panel both EIC and BoE PT are reduced as a percentage of Total Sales relative to what appears in the upper panel of Fig. 2.

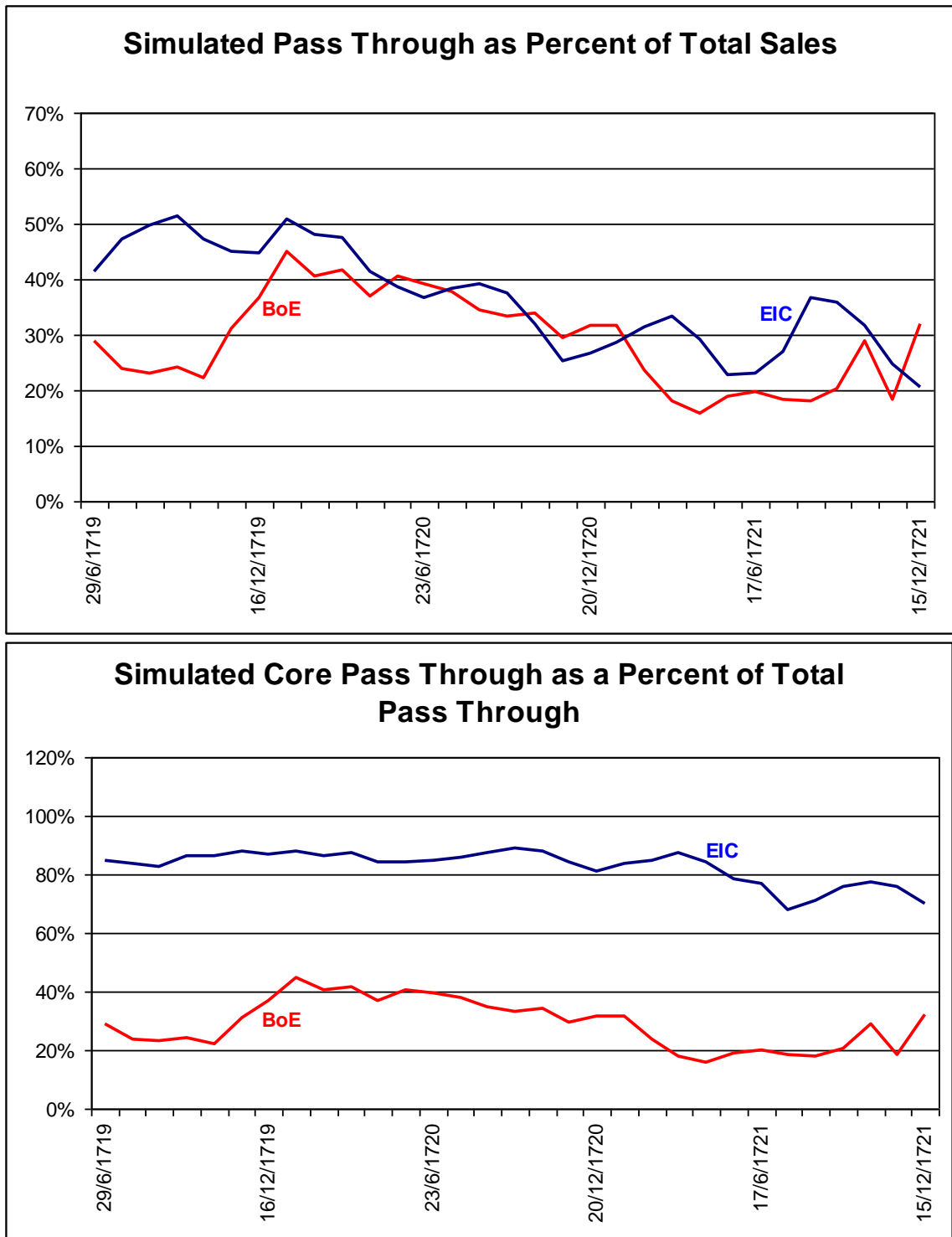
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<sup>3</sup> This is performed by the Python 2.6 program embodied in Networkx 1.3, `networkx.generators.degree_seq.directed_configuration_model`, following an algorithm laid down by Newman, Strogatz and Watts (2001). The empirical histograms are based upon the same monthly subgraphs whose features are pictured in Figs. 2 and 3.



**Fig. 5.** Simulated pass-through and core pass-through for Bank of England (BoE) and East India Company (EIC) stock trade on random graphs conditional upon empirical degree distributions and independent uniformly-distributed  $[0,1]$  random edge weights.





**Fig. 6.** Simulated pass-through and core pass-through for Bank of England (BoE) and East India Company (EIC) stock trade on random graphs conditional upon empirical joint node-degree and edge-weight distributions.

There is no surprise that some of the features of Fig. 2 can be mimicked by simulations on random graphs based upon empirical frequency-of-trade and size-of-trade distributions. But it is clear too that there is more information in our networks that need to be exploited to more fully explain the features of Figs. 2 and 3. What have clearly been left out are the social character of traders and the dynamics of inventories that they handle.

#### **4. The dynamic behaviour of inventories and intermediation**

Inventories must figure in the importance of a node in our networks, but we would need a model of the joint determination of inventories with edge weight (trade) flows before we can proceed further with simulation exercises such as those presented in the previous section. An economic model in which financial intermediaries optimize some function of trade flows and inventories will dictate the shape of their joint distribution. But what kind of inventory behaviour would such a model have to explain? To search for an answer to this, we proceed on two fronts in an: i) by describing the interesting global behaviours with respect to inventories in our networks and ii) by describing the extent to which network nodes can be assigned to social and professional classes that relate to inventory and PT-flow behaviours. In the process, it is discovered that two different styles of financial intermediation naturally emerge in our networks – brokerage and dealership.

At any time large numbers of people did not trade, even during the height of the Bubble, so we cannot expect that shifts in inventory distributions would be very great, except over long periods. Amongst active traders, however, inventories did shift significantly and there were trends in that regard both with respect to the social attributes of inventory owners and how buyers and sellers networked with each other.

Corporate shares can be expected to earn positive returns and are like capital goods in that respect. Decisions to acquire and to dispose of such goods can be optimally managed to respond to expectations in returns for such goods. The more an individual earns from financial intermediation, however, the more inventories will figure in his cost of doing business. We cannot argue that the physical carrying costs of stock inventories would be as large as they would be for inventories of physical commodities, but we can argue that the costs of controlling risks associated with such carriage could be significant. Intermediaries might be acting like speculators and will need personal capital or will have to borrow in order to fund their investments. Inventories of stock can act as collateral for borrowing, but the lower their quality as collateral, the larger inventories will have to become to serve as collateral for a given amount of borrowing. Larger inventories may be a response to speculative losses (losses to personal capital) and/or a lowering in the quality of inventories because they have lost some of their liquidity (Brunnermeier and Pedersen, 2009; Comerton-Forde, Hendershott et. al., 2010). On the other hand, before the appearance of the specialist market-maker of today, the possession of inventories might also have been a way of signalling to the markets that a speculator stood ready to buy and sell and have been a factor in reducing his search costs for customers. In equilibrium, strong financing for speculators, high-quality inventories that can act as collateral and low customer-search costs will tend to produce intermediaries that can operate with small inventories relative to the flows they service. Otherwise with weak financing for speculators, low-quality inventories and high customer-search costs, we will expect to find that intermediaries will have to have high inventories relative to the flows they service.

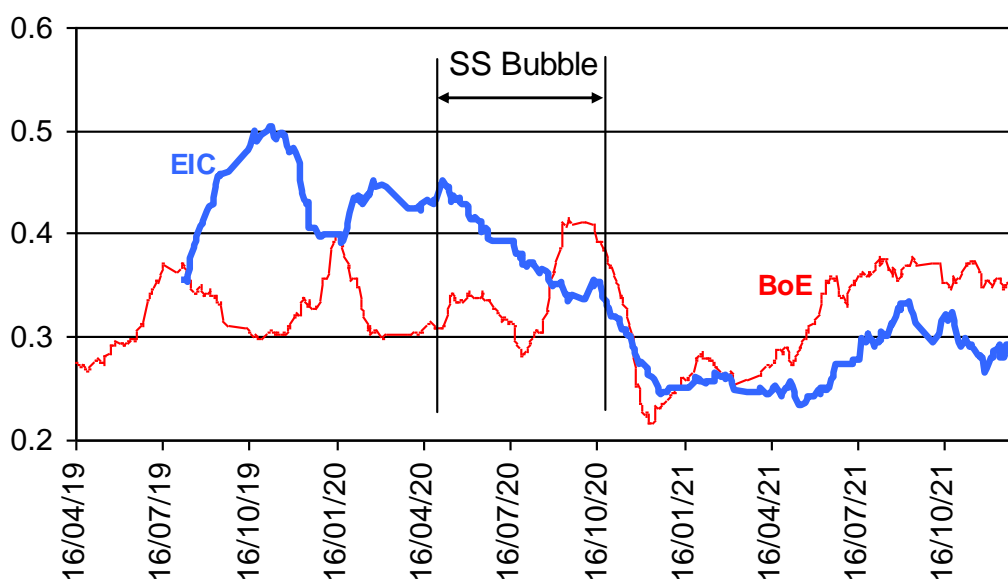
In our networks total inventories of stocks are fixed and therefore all changes in inventories must sum to zero. We would nevertheless expect that the distributions of inventories, especially amongst speculators, would change as the Bubble crisis unfolded. Speculators would experience gains and losses, which affects their personal capital. They would then have to adjust their inventories of stock by size and quality as collateral in their efforts to manage liquidity risk. It behooves us therefore to examine the inventory history of buyers and sellers of shares. Instead of defining an edge weight between buyer and seller in terms of trade flows, suppose that we redefine edge weights in terms of the relative size of buyers' and sellers' inventories. Imagine two persons who are counterparties in a transfer of shares. A logarithm of the relative inventories of the two would be approximately zero as long as the two inventories were not too different in size. Taking into account that a buyer's inventory of stock can be zero at time of purchase, consider the properties of the following function ( $RINV_{uw}$ ) of the relative inventories of a buyer ( $w$ ) and a seller ( $u$ ):

$$RINV_{uw} = \log_{10} \left[ \frac{1 + Inv_w}{Inv_u} \right] \quad (3)$$

where  $Inv_w$  stands for the stock inventory of node  $w$ .

When buyers' and sellers' inventories are independently and homogeneously distributed,  $RINV_{uw}$  will be expected to be  $\log_{10}(2) = 0.3$  between all nodes. We could further imagine that the distributions of inventories could depart from homogeneity over time, but not be able to do so indefinitely. For example, buyers' inventories could not indefinitely be twice the size of sellers' inventories ( $RINV_{uw} = 0.5$ ); eventually buyers' inventories would have to start to decline relative to sellers' inventories. Thus 0.3 has to be an attractor for  $RINV_{uw}$ , although we cannot yet be

specific as to its strength as an attractor. In Fig. 7 is illustrated a 90-day moving average trend for  $RINV_{uw}$  for both BoE and EIC stocks. In the figure is also illustrated the 6-month period (end April to end October, 1720) that encompasses the market boom and crash in share prices. Clearly the South Sea Bubble divides our data into two distinct periods in terms of inventory behaviours. Although there clearly appears to be trend at all times, average  $RINV_{uw}$  stays much closer to 0.3 after September 1720 than it does in the period before. In the earlier period the deviation from 0.3 is marked and the strength of 0.3 as an attractor is most evident. What is most striking, however, is that before the Bubble the trends for BoE and EIC appear to follow a mutual countercycle, whereas after the Bubble the trends co-move with each other. Coincidence in this regard is excluded. We can explain the pre-Bubble trends in terms of the behaviour of the only group of individuals that can we associate with professional financial intermediation, the goldsmith bankers and brokers (the GSBs).



**Fig. 7.** Log-relative buyers' and sellers' inventories for Bank of England (BoE) and East India Company (EIC) stocks, 90-day moving averages, 1719-21.

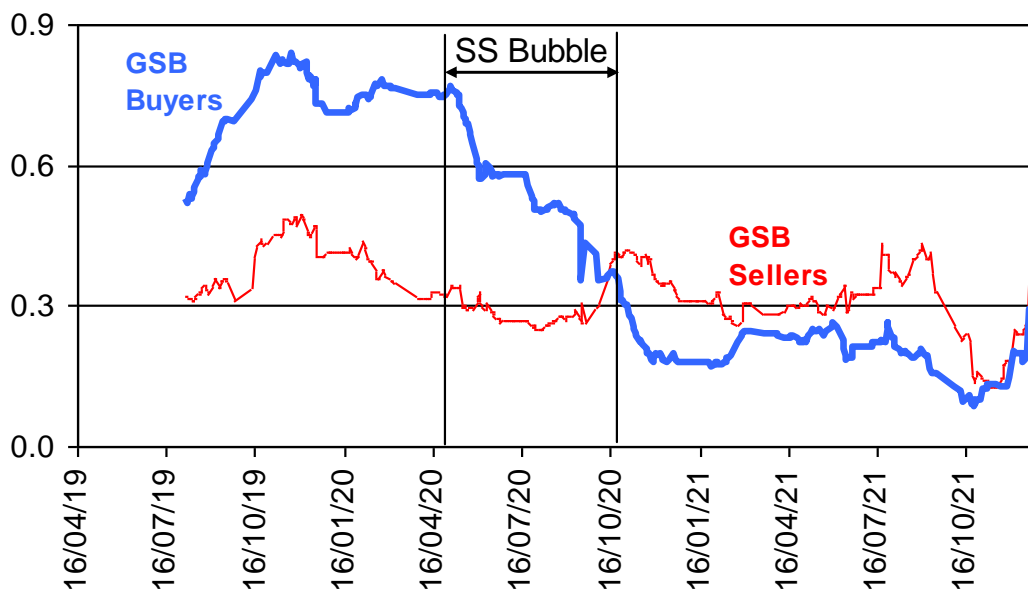
Prior to the market collapse in September 1720, purchases of EIC stock, as opposed to purchases of BoE stock, were dominated by relatively large buyers. As far as EIC stocks are concerned, Fig. 7 is consistent with the usual history of the South Sea Bubble that states that 1720 was a year in which specially inexperienced investors were drawn towards the stock markets. After short and intense inventory accumulations in late summer 1719 and in early 1720, the Bubble period was largely marked by a steady downward trend in the size of buyers' inventories relative to those of sellers. Inexperienced investors would have to buy, by necessity, from people who possessed much larger inventories of stock. Another line of reasoning, however, is possible. What contemporaries and historians have characterised as a rise to prominence of inexperienced investors might have been confused with the rise to prominence of new classes of stock traders who were perhaps displacing formerly prominent traders in stock. All classes of traders may have already been present in the market as investors, but some classes were previously active in trade and others were relatively dormant in trade before and after the South Sea Bubble. If the trading roles of such classes were interchanged, we might very well see the inventory dynamics that we have found so far. What may have appeared to contemporaries as a new type of stock market participant may well have been a person who was an experienced investor, and who may well have had even large inventories of stock, but who was newly attracted to active trading in 1720.

If there was one class of stock owner/trader which famously underwent great changes during the South Sea Bubble, it was surely the previously discussed GSBs. Large numbers of them allegedly went to the wall as trade credit began to shrink in the summer of 1720. As prominent members of the financial community at the time, they held large amounts of stock, but as their financial difficulties grew, their

prominence in trade suffered a drastic change. With our data we can define, for the first time, the extent of this class's involvement in stock ownership and trade throughout the Bubble year and can present strong evidence that the inventory trends in Fig. 7 have much to do with the inventory behaviour of goldsmith bankers and brokers. In Fig. 8 is illustrated the trends in  $RINV_{uw}$  for GSB traders as buyers and sellers separately. The figure clearly shows that in the years 1719-21 GSBs sold stock to other individuals (inclusive of other GSBs) who had inventories generally no larger nor smaller than their own inventories. As buyers of stock quite prior to the Bubble, however, GSBs behaved quite differently. Their inventories were much larger (up to 7 times larger) than the inventories possessed by persons from whom they purchased stock. The decline in the relative size of their inventories was rapid at the commencement of the Bubble and the decline did not stop until the Bubble itself collapsed. We know that the trends in Fig. 8 are driving the overall EIC inventory trends in Fig. 7 because GSB trade in this period was such a large percentage of trade. We know too that GSB inventory adjustments in this period were largely a movement away from inventories in EIC stock into inventories of relatively low-risk BoE stock – precisely what appears to be the ‘flight-to-quality’ phenomenon often noted as the hallmark of a liquidity crisis.<sup>4</sup>

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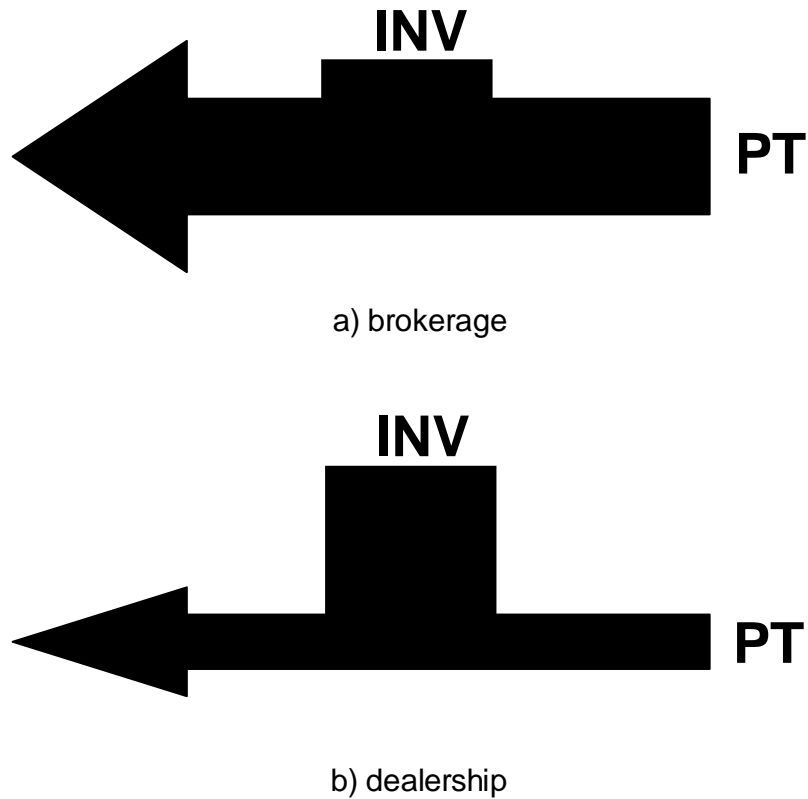
<sup>4</sup> See also discussion with regard to Figs. 9 and 10 in Mays and Shea (2011).



**Fig. 8.** Log-relative buyers' and sellers' inventories for EIC stocks, GSBs as sellers and GSBs as buyers separately, 90-day moving averages, 1719-21.

Flight to quality may have saved some GSBs from destruction, but we know that overall it did not. By the end of 1720 GSBs were no longer the dominant traders or inventory holders of either BoE or EIC stock. Their departure from the markets was associated with a change in the structure of intermediation as well. The economic distinction between brokerage and dealership is made naturally in our network setup. We define brokerage to be the facilitation of pass-through with the aid of little or no inventories. Opposite to brokerage is dealership, in which inventories are relatively large in the presence of PT or CPT (Fig. 9).

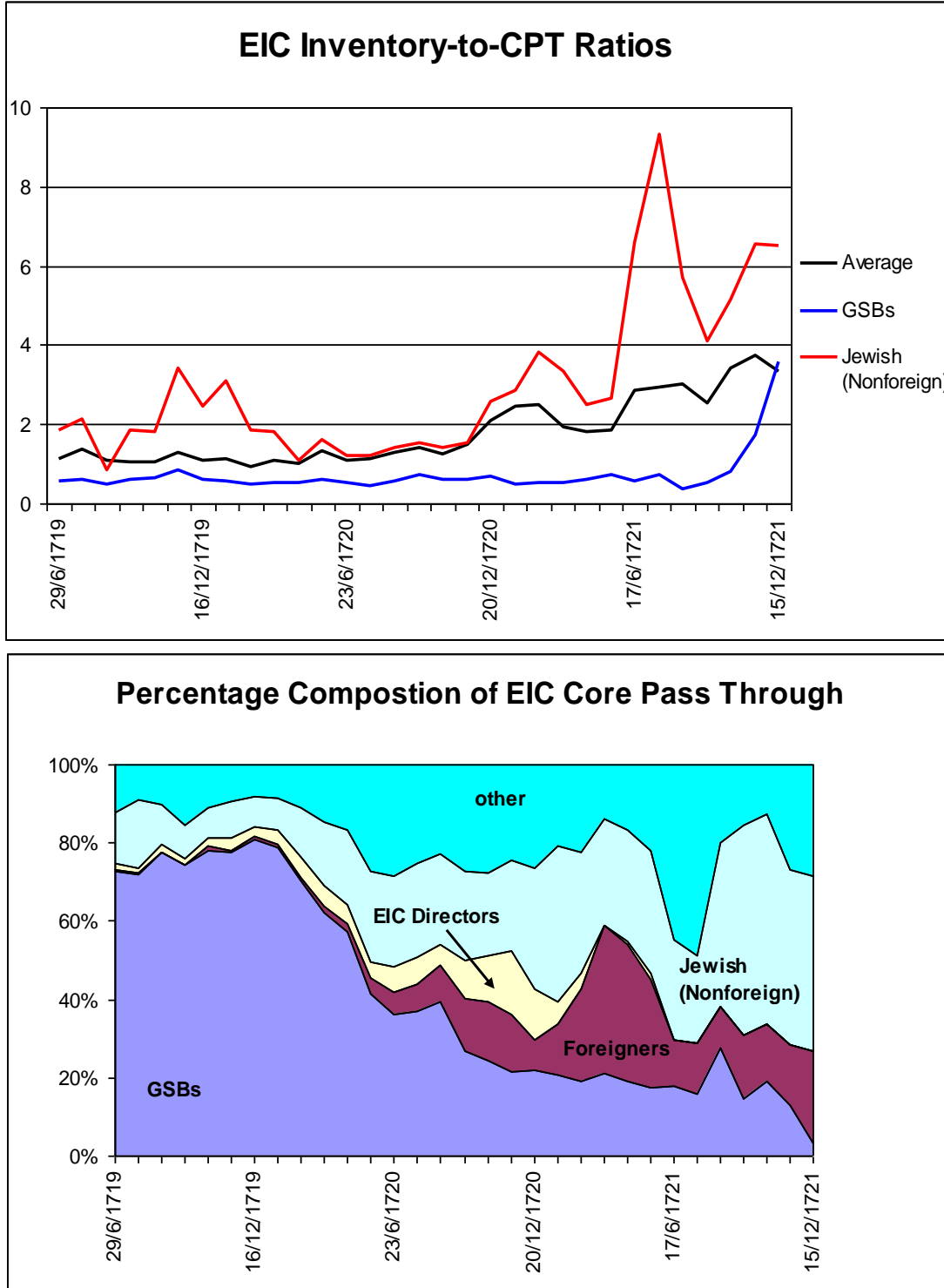




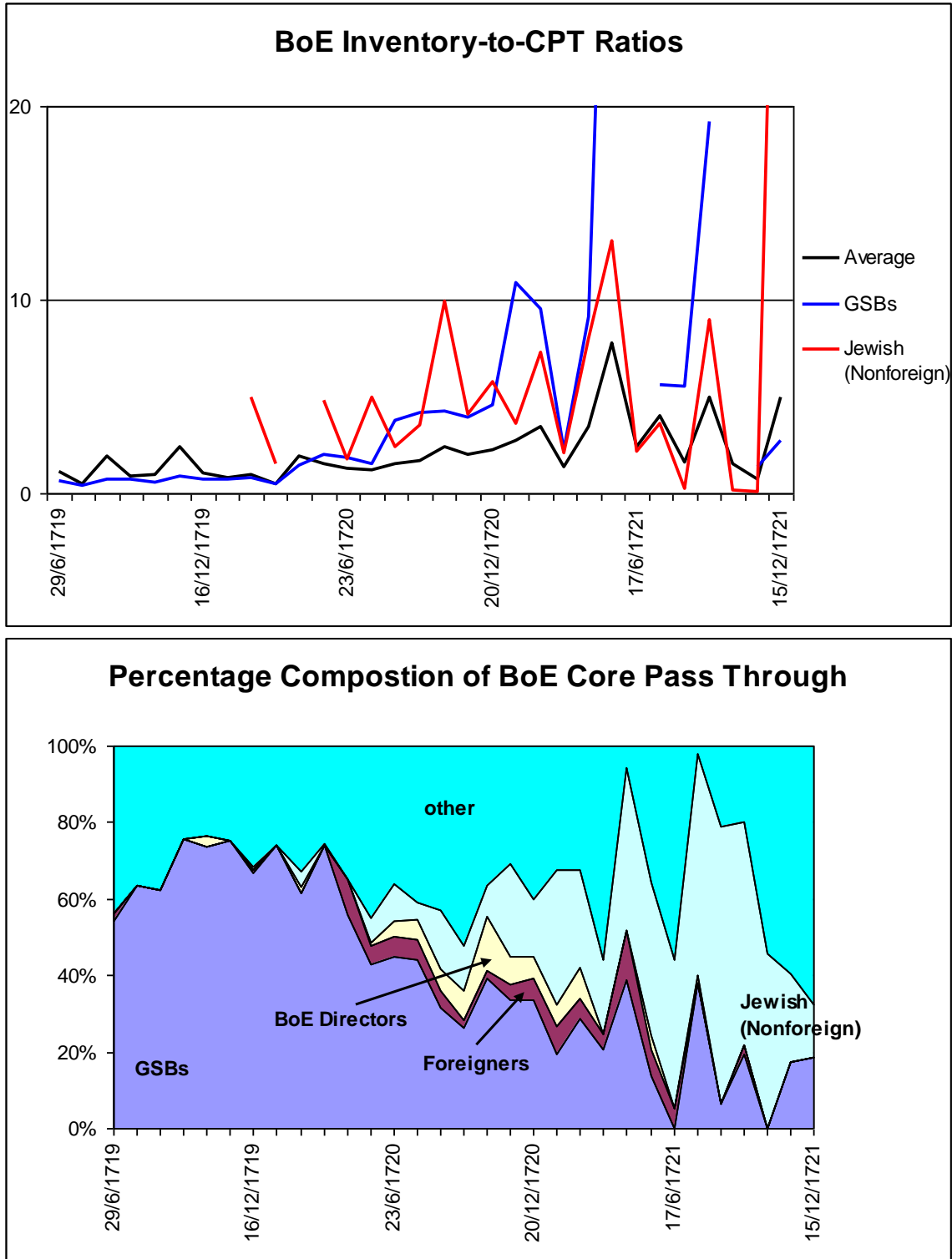
**Fig. 9.** Financial intermediation naturally divided into a) brokerage and b) dealership in terms of inventories (INV) and pass-through (PT).

GSBs were largely brokers; they did indeed command very large inventories, but not so large relative to the amounts of PT they facilitated. With the demise of the GSBs intermediation did not end, but was placed on a different footing – one that depended upon dealership more than it did on brokerage. Persons, largely of the merchant class, who were already substantial investors took over from GSBs in the facilitation of PT and CPT. During the Bubble itself such facilitators also included company directors themselves, but for the most part they were foreign merchants or were British-domiciled Jews, also largely of the merchant class. This is clearest in the case of EIC stock (Fig. 10). In BoE trade dealership also displaced brokerage in intermediation, although it is more difficult to see trends in this regard by social affiliations (Fig. 11) because BoE CPT itself became quite small and more volatile as a component of total sales and PT (Fig. 2). The path towards dis-intermediation was

thus marked by highly volatile inventory behaviour by the formerly dominant intermediaries - GSBs. And with their decline and demise as intermediaries, the form of intermediation itself moved from brokerage to dealership.



**Fig. 10.** Brokerage, dealership and CPT in EIC stock by social affiliation, 1719-21.



**Fig. 11.** Brokerage, dealership and CPT in BoE stock by social affiliation, 1719-21.

## 5. Conclusions and directions for further research

Historians have long known that social and professional affiliations in the stock markets of the early 18<sup>th</sup> Century were important. Our understanding, however, of the effects of affiliation on trade, intermediation and ownership has been incomplete. When what trading data we have is organised into a stock-flow network, significant evidence of much of what we suspected we would find and a good number of surprises, as well, emerge. We have defined networks of trade in terms of weighted multidigraphs. And we have defined the importance of nodes (stock owners) in terms of their importance in trade. Frequency of trade (node degree) and size of trade figure in determining a node's importance through our measures of pass through (PT) and core pass through (CPT). PT and CPT are not just flows – they are flows that are most closely associated with financial intermediation. Therefore, when we look at node importance in terms of PT relative to total sales or in terms of CPT relative to PT, the most important nodes are most likely also to be the most important financial intermediaries. Not surprisingly, the goldsmith bankers and brokers (the GSBs), as a social/professional group, dominated intermediation in the markets prior to the Bubble. More surprising, however, is that their importance began to rapidly decline even before the stock market boom of 1720 commenced. Equally surprising is that intermediation was not immediately harmed by the withdrawal of GSBs from the markets. To a large extent a merchant class, much of it Jewish and much of it foreign, stepped in and maintained previous levels of intermediation to at least the end of 1720. Aided a little by company directors too, merchant classes operated with higher inventories than did the GSBs. Intermediation in the stock markets thus started to move from brokerage towards dealership.

With regard to the South Sea Bubble itself, have we found any information that can further our understanding of it? The demise of the GSBs has every appearance of a cascade in our network data and it apparently pre-dates the stock market boom itself (Figs. 7, 8, 10 and 11; Figs. 9 and 10, Mays and Shea, 2011). We can speculate that it was the removal of GSB influence that may have enabled the stock markets to move to a newly inflated valuation of equity values. This would a possibility in a social learning model, such as that presented by Golub and Jackson (2010). Further research, however, is needed to affirm what happened to the GSBs – whether their ownership and intermediation in stocks truly declined or were simply moved into other markets, such as other companies' share markets. The higher risk share markets, such as those for the Royal African Company's shares, offer some further scope for study along these lines.

Clearly too an effort is now required in developing behavioural models of financial intermediation (with inventories) on a network. Why social and professional affiliations would appear to be correlated with the scale of intermediation (PT), the density of intermediation (CPT) and the style of intermediation (brokerage vs. dealership) remains unclear. It may have been the case, for example, that the demise of the GSBs made room for a new social class of financial intermediaries who were simply inexperienced in brokerage and who would in time master it. Or perhaps the credit conditions that allowed brokerage to dominate in intermediation disappeared in 1720 and dealer intermediates were able to competitively displace the GSBs because they had better social connections. It will take some further research before we can isolate such social network effects from the economic explanations of what happened to intermediation in the course of the South Sea Bubble.

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