Online Appendix to Credit Provision and Stock Trading: Evidence from the South Sea Bubble

This appendix provides supplementary material for *'Credit Provision and Stock Trading: Evidence from the South Sea Bubble'.* The first sections provide a detailed description of data sources. We start by explaining the organization of the ledger books and transfer files, and how we collect trading prices for stocks. These data sources provide the data used in the main analysis. We also describe how we retrieve the names of investors that subscribe into new equity issuances. Moreover, we explain the computation of the RAC prices in the first weeks of May 1720. Finally, we provide additional tests that validate the main results, and provide evidence that investors also mimic the borrowing and trading behavior of other traders in their network.

A Data appendix

A.1 Stock ledgers, transfer files and loan ledgers

We hand collect every transaction in three main shares during the South Sea bubble episode: East India Company, Bank of England, and New Royal African Company. Our main data sources are the Bank of England and East India Company stock ledgers that consist of trader-specific accounts recording all buys and sells (see Figure 1a). Each account is linked to an index containing trader names and characteristics (titles, street address and occupation, see Figure 1b). In addition to trader-specific accounts, transactions are also signed by both buyers and sellers in so-called transfer files which can be considered as formal share sales agreements. We use any additional investor information in these transfer files to enrich our database. This implies that we observe every transaction of each individual trader in our sample period with buyer and seller identities as well as their characteristics. We complement the Bank of England and the East India Company data with transaction information of the new Royal African Company. Since the ledger books have not survived, we retrieved all transactions and investor names from the company's transfer files. Using the universe of trades, we compute daily holdings and trading gains of each trader active in at least one of these three companies.

We collect loan holder data from the Bank of England's ledger books and, because of the accurate internal recording system of the Bank, we are able to precisely link each investor's daily loan positions to her share trading activities. The loan ledger book provides various details of the loan contract: name of the borrower, origination and repayment date as well as interest due. We also collect the identities of the South Sea borrowers to make sure that these loan holders are not over-represented in our treatment or control group.[1]

Since we study trading behavior during the 1720 South Sea Bubble our sample period begins on 1st January, 1720 and it ends on 6th October 1720, the day the Bank of England wound up the loan facility.[2] Figure 3 shows that our sample consists of 4,657 Bank of England traders, 1,982 East India traders and 1,814 Royal African traders, with many investors holding shares in multiple companies. The average trader holds £819. Our sample covers about 50% of the market in terms of January 1720 market capitalization. We define the market here as all publicly traded companies at the beginning of 1720. Anderson (1787, pp. 90-94) gives an overview of these companies with their nominal capital base and number of outstanding shares. We multiply the number of outstanding shares with the daily trading price on 1 January 1720 from Castaign (1720). We argue that using market valuations is the most accurate measure of the relative shares of the market since the quoted prices (rather than the nominal value) are relevant for investors aiming to acquire a certain stock.

In total, our sample contains 659 (606) unique shareholders who hold a Bank (South Sea) loan. The average Bank of England (South Sea) loan holder holds £1,018 (814) in equity (vis-à-vis 819 for the average investor). Furthermore, the table suggests that loan holders trade more actively, and are more likely to subscribe to new share issues. Moreover, our sample consists for more than 80% of male investors and men are also more likely to take a loan. The male over-representation can be explained by limited property rights for married women. A married woman was placed under the guardianship of her husband upon marriage and therefore only allowed to hold or trade assets under special circumstances (Staves, 2013; Froide, 2016).[3]

[1]We use the House of Lords' investigation into the South Sea affairs to extract names of South Sea Company loan holders as well as the amount they borrowed. *An abstract of the ledgers of the loan of stock*, box 157, parchment collection, House of Lords Records Office.

[2]We stop our sample period on October 6 to make sure that our results are not driven by the margin call made the Bank of England.

[3]Despite their legal status, married women were able to invest using two different strategies. First, a woman's separate property defined under a pre-nuptial agreement was not placed under the husbands' guardianship. As pre-nuptial contracts became common in the seventeenth century, this allowed women to invest in equity (Froide,

[Figure 1 about here.]

[Figure 2 about here.]

[Figure 3 about here.]

A.2 Subscriptions to new share offerings

At the height of the South Sea boom, many companies took advantage of high valuations by issuing new shares. The investors subscribing to receive new shares took large risks and almost certainly incurred losses. We collect subscriber names and amounts of new share offerings of the South Sea (third and fourth subscription) and investor names in the shareholder register of the London Assurance Company. We match the loan positions to investor demand for shares in new equity offering in the South Sea Company (two rounds) and the London Assurance Company through the names retrieved from subscription lists.[4]We obtain information about 4,481 (2,569) traders for the South Sea third (fourth) subscription and 618 traders for London Assurance's shareholder register list.[5] We ultimately match 1,785 (974) South Sea investors in the third (fourth) subscription and 322 investors with positions in the London Assurance around its peak value.

The South Sea Company was the first company to take advantage of high valuations by opening a third subscription on June 17th and a fourth on August 24th (see also the section describing the historical setting in the paper). Investors subscribed to these new stocks by making a down-payment and writing down, before a company official, their names and desired share amounts on

2016, pp.95). The use of pre-nuptial contracts was especially prevalent in aristocratic circles since noble families typically tried to protect their wealth. In line with this notion we find that unmarried women are three times more likely to have a nobility title in our sample. Second, many married women received a small allowance to buy necessities called 'pin money' (Staves, 2013, pp.131-162). Froide (2016, pp.97-99) shows anecdotal evidence of several married women that saved up their pin money and use these funds to invest in financial markets. The use of pin money to invest in securities was also legally upheld in a court ruling. In the case *Wilson v. Pack (1710)* it was decided that any assets that were bought using pin money, and interest thereon, legally belonged to the married woman. As a result of these legal restrictions, 95% of the female investors in our sample have a written note in their investor-specific account that they are either never married or widow.

[4]In case of large uncertainty we do not match: for example, we cannot link a South Sea subscriber named John Smith because our ledger sample contains 26 John Smiths and we would need more characteristics to find unique matches.

[5]The South Sea subscription lists have been retrieved from the House of Lords archive: HL/PO/JO/10/5/57-63, and the London Assurance shareholder register lists are collected from the London Metropolitan Archives: MS 8725/3.

lists set up by the company. New South Sea shares were sold to investors at a price of £1,000 per share when the market price was about £750, on June 17th 1720 - the time of the third subscription -, and £820 on August 24, the day of the fourth subscription.[6] Subscribers were required to pay 10% of the subscription price for the third subscription and 20% on the fourth: the remaining amounts were going to be paid in subsequent installments according to a pre-defined subscription plan. All subscriptions in 1720 were oversubscribed, i.e. there were more subscribers than new shares to be issued. The company decided which subscribers were entitled to receive new stocks and sent out subscription receipts certifying the right to receive shares. However, as a result of the South Sea Company's financial troubles, the receipts of the third and the fourth subscription were never delivered. As the price of South Sea shares in the secondary market never reached £1,000, ex-post, South Sea subscribers could only lose money even if they received the shares.[7]

The second equity issuance we use is from the London Assurance Company (LAC). On August 12 1720, the LAC took into its shareholders' base investors that in December 1719 subscribed to the shares of another insurance company, Ram and Colebrook's. Ram and Colebrook's shares were swapped with LAC shares, and the conversion was based on the notion that the LAC market price at the conversion date (about £100, the highest price LAC shares recorded in 1720) was the true value of the stock.[8] Investors who agreed to the swap, held a long position in the LAC at its peak price. While shareholders accepting the swap were registered in the company's book on August 12, shares were distributed only in September 1720. Ex post, converting shareholders realized a loss because the August 12th conversion value was £100 per share and the price in September was between £60 and £80 per share.[9]

[6] The South Sea Company also issued shares before the Bank of England opened its loan facility: on April 14 and April 29, 1720. The price of the first subscription, £300, was in line with the market price. The price of second subscription, £400, was about 10% higher than the market price.

[7] There is a secondary market for subscription receipts, but it was difficult to generate profitable trading strategies as most of the transactions in this market are "for time". In "for time" transactions, the seller promises to deliver her receipts to the buyer once she receives them from the company and the buyer defers payment until the receipt is received. As the receipts of the third and fourth subscriptions were never delivered, "for time" transactions could not be executed, and, also in this case, the original subscriber made a loss (Dale, 2004, p.164).

[8] In particular, each £100 nominal value of Ram and Colebrook's shares was exchanged for a LAC share of £25 par value.

[9] For a detailed description of the LAC subscription process see Acheson, Aldous, and Quinn (2023).

A.3 Prices and dividends

We retrieve price data for the Bank of England, East India Company, Royal African Company, South Sea Company and London Assurance Company from Castaing's Course of the Exchange. Dividend amounts and dividend payment dates are obtained from the court of director minutes.[10] The Royal African Company does not pay dividends during our sample period.[11]

Prices are interpolated over a maximum of three days. Figure 1 in the paper shows price series for companies in our sample and documents large cross-sectional dispersion in bubble size with London Assurance, South Sea Company and Royal African Company bubbling much stronger than the other companies.

A.4 Royal African Company prices in May 1720

Since there are no price quotations available for the new 'engrafted' Royal African shares in the first few weeks of May we adopt an algorithm to infer prices for this period from the price quotes of the old Royal African Company.[12] We exploit the fact that the 'engrafted' and old Royal African shares are claims to the same stream of future cash flows except for the promised April 1721 dividend. This notion is confirmed by Carlos, Moyen, and Hill (2002) as they document that old and new Royal African prices are unsurprisingly highly correlated: 0.9962. The procedure is straightforward as we first regress old prices on new prices using a sample period of June 1st, 1720 to August 31st, 1720.[13] In the second step we use the estimated coefficient and the available old Royal African price quotes to infer daily prices of the 'engrafted' Royal African shares up to May 28th. This procedure produces a floating price of £51.20 on May 2nd, which is well above the underwriter's price (Joseph Taylor paid £4.84) but considerably lower than the nominal book value of £100.

[10] Digitalized versions of the court of director meetings for the Bank of England and the East India Company can be retrieved via the websites of the Bank of England archive and Adam Matthew Digital respectively.

[11] See Scott (1912) Volume II - p.35.

[12] 9The first price quote of Royal African subscription shares by Castaign was on May 28th, 1720.

[13] We select this specific period to exclude the potential effect of periodic installment payments of subscribers on the price of the new Royal African Company. The procedure required buyers of the new Royal African shares to pay an initial payment of £8 and three remaining installment payments that were due on on 1 June (£8), 1 September (£5) and 1 December (£7).

B Additional results

B.1 Excluding South Sea Loan holders

We replicate the main results using a sample that excludes South Sea loan holders. This analysis validates that our findings are not driven by an over- or underrepresentation of South Sea borrowers in the treatment or control group.

[Table 1 about here.]

[Table 2 about here.]

B.2 Optimal leverage and portfolio rebalancing

The results in Table 4 in the paper are also consistent with portfolio rebalancing by investors who seek to maintain a constant (optimal) leverage ratio.[14] For instance, an investor with a power utility function and constant risk premium has an optimal leverage ratio that is time invariant ($\frac{\mu - r_f}{\gamma\sigma^2}$). If we define an investor's leverage ratio as the value of the risky assets divided by the investor's wealth

$$\frac{\sum_{i=1}^{N} P_s * N_s}{\sum_{i=1}^{N} P_s * N_s + C - B}, \tag{1}$$

where P_s represents the price of stock s, N_s the number of stocks s held, C the investor's cash holdings and B the amount borrowed by the investor. Then, it is straightforward to see that positive price shocks have a deleveraging effect, if cash holdings (C) are smaller than B. It is also important to note that share sales and purchases affect the numerator (value of the risky assets) of the leverage ratio in equation (1) but not the denominator (investor's wealth). Because a purchase (sale) creates a cash-outflow (cash-inflow) equal to the value of the purchase (sale). This implies that an investor who experienced a positive price shock - and therefore a drop in leverage ratio - can bring the leverage ratio back to its original level by buying stocks. This rebalancing mechanism is thus consistent with our finding that investors buy shares after a recent price increase.

[14]We thank Michael Brennan for this valuable suggestion.

However, there is one important difference between the rebalancing mechanism described above and naive extrapolation of past returns. Equation (1) shows that an investor can buy *any* share to lever up. In contrast, naive extrapolation predicts that an investor who has experienced a positive shock to share j, will buy that particular share j. Hence, naive extrapolation can thus be regarded as a special case of the rebalancing mechanism. We design a simple test to determine whether our findings are simply a manifestation of a broader rebalancing exercise. More specifically, we test whether an investor who has realized a positive return on a particular stock, say the Royal African Company, is also more likely to buy Bank of England or East India Company shares to bring the leverage ratio back to its initial position:

$$Buy_{ijt} = \lambda_i + \delta_t + \gamma Loan_{it}^{BOE} \times \sum_{s \neq j} w_{is} R_{s,t-\tau} + \eta_{it}, \tag{2}$$

where Buy_{ijt} is a dummy variable that takes the value of 1 if investor i buys share j at time t. λ_i are investor fixed effects and δ_t date fixed effects. $R_{s,t-\tau}$ denotes the return on security s over the past τ trading days and $w_{is} \in [0,1]$ investor i's portfolio weight for security s and $Loan_{it}^{BOE}$ a dummy that takes the value of one if investor i holds a Bank of England loan at t. Portfolio rebalancing predicts a positive γ, because investors can buy *any* risky asset to revert leverage ratios. Investors do not necessarily need to buy the security that recently experienced a positive price shock. We present the results in Table 3 using 6 trading days past returns (as in the main specifications in the paper). Column 1 considers whether investor i buys Bank of England stock at date t as a function of the past returns of the East India Company and Royal African Company. Similarly, in column 2 and 3 we study the East India Company and Royal African Company buys as a function of the returns on the other two companies in our sample. The results show that there is no statistically significant relationship between past portfolio returns and the probability to buy another stock. These findings are inconsistent with a broader rebalancing mechanism predicting that investors buy *any* share after experiencing a deleveraging through a price increase.

[Table 3 about here.]

B.3 Network Effects

We also test whether a trader's propensity to take a loan depends on the borrowing activity of peers within the same network. In our analysis, we consider two networks. The first network relies on physical proximity and classifies traders in the same network if they lived in the same neighborhood in the City of London. One of the trader characteristics that we retrieve from the ledger index is a trader's home address. We find that addresses in London are often recorded with great detail, while we only observe the city of residence for traders living further away. Figure 1 in the paper, for instance, documents that John Myster lives at Charterhouse Square in London and Robert Myre senior at Leadenhallstreet, while we observe no street address for Jacob de Meij and Pieter Hugueton who live in Amsterdam. The great detail of the London addresses allows us to categorize investors who live in the City of London into neighborhoods. Historically, the City was divided in 27 neighborhoods known as wards. We use this information to construct a second measure of traders' networks based on traders' place of living. To precisely measure the possible influence of peers on investments decisions, we restrict this network analysis to traders located in the City of London. We consider the area small enough to credibly assume that investors living in the same ward interacted and talked about stock market investments and margin loans. We use the wards to study peer effect among traders, i.e. we implicitly assume that investors living in the same ward interacted and talked about stock market investments and their margin loans.

The second network is based on mandated trading and interpersonal ties. Most investors traded their own shares. However, some traders authorized agents to act on their behalf using the so-called letters of attorney. These letters were common for traders who lived far from the London Stock Exchange and unable to buy or sell on the Exchange directly. For each Bank of England transaction, transfer files indicate whether an individual traded on behalf of another buyer or seller by summarizing the key features of the mandate and referring to the letter of attorney. For instance, Figure 5 shows that Humphrey Henchman sold £1,500 nominal of Bank of England stock to the Earl of Orkney who was represented by Alexander Gordon. The file also indicates that Gordon held the right to buy and sell unlimited amounts of stocks and collect dividends for the Earl since August 10th, 1719. The transaction is also signed by Henchman and Gordon.[15]

In our sample, a total of 802 transactions (i.e. 3% of the total number of transactions in our sample) involve an agent representing either the buyer or the seller, and in 159 transactions both buyer and seller were represented by an agent. We use the trader-agent relationships to identify investor networks. Specifically, we assume that information flowed from one client to another if both were represented by the same agent. This is important because many traders that were represented by agents lived relatively far away from the Exchange. Our data reveals that 75% of the traders who used agents lived outside the City of London with 25% of them living abroad. Given the long traveling times, written letters were the most important way of communication. The archival records shows that letters from agents not only reported news about execution of the orders, but also lots of information about the market and the behavior of other traders.[16]

For both proxies, we find that investors were more likely to take a loan when other traders in the same network took a loan in the past 30 days. We obtain these findings using two distinct and separate networks, reducing the probability that an omitted variable generates both results. Moreover, the regressions based on trading agents also control for location$\times$date fixed effects, absorbing any effect that is unique to a trader's place of residence over time.

There are potentially many factors that drive a loan holder's trading behavior and one could simply be mimicking other investors' trades. Therefore we also test whether loan holders were more inclined to buy when the number of stock purchases in their network was high. To test this conjecture, we regress a buy dummy on the interaction of a margin loan dummy and the number of stocks purchased in the trader's ward during the past trading week.

B.3.1 Network effects in borrowing

In this section, we study the relationship between trader networks and the probability to take a loan. In other words, are investors more inclined to use the Bank loan facility when traders in their network also collateralize stocks? We test this conjecture using two very different networks. The

[15] The available evidence suggests that agents were merely executing orders given by their clients. They did not have any autonomy in deciding trading strategies and they ought not to be seen as fund managers.

[16] See for instance Wilson (1941, pp.95-102)

first network consists of traders who live in the same neighborhood and the second type consists of traders that are connected through a representative who trades on their behalf.

In the first analysis, we restrict our sample to traders for which we observe street addresses in London and that can thus be classified into wards. Figure 4 shows that some wards close to the exchange, such as Walbrook and Bridge, had relatively few loan holders. In contrast, some wards further away, such as Farringdon Without and Castle Baynard, have more loanholders. Hence, market proximity is not the only factor that drives the decision to collateralize stocks. In Table 4, we test whether a trader is more inclined to take a loan when large loan amounts have been taken up in his ward over the past week. The unit of analysis is trader i at time t, and we relate the daily probability that an investor takes a loan to the total loan amount that was issued to traders in the ward over the past week. We study a horizon of one trading week because information flows quickly from one investor to another within a small area like a ward. We perform this analysis using a linear probability model. We find that a 10% increase in the neighborhood loan sum increases the probability that a trader takes a loan by 10%.[17] The effect becomes economically a bit larger and remains statistically significant when we control for the average tendency to collateralize stocks by including date fixed effects in column 2. Note that the vector of demographic controls that is included in column 1 and 2 contains many time-invariant trader characteristics that have large explanatory power for the decision to take up loans in Table 3 in the paper. We further control for the number of South Sea loans and the average return in the ward. Hence, our findings cannot be explained by a more general inclination to borrow or investors' average trading performance. Column 3 shows that controlling for unobservable time-invariant trader characteristics does not change our findings. In particular, investors are still 10% more likely to borrow if the sum of loans in their ward increases by 10% after controlling for trader fixed effects.

An immediate challenge for our analysis is to separate the effect of peer decisions on employee choices from the effects of selection and exposure to common shocks (Manski, 1993). Therefore, we connect traders through agents who held mandates to trade on behalf of clients. If two traders were connected to the same agent, they were part of the same network. We sum the loan amount

[17] We exclude each trader from the ward loan sum and thereby make Network $\text{loans}_{it-6}^{Ward}$ and Network $\text{loans}_{it-30}^{Agent}$ trader specific.

in each network and use it as explanatory variable in a linear probability model for a trader's decision to collateralize stocks. We sum loan amounts in an agent's network over the past 30 days. We choose a longer horizon because it seems reasonable to assume that information travels slower within a network of traders who lived largely outside London and were thus geographically more distant from each other. Column 4 of Table 4 shows that a trader is 6% more likely to collateralize stocks if the amount of loans in her network increases by 10%. This cannot be explained by time-invariant trader characteristics such as gender, market proximity and the average trading intensity before the bubble. We also control for the number of South Sea loans in the network and the natural logarithm of a trader's holdings at the beginning of the day. The effects are slightly larger when we control for time-invariant trader characteristics and the average tendency to collateralize stocks through trader and date fixed effects. In the final two columns of Table 4, we address the concern that total loan amount in a network could proxy for local economic factors. For instance, negative economic shocks to the local economy could lead to more local borrowing and also induce traders to collateralize their stocks. We include county×date fixed effects (π_{ct}) and ward×date fixed effects (ω_{wt}) to address this concern. We find that Bank shareholders are 8% more likely to borrow when the number of loans in their representative network increases by 10%, after controlling for ward×date fixed effects. The economic magnitude is very similar to the other specifications.

B.3.2 Peer effects in loan holder trading

There are potentially many factors that drive a loan holder's trading behavior and one could simply be mimicking other investors' trades. In this section we test whether loan holders were more inclined to buy when the number of stock purchases in their network was high. To test this conjecture, we regress a buy dummy on the interaction of a margin loan dummy and the number of stocks purchased in the trader's ward during the past trading week. The simplest version of our regression equation takes the following form:

$$Buy_{ijt}(d) = \alpha + \delta_1 Loan_{it}^{BOE}(d) \times NetworkBuys_{ijt-\tau} + \delta_2 Loan_{it}^{BOE}(d) + \delta_3 NetworkBuys_{ijt-\tau} + \delta_4 Holdings_{ijt-1} + \eta_{ijt}, \tag{3}$$

where $Buy_{ijt}(d)$ is a dummy that takes the value of one if trader i buys stock j at day t, $Loan_{it}^{BOE}(d)$ is a dummy that takes the value of one if trader i has a Bank loan at date t, $NetworkBuys_{ijt-\tau}$ is the natural logarithm of the total nominal value of stock j purchased in the network of trader i over the past τ trading days minus the nominal value purchased by trader i. As before, the network is identified by the ward of residence of trader i (if trader i lived in the City of London) or by the group of traders using the same trading agent as trader i (if trader i used a trading agent). $Holdings_{ijt-1}$ is the natural logarithm of trader i's nominal holdings of stock j at the beginning of day t. The coefficient of interest is δ_1 and a positive δ_1 indicates that loan holders are more likely to buy stock j when other traders living in the same ward purchased stock j in the previous trading week.

As in the main analysis in the paper, we progressively saturate equation (3) with a set of fixed effects capturing traders' characteristics. The version with the most complete set of fixed effects takes the following form:

$$\begin{aligned} Buy_{ijt}(d) = \alpha &+ \delta_1 Loan_{it}^{BOE}(d) \times NetworkBuys_{ijt-\tau} + \delta_2 NetworkBuys_{ijt-\tau} \\ &+ \delta_3 Holdings_{ijt-1} + \delta_4 Loan_{it}^{BOE}(d) \times TotalBuys_{ijt-\tau} \\ &+ \rho_{jt} + \kappa_{it} + \psi_{ji} + \xi_i \times NetworkBuys_{ijt-\tau} + \eta_{ijt}, \end{aligned} \tag{4}$$

where again ρ_{jt} are company×date fixed effects, κ_{it} are trader×date fixed effects, ψ_{ji} company×trader fixed effects and $\xi_i \times NetworkBuys_{ijt-\tau}$ are trader fixed effect interacted with past buys of stock j in the network of trader i. Equation (4) also includes the interaction term $Loan_{it}^{BOE}(d) \times TotalBuys_{ijt-\tau}$ where $TotalBuys_{ijt-\tau}$ indicates the natural logarithm of the total number of transactions in stock j over the past τ trading days minus the number of trades by trader i. We include this term to make sure that our findings are not driven by an increase of total trading volume that is a typical feature of a bubble.

We present the ward network results in Table 5. In column 1 we have the basic specification of equation (3), and in column 2 we add the margin loan dummy interacted with the total trading volume of stock j. From columns 3 to 6, we gradually saturate the equation with fixed effects by including company×date fixed effects, trader×date fixed effects, company×trader fixed effects and trader fixed effect interacted with number of shares of company j bought in the trader's ward during the past six days.

We find that loan holders are between 73% and 97% more likely than other traders to buy stock j when the number of ward purchases of stock j is equal to their sample average. These effects are again stronger in the early stages of the bubble when the number of purchases in the ward exceeds its sample average. The effect becomes somewhat smaller and statistically less significant when we include company×date fixed effects (ρ_{jt}) in column 3, but remains economically large. In particular, after including company date fixed effects, a loan holder is 69% more likely to buy a stock when the number of purchases over the past trading week equals its sample average. When, in column 4, we include trader×date fixed effects (κ_{it}), δ_1 becomes basically zero and the effect disappears altogether. This implies that time-varying trader characteristics explain both the self-selection of traders into the Bank loan facility and the loan holders' mimicking trading behavior. In the Online Appendix we show that excluding the South Sea loan holders does not materially affect our findings.[18]

[Figure 4 about here.]

[Figure 5 about here.]

[Table 4 about here.]

[Table 5 about here.]

[18] We also test whether investors in an agent's network mimic trading behavior of peers in the network and find no evidence of that. The results related to the agents network are in Table 7 and they are qualitatively similar to what we find for the ward network.

[Table 6 about here.]

[Table 7 about here.]

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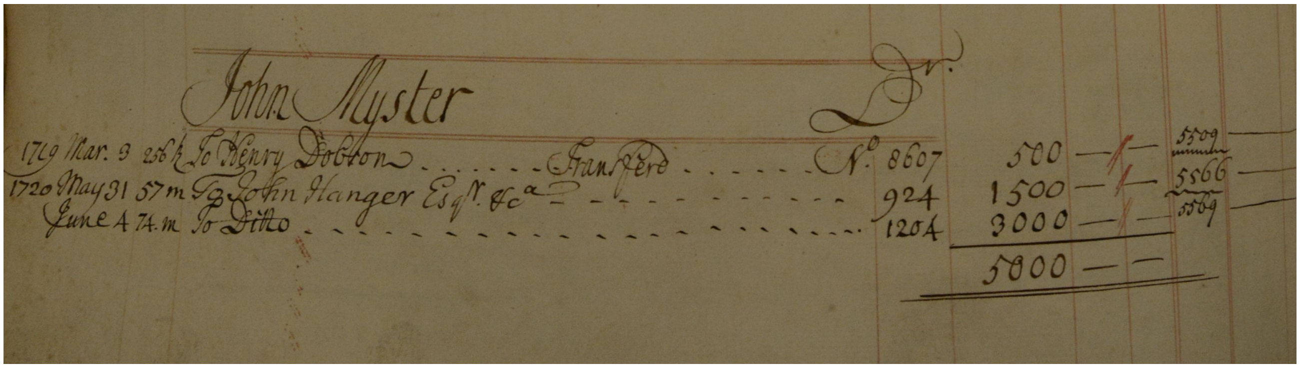
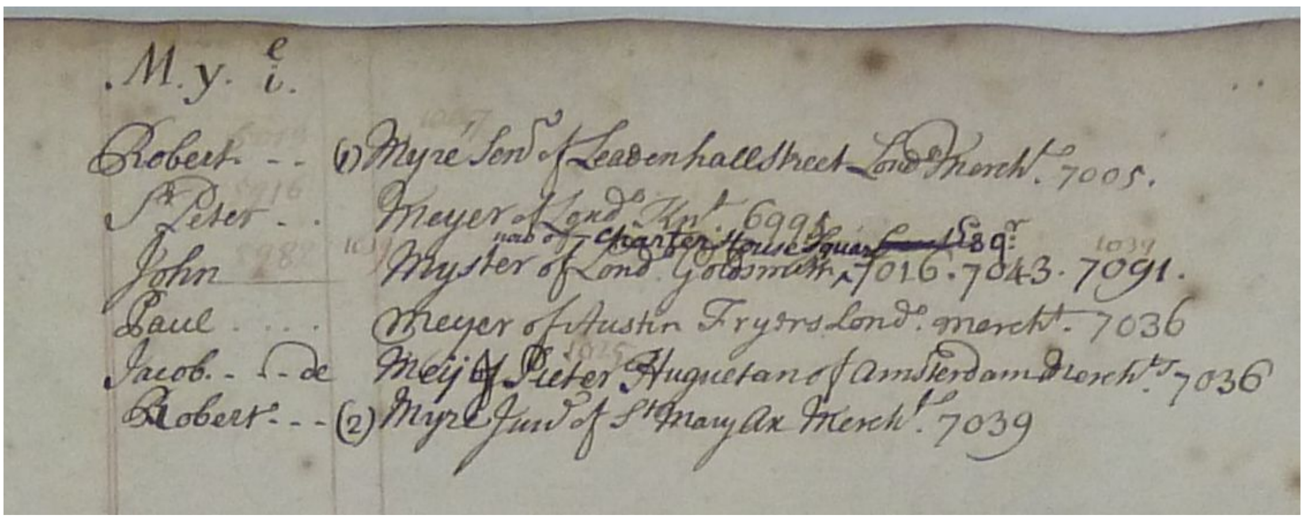
Figure 1: John Myster's financial records

(a) John Myster's stock sales



This figure displays John Myster's stock sales and was retrieved from the Bank of England stock ledger book.

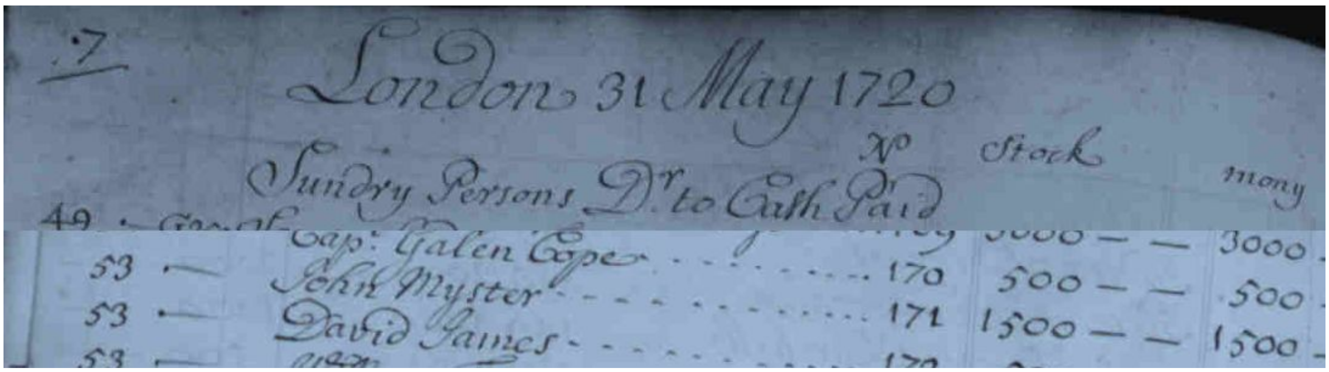
(b) John Myster's index entry



This figure displays John Myster's ledger index entry. The numbers indicate pages in the ledger book where Myster's accounts are registered.

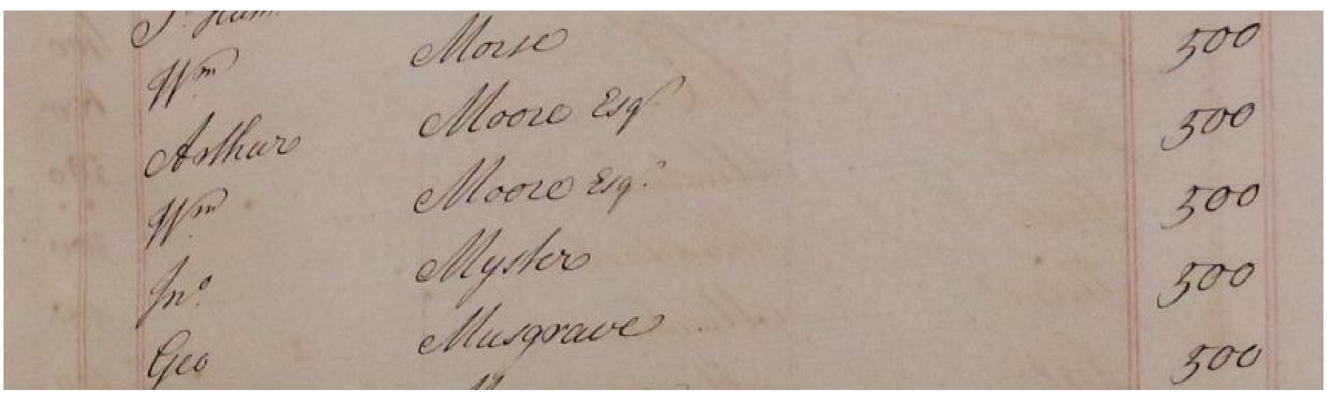
Figure 2: John Myster's loan position and subscriptions

(a) John Myster's Bank of England Loan



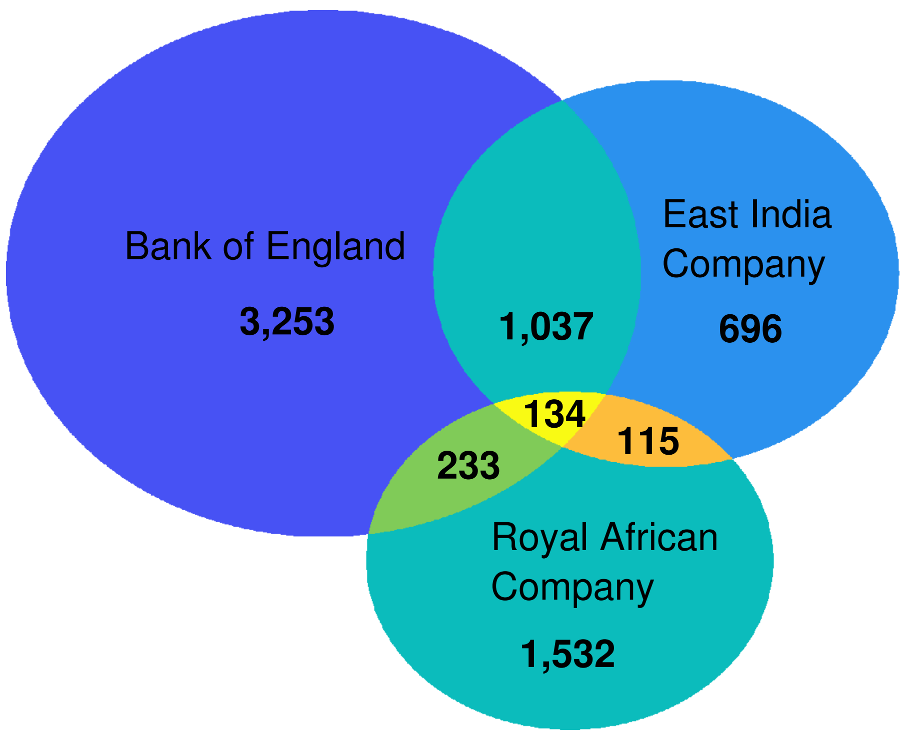
This figure displays John Myster's Bank of England stock loan as recorded in the loan book.

(b) John Myster's fourth South Sea subscription



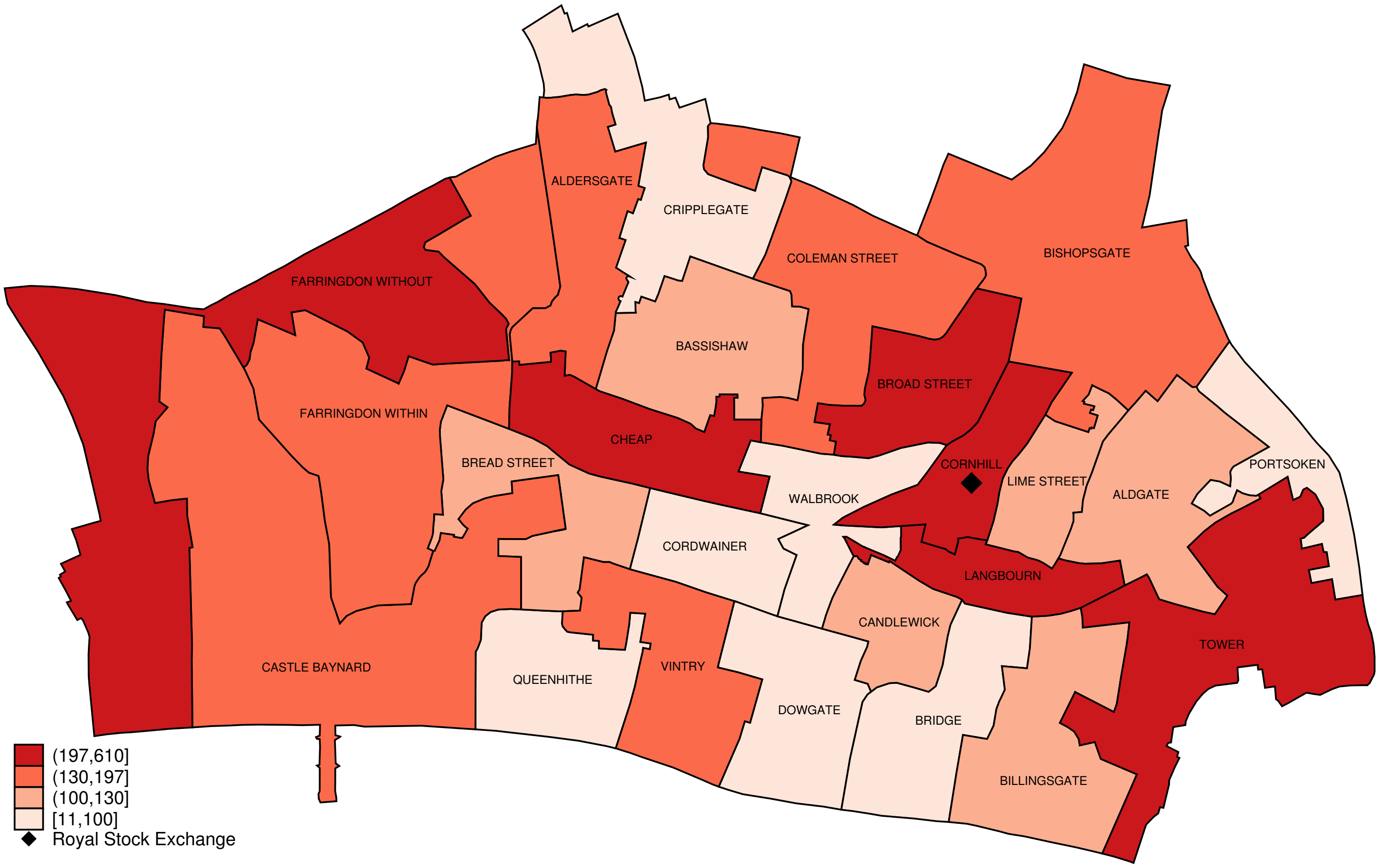
This figure shows John Myster's fourth South Sea Company subscription.

Figure 3: Number of traders per company



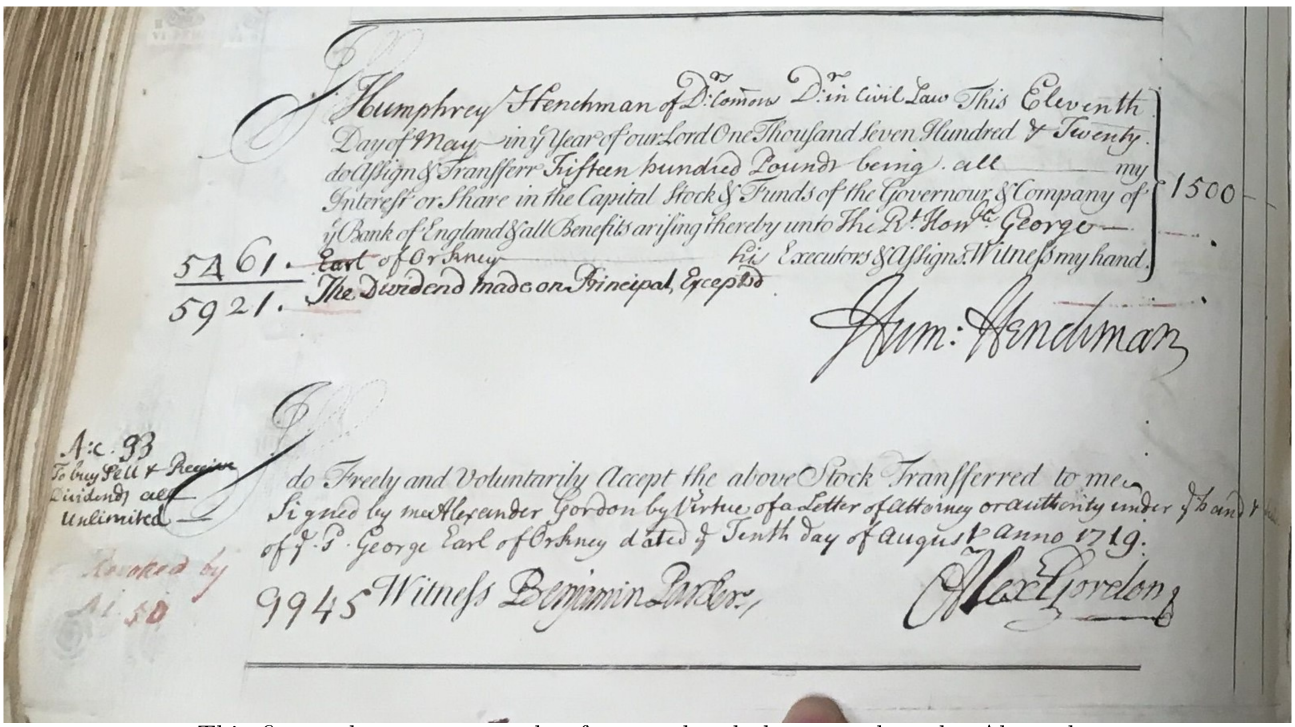
This figure shows how many investors are active in the three main companies in our sample, with overlapping areas indicating that traders are active in more than one company. For each of these three companies we collect daily holdings and each transaction for every individual shareholder, and we classify an investor as active if she trades at least once during our sample period (January 1, 1720 to October 6, 1720).

Figure 4: Numbers of shares pledged in the wards of the city of London



This figure displays the geographical location of the 27 wards in the City of London. We categorize wards into quartiles based on the total loan sum where darker colors indicate a quartile with a higher loan sum. The black square indicates the location of the London Stock Exchange.

Figure 5: Example of mandated trading


I Humphrey Henchman of Drs Commons Dr in Civil Law This Eleventh Day of May in ye Year of our Lord One Thousand Seven Hundred & Twenty do Assign & Transferr Fifteen hundred Pounds being all my Interest or Share in the Capital Stock & Funds of the Governour & Company of ye Bank of England & all Benefits arising thereby unto The Rt Honble George Earl of Orkney his Executors & Assigns Witness my hand. 1500

5461.
5921. The Dividend made on Principal Excepted

Hum: Henchman

A:c. 93
To buy Sell & Receive Dividends all Unlimited

I do Freely and Voluntarily Accept the above Stock Transferred to me Signed by me Alexander Gordon by Virtue of a Letter of attorney or authority under ye hand of ye Rt George Earl of Orkney dated ye Tenth day of August anno 1719.

9945 Witness Benjamin Parker

Alex Gordon

This figure shows an example of a mandated share purchase by Alexander Gordon on behalf of the Earl of Orkney on 11th of May, 1720. Gordon holds a mandate to buy and sell unlimited amounts of stocks and collect dividends. The stock seller is Humphrey Henchman.

Table 1: **Do loan holders behave as extrapolators? Excluding South Sea loan holders**

This table reports parameter estimates of a linear probability regression where the dependent variable is a buy dummy $Buy_{ijt}(d)$ that takes the value of one if trader i bought share j on date t. We exclude South Sea loan holders from our sample. The main independent variable is a loan dummy ($Loan_{it}^{BOE}(d)$) interacted with realized returns of stock j over the past τ trading days ($R_{jt-\tau}$) using opening prices. $Loan_{it}^{BOE}(d)$ takes the value of one if investor i has an outstanding margin loan with the Bank of England at date t. $Holdings_{ijt-1}(ln)$ denotes the logarithm of trader's i's nominal holdings in share j at $t-1$. Depending on the specification, we control for company×date fixed effects ($company - dateFE \quad (\rho_{jt})$), trader×date fixed effects ($trader - dateFE \quad (\kappa_{it})$), company×trader fixed effects ($company - traderFE \quad (\psi_{ji})$) and trader fixed effects interacted with realized returns in the last week ($traderFE \times R_{jt-6} \quad (\xi_i \times R_{jt-6})$). Standard errors clustered by trader and date are reported in parentheses. The symbols $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$
$Loan_{it}^{BOE}(d) \times R_{jt-4}$	0.047***						
	(0.016)						
$Loan_{it}^{BOE}(d) \times R_{jt-14}$		0.057**					
		(0.026)					
$Loan_{it}^{BOE}(d) \times R_{jt-6}$			0.063***	0.053**	0.038	0.042	0.021
			(0.022)	(0.021)	(0.027)	(0.029)	(0.031)
$Holdings_{ijt-1}$ (ln)	0.003***	0.003***	0.003***	0.003***	0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$Loan_{it}^{BOE}(d)$	0.004***	0.003***	0.004***	0.004***			
	(0.001)	(0.001)	(0.001)	(0.001)			
R_{jt-4}	0.000						
	(0.002)						
R_{jt-14}		0.001					
		(0.003)					
R_{jt-6}			0.002				
			(0.003)				
Intercept	0.002***	0.002***	0.002***	0.002***	0.002***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
R^2	0.004	0.004	0.004	0.007	0.514	0.544	0.547
N	1,402,961	1,412,283	1,407,622	1,407,622	1,407,622	1,407,622	1,407,622
$company \times dateFE \quad (\rho_{jt})$	No	No	No	Yes	Yes	Yes	Yes
$trader \times dateFE \quad (\kappa_{it})$	No	No	No	No	Yes	Yes	Yes
$company \times traderFE \quad (\psi_{ji})$	No	No	No	No	No	Yes	Yes
$traderFE \times R_{jt-6} \quad (\xi_i \times R_{jt-6})$	No	No	No	No	No	No	Yes

Table 2: **Do loan holders gain or lose during the South Sea Bubble? - Excluding South Sea loan holders**

In this table we regress investor-company specific realized returns, R_{ijt}, on $Loan_{it}^{BOE}(d)$, a dummy variable that takes the value of one if a trader held a margin loan of the Bank of England at date t and we exclude South Sea borrowers from our sample. R_{ijt} measures investor i's realized return in company j at date t coming from selling stock j or receiving dividends (see equation (1). We control for the natural logarithm of each trader i's nominal holdings in share j at the beginning of the trading day ($Holdings_{ijt-1}$ (ln)). Depending on the specification, we also control for company fixed effects (ν_j), trader fixed effects (ξ_i) and company×trader fixed effects (ψ_{ji}). The standard errors clustered by trader and date are reported in parentheses. The symbols $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	R_{ijt}	R_{ijt}	R_{ijt}	R_{ijt}
$Loan_{it}^{BOE}(d)$	-0.089***	-0.088***	-0.063**	-0.030
	(0.032)	(0.027)	(0.030)	(0.023)
$Holdings_{ijt-1}$	0.005	0.008	0.034***	0.040***
	(0.014)	(0.017)	(0.011)	(0.010)
Intercept	0.047	0.039	-0.028	-0.045*
	(0.070)	(0.078)	(0.038)	(0.027)
R^2	0.004	0.009	0.558	0.779
N	13,727	13,727	13,727	13,727
$companyFE \quad (\nu_j)$	No	Yes	Yes	No
$traderFE \quad (\xi_i)$	No	No	Yes	No
$company-traderFE \quad (\psi_{ji})$	No	No	No	Yes

Table 3: **Optimal leverage and share purchases**

In this table we report parameter estimates of a linear probability regression where the dependent variable changes depending on the specification. In the first column the dependent variable is a dummy that takes the value of 1 if trader i bought Bank of England stock at date t. In the second column the dependent variable is a dummy that takes the value of 1 if trader i bought East India Company stock at date t. In the third column the dependent variable is a dummy that takes the value of 1 if trader i bought Royal African stock at date t. $Loan_{it}^{BOE}(d)$ takes the value of one if investor i has a share loan outstanding with the Bank of England at t. $Portfolio\ Return_{it-6}$ are investor i's portfolio returns in the past 6 trading days of East India Company and Royal African Company (column 1), Bank of England and Royal African Company (column 2), Bank of England and East India Company (column 3). We control for trader fixed effects (ξ_i) and date fixed effects (υ_t). The standard errors clustered by trader and date are reported in parentheses. The symbols $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$BOE\ Buy_{it}(d)$	$EIC\ Buy_{it}(d)$	$RAC\ Buy_{it}(d)$
$Loan_{it}^{BOE}(d)$	-0.008***	0.001	-0.011
	(0.002)	(0.001)	(0.001)
$Portfolio\ Return_{it-6}$	-0.004	-0.016	0.005
	(0.005)	(0.013)	(0.008)
$Loan_{it}^{BOE}(d) \times Portfolio\ Return_{it-6}$	-0.016	0.005	0.014
	(0.024)	(0.048)	(0.022)
R^2	0.045	0.077	0.050
N	608,090	470,120	465,010
$traderFE\quad(\xi_i)$	Yes	Yes	Yes
$dateFE\quad(\upsilon_t)$	Yes	Yes	Yes

Table 4: **Network effects in borrowing**

This table reports parameter estimates of a linear probability regression where the dependent variable is a dummy that takes the value of one if trader i took a Bank of England loan or increased her Bank of England loan position on day t. In the first three columns we use the sub-sample of traders located in the City of London and in the last five columns we use the subsample of traders who employed trading agents. Network loans$^{Ward}_{t-6}$ is the number of Bank of England shares pledged in the previous week by other traders who lived in the ward where trader i lived; Network loans$^{Agent}_{t-30}$ is the number of Bank of England shares pledged in the previous 30 days by traders that used the same trading agent as trader i. Both network variables exclude trader i's pledged amounts. We also control for the number of shares pledged for a South Sea Company loan in the ward or agent network. $Holdings_{ijt-1}(ln)$ represents the logarithm of the nominal holdings the investor had at the beginning of the trading day. $\bar{R}^{WardNetwork}_{it}$ ($\bar{R}^{AgentNetwork}_{it}$) is the average realized return in the trader's ward (agent's network) computed over a 6 days (30 days) rolling window, where realized trader returns are value-weighted using average nominal holdings. Demographic controls includes $R_i^{1715-19}$, $TotTrades_i^{1715-19}$, New Investor (d), $Holdings_i^{1715-19}$, London$_i$ (d), Foreign$_i$ (d), Aristocrat$_i$ (d), Broker$_i$ (d), Male$_i$ (d). All these variables are defined in Table 3 in the paper. Standard errors are reported in parentheses. The standard errors in the City of London sample (columns 1-3) are double clustered by ward and date. Since there are only 27 wards in our sample, we bootstrap the standard errors using 1,000 bootstrap repetitions. In the sample of mandated trades (columns 4-8) standard errors are clustered by trader and date. The symbols $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Wards Sample			Mandated Trades				
	$Loan^{BOE}_{it}$	$Loan^{BOE}_{it}$	$Loan^{BOE}_{it}$	$Loan^{BOE}_{it}$	$Loan^{BOE}_{it}$	$Loan^{BOE}_{it}$	$Loan^{BOE}_{it}$	$Loan^{BOE}_{it}$
Network loans$^{Ward}_{it-6}$ (ln)	0.003***	0.002***	0.003***					
	(0.000)	(0.000)	(0.000)					
Network loans$^{Agent}_{it-30}$ (ln)				0.002***	0.002***	0.002***	0.002***	0.002*
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Holdings_{ijt-1}$ (ln)	0.002***	0.002***	0.004***	0.001***	0.000	0.001	0.002	0.004
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
$\bar{R}^{WardNetwork}_{it}$			-0.001*					
			(0.000)					
$\bar{R}^{AgentNetwork}_{it}$						0.000	0.000	-0.000
						(0.000)	(0.000)	(0.000)
R^2	0.008	0.012	0.015	0.002	0.033	0.033	0.145	0.303
N	101,777	101,777	99,815	49,396	49,396	48,598	43,433	9,358
Demographic controls	Yes	Yes	No	Yes	Yes	No	No	No
$traderFE \quad (\xi_i)$	No	No	Yes	No	No	Yes	Yes	Yes
$dateFE \quad (\zeta_t)$	No	Yes	Yes	No	Yes	Yes	No	No
$location \times dateFE \quad (\pi_{ct})$	No	No	No	No	No	No	Yes	No
$ward \times dateFE \quad (\omega_{wt})$	No	No	No	No	No	No	No	Yes

Table 5: **Network effects in loan holder trading**

This table reports parameter estimates of a linear probability regression of buy dummies on a loan dummy interacted with stock purchases in a trader's ward. We measure stock purchases in the ward as the number of buys in the same ward over the past trading week ($WardBuys^{Ward}_{ijt-6}$), excluding trader i's purchases. $Buy_{ijt}(d)$ takes the value of one if investor i buys share j on date t and $Loan^{BOE}_{it}(d)$ takes the value of one if investor i has a share loan outstanding with the Bank of England at t. All specifications control for the total number of buys of stock j at a given date excluding trader i: $TotalBuys_{ijt-6}$, and the logarithm of investor i's nominal holdings in stock j at the beginning of trading day t: $Holdings_{ijt-1}$. Depending on the specification, we control for company×date fixed effects (ρ_{jt}), trader×date fixed effects (κ_{it}), company×trader fixed effects (ψ_{ji}) and trader fixed effects interacted with the number of ward buys excluding trader i in the last week ($\xi_i \times WardBuys_{ijt-6}$). Standard errors clustered by trader and date are reported in parentheses. Since there are only 27 wards in our sample, we bootstrap the standard errors using 1,000 bootstrap repetitions. The symbols $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$
$Loan^{BOE}_{it}(d) \times WardBuys_{ijt-6}$ (ln)	0.002***	0.001***	0.001***	-0.000	-0.000	-0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
$Holdings_{ijt-1}$ (ln)	0.004***	0.004***	0.004***	0.004***	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$WardBuys_{ijt-6}$ (ln)	0.001***	0.001**	0.001	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Loan^{BOE}_{it}(d) \times TotalBuys_{ijt-6}$ (ln)		0.002**	0.002**	0.003**	0.003**	0.003*
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Loan^{BOE}_{it}(d)$	-0.001	-0.013**	-0.013***			
	(0.001)	(0.005)	(0.005)			
$TotalBuys_{ijt-6}$ (ln)		0.001***				
		(0.000)				
Intercept	0.001	-0.006***	0.002**	0.003**	0.008***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.005	0.005	0.008	0.463	0.492	0.495
N	547,504	547,504	547,504	459,255	459,255	459,255
$company \times dateFE$ (ρ_{jt})	No	No	Yes	Yes	Yes	Yes
$trader \times dateFE$ (κ_{it})	No	No	No	Yes	Yes	Yes
$company \times traderFE$ (ψ_{ji})	No	No	No	No	Yes	Yes
$traderFE \times WardBuys_{ijt-6}$ $(\xi_i \times WardBuys_{ijt-6})$	No	No	No	No	No	Yes

Table 6: **Network effects in loan holder trading - Excluding South Sea loan holders**

This table reports parameter estimates of a linear probability regression of buy dummies on a loan dummy interacted with stock purchases in a trader's ward and we exclude South Sea borrowers from our sample. We measure stock purchases in the ward as the number of buys in the same ward over the past trading week ($WardBuys^{Ward}_{ijt-6}$), excluding trader i's purchases. $Buy_{ijt}(d)$ takes the value of one if investor i buys share j on date t and $Loan^{BOE}_{it}(d)$ takes the value of one if investor i has a share loan outstanding with the Bank of England at t. All specifications control for the total number of buys of stock j at a given date excluding trader i: $TotalBuys_{ijt-6}$, and the logarithm of investor i's nominal holdings in stock j at the beginning of trading day t: $Holdings_{ijt-1}$. Depending on the specification, we control for company×date fixed effects (ρ_{jt}), trader×date fixed effects (κ_{it}), company×trader fixed effects (ψ_{ji}) and trader fixed effects interacted with the number of ward buys excluding trader i in the last week ($\xi_i \times WardBuys_{ijt-6}$). Standard errors clustered by trader and date are reported in parentheses. Since there are only 27 wards in our sample, we bootstrap the standard errors using 1,000 bootstrap repetitions. The symbols $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$
$Loan^{BOE}_{it}(d) \times WardBuys_{ijt-6}$ (ln)	0.002***	0.001***	0.001***	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
$Holdings_{ijt-1}$ (ln)	0.004***	0.004***	0.004***	0.004***	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$WardBuys_{ijt-6}$ (ln)	0.001***	0.001**	0.001	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Loan^{BOE}_{it}(d) \times TotalBuys_{ijt-6}$ (ln)		0.002**	0.002***	0.002**	0.002**	0.003**
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Loan^{BOE}_{it}(d)$	-0.001	-0.012**	-0.012***			
	(0.001)	(0.004)	(0.004)			
$TotalBuys_{ijt-6}$ (ln)		0.001***				
		(0.000)				
Intercept	0.001	-0.005***	0.002*	0.002**	0.007***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.005	0.005	0.008	0.463	0.494	0.498
N	490,960	490,960	490,960	411,825	411,825	411,825
$company \times dateFE \quad (\rho_{jt})$	No	No	Yes	Yes	Yes	Yes
$trader \times dateFE \quad (\kappa_{it})$	No	No	No	Yes	Yes	Yes
$company \times traderFE \quad (\psi_{ji})$	No	No	No	No	Yes	Yes
$traderFE \times WardBuys_{ijt-6} \quad (\xi_i \times WardBuys_{ijt-6})$	No	No	No	No	No	Yes

Table 7: **Network effects in loan holder trading - Excluding South Sea loan holders**

This table reports parameter estimates of a linear probability regression of buy dummies on a loan dummy interacted with stock purchases in a trader's ward, where we exclude South Sea borrowers from our sample. We measure stock purchases in the ward as the number of buys in the same ward over the past trading week ($WardBuys^{Ward}_{ijt-6}$), excluding trader i's purchases. $Buy_{ijt}(d)$ takes the value of one if investor i buys share j on date t and $Loan^{BOE}_{it}(d)$ takes the value of one if investor i has a share loan outstanding with the Bank of England at t. All specifications control for the total number of buys of stock j at a given date excluding trader i: $TotalBuys_{ijt-6}$, and the logarithm of investor i's nominal holdings in stock j at the beginning of trading day t: $Holdings_{ijt-1}$. Depending on the specification, we control for company×date fixed effects (ρ_{jt}), trader×date fixed effects (κ_{it}), company×trader fixed effects (ψ_{ji}) and trader fixed effects interacted with the number of ward buys excluding trader i in the last week ($\xi_i \times WardBuys_{ijt-6}$). Standard errors clustered by trader and date are reported in parentheses. Since there are only 27 wards in our sample, we bootstrap the standard errors using 1,000 bootstrap repetitions. The symbols $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$	$Buy_{ijt}(d)$
$Loan^{BOE}_{it}(d) \times NetworkBuys_{ijt-30}$ (ln)	0.003	0.002	0.002	-0.003	0.000
	(0.002)	(0.002)	(0.002)	(0.005)	(0.010)
$Loan^{BOE}_{it}(d)$	0.003	-0.081**	-0.083***		
	(0.003)	(0.031)	(0.030)		
$NetworkBuys_{ijt-30}$ (ln)	0.001	0.001	0.001	0.001*	
	(0.001)	(0.001)	(0.001)	(0.001)	
$Holdings_{ijt-1}$ (ln)	0.006***	0.006***	0.006***	0.005***	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Loan^{BOE}_{it}(d) \times TotalBuys_{ijt-30}$ (ln)		0.011**	0.012***	0.015**	0.019***
		(0.004)	(0.004)	(0.007)	(0.007)
$TotalBuys_{ijt-30}$ (ln)		0.001**			
		(0.000)			
Intercept	0.000	-0.005*	0.000	-0.002	0.004*
	(0.000)	(0.003)	(0.001)	(0.002)	(0.002)
R^2	0.012	0.012	0.017	0.545	0.621
N	279,036	279,036	279,036	279,036	279,036
$company \times dateFE \quad (\rho_{jt})$	No	No	Yes	Yes	Yes
$trader \times dateFE \quad (\kappa_{it})$	No	No	No	Yes	Yes
$company \times traderFE \quad (\psi_{ji})$	No	No	No	No	Yes
$traderFE \times NetworkBuys_{ijt-30} \quad (\xi_i \times NetworkBuys_{ijt-30})$	No	No	No	No	Yes