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Searching for informed traders in stock markets: The case of Banco Popular

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ABSTRACT

In this paper, we use several indicators of trade informativeness to search for informed traders on the final trading days of Banco Popular, the first and only bank resolution case to date in the euro area. In particular, we use the model proposed by Preve and Tse (2013) to estimate the adjusted daily probability of informed trading and the probability of symmetric order-flow shock using high-frequency transaction data. Our empirical results indicate that upon the anticipation of a possible liquidation of the bank, informed investors reacted to the bad news by placing more weight on it and that Banco Popular experienced large increases in both buy- and sell-orders during the last days of trading when the bank registered a significant depletion of its deposit base. Moreover, we find evidence supporting the presence of inside trading and illiquidity, especially after speculation in the media that the bank could face a liquidation. Our study has important implications for market participants and regulatory authorities.

1. Introduction

Information is a driving force of trading activities. Economic theory in particular suggests that the presence of private information has important implications for financial markets. For instance, institutional investors, primarily those trading in individual stocks, possess firm-specific information which is not available to the general public; therefore, they are regarded as better informed and more sophisticated traders than individual investors (Albuquerque et al., 2009).

There exists extensive research in Finance on informed trading behaviours in stock markets. Financial market microstructure theories divide traders into uninformed (with no special informational advantages) and informed (with private information) (see Glosten & Milgrom, 1985; Easley and O'Hara, 1987, among many others). The presence of private information in financial markets has been documented not only in equity markets (see, e.g. Dev, 2013; and Levi & Zhang, 2014), but also in bond markets (see Brandt & Kavajecz, 2004; Green, 2004; Pasquariello & Vega, 2007; and Menkveld et al., 2008, among others) and foreign exchange markets (see, e.g., Lyons, 2001; and Evans & Lyons, 2008). Moreover, Kagade (2009) contends that a peculiar feature of the banking sector is its information asymmetry.

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As the presence of asymmetric information in the market allows the informed traders to make a profit using the private information of informed trading, a large volume of the literature has developed various measure to gauge trade informativeness. In this regard, Easley et al. (1996) proposed the probability of informed trading (PIN) model to directly measure information asymmetry in stocks with high trading levels using the model of Glosten and Milgrom (1985) to estimate the proportion of informed traders from the dynamics of the signed order process.[1] Later, Duarte and Young (2009) extend the PIN model including an order-flow shock component and proposed the adjusted PIN (APIN), which measures asymmetric information, net of unrelated illiquidity effects. Besides, Duarte and Young (2009) introduce the probability of symmetric order-flow shock (PSOS) to measure the relative intensity of trades due to different opinions on public information events and consider it a measure of illiquidity unrelated to asymmetric information. Moreover, Tay et al. (2009) apply the asymmetric autoregressive conditional duration (AACD) model of Bauwens and Giot (2003) to estimate PIN using irregularly spaced transaction data, allowing for interactions between consecutive buy-sell orders and accounting for the duration between trades and the volume of trade. More recently, Preve and Tse (2013) propose a method to estimate daily APIN and PSOS by extending the method in Tay et al. (2009) using high-frequency transaction data.

In this paper, we make use of the model proposed by Preve and Tse (2013) to measure the likelihood of information-based trading and quantify the amount of private information during the final trading days of Banco Popular, the first bank rescued by the European Single Resolution Board (SRB). We believe that Banco Popular is a relevant and interesting case since it was the sixth-largest banking group in Spain before the SRB placed it under resolution. It was bought by Banco Santander as part of a rescue package in June 2017. The decision was made after the European Central Bank (ECB) detected a stressed liquidity situation and considered that Banco Popular was "failing or likely to fail" on 6 June 2017. The SRB and the Spanish National Resolution Authority decided on 7 June 2017 that the sale was in the public interest since it protected all depositors of Banco Popular and avoided adverse effects on financial stability and the real economy. The perceived lack of transparency regarding the SRB's treatment of Banco Popular has prompted a rash of litigation from both bondholders and shareholders for the possible use of privileged information by some agents and bringing to light several shortfalls of this crisis management system (Lupinu, 2020). To the best of our knowledge, this is the first study to formally search for the presence of informed traders by using the performance of this bank whose quoted prices have been reported to be affected using allegedly informational advantages derived from confidential information. Our paper aims to shed further light on the scarcely explored and still an open debate in the literature and provide unique insights from which to draw lessons on how to deal with similar processes in the future. This is especially relevant in the context of the current global pandemic were holdings by banks of domestic sovereign debt have surged and could trigger the "diabolic loop" established between the government and the banking system and could threaten macro-financial stability and lead to potential bank solvency vulnerabilities (IMF, 2020).

The key findings of this paper are summarized as follows: i) upon the anticipation of a possible liquidation of the bank, informed investors reacted to the bad news by placing more weight on it; ii) the Banco Popular experienced large increases in both buy- and sell-orders during the last days of trading, iii) the estimated daily probability of a common shock experienced a significant increase on the last trading days; and iv) there existed an increase in the proportions of trades induced by private information and the presence of disputable public information and illiquidity after the disclosure in the media that the bank might face wind-down. All in all, our results suggest the presence of information asymmetry and heterogeneous informed traders during the last trading days of Banco Popular.

The rest of the paper is organized as follows. Section 2 outlines the econometric framework to quantify the presence of informed. Section 3 presents our data and reports the empirical results. Finally, Section 4 summarizes the findings and offers some concluding remarks.

2. Econometric methodology

We use the model proposed by Preve and Tse (2013). This model has two foundations. First, it is based on the Duarte and Young (2009)'s APIN model, which extend Easley et al. (2002) by allowing for the arrival rate of informed buyers to be different from the arrival rate of informed sellers, but also by permitting both buy- and sell-order flows to upturn on certain days even when there is no news. Therefore, the APIN is the expected number of informed trades regarding the expected number of uninformed, informed, and symmetric order-flow shock trades. Second, it is an extension of the Tay et al. (2009) model to estimate PIN using irregularly spaced transaction data based on the AACD model of Bauwens and Giot (2003) for trade directions.

Therefore, the Preve and Tse (2013) model allows us to compute APIN daily, but also it allows us to estimate the probabilities of good, bad and no news and conditional shocks assuming time-varying probabilities using the AACD model.

Next, we define the specification and estimation of the APIN-AACD model following Preve and Tse (2013).

2.1. Specification of the APIN-AACD model

Market participants are heterogeneous in terms of, for example, preferences, financial constraints, access to private information, or abilities to process public information, and accordingly their behaviour differ. In this regard, like in the PIN-AACD model of Tay et al. (2009), the APIN-AACD model of Preve and Tse (2013) assumes that each trading day may be classified as one with news or no news, and there are two types of traders: informed traders who trade based on relevant news information and uninformed traders who trade

[1] The PIN model has been widely used in the financial literature and it has been empirically tested to directly evaluate the probability of insiders' action (see, e. g., Easley et al., 2002, 2005; and Aktas et al., 2007).

for reasons not accounted for relevant information.

Let be the duration between trades ($i = 1, \ldots, N$ being N is the total number of trades for all days), such as $x_i = t_i - t_{i-1}$ being t_i the time for the trade in period i. Let the latent trade direction variable be denoted by$y_i \in \{-1, 1\}$, where $j = -1$ indicates a sell-initiated trade, and $j = 1$ a buy-inititated trade. Conditional on the set information in i-1 (Φ_{i-1}), trade direction at time t_i follow latent point processes. Consider that buy and sell orders, that is, $[B_i(s_i), s_i \geqslant 0]$ and $[S_i(s_i), s_i \geqslant 0]$ are latent Poisson processes with intensities, λ_{1i} andλ_{-1i}, respectively. Under the Poisson process, the latent duration is exponentially distributed with mean$\psi_{ji} = 1/\lambda_{ji}$, given$\Phi_{i-1}$. The conditional joint distribution of duration and the latent trade direction, which are independent conditional onΦ_{i-1}, can be defined by:

$$f(x_i, y_i | \Phi_{i-1}) = \prod_{j=-1,1} \left(\frac{1}{\psi_{ji}}\right)^{1_{\{y_i=j\}}} \exp\left(-\frac{x_i}{\psi_{ji}}\right) \tag{1}$$

where $1_{\{y_i=j\}}$ is an indicator function which takes value one if $y_i = j$ and 0 otherwise.

The APIN-AACD model allows calculate APIN based on a specific day as well as over intraday intervals using high-frequency transaction data.

It is worth noting that intensities can be also different for each trading day depending on the state of news. Unlike Tay et al. (2009) which consider three states such as no news (N), good news (G), bad news (B), the Preve and Tse (2013) model consider three additional daily states representing trading days in which the conditional intensity of buy and sell orders increase due to common shock as in Duarte and Young (2009). These new states are no news and a common shock (CN), good news and a commons shock (CG) and bad news and a commons shock (CB). Therefore, the state set for each trading day can be defined as $S = \{N, G, B, CN, CG, CB\}$.

The activity of privately informed traders generates prices movements as new information is revealed as a result of their trading (see, e.g., Kyle, 1985). To reflect the activities of informed and uninformed traders, but also symmetric order-flow shock trades, the conditional expected duration, ψ_{ji}^s, for trade direction j in state $s \in S$ for the i-th trade, givenΦ_{i-1}, is formuled in the APIN-AACD model. ψ_{ji}^s is modelled using the logarithmic asymmetric conditional expected duration (logarithmic AACD), which will reflect changes in trade intensity. For example, the APIN-AACD(p,q) model for the conditional expected duration for the no-news day can be written by the following expression extended with volume to allow impact trade intensity:

$$\log\psi_{ji}^N = \nu_{j,1} 1_{\{y_i=1\}} + \nu_{j,-1} 1_{\{y_i=-1\}} + \sum_{r=1}^{p} \alpha_{jr} \log x_{i-r} + \sum_{r=1}^{q} \beta_{jr} \log\psi_{ji-r}^N + c_j y_{i-1} \log\upsilon_{i-1} \tag{2}$$

where p and q are the polynomial lag orders for observed duration and expected duration, respectively, and υ_{i-1} is the volume of the trade at time t_{i-1} (for simplicity, we have omitted the covariation with high lagged periods). $\Gamma = \left\{\nu_{j,-1}, \nu_{j,1}, \alpha_{j1}, \ldots, \alpha_{jp}, \beta_{j1}, \ldots, \beta_{jq}, c_j\right\}, j = -1, 1$ is the vector of unknown parameters to be estimated in the AACD model and their interpretation is as follows: $\nu_{j,-1}$ represents the effect of buy or sells after a sell, while $\nu_{j,1}$ denotes the effect of buy or sells after a buy; α_{jr} and $\beta_{jr}(r = 1,\ldots,(p,q))$ are the coefficients for past observed durations, and conditional expected durations depending on buy and sells; and c_j is the coefficient for the effect of large buy orders ($j = 1$) or sell orders ($j = -1$), respectively. The process is stationary when $\sum_{r=1}^{p}\alpha_{jr} + \sum_{r=1}^{q}\beta_{jr} < 1$.

Equations for remaining conditional expected durations for each state,ψ_{ji}^s, $i = 1, \ldots, n; j = -1, 1; s \in S$, are given in Table 1 jointly with the trade intensities $\left(\lambda_{ji}^s, \ i = 1, \ldots, n; j = -1, 1; s \in S\right)$ based on the latent Poisson process conditional of trade direction j in state $s \in S$ for a buyer- or seller-initiated trade.[2]

Interpretation for some of these expressions can be summarized as follows. For example, for a bad-news day and seller-initiated trade, conditional expected duration model can be expressed as $\psi_{-1i}^B = \psi_{-1i}^N \exp(-\mu_B)$ (or $\log\psi_{-1i}^B = \log\psi_{-1i}^N - \mu_B$), while for a buyer-initiated trade in the same day, the expression can be defined by $\psi_{1i}^B = \psi_{1i}^N$ (or $\log\psi_{1i}^B = \log\psi_{1i}^N$). On the other hand, expression for the implied conditional Poisson intensity in a no news day for both the buyer- and seller-initiated trades are $\lambda_{1i}^N = \frac{1}{\psi_{1i}^N}$ and $\lambda_{-1i}^N = \frac{1}{\psi_{-1i}^N}$, respectively. Other example can be $\lambda_{1i}^G = 1/\psi_{1i}^G - \lambda_{1i}^N$, which represents the trade intensity for a buyer-initiated trade in a good-news day.[3]

In the APIN-AACD model, the days with news, bad news and common shocks occur with probabilities θ_{Ed}, θ_{Bd} and θ_{Cd}, respectively. These probabilities which are not constant and vary over days can be calculated depending on the volume of the buy- and sell-orders using a logistic way, as in Preve and Tse (2013), and as follows. First, the probability of news for the d-th day is defined by:

$$\theta_{Ed} = 1 - \frac{1}{1 + \exp\left(\gamma_1 + \gamma_2\left[\log\left(V_d^B + V_d^S\right) - \log\left(\overline{V}^B + \overline{V}^S\right)\right]\right)}$$

where V_d^B and V_d^S are the numbers of lots traded on day d initiated by buy- and sell-orders, and $\overline{V}^B$ and $\overline{V}^S$ are the average number of lots

[2] It is worth noting that the Poisson assumption is adopted so that the hazard rate is constant and is equal to the reciprocal of the expected duration, which is used as a measure of the trade intensity.

[3] It is worth noting that trade intensity for a good news day and $j = 1$ can be also written as:$\lambda_{1i}^G = 1/\psi_{1i}^G - \lambda_{1i}^N = \frac{1}{\psi_{1i}^N \exp(-\mu_G)} - \frac{1}{\psi_{1i}^N} = \lambda_{1i}^N(\exp(\mu_G) - 1)$.

Table 1
Expressions for the conditional expected duration and trade intensities in the APIN-AACD model using the formulas in Preve and Tse (2013).

State	Conditional expected duration		Intensities based on latent Poisson process	
s	$\psi_{ji}^{s}=$		$\lambda_{ji}^{s}=$	
	j = 1 (buy-initiated trade)	j = −1 (sell-initiated trade)	j = 1 (buy-initiated trade)	j = −1 (sell-initiated trade)
N	Defined by Eq. (1)	Defined by Eq. (1)	$1/\psi_{1i}^{N}$	$1/\psi_{-1i}^{N}$
G	$\psi_{1i}^{N}\exp(-\mu_G)$	ψ_{-1i}^{N}	$1/\psi_{1i}^{G}-\lambda_{1i}^{N}$	
B	ψ_{1i}^{N}	$\psi_{-1i}^{N}\exp(-\mu_B)$		$1/\psi_{-1i}^{B}-\lambda_{-1i}^{N}$
CN	$\psi_{1i}^{N}\exp(-\mu_{CN})$	$\psi_{-1i}^{N}\exp(-\mu_{CN})$	$1/\psi_{1i}^{CN}-\lambda_{1i}^{N}$	$1/\psi_{-1i}^{CN}-\lambda_{-1i}^{N}$
CG	$\psi_{1i}^{N}\exp(-\mu_G-\mu_{CG})$	$\psi_{-1i}^{N}\exp(-\mu_{CG})$	$1/\psi_{1i}^{CG}-\lambda_{1i}^{N}-\lambda_{1i}^{G}$	$1/\psi_{-1i}^{CG}-\lambda_{-1i}^{N}$
CB	$\psi_{1i}^{N}\exp(-\mu_{CB})$	$\psi_{-1i}^{N}\exp(-\mu_B-\mu_{CB})$	$1/\psi_{1i}^{CB}-\lambda_{1i}^{N}$	$1/\psi_{-1i}^{CB}-\lambda_{-1i}^{N}-\lambda_{-1i}^{B}$

Notes: ψ_{ji}^{s} is the conditional expected duration on the state s for j = 1, −1 trades, which is equal to the expression into the cell. The positive constants: μ_B, μ_{CB}, μ_G, μ_{CG} and μ_{CN} are unknown parameters. λ_{ji}^{s} is the intensity on state s for j = 1, −1 trades based on the latent Poisson process. These trade intensities are not constant over time.

traded per day initiated by buy and sell orders, respectively. γ_1 and γ_2 are unknown parameters, and γ_2 is expected to be strictly positive.

Second, conditional on the arrival of news, the probability of bad news on day d can be calculated as:

$$\theta_{Bd}=1-\frac{1}{1+\exp\left(\gamma_3\left(\log V_d^B-\log\overline{V}^B\right)-\gamma_4\left(\log V_d^S-\log\overline{V}^S\right)\right)}$$

where γ_3 and γ_4 are unknown parameters expected to be strictly positive.

And finally, the common shock days occur with probability θ_{Cd} and they can be calculated as:

$$\theta_{Cd}=1-\frac{1}{\exp\left(\gamma_5\left(\log V_d^B-\log\overline{V}^B\right)_+-\gamma_6\left(\log V_d^S-\log\overline{V}^S\right)_+\right)}$$

where the indicator function, $(u)_+$, equals u if $u>0$ and zero otherwise. It is worth noting that $\gamma_5\geqslant 0$ for that θ_{Cd} lies between 0 and 1.

Based on the above probabilities, we can construct the daily state probabilities, π_{sd}. Table 2 shows equations for all these probabilities which are based on the probabilities of news, bad news and common shocks.

As we can observe, daily state probabilities are also not constant and vary over days. Interpretation of expressions in Table 2 can be done as follows. For example, for a day with no news, the daily state probability is $\pi_{Nd}=(1-\theta_{Ed})(1-\theta_{Cd})$, and for a day with common shock and bad news, the daily state probability is defined by$\pi_{CBd}=\theta_{Ed}\theta_{Bd}\theta_{Cd}$, respectively.

Based on the Poisson assumption and conditional on Φ_{i-1}, the expected number of trades (buys (B) and sells (S)) due to all traders in the fixed interval, $(t_{i-1},t_i]$ can be written as:

$$E[B(x_i)+S(x_i)/\Phi_{i-1},x_i]=(P_{1i}+P_{2i}+P_{3i})x_i$$

where $P_{1i}=\lambda_{1i}^{N}+\lambda_{-1i}^{N}$ is the part due to the uninformed trades, $P_{2i}=\pi_{Gd}\lambda_{1i}^{G}+\pi_{Bd}\lambda_{-1i}^{B}$ is the part due to the informed trades, and $P_{3i}=\pi_{CBd}\left(\lambda_{1i}^{CB}+\lambda_{-1i}^{CB}\right)+\pi_{CGd}\left(\lambda_{1i}^{CG}+\lambda_{-1i}^{CG}\right)+\pi_{CNd}\left(\lambda_{1i}^{CN}+\lambda_{-1i}^{CN}\right)$ is the part due to the symmetric order-flow shock trades.

Hence, the both daily asymmetric probability informed trading (APIN) and the probability of symmetric order-flow shock (PSOS) can be calculated over all days as:

$$APIN_d=\frac{\sum_{i=1}^{N_d}P_{2i}x_i}{\sum_{i=1}^{N_d}(P_{1i}+P_{2i}+P_{3i})x_i}\text{ and }PSOS_d=\frac{\sum_{i=1}^{N_d}P_{3i}x_i}{\sum_{i=1}^{N_d}(P_{1i}+P_{2i}+P_{3i})x_i}$$

where$N_d=B_d+S_d$, denotes the number of all trades on day d, that is, the sum of total buy-initiated and sell-initiated trades in this day.

It is noteworthy that if $\theta_{Cd}=0$, then the APIN-AACD expression reduces to the PIN-AACD given that $P_{3i}=0$, and PSOS is zero.

2.2. Estimation of the APIN-AACD model

The estimation of the APIN-AACD model can be done by maximum likelihood.

The likelihood function (L) for all days in the sample can be written by:

$$L=\prod_{d=1}^{D}\left[\sum_{s\in S}\pi_{sd}\left(\prod_{i=1}^{N_d}f_s(x_i,y_i|\Phi_{i-1})\right)\right] \tag{3}$$

where $f_s(x_i,y_i|\Phi_{i-1})$ is defined by Eq. (2) and can be written as,

Table 2
Expressions for the daily state probabilities in the APIN-AACD model using the formulas in Preve and Tse (2013).

State s	Daily (d) state probabilities π_{sd} =
N	$(1-\theta_{Ed})(1-\theta_{Cd})$
G	$\theta_{Ed}(1-\theta_{Bd})(1-\theta_{Cd})$
B	$\theta_{Ed}\theta_{Bd}(1-\theta_{Cd})$
CN	$(1-\theta_{Ed})\theta_{Cd}$
CG	$\theta_{Ed}(1-\theta_{Bd})\theta_{Cd}$
CB	$\theta_{Ed}\theta_{Bd}\theta_{Cd}$

Notes: π_{sd} = be the probability of state s in S on day d.θ_{Ed}, θ_{Bd} and θ_{Cd} are the probability of a day containing news, the probability of bad news, and probability of a common shock on day d, respectively.

$$f_s(x_i, y_i|\Phi_{i-1}) = \left(\frac{1}{\psi^s_{1i}}\right)^{1_{\{y_i=1\}}}\left(\frac{1}{\psi^s_{-1i}}\right)^{1_{\{y_i=-1\}}}\exp\left(-\left(\frac{1}{\psi^s_{1i}}+\frac{1}{\psi^s_{-1i}}\right)x_i\right)$$

As we can observe, the joint density is based on the exponential assumption and incorporate variation with respect to the state of news and common shocks.

Expression (3) allows us to estimate the vector of parameters, $\Theta = \left\{v_{j,-1}, v_{j,1}, \alpha_{j1}, ..., \alpha_{jp}, \beta_{j1}, ..., \beta_{jq}, c_j, \mu_B, \mu_{CB}, \mu_G, \mu_{CG}, \mu_{CN}, \gamma_1, ..., \gamma_5\right\}$, $j = 1, -1$ using the maximum likelihood method. It is worth noting that the vector Θ includes the parameters defined in the AACD(p,q) model, the constant parameters defined in the trade intensities (see Table 1), and represented by $\mu_B, \mu_{CB}, \mu_G, \mu_{CG}$ and μ_{CN}, but also the coefficients for probabilities of news, bad news and common shocks that appear in the logit expressions($\gamma_1, ..., \gamma_5$).

3. Data and empirical results

3.1. Data

We use the transaction durations of a listed stock of the Spanish commercial bank named Banco Popular on 21 consecutive trading days from 2 January to 6 June 2017. Data were obtained from *Bolsas y Mercados Españoles* (BME, the operator of all stock Markets and financial systems in Spain) and represent positive transaction durations. In particular, our sample consists of 228,666 intraday observations without zeros.

Our sample covers the last 109 trading days of Banco Popular. This historical episode is particularly informative because numerous events were recorded whose impact is worth examining. Fig. 1 presents the closing price and the daily variance of Banco Popular during this period.[4] The figure includes important events that impact both variables and that could have given rise to the presence of private information. Selected events are discussed below.

Following the Global Financial Crisis, the Spanish banking system underwent major reorganization leaving 14 banks out of 55 in 2008 (see Igan et al., 2019). Banco Popular, Spain's sixth-largest bank, complied with all regulatory capital requirements, although it had sizeable problem assets and was one of the weakest banks in the 2016 EBA stress test. After showing signs of distress in 2016, the bank reported on 3 February 2017 a €3.5 billion loss for 2016, owing partly to increased provisions to expedite the cleaning of old assets. Following this statement, the bank's stock rating was downgraded to negative by Fitch on 15 February and Moody's on 15 March, and the bank's chairman was ousted at a tumultuous Shareholders Meeting on 15 March. An internal audit revealed extra provisioning needs of €600 million in April 2017, prompting the company to unveil a strategy to sell non-core companies and raise capital and increasing the possibility of selling the bank to a competitor. In May 2017, the bank recorded another loss of about €150 million in the first quarter of 2017 and the rating agencies undertook successive downgrades in the bank's credit rating reflecting concerns over its exposure to bad real estate assets.

This credit risk was aggravated by a reputational risk due to the news of Banco Popular's situation. In particular, on 11 May 2017, a digital newspaper disclosed that the bank mandated an urgent sale of the bank on account of the risk of bankruptcy and that its chairman informed other credit entities of an urgent liquidity need as a consequence of the massive deposit withdrawal. The same day the Spanish National Securities Market Commission: (the Spanish government supervisory agency) issued a public statement by the bank categorically denying this information. After rumours on 15 May that the ECB was closely monitoring the bank's performance and statements by the SRB on 23 and 31 about possible solvency problems that encountered substantial deposit outflows and liquidity

[4] Following Parkinson (1980), we estimate the daily variance using daily high and low prices, on day t we have: $\widetilde{\sigma}^2_t = 0.36[\ln(P^{MAX}_t) - \ln(P^{MIN}_t)]^2$, where P^{MAX}_t it is the maximum (high) price on day t, and P^{MIN}_t is the daily minimum (low) price. Given that $\widetilde{\sigma}^2_t$ is an estimator of the daily variance, the corresponding estimate of the annualized daily per cent standard deviation (volatility) is $\sigma^2_t = 100\sqrt{365\sigma^2_t}$.

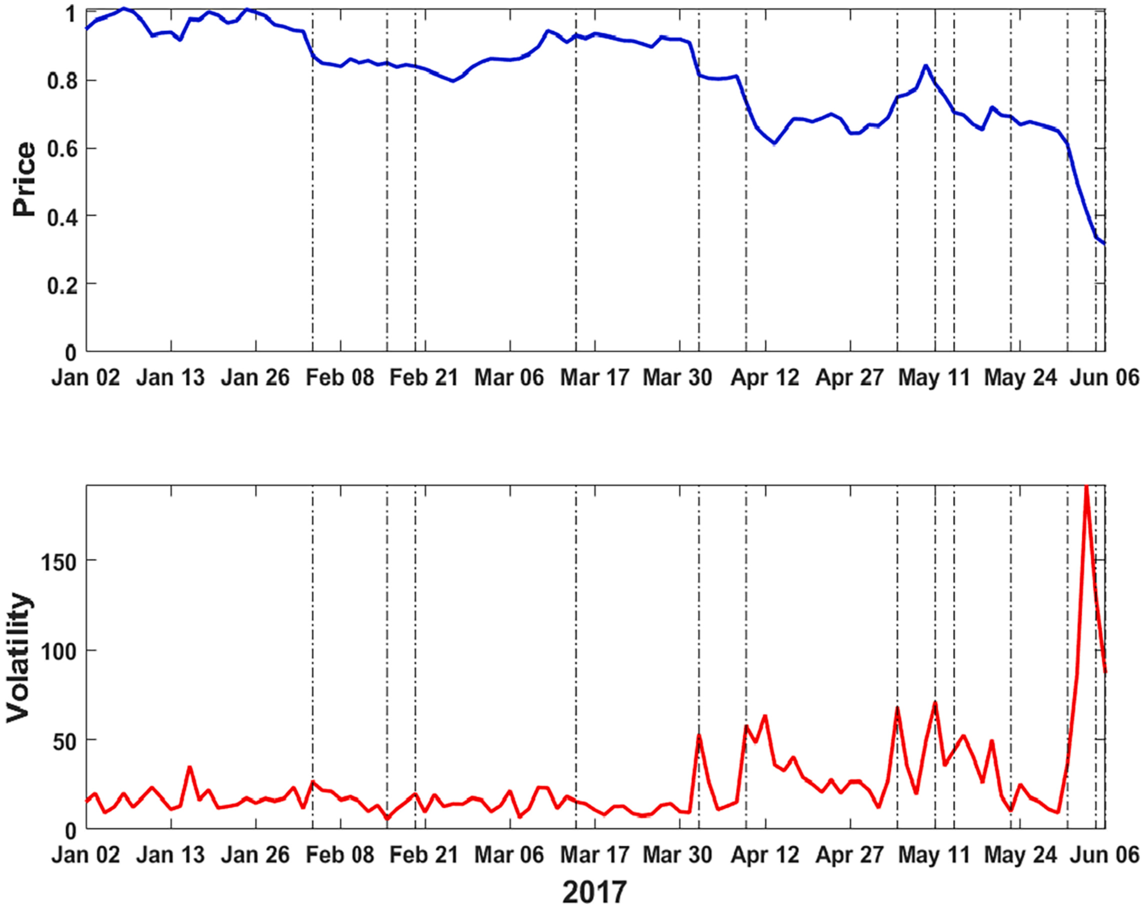

Fig. 1. Daily price and daily volatility for Popular (2 January to 6 June 2017).

shortages, market pressures intensified on 1 June 2017[5] and the Eurosystem granted significant emergency liquidity support on 2 June, as deposit outflows accelerated.

Following further alarming announcements, the bank experienced increasing deposit outflows and on 5 June, some organizations and public administrations withdrew liquidity from Banco Popular.

As a consequence of this mounting and multiple risks, on 6 June 2017, the ECB determined that the significant deterioration of the liquidity situation of the bank in previous days led to a determination that the entity would have, shortly, been unable to pay its debts or other liabilities as they fell due. Consequently, the ECB determined that the bank was failing or likely to fail and duly informed the SRB, which adopted on 7 June a resolution scheme entailing the sale of Banco Popular to Banco Santander.[6] This decision aimed to remove a source of uncertainty in the Spanish banking system and Euro area financial markets more generally.

The Banco Popular resolution marks a milestone in the development of the incipient European Banking Union, remains to this date the only bank resolution that has taken place under Europe's Bank Recovery and Resolution Directive and provides an important precedent. In this regard, the IMF (2020) cites Banco Popular as a good example of a bail-in resolution tool (without causing systemic disruption), in which the quick and well-coordinated resolution helped to maintain financial stability while avoiding the need of public funds.[7] The handling of information during the decision-making process sparked controversies that could have potentially led to a loss of confidence and contagion risks (Schillig, 2016, 311). In this sense, the dependency of the process on the presence of prospective buyers was stressed by critics (Brundsen, 2017).

[5] This behaviour is consistent with the findings offered in Haugen and Baker (1996) and Fama and French (1988) showing overreaction to a sustained record of extraordinary performance (whether good or negative).

[6] *See* https://srb.europa.eu/en/content/banco-popular.

[7] While no broad-based contagion occurred, selective but significant contagion was visible across the capital structures of some of Popular's weakest local peers (Financial Times, 2017; Goldman Sachs, 2017a), and Popular's bail-in did result in a further deterioration of funding costs for smaller versus larger players in the broader European banking space (Goldman Sachs, 2017b).

Looking at Fig. 1, we observe that most of the above-mentioned event significantly impact both the evolution of the price and daily volatility of the stock.[8]

Following Pérez-Rodríguez et al. (2021), we remove the deterministic component of observed durations and use a simple method to adjust the diurnal pattern of intraday trading activities.

Table 3 shows some summary statistics of the dataset and reports estimates of the state probabilities as well as the PIN measure of Easley et al. (2002) and the APIN and PSOS measures of Duarte and Young (2009) obtained from their classic estimators. Results indicate that the average number of trades per day is 5400. More than 66% of the trades for all stocks are buy orders. PIN is 0.12 and APIN is 0.13, suggesting that the estimated proportion of trades induced by private information is around 12%. Finally, PSOS is 0.02, indicating that Banco Popular share was not an illiquid stock during the entire sample period.

3.2. *Empirical results*

To compare results from different probability informed trading models with time-varying probabilities, we estimate the PIN-AACD of Tay et al. (2009) considering that and the APIN-AACD using the Preve and Tse (2013) model, respectively. To the best of our knowledge, this is the second study to implement the Preve and Tse (2013) model after their original paper, since it requires data of the duration between two consecutive transactions and the volume of each transaction in addition to trade direction that, in general, are not always available to the academic researcher.

Neverttheless, stock and option trading prior to mergers and acquisitions announcements (see, e.g., Jayaraman et al., 2001; Cao et al., 2005; or Heitzman & Klasa, 2021) and asset returns surrounding earnings announcements (Steven et al., 2004; or Cheng & Leung, 2008, among others) have been the main topic of informed trade analysis. The only previous analysis for a bank rescue in the literature is that of Pérez-Rodríguez et al. (2021), who assess the potential importance of heterogeneous traders in the 21 final trading days of Banco Popular. These authors apply a self-exciting threshold autoregressive conditional duration model to high-frequency transaction durations from 9 May to 6 June 2017 and find evidence of different reaction of market participants to new information entering market. Our work complements and extend the Pérez-Rodríguez et al. (2021) by using more appropriate methods to identify the presence of informed trading incorporating both asymmetric information and symmetric order-flow shocks. Given the prevalence of heterogeneity in trader types in financial markets, we consider incorporating these features could generate novel insights that would remain otherwise hidden in the previous analysis.

In our empirical application, estimation of PIN- and APIN-AACD models with time-varying probabilities were performed using Preve and Tse's (2013) Matlab codes with the interior-point algorithm (BFGS) and numerical derivatives. Following a standard practice in the literature, we imposed some initial conditions and constraints in the optimization problem to obtain a local minimum. On the other hand, although the Hessian was calculated in our constrained problem, its results were inaccurate and therefore the standard errors of the estimate could not be calculated correctly.[9] Due to these assumptions and restrictions, some caution is necessary when interpreting the results. However, as will be seen, the estimated parameters are reasonable and plausible, given that they not only seem to adequately explain the behaviour of the stock during the relevant events recorded in the study sample but are also in line with the findings of other articles that empirically investigate analogous events in other contexts. Thus, while acknowledging the existence of a trade-off between successful model building and empirical accuracy of statistical assumptions and procedures, we adopt Friedman's (1953) pragmatic approach to economics to concentrate strictly on problem-solving and focus on explanatory power and fruitfulness. In particular, we entrust the validation of the model to the comparison of the estimated results with the observed events.

Table 4 reports the results from maximum likelihood estimates of PIN-AACD and APIN-AACD models considering the AACD(1,1) specification for the time-varying conditional expected durations, which was preferred to other specifications in terms of information criteria.[10] Table 4 also shows the constant parameters for each state according to the conditional duration expectation model, the number of observations used and the Akaike information criteria (AIC).

Based on the AIC results, we can consider that the APIN-AACD(1,1) is preferred to the PIN-AACD(1,1) model. In this sense, we will focus our comments on the parameters of the former, keeping in mind the limitations previously indicated. First, regarding the coefficients of model (Table 4, Panel A), the parameter of the persistence in the AACD(1,1) model for both buys and sells: $\widehat{\beta}_1 + \widehat{\alpha}_1$ and$\widehat{\beta}_{-1} + \widehat{\alpha}_{-1}$, respectively, are less than 1. Note that the persistence is not high (i.e., 0.9 for both buy and sells, approximately) and therefore, we could consider that conditional expected duration is a stationary process.

Coefficients for buy after buy ($\widehat{\nu}_{1,1}$) and sells after sale and buy ($\widehat{\nu}_{-1j}, j = -1, 1$) are negative, only being positive the coefficient for buy after sell ($\widehat{\nu}_{1,-1}$). Finally, in contrast with Preve and Tse (2013), we observe that that $\widehat{c}_{-1} < 0$ and $\widehat{c}_1 < 0$ for both models. These results could imply that large buy and sell orders induce shorter conditional expected durations. This may reflect the effect of short selling constraints that traders without a long position cannot speculate on their negative private information (Barron et al., 2008). Notice that, like Preve and Tse (2013), our results could suggest that volume plays an explicit role in predicting the trade direction. Finally, our findings are in line with those presented in Pérez-Rodríguez et al. (2021) regarding the presence of heterogeneous traders

[8] Formal analysis using an event study approach (not shown here to save space, but available from the authors upon request) strongly supports the role of most of these events in the dynamic evolution of the price and daily volatility of the Banco Popular during the examined period.

[9] See the Matlab documentation for fmincon regarding this problem.

[10] Due to the aforementioned statistical problems, we do not report the standard errors in Table 4 and the interpretation of the statistical significance of the parameters has been omitted.

Table 3
Summary statistics and estimated state probabilities, PIN, APIN and PSOS using classic models (2 January to 6 June 2017).

Panel A: Summary statistics	
Frequency of buy orders (%)	61.79
Frequency of sell orders (%)	38.21
Average daily trade volume	5,400.59
Average daily number of buy-orders	3,391.94
Average daily number of sell-orders	2,008.65
Panel B: Estimated PIN results (EHO, 2002)	
π_N	0.5315
π_G	0.5066
π_B	0.0468
PIN	0.1151
Panel C: Estimated APIN-PSOS results (Duarte and Young, 2009)	
π_N	0.8881
π_G	0.0281
π_B	0.0281
π_{CN}	0.0523
π_{CG}	0.0017
π_{CB}	0.0017
APIN	0.1276
PSOS	0.0181

Table 4
Estimation results for the PIN and APIN-AACD models (2 January to 6 June 2017).

	PIN-AACD(1,1)	APIN-AACD(1,1)
Panel A: Coefficients for AACD(1,1) model		
$\nu_{1,-1}$ (buy after sell)	0.1212	0.0822
$\nu_{1,1}$ (buy after buy)	−0.0763	−0.1787
β_1 (lagged duration for buys)	0.7695	0.6545
α_1 (conditional duration for buys)	0.1287	0.2421
c_1 (volumen for buys)	−1.0880	−1.5591
$\nu_{-1,-1}$ (sell after sell)	−0.3126	−0.2564
$\nu_{-1,1}$ (sell after buy)	−0.4619	−0.4112
β_{-1} (lagged duration for sells)	0.3501	0.3747
α_{-1} (conditional duration for sells)	0.5438	0.5183
c_{-1} (volumen for sells)	−1.3434	−1.2310
μ_G	0.0960	0.1773
μ_B	0.2518	0.1396
μ_{CN}	–	0.2636
μ_{CG}	–	0.2703
μ_{CB}	–	0.1975
Panel B: Coefficients for probabilities of no news, bad news and common-shocks.		
γ_1	−0.8178	−0.5797
γ_2	2.2428	0.8251
γ_3	5.5045	11.4846
γ_4	8.2631	12.3311
γ_5	–	4.8111
AIC	−62.9994	−57.1741
Number of intraday observations	228,665	228,665

Notes: This table reports the maximum likelihood estimation of the PIN- and APIN-AACD(1,1) models. AIC is the Akaike information criterion.

during final trading days of Banco Popular.

Second, focusing on results in Table 4 (Panel B), it is worth noting that the estimates of $\widehat{\gamma}_2$ through $\widehat{\gamma}_5$ are all positive for our stock, although $\widehat{\gamma}_1$ is negative. These parameters allow us to estimate time-varying probabilities related to news, the probability of bad news, and probability of a common shock on day d, respectively:$\widehat{\theta}_{Ed}$, $\widehat{\theta}_{Bd}$ and $\widehat{\theta}_{Cd}$. However, given that $\widehat{\gamma}_1$ is negative, it implies that the estimated probability of news is less than 0.5. These probabilities are then used to obtain the daily state probabilities as in Table 2, which will be showed in Fig. 1 for the PIN-AACD(1,1) model and Fig. 2 for the APIN-ACCD(1,1) model, respectively.

Table 5 presents the results of the main descriptive statistics of daily state probabilities, as well as the PIN-AACD(1,1) obtained using the Tay et al. (2009) model (Panel A) and the APIN- and PSOS-AACD(1,1) obtained using the Preve and Tse (2013) model (Panel B). In mean terms, as can be seen, while there is a reduction in both the probability of no news (with or without common shocks) and the probability of good news (with or without common shocks) of the Preve and Tse (2013) model with respect to the corresponding probabilities estimated using the Tay et al. (2011) model, the probability of bad news (with or without common shocks) increases. This latter result supports the hypothesis that investors react asymmetrically to good and bad news when faced with ambiguous information (see, e.g., Miller, 1977; and Epstein & Schneider, 2008). Specifically, in our case, upon the anticipation of a possible liquidation of the bank, informed investors react to the bad news by placing more weight on it. The results also show that the estimated measure of illiquidity (PSOS-AACD) is larger than the estimated measure of asymmetric information (APIN-AACD), further confirming that Banco Popular experienced large increases in both buy- and sell-orders during the last semester of trading.

Taking advantage of the capacity of our approach to produce time-varying and relatively accurate measures of information-based trading, Fig. 2 displays the graphs of the estimated daily probabilities of good news, no news and bad news for the PIN-AACD(1,1) model. It can be seen that the model-implied probability of good news present more volatile periods, with values exceeding 0.8, around the bank announced on 3 February unexpected losses for 2016, the media reports suggesting that it might need to be resolved and at the end of the studied period. In contrast, the estimated probability of bad news appears to be quite stable throughout the sample period, being lower than 0.2. Finally, the probability of no news day is high for all the period (with an average probability of 0.74 during the analysed period), except for the beginning and at the end of the sample. In conclusion, we observe a predominate of days of no news, but it is interesting to note that days with good news show probabilities close to 0.5 and higher at the end of the period.

Fig. 3 shows the plots of the estimated daily state probabilities for the APIN-AACD(1,1) model. For this model, the estimated probability of good news without common shock ($\widehat{\pi}_G$) is more stable over time compared to the probability of good news in the PIN-AACD(1,1) model. In particular, this probability is less than 0.5 for all days. However, the estimates of the probabilities of events with common shocks (three last panels) are close to zero in many cases. It is due to the fact that $\widehat{\theta}_{Cd} = 0$ for many days. Thus, there is no evidence of symmetric order-flow shock for these days. Estimates of the probabilities of events with common shock, on the other hand, are erratic and infrequent. The estimated daily state probabilities are zero for most days, but may be quite large (exceeding 0.5) during the events related with the bank experiencing a substantial deterioration of its liquidity position after 31 May 2017, primarily driven

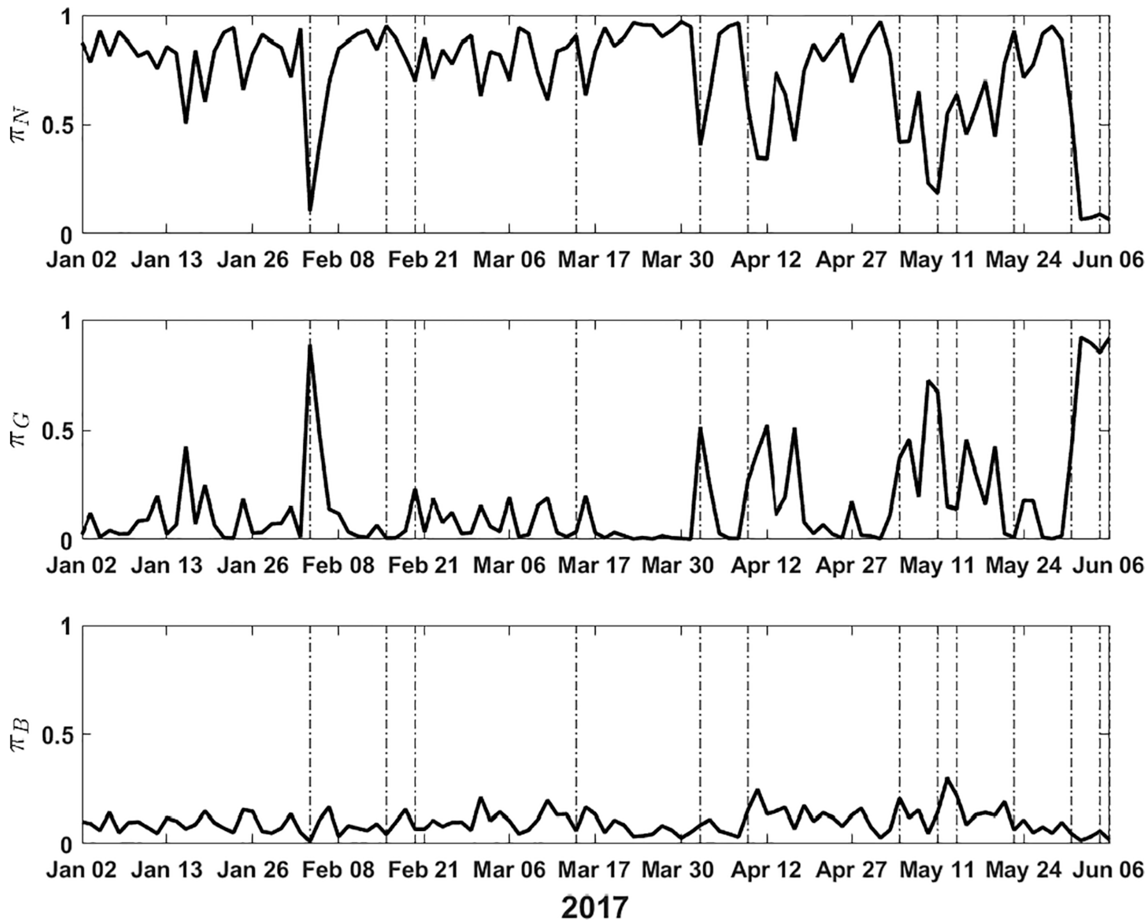

Fig. 2. Estimated daily state probabilities for the PIN-AACD(1,1) model of Popular (2 January to 6 June 2017).

Table 5
Descriptive statistics of daily state probabilities, PIN-AACD(1,1), APIN- and PSOS-AACD(1,1) daily estimates (2 January to 6 June 2017).

	Mean	Median	Minimum	Maximum	Range	Iqr	Std
Panel A: Descriptive statistics for PIN-AACD results							
π_N	0.7391	0.8250	0.0663	0.9694	0.9032	0.2630	0.2271
π_G	0.1614	0.0685	0.0011	0.9176	0.9165	0.1751	0.2236
π_B	0.0995	0.0919	0.0112	0.3011	0.2899	0.0756	0.0530
$PIN-AACD$	0.0410	0.0192	0.0003	0.2081	0.2078	0.0473	0.0527
Panel B: Descriptive statistics for APIN-AACD results							
π_N	0.6058	0.7004	0.0000	0.8250	0.8250	0.1548	0.2363
π_G	0.1334	0.1145	0.0000	0.3225	0.3225	0.1304	0.0858
π_B	0.1179	0.1088	0.0000	0.3023	0.3023	0.1300	0.0801
π_{CG}	0.0674	0.0000	0.0000	0.4497	0.4497	0.0242	0.1379
π_{CN}	0.0416	0.0000	0.0000	0.5739	0.5739	0.0066	0.1061
π_{CB}	0.0340	0.0000	0.0000	0.4582	0.4582	0.0058	0.0900
$APIN-AACD$	0.0192	0.0169	0.0000	0.0461	0.0461	0.0188	0.0123
$PSOS-AACD$	0.0324	0.0000	0.0000	0.2319	0.2319	0.0097	0.0686

Notes: Iqr is the interquartile range and Std is the standard deviation. Range, Iqr and Std are measures of dispersion or variability of the daily estimates.

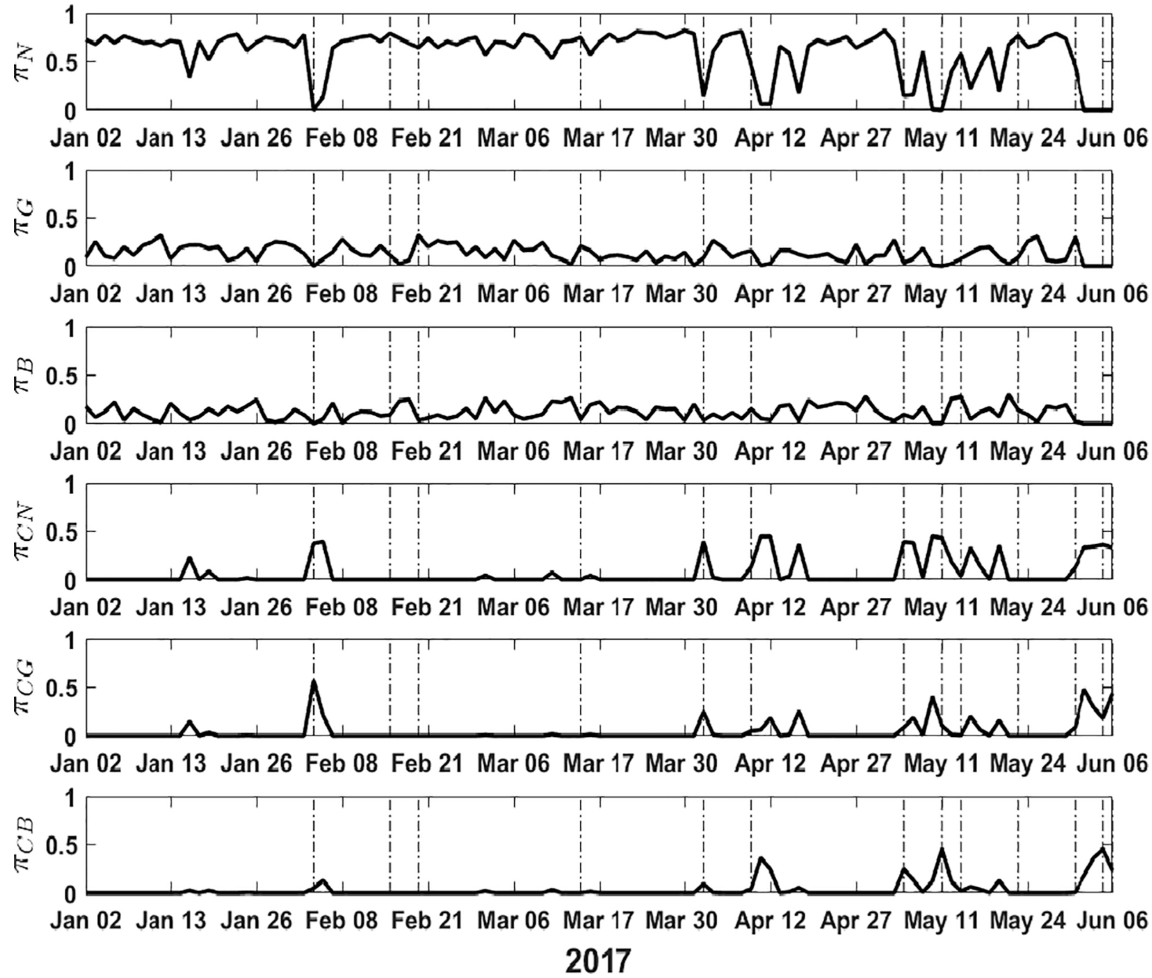

Fig. 3. Estimated daily state probabilities for the APIN-AACD(1,1) model of Popular (2 January to 6 June 2017).

by a significant depletion of its deposit base. This last result suggests that the pattern of $\hat{\pi}_{Gd}$ in the PIN-AACD(1,1) model may be due to common-shock trading caused by disagreement in information interpretation. According to Chan (2003), equities that are exposed to more public news exhibit more underreaction. We also observe that the average $\hat{\pi}_{CNd}$ estimated from the APIN-AACD(1,1) model is lower than $\hat{\pi}_{CN}$ obtained from the Duarte and Young (2009) model (see Table 3). Interestingly, we observe a significant increase in the probability of good news around events related to the release of earnings results and credit agency rating revisions, but those positive expectations were disappointed by announcements of larger-than-expected losses. This finding is consistent with the inverse relationship between the information available to investors and the greater the loss/profit mispricing detected by Balakrishnan et al. (2010), as well as with Martikainen (1998)'s discovery that permanent losses have a significant information content.

Finally, Fig. 4 presents the plots of PIN/APIN/PSOS for the Banco Popular stock to shed insights on how information environments change during the period under study. A glance at that figure suggests that APIN is more stable than PIN. While APIN is less than 0.05 all days, PIN fluctuates in some days of January-February and the last days over 0.1 suggesting an increase in the proportions of trades induced by private information. Since PIN also captures educated trading by investors who are exceptionally competent at evaluating public news, the detected pattern is consistent with the view of Kim and Verrecchia (1994) and Barron et al. (2008) that investors who are better able to appraise the firm's performance based on the announcements may swiftly regain information advantage. On the other hand, PSOS behaves quite similarly to PIN. In particular, while PSOS is zero for many days, it also fluctuates to above 0.1 at the beginning and the end of the study period. We also note that PSOS is different than zero for some periods. Particularly, it is worth noting that common-shock traders are present at the beginning and the end of the period under study indicating diverse opinions and beliefs among investors triggered by the released public information. However, for the rest of the period, it remains zero, indicating that common-shock traders are absent from the market. Note that an announcement with a larger surprise causes more divergence of opinion among investors (as measured by PSOS on and after the announcement day), corroborating Bamber's (1987) claim that the surprise content of the announcement and disagreement about the signal's interpretation are linked. We detect a considerable decrease in PIN after key events, which supports Tetlock's (2010) argument that public announcements help resolve information asymmetry. On the other side, we observe a significant increase in PSOS, indicating a range of investor reactions to the newly published public data. On the other side, we observe a significant increase in PSOS, indicating a range of investor reactions to the newly published public data. This is in line with the findings of Vega (2006), who document that stock prices underreact to difficult-to-interpret public information. Similarly, Zhang (2006) finds that when there is more uncertainty about public information, there is higher underreaction. Furthermore, the average PSOS and APIN computed from the APIN-AACD(1,1) model (see Table 5) are lower than the PSOS and APIN estimated using the Duarte and Young (2009) model (see Table 3). Generally, these results are consistent with those of Duarte and Young (2009) and in our case suggest the presence of inside trading and illiquidity around the negative press coverage (11 May 2017) and especially after the significant deposits lost registered since 31 May, once it was disclosed in the media that the bank might face wind-down. This finding is consistent with the behavioural model of investor sentiment presented in Barberis et al. (1998). Note also that we find a direct relationship between the PIN measure and illiquidity levels of Banco Popular stock as observed in Griffiths et al. (2000).[11] This behaviour is in line with Easley and O'Hara's (1987) theoretical model, which predicts that when informed traders gain access to private information, the arrival rate process is altered.

4. Concluding remarks

Market participants are heterogeneous in many aspects such as liquidity constraint or capacity in processing information (see Peng, 2005; and Hommes, 2006, among others). In this paper, we have attempted to assess the potential importance of different types of traders (i.e., traders with public or private information) in the final trading days of Banco Popular, the first and only bank to date rescued by the European Single Resolution Board. Since the information asymmetry may be more pronounced during events such as the one currently being discussed, we applied a series of indicators proposed in the financial literature to search for the existence of informed traders, thus shedding insights on how information environments change before and after a perceived risk of bankruptcy.

In particular, we have applied not only the model proposed by Preve and Tse (2013) to estimate the daily probability of adjusted informed trading (APIN) and the probability of symmetric order-flow shock (PSOS), but also the PIN model of Tay et al. (2009), using high-frequency transaction data. These models are sufficiently flexible to cope with the variations in information asymmetry and belief heterogeneity over time. We have found that upon the anticipation of a possible liquidation of the bank, informed investors reacted to the bad news by placing more weight on it and that the estimated daily probability of a common shock, caused by disagreement in information interpretation, experienced a significant increase on the last trading days. Moreover, we obtain that the estimated measure of illiquidity (PSOS-AACD(1,1)) is larger than the estimated measure of asymmetric information (APIN-AACD(1,1)), further indicating that Banco Popular experienced large increases in both buy- and sell-orders during the last days of trading, suggesting the evolution of the estimated daily PIN, APIN and PSOS the presence of inside trading and illiquidity, especially after the disclose in the media that the bank might face wind-down.

As in every empirical analysis, the results must be treated with some caution since they have been obtained using a given set of data over a certain time period and based on a given econometric methodology that, in our particular case, has required imposing some initial conditions and constraints on the optimization problem to deal with estimation complexity and reduce computational needs. In this context, our findings suggest the presence of informed traders with private information that was not available to the general public

[11] Griffiths et al. (2000) also report those aggressive sales are more likely motivated by liquidity than aggressive purchases, as can be the case in the last trading days of Banco Popular.

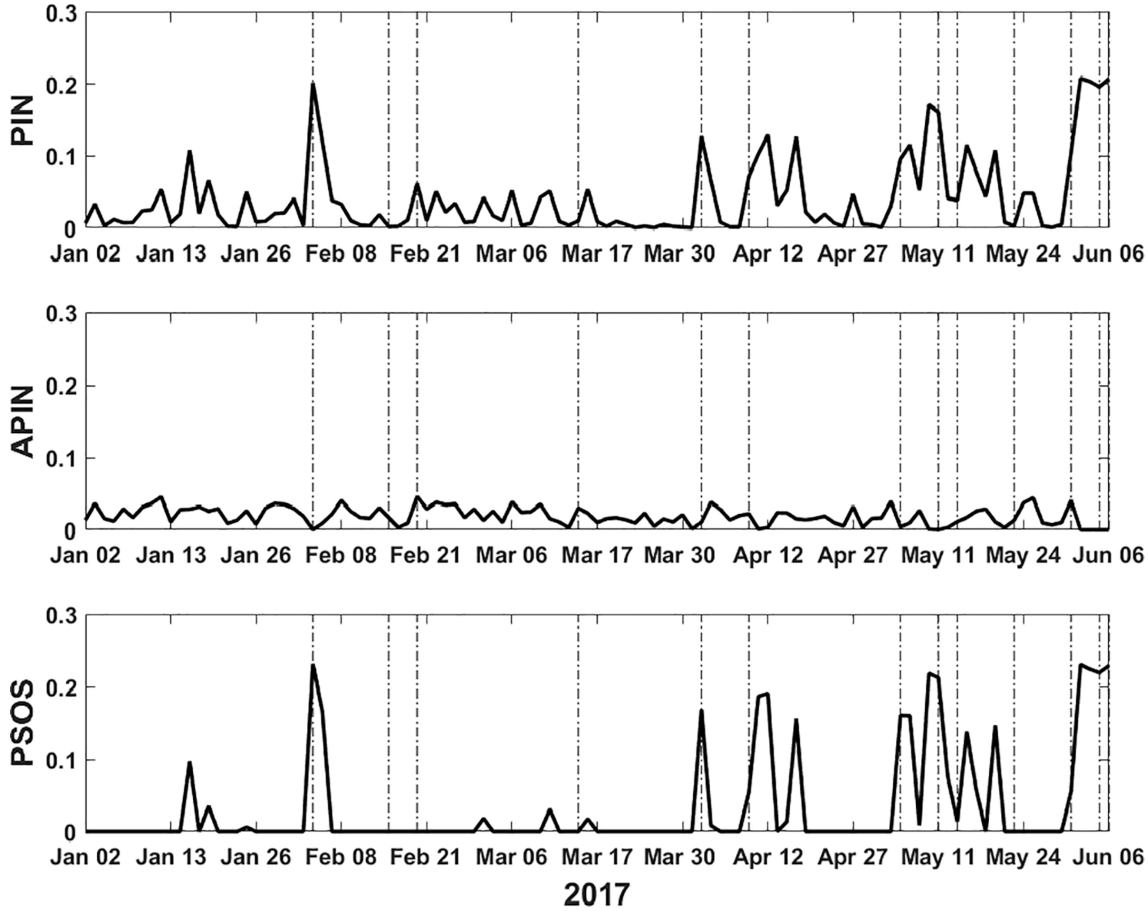

Fig. 4. Estimated daily PIN, Adjusted PIN and PSOS for Popular (2 January to 6 June 2017).

calling for more discipline on the part of resolution authorities, sending the signal that they will not be able to simply shield themselves behind confidentiality in the face of investors' claims (Grünewald, 2017). As insider trading discourages business investment and reduces the efficiency of corporate conduct (see, e.g., Manove, 1989), this call for the regulatory and resolution measures under implementation to promote shareholders and creditors capitalization in order to restore market discipline by aligning bank funding costs more closely with risks as advocated by Toader (2015).

On the other hand, our findings, like those of Brogaard et al. (2022), show that market efficiency is dynamic, and that the dynamics are substantially influenced by the environment. Our empirical results also complement a finding of Bailey et al. (2018) who found that belief variations drive many events, and beliefs are impacted and updated through a variety of mechanisms, including information disclosure, market pricing, social interaction, and behavioural contagion.

We look forward to seeing more extended studies in future research when new case studies on SRB bank resolutions become available.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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