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Adverse selection and the presence of informed trading☆

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ABSTRACT

We combine two concepts of informed trading – contrarian trades and stealth trading – to develop proxies for the probability of informed trading. These proxies are used to test the link between informed trading and adverse selection as measured by bid–ask spreads and stock illiquidity. The estimation results show that these proxies, which are based on the probability of contrarian trading (PC) and progressively refined thereon, are all highly significantly positive in various empirical specifications of the cross-sectional determinants of spreads and illiquidity across stocks, and after controlling for important firm characteristics and trading factors. The robustness of our PC-based proxies for informed trading in these analyses, especially for the further refined measures, suggests that they successfully capture the adverse selection component of bid–ask spreads and illiquidity due to information asymmetry.

1. Introduction

The hypothesis on the positive link between adverse selection and informed trading is extensively discussed in the market microstructure literature. Early on, researchers focused on the interaction between competitive market makers and informed traders who have access to private information about asset values. Facing an adverse selection problem, market makers have an incentive to adjust bid–ask spreads or price impact to account for the presence of information-based trading activity (Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985; Easley and O'Hara, 1987). More recently, research has extended to the behavior of strategic liquidity suppliers who submit limit orders to exploit market conditions or possibly private signals about orders of other market participants. In this setting, the marginal cost and markup of supplying liquidity increase with the degree of adverse selection (Glosten, 1994; Bernhardt and Hughson, 1997; Biais et al., 2000).[1] Regardless of changes in market structure and trading mechanisms over time, a central tenet remains: an adverse selection problem arises whenever one party has superior information over its counterparty in the trading process. As a result, bid–ask spreads and price impact are likely to rise in the presence of adverse selection.

Early attempts to test this hypothesis focus on the decomposition of trading costs into three components: order handling, inventory control, and adverse selection given competitive market makers (Glosten and Harris, 1988; Hasbrouck, 1991; George et al., 1991;

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[1] See Biais et al. (2005) for an excellent survey of the market microstructure literature.

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Lin et al., 1995; Huang and Stoll, 1997; Madhavan et al., 1997; Neal and Wheatley, 1998; Van Ness et al., 2001). Most findings in these studies are mixed at best. Recent empirical studies also examine strategic liquidity suppliers using limit orders in dealer markets and find that their oligopolistic rents increase with the degree of adverse selection (Sandas, 2001; Biais et al., 2002).

Easley et al. (1996) test the above hypothesis by examining the spread difference between active and infrequently traded stocks listed on the NYSE specialist market. Specifically, they develop a measure of the probability of informed trading (PIN) that is based on the estimation of a probabilistic sequential-trading model using transaction level stock data. They find that spreads are positively related to informed trading as measured by PIN. However, in a highly cited study, Duarte and Young (2009) raise an important caveat by arguing that the effect of PIN is primarily due to a symmetric order flow shock rather than asymmetric information and suggest that the estimated PIN is confounded by an illiquidity effect unrelated to information. More recently, Easley et al. (2011, 2012) develop a volume-synchronized probability of informed trading (VPIN) measure, which extends the original PIN model to overcome the data aggregation problem. As with PIN, order imbalance is a key signifier of informed trading activity (or "order flow toxicity"), and VPIN thus links this concept to trading volume at high frequencies. However, Andersen and Bondarenko (2014a,b) show that VPIN is, by construction, correlated with shocks to trading volume and past return volatility and it appears to be a proxy for these variables. Once controlling for volume, they find that VPIN has no incremental predictive power in explaining return volatility. This raises the possibility that VPIN, like the PIN measure, may not be reliably capturing informed trading activity because it is confounded by other trading-related effects, namely, volume and illiquidity.

In light of the discussion above, the aim of this study is twofold: (1) to develop a more reliable measure of the probability of informed trading that is motivated by relevant theory and (2) to employ such a measure to test the relationship between adverse selection and informed trading. To achieve the first aim, we combine two concepts of informed trading – informed contrarian trades and strategic stealth trading – to develop our proxies for informed trading. The literature on informed contrarian trades suggests that informed traders tend to trade against the crowd, which tends to herd on current unexpected news or returns (Campbell et al., 1993; Avramov et al., 2006; Chang et al., 2014). Campbell et al. (1993) develop a model in which informed trading leads to permanent price impact whereas uninformed trading only results in temporary price pressure that is likely to be reversed. Avramov et al. (2006) define daily sell orders in face of unexpected positive (negative) returns as "contrarian trades" ("herding trades"). They show that herding trades exhibit significant negative serial correlation, while contrarian trades display insignificant autocorrelation. Thus, contrarian (herding) trades are broadly akin to informed (uninformed) trades. Chang et al. (2014) apply this concept of informed contrarian trades further to both buy and sell orders at 15-minute intervals throughout the trading day to develop a standalone measure of the dynamic intraday probability of informed trading (DPIN).

In this paper, we adopt the same generally accepted approach that uses the probability of contrarian trades, which we will refer to as "PC", as a starting point to construct proxies for the probability of informed trading. However, we also recognize that contrarian trades, in and of themselves, are at best coarse proxies for informed trades. This is because trades that simply appear contrarian in direction may also come from uninformed traders who actually do not have access to private information and just happen to trade in this particular direction, e.g., for liquidity purposes. Thus, we use the probability of contrarian trades, *PC*, only as a first building block on which we develop progressively refined PC-based proxies for the probability of informed trading. This is done by applying filters to *PC* to remove those trades that are associated with known behaviors of uninformed traders, while retaining those trades that are associated with known behaviors of informed traders. The aim of this sieve-like approach is to isolate informed trades and thus more accurately measure the probability of information based trading activity.

The first primary filter we apply is closely related to the concept of strategic stealth trading. Barclay and Warner (1993), Hasbrouck (1995), Chakravarty (2001), and Alexander and Peterson (2007) find evidence of stealth trading by institutional investors such that their trades, which are generally medium-sized, tend to have large cumulative price impact. Keim and Madhavan (1995) find that institutional investors often break up their large orders into a series of small-to-medium-sized trades. Chordia and Subrahmanyam (2004) show that it can be optimal for informed traders to break up their large orders. This literature thus suggests that informed trading is more likely to come from small-to-medium-sized trades than from large-sized trades. Chakravarty (2001) and Alexander and Peterson (2007) also find that while large-sized trades are rare, they are more volatile and render a disproportionally large contribution to trading volume. In light of this, all else equal, informed trading is more likely to occur on days when large-sized trades are sparse and trading volume is low. Thus, we use the probability of contrarian trades conditional on low daily trading volume as our first refinement to *PC*, and denote this measure as *PCL* (where *L* stands for *low* trading volume).

The literature on behavioral finance emphasizes that unsophisticated investors may be subject to various behavioral biases when they trade. To the extent that uninformed traders are less sophisticated than their informed counterparts, they are more susceptible to behavioral biases. Avramov et al. (2006) and Chang et al. (2014) employ this concept to refine their measures of informed trading by ruling out two notable behavioral biases: trend chasing and the disposition effect. Following the same insight, we then further refine our *PCL* measure of informed trading by imposing corresponding rationality conditions to rule out these two behavioral biases. In our setup, buy (sell) trades in the presence of both negative (positive) unexpected returns and negative (positive) past cumulative returns are classified as informed contrarian trades against trend chasing. We can thereby calculate the probability of contrarian trades against trend chasing and use it as our second refined PC-based proxy for the probability of informed trading, which we denote as *PCLT* (where *T* stands for *trend* chasing). The disposition effect suggests that uninformed investors will be less willing to sell shares following negative cumulative returns. Thus, sells taking place when unexpected returns are positive and cumulative returns are negative reflect informed contrarian trading overcoming the disposition effect and hence are more likely initiated by informed traders. Thus, adding the disposition effect to the *PCLT* measure, we can calculate the probability of contrarian trades against both trend chasing