Journal of Banking & Finance 64 (2016) 188–204

Contents lists available at ScienceDirect

Journal of Banking & Finance

journal homepage: www.elsevier.com/locate/jbf

Assessing the information content of short-selling metrics using daily disclosures

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ARTICLE INFO

Article history:
Received 18 December 2014
Accepted 23 December 2015
Available online 30 December 2015

JEL classification:
G11
G12
G14

Keywords:
Short selling
Information content
Short interest
Short flow

ABSTRACT

As a consequence of the 2008 financial crisis, the Australian regulator mandated daily reporting and disclosure of both short flow and short interest at an individual stock level. This provides a unique opportunity to study the nature and source of information embedded in each metric. Our empirical findings are consistent with short sellers being heterogeneous with respect to their information. Short flow is strongly related to recent returns and buy-order imbalance, and both anticipates and reacts to price-relevant announcements. In contrast, short interest is related to the mispricing of firm fundamentals. The distinct differences in the nature of information embedded in the two metrics provide an economic rationale for both the unique ability of each metric to predict returns and the future horizons over which the information is relevant.

1. Introduction

At the height of the 2008 financial crisis, concerns about the impact of short selling on market quality led many countries to impose temporary bans on shorting.[1] In the aftermath, the activities of short sellers have been heavily scrutinized by market regulators, researchers and the media. Mandatory disclosure regimes of varying forms have subsequently been implemented in many markets.

The rationale for disclosure is premised on the belief that there is information content in short selling.[2] Diamond and Verrecchia (1987) demonstrate that, in the presence of short sale constraints, short sellers are predominantly informed traders. As such, high levels of short interest generally reflect bad news/sentiment. Indeed, the empirical literature documents strong evidence that short-selling activity conveys information about future returns. Short flow (i.e., the ratio of short transaction volume to total trading volume) is inversely related to future stock performance (Boehmer et al., 2008; Diether et al., 2009; Engelberg et al., 2012; Chang et al., 2014). Similarly, short interest (i.e., the ratio of aggregate short positions to the number of shares outstanding) negatively predicts future returns (Senchack and Starks, 1993; Desai et al., 2002; Asquith et al., 2005; Ackert and Athanassakos, 2005; Au et al., 2009).

While many studies focus on the negative returns of heavily shorted stocks, Boehmer et al. (2010) conjecture that the relative *absence* of shorting conveys positive information. Consistent with prior literature, their heavily-shorted portfolio underperforms over the subsequent month. However, lightly-shorted stocks generate significant positive abnormal returns. Boehmer et al. (2010) conclude that short sellers are adept not only at identifying overvalued stocks to short, but also undervalued stocks to avoid. Similarly, using UK daily stock lending data to proxy for short interest, Au et al. (2009) also find that lightly-shorted stocks generate positive risk-adjusted returns.

Given the weight of evidence that short-selling activity is informative for future returns, researchers are beginning to explore the

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[1] Primarily, these bans targeted financial stocks (US, UK, Germany, Canada, France, Switzerland). However, some countries went as far as restricting short selling on *all* equities (Australia, Italy, Japan, Singapore, Korea, Netherlands, Taiwan). For studies on the impact of the 2008 ban on financial markets, see Boehmer et al. (2013) and Beber and Pagano (2013).

[2] For example, the International Organization of Securities Commissions' Task Force on Short Selling states that the international disclosure initiative will enhance investor confidence by ensuring that markets are fair, efficient and transparent (IOSCO, 2009). Similarly, the Australian Securities and Investments Commission (ASIC) argues that short selling disclosure allows investors to better understand share-price movements and the overall bearish sentiment towards a stock, thereby informing decision making and assisting pricing efficiency (ASIC, 2010).

http://dx.doi.org/10.1016/j.jbankfin.2015.12.009
0378-4266/

precise nature and source of short sellers' information. An obvious starting point is the notion that short-selling activity reflects private information about upcoming value-relevant news. Short flow increases around firm-specific events such as earnings announcements (Boehmer et al., 2012; Christophe et al., 2004; Berkman and McKenzie, 2012), analyst downgrades (Boehmer et al., 2012; Christophe et al., 2010), seasoned equity offerings (Henry and Koski, 2010), private placements (Berkman et al., 2014), public revelation of financial misconduct (Karpoff and Lou,2010) and the disclosure of company insiders' trading (Chakrabarty and Shkiko, 2013).

Moving beyond news events, the price impact of which is likely to be swift, some short sellers trade on information that is relevant over longer horizons. Dechow et al. (2001, p. 78) depict short sellers as sophisticated investors who incur large transaction costs to identify and trade overpriced securities. They document that short sellers position themselves in stocks with poor fundamentals, with an expectation of profiting from the eventual reversion to fair valuations. In a similar vein, Curtis and Fargher (2014) argue that short sellers utilize financial statement analysis to identify overpriced securities. In addition to fundamental ratios (book-to-market, earnings yield, value-to-price), they also demonstrate that short sellers seemingly take valuation signals from accruals and asset growth. Using 11 accounting-based fundamental variables, Drake et al. (2011) find that short sellers are highly informed about the likely implications of fundamental information for future returns.

Clearly, the nature and sources of information that potentially motivate short trading are diverse. As such, short sellers are likely to be heterogeneous with respect to their information and investment horizon. At present, however, relatively little is known about the *unique* information content of alternate short-selling metrics. For example, prior research has not investigated whether the fundamental information embedded in short interest also manifests in short flow, or if information events and technical trading captured in short flow are also reflected in short interest. To the extent that short flow and short interest reflect similar information, there are important regulatory and disclosure implications. If, however, the source and nature of information embedded within each metric differs, there are obvious implications for pricing efficiency and transparency, as well as for the likely future horizons over which the information content of each metric is relevant.

For a number of reasons, empirically identifying the unique information content of each short-selling metric and sources thereof is challenging. Unavoidably, much of the prior work has been constrained by the availability of a single metric (either short flow *or* short interest). Further, even in jurisdictions where both metrics are available, there is often a mismatch between the frequency with which they are collated and reported.[3] To this end, the current paper benefits significantly from changes to the short-selling disclosure regime implemented in Australia in the aftermath of the 2008 financial crisis. Since mid-2010, short selling in Australian equities has been subject to a mandatory disclosure regime that encompasses *both* short flow and short interest. Data at the individual stock level are reported to regulators on a daily basis. Further, there is little delay in this information reaching the public domain. Short transaction volumes are publicly disclosed the following day whilst short positions are disclosed the day following settlement (i.e., $T+4$ after the trade). As such, while Australia's daily reporting and disclosure regime falls short of real time, it is arguably the most comprehensive and timely reporting of short sales data in the world.

Aided by this unique regulatory environment, this paper makes two important contributions. First, we study the nature and source of information that is reflected in each short-selling metric. Drawing on the existing literature, we conjecture that short flow (a transactional measure) is more likely to capture short-term technical trading and/or value-relevant news surrounding company announcements. In contrast, short interest (a positional measure) is likely to embed information about firm fundamentals and associated mispricing that will be corrected over horizons longer than the immediate. Australia's dual reporting regime facilitates an exploration of the unique information in short flow and short interest. In particular, the high-frequency (i.e., daily) reporting of short-selling activity greatly enhances our ability to study the nature and source of information around news events.

The second contribution is to assess the relative importance of the information content of short flow and short interest by way of their ability to predict cross-sectional differences in returns. To the extent that each metric embeds unique information, short flow and short interest should have independent ability to predict future returns. Further, it follows that the horizon over which the predictive ability exists will likely reflect the nature and source of information within each metric. Our data provides a level playing field on which to compare the two metrics of short-selling activity. In much the same way that our daily sample is integral to identifying the nature of information within each metric, it is also essential to studying the predictive ability when the relevance of the information content is likely to be short lived.

The key findings of the paper are summarized as follows. There is clear evidence that alternate short-selling metrics reflect different facets of the short sellers' information set. A stock's short flow is strongly related to its recent returns and current buy-order imbalance, consistent with short sellers engaging in short-term contrarian trading and voluntarily providing liquidity during periods of temporary buying pressure. While these findings mirror US results of Diether et al. (2009), we provide new evidence that this information is unique to short flow – the same information does not manifest in change in short interest (an alternate transactional measure that nets out short covering). Similarly, only short flow data appears to both anticipate imminent price-relevant announcements and react to news, increasing following bad earnings news and decreasing after good non-earnings news. One caveat is warranted – while the influence of news on short flow is statistically strong, the economic significance is modest at best.

While there is little evidence that it conveys information about news, short interest appears to embed information about firm fundamentals and associated mispricing. Short interest (or a lack thereof) reflects the aggregate sentiment of short sellers over the longer-term prospects of a stock. We document that short sellers target overpriced stocks, with high levels of short interest disproportionately concentrated in overpriced stocks. Further, there is an unduly low level of high shorts amongst under-priced stocks, suggesting that short sellers are adept at avoiding them. There is no evidence that short flow is related to mispricing.

By identifying the differential information captured by alternate short-selling metrics, we are able to provide better context to understand both the unique ability of short flow and short interest to predict future returns and the horizons over which their information content is relevant. The importance of information captured by a short metric is assessed with reference to the cross-sectional difference in returns to portfolios of stocks sorted on the metric. The results show that future portfolio returns are negatively associated with both short flow and short interest. For short flow, the return differential between extreme quintiles is in

[3] For example, Boehmer et al. (2008) compare the relative informativeness of short flow (estimated from proprietary intraday data aggregated over the most-recent five days) and short interest (based on changes in publicly-released short interest data from the previous month). Similarly, Blau et al. (2011) examine the information content of short flow (sourced from a combination of Reg SHO and NASDAQ proprietary data, sampled daily and aggregated to monthly frequency) and short interest (sampled monthly from Compustat).

the vicinity of 140–160 bps per month. However, consistent with our findings that the nature of information captured by short flow is likely to be relevant over short horizons, the importance of short flow peaks at 10 days and does not extend beyond 20 days. For portfolios sorted on short interest, the return differential ranges from 90–180 bps per month. Unlike short flow, short interest has implications for future returns over longer horizons, extending beyond the immediate term out to at least 60 days. This finding is consistent with short interest capturing short sellers' prediction that mispriced fundamentals will revert to fair values in due course.

While portfolio sorts do not assess the uniqueness of the information content within each metric, regression analysis confirms not only that both short flow and short interest are negatively associated with future returns, but that each metric has unique predictive power for returns. Complementing the portfolio analysis, the unique predictive ability of short flow is short lived, not extending beyond 20 days. The information content of short interest remains significant out to horizons of at least 60 days. By and large, these findings are robust to a raft of methodological variations and alternate definitions of the short-selling metrics.

Taken together, the empirical evidence presented in this paper is consistent with the notion that short sellers are a sophisticated yet heterogeneous group of traders. They appear to trade on different sources of information which have relevance for distinct future horizons reflecting the nature of the information. The findings yield important implications not only for other investors wishing to extract information from short-selling activity but also for regulators whose mandate involves promoting transparency and investor confidence.

2. Short selling regulations and disclosure requirements in Australia

Short selling regulation and disclosure requirements in Australia came under scrutiny during the 2008 financial crisis resulting in a series of regulatory reforms. First, naked short selling was permanently banned. Second, a temporary ban on covered short selling was imposed for non-financial stocks (from 21 October 2008 to 19 November 2008) and for financial stocks (from 21 October 2008 to 25 May 2009). Third, and most importantly, a new reporting regime was introduced to increase the transparency of short selling activity for both investors and regulatory bodies. The new reporting regime comprised two components: (a) short sale transaction reporting and (b) short position reporting.[4]

Short sale transaction reporting was introduced as an interim measure in September 2008 but became law in December 2008 when the Government passed the *Corporations Amendment (Short Selling) Act 2008*. At the close of each day's trading, or by 9am the following day at the latest, brokers report the total number of shares sold short for each security to the Australian Securities Exchange (ASX). The aggregate short volume for each security is published on the ASX website the following day in the form of "gross short sales reports".

Following extensive public consultation, short transaction reporting was augmented by daily short position reporting in June 2010. Short sellers report their short position to the Australian Securities and Investments Commission (ASIC) within three business days of the trade, and each day thereafter until the position is covered. A threshold applies such that only short positions of more than AUD 100,000 or 0.01% of total shares on issue must be disclosed. Similar to the role played by the ASX with short flow data, ASIC aggregates individual short positions by security and makes them publicly available the day after they are reported in the form of "short position reports".

It is pertinent to note that the implementation of short transaction reporting was not problem free. In a July 2012 Regulation Impact Statement, ASIC noted that 60% of brokers had difficulty complying with their reporting obligations. Specifically, the use of algorithmic trading made it difficult for the broker to know at the time an order was placed whether it would result in a short sale. ASIC therefore assumed a no-action position for breaches of short transaction reporting obligations. This no-action position, which ended on 31 December 2011, meant that the level of short sale transactions was under-reported prior to 2012. Therefore, we restrict our analysis to after 31 December 2011 to eliminate this under-reporting problem.

3. Data

Short transactions and short position data are obtained from the ASX and ASIC websites respectively. As noted above, to ensure data quality, this paper examines short selling activity over the period spanning 3 January 2012 to 30 June 2014. The resulting time series comprises 629 daily observations of stock-level short flow and short interest.

The analysis is restricted to the constituents of the S&P/ASX200 Index. As the primary benchmark for the Australian market, the S&P/ASX200 represents the investable universe for many institutional investors.[5] This sample choice is compelled by the fact that stocks outside the benchmark index are difficult and expensive to short. Table 1 illustrates that shorting is virtually non-existent outside the 200 largest stocks. As such, low (or no) short-selling activity in non-index stocks may be more indicative of impediments to shorting than lack of negative sentiment.

A number of procedures are performed to cleanse the short selling data of obvious errors and produce a panel suitable for the empirical analysis. First, we construct a sample that has both short flow and short interest data for each stock on each day. Since the ASX gross short sales reports only contain non-zero short volume, a stock that does not appear in the report on any given day is assumed to have zero short flow. Similarly, a stock that does not appear in the ASIC short position report on any given day is assigned zero short interest.[6] Second, we correct for potential errors in short interest data that have been noted by ASIC, which appear as spikes in short interest that reverse within a few days. The fact that these spikes tend to occur on days where the change in short position exceeds trading volume indicates that they are likely to be data errors. To cleanse the data of these spikes, we identify situations where the day-to-day change in short position exceeds trading volume, yet the short position reverses within three days. On those occasions (which occur on 0.84% of stock-day observations), the suspect short position is replaced with the short position one day prior to the spike.

[4] There are some minor differences in the reporting obligations for the two components. Certain forms of exempted naked short sales are included (excluded) in short interest (short flow) reporting. Appendix A provides details of these exemptions.

[5] S&P/ASX200 stocks account for approximately 90% of the total ASX market capitalization. The remaining 10% comprises approximately 1655 small and micro-cap companies.

[6] 'Missing' short interest data could result from shorting that falls below the reporting thresholds (AUD 100,000 or 0.01% of total shares on issue) or simply the fact that the stock in question has zero short interest on the day in question. Our treatment assumes the latter. The proportion of stock-day observations with missing short interest is only 1.76%. Missing observations are concentrated in stocks with very low levels of short interest, with the mean (median) short interest immediately prior to missing observation of 0.2% (0.007%). The results are unchanged if we adopt an alternate treatment of replacing missing observations with the last reported short interest.

Table 1
Summary statistics.

	Mean	Std dev	Min	25th	Median	75th	Max
Panel A: short sample (S&P/ASX200 stocks)							
No. of stocks	199	3	193	198	199	201	206
Size (AUD million)	6,250	15,383	121	849	1,759	4,596	115,560
Book to market	0.73	0.57	0.03	0.37	0.63	0.98	4.54
Short flow (*SF*)	21.49%	12.26%	1.17%	12.50%	19.47%	28.31%	70.18%
Short interest (*SI*)	2.55%	3.08%	0.02%	0.52%	1.39%	3.37%	18.78%
Change in short interest (*dSI*)	0.00%	0.18%	−1.08%	−0.03%	0.00%	0.03%	1.00%
Panel B: ASX population							
No. of stocks	1,855	31	1,798	1,832	1,858	1,873	1,907
Size (AUD million)	798	5,476	0.28	7	26	146	115,560
Book to market	1.38	2.48	0.00	0.41	0.85	1.55	50.00
Short flow (*SF*)	2.79%	8.65%	0.00%	0.00%	0.00%	0.00%	70.18%
Short interest (*SI*)	0.32%	1.30%	0.00%	0.00%	0.00%	0.00%	18.78%
Change in short interest (*dSI*)	0.00%	0.10%	−1.61%	0.00%	0.00%	0.00%	1.53%

Panel A reports summary statistics for our sample of S&P/ASX200 index stocks and Panel B reports summary statistics for the population of ASX-listed stocks. The sample comprises 629 days spanning 3 January 2012 to 30 June 2014. The reported numbers are the time series mean of the daily cross-sectional statistics. Before commencement of trading on each day t, the ASX publishes the total volume of short sales by security on day $t-1$. A stock's short flow (*SF*) is calculated as the volume of shares sold short on day $t-1$, scaled by total trading volume. Before commencement of trade on each day t, the ASIC publishes the cumulative quantity of shorted shares remaining uncovered as at day $t-4$. A stock's short interest (*SI*) is calculated as the cumulative quantity of short positions on day $t-4$, scaled by total number of shares outstanding. If a stock's short flow or short interest is not reported on a given day, a value of zero is assigned to that stock-day observation. A stock's change in short interest (*dSI*) is the day-to-day change in *SI*. Data for market capitalization and book-to-market ratio are sourced from Datastream. Stock-day observations with negative BM are excluded.

The short selling data is supplemented by daily stock-level data sourced from Datastream. For each sample stock, we obtain returns, trading volume, number of shares on issue, market capitalization and book-to-market ratio. Since the short sale data is unadjusted for capital events, it is important to use unadjusted trading volume data (i.e., Datastream data type *UVO* rather than *VO*). Datastream data are linked to short sales via ASX ticker codes, after carefully checking for possible changes resulting from name changes and delisting. Stocks with a negative book-to-market value, which account for just 2% of our sample, are removed.

The analysis centers on two key metrics: a short flow ratio (*SF*) and a short interest ratio (*SI*). For each stock on each sample day, *SF* is calculated as short volume (from the ASX gross short sales report) divided by the total trading volume on the day (from Datastream). This definition of *SF*, which captures the 'flow' aspect of short selling, is consistent with previous studies by Boehmer et al. (2008), Diether et al. (2009), Engelberg et al. (2012), Boehmer and Wu (2013), Chang et al. (2014) and Lynch et al. (2014). *SI* is calculated as the short position on a given day (from the ASIC short position report), scaled by the number of shares on issue (from Datastream). Capturing the 'stock' aspect of short selling, our construction of *SI* is consistent with Figlewski (1981), Dechow et al. (2001), Desai et al. (2002), Asquith et al. (2005), Au et al. (2009), Boehmer et al. (2010), Blau et al. (2011) and others.

Table 1 Panel A presents summary statistics for the sample. On each day, the summary statistics (mean, standard deviation, min, max, percentiles) are calculated from the cross-section of sample stocks. Table 1 then reports the time series average of the daily cross-sectional statistics. On average, the sample comprises 199 stocks per day. The mean (median) market capitalization of sample stocks is $6.250 billion ($1.759 billion). For the population of ASX-listed stocks, Table 1 Panel B reports a mean (median) market capitalization of just $798 million ($26 million). Given the well-known empirical problems associated with small stocks (e.g., illiquidity, microstructure bias in daily returns), this further motivates the focus of this study on S&P/ASX200 stocks.

On average, *SF* represents 21.49% of sample stocks' daily trading volume and *SI* accounts for 2.55% of the total number of shares on issue. These statistics reflect non-trivial levels of short-selling activity, therefore demonstrating both the ability and willingness of market participants to execute short sales in our sample stocks. However, it is also important to note that short trading outside the S&P/ASX200 constituents is negligible. For the ASX population, Panel B reports mean *SF* (*SI*) of just 2.79% (0.32%). Further analysis (untabulated) reveals that mean *SF* for stocks ranked 201–300 (301–500) falls from 21.49% to 8.59% (2.40%). Similarly, for the same partitions, mean *SI* falls from 2.55% to 0.91% (0.25%). In fact, more than 75% of ASX-listed firms have no short trades whatsoever. Daily trading volumes also fall dramatically outside the S&P/ASX200 index. This conspicuous absence of shorting and severely reduced liquidity among stocks outside the S&P/ASX200 Index suggests that they will be both more difficult and expensive to short, hence motivating our focus on the largest 200 stocks.

Fig. 1 Panel A plots the time series of *SF* and *SI*. Stock-level metrics are averaged on a value-weighted basis to construct 'aggregate' market-level metrics. Aggregate *SF* does not exhibit any obvious trend over the sample period. It ranges from a low of 11.39% in June 2012 and a high of 36.84% in April 2014. Aggregate *SI* is less volatile and highly persistent. Fig. 1 Panel B plots the level of the S&P/ASX200 index and its volatility index (VIX). Intuitively, the market index is negatively correlated with VIX (−0.60). Similarly, *SI* is positively correlated with VIX (+0.63) and negatively correlated with the S&P/ASX200 index (−0.92).

4. The nature and source of information in short-selling metrics

There is strong empirical evidence that short-selling metrics are negatively related to future returns, consistent with short sellers having value-relevant information. There is also an emerging literature that seeks to identify the nature and source of short sellers' information. Given the variety and breadth of possible information sources, it is highly probable that short sellers are heterogeneous in terms of both the nature of their information and their investment timeframe.[7] This raises an interesting question as to whether

[7] Prior evidence suggests that short sellers are heterogeneous in their investment horizon. On one hand, Geczy et al. (2002) and Diether (2008) find that equity loans, the precursor of a short sale, are closed out quickly (in the order of a few days to a few weeks). On the other hand, using aggregate short interest and short volume on the NYSE, Boehmer et al. (2008) estimate that the average short position lasts about 37 days, implying that some short transactions take months to close out. Jones et al. (2015) find that the actual duration of short positions varies greatly from 16 days in France to 25 days in UK and 52 days in Spain. Short sellers are also heterogeneous in their trading style. Comerton-Forde et al. (2015) document two distinct types of short sellers – those that provide liquidity and those that demand it.

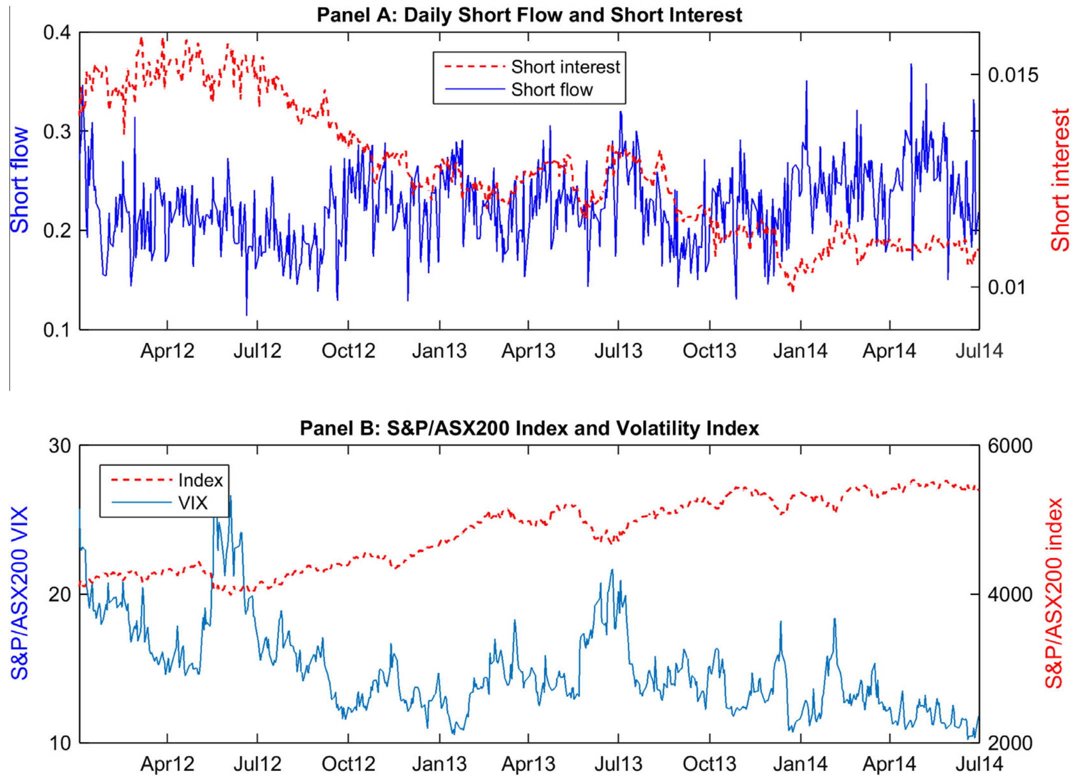

Fig. 1. Aggregate short selling in S&P/ASX200 stocks over time. Panel A plots the time series of daily aggregate short flow and short interest. The 'aggregate' short selling metrics are an average of individual stock's short flow and short interest, weighted according to their market capitalization. Panel B reports the value of the S&P/ASX200 index and volatility index (VIX) over the sample period from 3 January 2012 through 30 June 2014.

different metrics of short-selling activity reflect different information. To the extent that the nature of information captured in short flow and short interest differs, the metrics may have unique predictive ability for returns, possibly over differing future horizons. In this section, we consider the kind of information that is likely to manifest in each metric and then test our conjecture using our daily sample of stock-level short flow and short interest.

The trading of short sellers is often attributed to their assumed knowledge of negative private information about forthcoming company announcements. Fox et al. (2010, p. 33) provide a number of reasons why 'near-announcement inside information short selling' is expected to manifest in the volume of short trading over a brief window (no more than 5 days) preceding the announcement.[8] Even in the absence of impending news-related information, the volume of shorts may be influenced by price and order-book patterns. For example, Diether et al. (2009) propose that short sellers are sophisticated traders who enter short-term contrarian positions after recent price rises and/or in response to temporary buy-order imbalances. Therefore, we conjecture that short flow is likely to reflect imminent news/announcements and short-term price/volume patterns. Given the nature of this information, the horizon over which the information content of short flow has predictive ability will likely be short. Of course, this information may also manifest in short interest (or changes thereof). Diether et al. (2009) note that the coarse monthly short interest data utilized in much of the prior US literature does not permit researchers to study short-term trading strategies. In contrast, Australia's daily reporting of short interest allows a careful analysis of its information content, particularly surrounding news and price-relevant announcements.

With respect to the likely nature of the innate information content of short interest, our intuition is that short interest reflects negative sentiment over the longer-horizon prospects for a stock. There are two reasons for this. First, intraday shorting by design does not make its way into daily short interest statistics. Second, short trades that are motivated by information which is relevant over short durations are quickly removed from short interest when these positions are covered. Therefore, largely by construction, the short interest metric reflects information relevant over longer horizons. Intuitively, long-horizon performance is intrinsically linked to firm fundamentals. Therefore, we conjecture that short interest captures mispricing of the underlying fundamentals of the firm. More specifically, high levels of short interest signal overpriced stocks that short sellers anticipate will revert to fair values in due course.

Our daily sample of short flow and short interest allows us to explore the nature of information most likely to be gleaned from each metric. We begin by employing a regression approach to study the extent to which each short-selling metric encapsulates recent price and order-book patterns. In addition to time-t short flow and short interest, the day-to-day change in short interest (dSI) is included as a third metric. Since dSI is essentially a measure of short volume that is net of short covering, it allows an examination of the extent to which information in short flow manifests itself in short interest. When a large part of short selling is intraday and/or made to buyers who cover their existing short positions, the response of SF and dSI to information may differ, contributing to differential information content between SF and SI. Given the skewness in SI (see Table 1), we use $\ln(SI)$ throughout the paper when estimating regressions involving short interest.

[8] Reasons include: (i) to minimize the time between entering the short and covering it, (ii) to minimize the risk of detection, (iii) to minimize the risk that other factors will move price adversely, and (iv) information is more credible and reliable when it is received close to the announcement.

Following Diether et al. (2009), there are two key independent variables. First, the association of time-t short-selling activity with stock returns over the past five days $r(-5,-1)$ tests the notion that short sellers are contrarian traders. Second, the time-t buy-order imbalance $oimb^{+} = \max(0, oimb)$ considers the possibility that short sellers are voluntary liquidity providers, stepping in during periods of temporary buying pressure with an anticipation of profiting as the pressure subsides.[9] Finally, a number of control variables are included to accommodate: (i) the contemporaneous stock return, (ii) autocorrelation in the short metric and turnover, and (iii) recent past order imbalance.[10] The panel regressions are estimated with stock and day fixed effects and standard errors clustered by both stock and day (Thompson, 2011).

Table 2 Panel A provides strong evidence that short flow reflects short-term contrarian trading. In model (1), *SF* is significantly positively related to recent returns ($\beta = 0.2179$, $p < 0.01$). The economic influence is noteworthy – a recent return of 10% implies an increase in short selling of 2.2% of average daily trading volume. With the inclusion of other control variables (model 2), the relation remains highly statistically significant albeit with reduced magnitude ($\beta = 0.1391$, $p < 0.01$). Panel A also reports a significant positive relation between contemporaneous (but not lagged) buy-order imbalance and short flow, providing support for the notion that the *SF* metric captures the activity of the short sellers who are voluntary liquidity providers.

While the tenor of these findings for short flow is remarkably similar to the US findings of Diether et al. (2009), our data also allows consideration of whether price and order-book patterns manifest in short interest. In Table 2 Panel B (Panel C), the evidence that short interest (change in short interest) reflects contrarian trading is less emphatic. In Panel B models (1) and (2), there is no statistical association between *SI* and either $r(-5,-1)$ or $oimb^{+}$. At face value, Panel C suggests that *dSI* is positively associated with recent returns ($\beta = 0.0385$, $p = 0.019$). However, this association does not survive controlling for other variables. Further, there is no evidence that changes in short interest increase with contemporaneous buy-order imbalance. The different findings for *SF* and *dSI* are particularly interesting. Panel A documents that some short sellers trade on past returns and current order imbalance. However, viewing *dSI* as a measure of short flow net of short covering, the non-finding in Panel C raises the possibility that short sellers motivated by technical considerations may be trading against others who are buying to close their existing short positions, leading to minimal net impact on short interest.

Our second line of enquiry centers on the behavior of short sellers surrounding news. Short selling is often portrayed as the outcome of informed trading in anticipation of negative news. However, there is also a suggestion that short sellers do not necessarily have a prior informational advantage, but are simply highly adept in reacting to the release of news (Engelberg et al., 2012). With very few exceptions, data availability limits analysis of this type to studying how short flow behaves around important news. In the following analysis, we examine the extent to which value-relevant news manifests in short flow and short interest.

From the Company Announcements database maintained by SIRCA, we identify all announcements classified by the ASX as 'price sensitive'. Over the time horizon of our study, there are 6,679 such announcements for S&P/ASX200 stocks, each time stamped to facilitate accurate identification of the announcement day. While the majority of announcements reflect genuinely value-relevant information (e.g., earnings announcements, trading updates, major contracts, mergers, etc), it is inevitable that the importance of some announcements is more questionable. To ensure that our analysis features announcements most likely to represent value-relevant news, we proceed as follows. For each ASX release labeled as 'price sensitive', we compare the announcement-day returns of the announcing stock and the ASX200 constituents. In a similar fashion to Engelberg et al. (2012) and Akbas (2015), the announcement is classified as good (bad) news only if the announcing stock's return is in the top (bottom) quintile of the population on that day.

Table 3 examines the extent to which each metric captures short-selling activity in anticipation of, contemporaneous with or in reaction to price-relevant news. After controlling for recent returns $r(-5,-1)$, the time-t short metric (either *SF*, ln(*SI*) or *dSI*) is regressed on a series of dummy variables indicating whether a price-relevant announcement occurs over the subsequent five days (model 1), contemporaneously at time t (model 2) or over the previous five days (model 3).

The first set of results pertains to all price-relevant announcements. Comparing across panels, *SF* is the only metric that potentially reflects anticipatory short selling, increasing by 0.0070 ($p < 0.01$) prior to bad news. However, there is no evidence that *SF* declines prior to positive announcements.[11] Further, *SF* is not contemporaneously effected by news of either sentiment. Panel A does, however, suggest that *SF* captures the reaction of short sellers to announcements, with short flow increasing (decreasing) in the days following bad (good) news. In general, these findings are broadly consistent with Engelberg et al. (2012, Table 3), who report evidence that *SF* captures modest anticipation, but more so, intuitive reaction to news. The findings in Table 3 Panel A must be tempered by their modest economic importance. Table 1 shows that the mean and standard deviation of *SF* are 0.2149 and 0.1226 respectively. Hence, an increase of 0.0070 equates to a mere 0.0070/0.1226 = 0.06 standard deviation movement. As such, the evidence that *SF* anticipates and reacts to announcements is largely statistical in nature.

Table 3 Panel B and Panel C provide little evidence that short interest is influenced by news. Noting that the dependent variable in Panel B is ln(*SI*), short interest is approximately 3.56% higher than average levels when a bad news announcement occurred over the previous five days. However, the statistical significance of this finding is underwhelming ($p = 0.053$). In Panel C, unlike *SF* (Panel A), *dSI* does not capture anticipatory short selling on bad news. This may indicate that the short trades reflected in *SF* are neutralized by short covering, resulting in no net change in short positions before announcements. While there is some evidence that short sellers increase their bet on and after the announcement of bad news, the magnitude is small compared to the level of short interest. Daily change in short interest increases by 0.000098 ($p = 0.046$) on announcement and 0.000036 ($p = 0.053$) over the following five days (nb: *dSI* is scaled by 100 in Panel C). There is also weak evidence that short sellers scale back their shorts on announcement of good news, although the magnitude is again economically small (-0.000081, $p = 0.066$).

To consider the possibility that earnings announcements attract more attention from short sellers, the remainder of Table 3 partitions the full sample of ASX price-relevant announcements into earnings and non-earnings announcements. In brief, the

[9] The daily buy-order imbalance of a stock (*oimb*) is the differential between daily buys and sells, scaled by daily volume. We calculate this imbalance using *AusEquities* data obtained from SIRCA. Unlike US data, where the trade direction must be inferred (for example, as per Lee and Ready, 1991), the *AusEquities* data explicitly identifies buyer- and seller-initiated trades.

[10] In a preliminary analysis, effective bid-ask spread and intraday volatility were also included to test whether short sellers are opportunistic risk bearers during periods of heightened uncertainty. Similar to the findings of Diether et al. (2009), our results did not support this hypothesis and these variables are omitted in the interest of brevity.

[11] Note that *SF* would only decline prior to positive news if the recipients of the information held existing short positions. Otherwise, the information is likely to manifest via long positions.

Table 2
Past returns, order imbalance and short-selling metrics.

	Panel A		Panel B		Panel C	
	Dependent variable is *SF*		Dependent variable is ln(*SI*)		Dependent variable is $dSI \times 100$	
	(1)	(2)	(1)	(2)	(1)	(2)
$r(-5,-1)$	0.2179***	0.1391***	0.1873	0.0540	0.0385**	0.0280
oimb$^+$		0.0359***		0.0179		−0.0258***
r(t)		0.1845***		0.1370		−0.0197
$oimb^+(-5,-1)$		−0.0265*		−0.3313*		0.0327***
$tv(-5,-1)$		0.3482		10.2596		0.1647
$SF(-5,-1)$		0.5334***		2.2837***		0.0897***

This table reports the results of a regression of various metrics of short-selling activity on a number of explanatory and control variables. In Panel A, Panel B and Panel C, the dependent variable is the time-*t* short flow (*SF*), log short interest (ln(*SI*)) and change in short interest (*dSI*) respectively. The key independent variables are a stock's return over the previous five days $r(-5,-1)$ and the time-*t* buy-order imbalance $oimb^+ = \max(0, oimb)$. The control variables are the contemporaneous time-*t* stock return $r(t)$, the average daily buy-order imbalance over the previous five days $oimb(-5,-1)$, the average daily share turnover over the previous five days $tv(-5,-1)$, and the average short flow over the previous five days $SF(-5,-1)$. The estimation involves a panel regression with stock and day fixed effects, and standard errors clustered by stock and day. All variables are winsorized at the 2.5/97.5 percentiles. *, **, *** denote statistical significance at 10%, 5% and 1% levels respectively.

Table 3
Effects of price-relevant announcements on short-selling metrics.

	Panel A: *SF*			Panel B: ln(*SI*)			Panel C: $dSI \times 100$		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
All price-relevant announcements									
Badnews(1,5)	0.0070***			0.0150			0.0010		
Goodnews(1,5)	0.0019			0.0205			−0.0011		
Badnews(t)		−0.0001			0.0222			0.0098**	
Goodnews(t)		−0.0039			0.1096			−0.0081*	
Badnews(−5,−1)			0.0098***			0.0356*			0.0036*
Goodnews(−5,−1)			−0.0041**			0.0135			−0.0016
$r(-5,-1)$	0.1795***	0.1798***	0.1965***	0.1554	0.1557	0.1810	0.0405**	0.0407**	0.0468**
Earnings announcements only									
Badnews(1,5)	0.0077**			0.0188			0.0012		
Goodnews(1,5)	0.0051			0.0120			0.0026		
Badnews(t)		0.0036			0.0293			0.0155**	
Goodnews(t)		−0.0033			0.0318			−0.0089	
Badnews(−5,−1)			0.0204***			0.0452			0.0120***
Goodnews(−5,−1)			−0.0019			0.0245			0.0003
$r(-5,-1)$	0.1796***	0.1799***	0.1895***	0.1548	0.1554	0.1652	0.0406**	0.0406**	0.0457**
Non earnings announcements									
Badnews(1,5)	0.0071***			0.0134			0.0013		
Goodnews(1,5)	−0.0015			0.0211			−0.0022		
Badnews(t)		−0.0004			0.0231			0.0081	
Goodnews(t)		−0.0044			0.0141			−0.0079*	
Badnews(−5,−1)			0.0044			0.0350*			0.0006
Goodnews(−1,−1)			−0.0057**			0.0058			−0.0016
$r(-5,-1)$	0.1794***	0.1799***	0.1866***	0.1557	0.1556	0.1786	0.0404**	0.0406**	0.0426**

This table examines the extent to which various metrics of short-selling activity reflect price-relevant announcement events. Panel A, Panel B and Panel C relate to the time-*t* short flow (*SF*), log short interest (*SI*) and change in short interest (*dSI*) respectively. For each announcement flagged by the ASX as price-relevant, we only regard it as bad (good) news if the announcing stock's announcement-day return is in the lowest (highest) quintile amongst the S&P/ASX 200 constituents on that day. The time-*t* short-selling metric is regressed on a series of dummy variables capturing news, along with a control variable capturing recent stock returns over the previous five days $r(-5,-1)$. The news dummies with positive (negative) indices takes the value of unity if a price-relevant announcement occurs over the following (prior) five days, hence capturing anticipation (reaction) of short selling to news. The news dummies with a time-*t* index capture a contemporaneous effect of news on short-selling activity. The estimation involves a panel regression with stock and day fixed effects, and standard errors clustered by stock and day. All variables are winsorized at the 2.5/97.5 percentiles. *, **, *** denote statistical significance at 10%, 5% and 1% levels respectively.

key takeaways do not change materially. The anticipation of *SF* to bad news is consistent across earnings and non-earnings announcements (increasing by approximately 0.0070). The reaction of *SF* to bad news appears to be driven by bad earnings announcements (0.0204, $p < 0.01$), while its reaction to positive announcements (−0.0057, $p = 0.012$) are non-earnings related. Similarly, the contemporaneous and subsequent increase in *dSI* on price-relevant announcements appears to be earnings related. One possible explanation is that some short sellers trade on the widely-documented post earnings announcement drift phenomenon. Overall, the findings suggest that, while information events such as corporate announcements are statistically related to *SF*, their economic influence is negligible. The *SI* and *dSI* metrics do not appear to anticipate or react to news.

Our third and final consideration of the source and nature of information in short-selling metrics focuses on the notion that short sellers target stocks that are overpriced in anticipation of an eventual correction. We differentiate this scenario from the previous analyses with reference to the likely time horizon over which the correction takes place. Shorting to exploit past return patterns, buy-order imbalance or news events implicitly presumes price correction over the immediate horizon. In contrast, the analysis here is concerned with fundamental mispricing that is likely to be corrected over longer horizons.

Since short interest reflects information likely to be relevant over longer horizons, we conjecture that the level of short interest will be higher (lower) for stocks that are over (under) priced. Naturally, testing this conjecture requires a measure of stock-level

Table 4
Chi-squared tests of independence between mispricing and short-selling metrics.

Level of short-selling activity	Under priced (%)	Neutral (%)	Over priced (%)	Chi-square statistic
Panel A: short interest (SI)				
Low	22.77	61.18	16.05	584
High	18.04	59.17	22.79	($p < 0.001$)
Panel B: short flow (SF)				
Low	21.54	58.01	20.45	149
High	18.30	62.20	19.51	($p < 0.001$)
Panel C: change in short interest (dSI)				
Low	20.30	60.32	19.38	14.90
High	19.74	59.73	20.53	($p < 0.01$)

Panel D: concentration of low and high levels of SI in overpriced quintile

	AG (%)	ACC (%)	GP (%)	ROA (%)	BM (%)	MOM (%)	SIZE (%)
Low *SI*	15.17	16.15	18.09	19.63	16.93	13.06	34.78
High *SI*	23.41	22.72	21.35	20.26	22.17	24.90	9.55

Stocks are sorted into three groups according to a mispricing index which is calculated in the spirit of Stambaugh et al. (2015) based on seven return anomalies that have been extensively documented in the Australian market. For each short-selling metric – short interest (*SI*), short flow (*SF*) and changes in short interest (*dSI*) – stocks are classified as having a low or high level of shorts using the median of the metric. Under the null hypothesis that high shorts are randomly distributed across mispricing groups, 20% of the observations are expected in the underpriced and overpriced groups, with 60% expected in the neutral group. The Pearson chi-squared statistic tests whether departures of observed from expected frequencies are statistically significant. Panel A, Panel B and Panel C tabulate the proportion of high and low shorts across mispricing groups for *SI*, *SF*, *dSI*. For each component of the mispricing index, Panel D reports the concentration of low and high levels of *SI* in the over-priced group. AG, ACC, GP, ROA, BM, MOM and SIZE denote the anomaly variables asset growth, accruals, gross profitability, return-on-assets, book-to-market, momentum and size respectively.

mispricing, which is not directly observable. In a recent paper, Stambaugh et al. (2015) propose a method of constructing a proxy for mispricing based on well-documented return anomalies. We adopt a similar approach to studying the extent to which alternate short-selling metrics reflect views on mispricing.

In the spirit of Stambaugh et al. (2015), our stock-level mispricing proxy is based on seven return anomalies that have been extensively documented in the Australian equity market (specifically, firm size, book to market, prior 6-month momentum, asset growth, accruals, gross profitability and return on assets).[12] For a given anomaly variable, each stock in the population is assigned a percentile rank. The lowest (highest) rank is assigned to the stock with the highest (lowest) expected return according to the anomaly. For example, after sorting on book-to-market ratio, value (growth) stocks are assigned low (high) percentile rankings. This ranking procedure is repeated daily for each of the seven anomaly variables. Following Stambaugh et al. (2015), the 'mispricing index' for each stock is the arithmetic average of that stock's ranking across the seven anomalies.[13] Stocks with high and low values for the mispricing index are classified as most-likely to be over- and under-priced respectively. For our sample of S&P/ASX200 stocks, the mispricing index is close to symmetric, with a mean (median) of 0.4963 (0.4893) and standard deviation of 0.0768. Nonetheless, there is considerable dispersion in the degree of mispricing, with sample stocks ranging from 0.23 (underpriced) to 0.85 (overpriced).

Given a stock-level measure of mispricing, we proceed to test the extent to which alternate short-selling metrics reflect sentiment on mispricing. Our approach is along the lines of Dechow et al. (2001, Table 2) who document that short sellers position themselves in stocks with low ratios of fundamental-to-market value. First, all sample stocks are sorted into three groups on the basis of their mispricing index. The 'underpriced' and 'overpriced' groups comprise stocks in the lowest and highest mispricing quintiles respectively, while the 'neutral' group contains the balance. Second, stocks are independently classified as either having a 'low' or 'high' level of shorts according to a given metric (either *SI*, *SF* or *dSI*). With reference to Table 1 summary statistics, and particularly given the skewness of short interest, we utilize the median value of each short-selling metric to differentiate low and high shorts. The intersection of these classifications generates a 2×3 contingency table from which we implement Pearson chi-squared tests of whether observed frequencies depart from expected frequencies under the null that stocks are independently distributed across the grid. Specifically, if high shorts are randomly distributed across mispricing groupings, we expect 20% of observations to fall in the overpriced quintile, 20% to fall in the underpriced quintile and the remaining 60% to fall in the neutral grouping.

Table 4 Panel A documents a disproportionate concentration of stocks with a high level of *SI* in the overpriced grouping (22.79%). Similarly, overpriced stocks with low levels of *SI* are under-represented (16.05%). Conversely, these concentrations reverse amongst under-priced stocks – only 18.04% have a high level of *SI*, while there is a disproportionate occurrence of low levels of *SI* (22.77%). The chi-squared test rejects the notion that these departures of observed from expected frequencies have arisen by chance. As such, these findings are consistent with our intuition that short interest captures views about the likely degree of over-pricing in stocks.

In contrast, there is little evidence that short flow captures the same sentiment. In the overpriced grouping, with reference to the 20% expected frequency, Panel B documents an *under* representation of stocks with high levels of *SF* (19.51%) and an *over* representation of stocks with low levels of *SF* (20.45%). It is important to note that the directions in which these observed frequencies depart from expected are contrary to those that would suggest that *SF* embeds information about mispricing. Further, while the departures are modest, the chi-squared test rejects the null that high levels of *SF* are randomly distributed across mispricing groupings. With respect to changes in short interest (*dSI*), the tenor of findings in Table 4 Panel C is similar to the findings for short interest in Panel A. The concentration of stocks with a high level of *dSI* in the overpriced group is marginally above expected (20.53%), while there are fewer overpriced stocks with low levels of *dSI* (19.38%). For under-priced stocks, the patterns in Panel C are also similar to Panel A. Overall, the Pearson chi-squared test statistic is dramatically reduced ($\chi^2 = 14.90$) although still significant at conventional levels.

Given that the mispricing index is a composite ranking based on seven return anomalies, we conclude our analysis by examining whether any particular component of the index stands out as

[12] See, for example, Gharghori et al. (2009), Dou et al. (2013) and Zhong et al. (2014).

[13] Stambaugh et al. (2015, p. 9) argue that, despite being a crude approach, averaging ranks across many anomalies diversifies away some noise within each individual anomaly and thereby increases the precision of the composite mispricing measure.

Table 5
Short flow and future stock returns.

	No. of Stocks	Short Flow	Short interest	Size ($m)	BM	Past 1-month return	Past 6-month return
Panel A: portfolio summary statistics							
Low	40	9.17	1.78	2,745	0.81	0.20	6.08
2	40	15.08	1.97	6,442	0.70	0.60	3.87
3	40	19.40	2.23	7,802	0.71	0.94	3.76
4	40	24.39	2.64	7,972	0.73	1.02	3.18
High	40	34.22	4.02	5,992	0.75	0.52	−0.53

Panel B: Future K-day holding period returns (expressed on a per-month basis)

	Raw returns							Risk-adjusted returns						
	$K = 1$	$K = 3$	$K = 5$	$K = 10$	$K = 20$	$K = 40$	$K = 60$	$K = 1$	$K = 3$	$K = 5$	$K = 10$	$K = 20$	$K = 40$	$K = 60$
Low	1.77**	1.90**	1.97**	2.01**	1.81*	1.52	1.39	1.30***	1.39***	1.43***	1.47**	1.30**	0.91	0.75
2	0.89	0.90	0.82	0.88	0.76	0.67	0.68	0.34	0.38	0.33	0.36	0.21	0.12	0.12
3	0.66	0.42	0.43	0.45	0.50	0.58	0.62	0.24	−0.06	−0.07	−0.05	−0.03	0.03	0.05
4	−0.13	0.10	0.12	0.16	0.19	0.41	0.50	−0.71	−0.42	−0.40	−0.40	−0.36	−0.14	−0.07
High	0.16	0.36	0.40	0.29	0.36	0.45	0.50	−0.26	−0.10	−0.08	−0.16	−0.10	−0.02	−0.01
Low–high	1.61***	1.54***	1.57**	1.72**	1.45*	1.07	0.89	1.56***	1.49***	1.51***	1.63***	1.40**	0.94	0.76

Each day t, the sample comprises all stocks that were members of the S&P/ASX200 index in the prior month. Short flow (*SF*) is calculated as the volume of shares sold short over the last 5 days, scaled by total trading volume over the same period. Stocks are then assigned to quintile portfolios based on their *SF*. After skipping one day, equal-weighted portfolio returns are calculated over a K-day holding period (K = 1, 3, 5, 10, 20, 40, 60 days). The portfolio sorting procedure is repeated each day generating a series of K overlapping portfolios, which are then averaged to give the daily return to the portfolio. The sample period spans 3 January 2012 through 30 June 2014 (629 days). To facilitate comparison across holding periods of varying lengths, the table reports portfolio returns on a per month basis. Statistical inference utilizes Newey–West standard errors, where the number of lags is the length of the holding period. Risk-adjusted returns are based on the Fama–French three-factor model, augmented with momentum and contrarian factors. Portfolio characteristics (*SF*, *SI*, size, BM, 1-month return and 6-month return) are the time series mean of the daily cross-sectional means. Size is market capitalization in millions. BM is the stock's book-to-market flow. A stock's day-t 1-month and 6-month prior return are calculated up to day $t - 1$. *, **, *** denote statistical significance at 10%, 5% and 1% levels respectively.

conveying more information. For each component of the mispricing index, Table 4 Panel D focuses on the proportion of low and high levels of *SI* amongst the most-overpriced grouping. By and large, the inferences for each component are consistent with the inferences drawn above for the mispricing index as a whole.[14] Overpriced stocks have a disproportionately high (low) concentration of high (low) shorts. Prior 6-month momentum stands out for having the largest departures of observed from expected frequencies, consistent with an extensive Australian literature that documents strong profits to medium-horizon momentum trading. Overall, the results in Panel D suggest that SI captures different facets of overvaluation, consistent with the notion that short sellers are heterogeneous.

To summarize, the findings in this section are consistent with the notion that short sellers are heterogeneous with respect to the nature and source of their information. Further, different metrics of short-selling activity appear to reflect different aspects of the information set. Short flow alone appears to capture short-term contrarian trading and temporary order-book patterns. Similarly, imminent price-relevant announcements of a negative nature are reflected in *SF*, but not *SI* or *dSI*. Short flow also reacts to price-relevant announcements, increasing after bad earnings news and decreasing following positive non-earnings news. While statistically significant, these findings must be cautiously interpreted in light of the modest economic magnitude of the relationships. The information content of short interest appears to relate to negative views over the longer-horizon prospects of a stock. Although not overwhelming, there is some support for the notion that high levels of *SI* are concentrated in stocks most likely to be overpriced. We also document a disproportionately low level of high shorts amongst under-priced stocks, suggesting that short sellers are adept at identifying and avoiding them.

[14] The only component of the mispricing index inconsistent with the main findings relates to the size anomaly. This is unsurprising. Since our study focuses on the S&P/ASX200 constituents, the percentile rankings based on size are very tightly clustered (i.e., they are all large caps). This potentially contaminates our endeavours to form meaningful size quintiles. For every other component anomaly, however, there is considerable variation in the percentile rankings.

5. The relation between short-selling metrics and future returns

The findings in Section 4 are suggestive of differences in the nature and source of information captured by short flow and short interest. It follows that these metrics of short-selling activity are likely to exhibit unique ability to predict future returns. Further, the heterogeneous nature of information held by short sellers is expected to manifest in differential horizons over which each metric has predictive power. This section uses portfolio sorts and regression analysis to explore these issues.

5.1. Portfolio sorts

To the extent that it is information driven, short selling-activity will be associated with cross-sectional variation in future stock returns. Specifically, since short selling should be more prevalent in stocks subject to the most pessimistic information, heavily-shorted stocks are expected to underperform lightly-shorted stocks. In this section, we study the information content of short-selling metrics using a portfolio-sorting approach.

On each day t, stocks are sorted into quintiles based on *SI* levels as at day $t - 4$. The time lag reflects the 4-day delay in publication of short position reports. Similarly, quintile portfolios are formed using day $t - 1$ *SF* metrics (due to 1-day delay in the short flow publication). Rather than rely on a single-day measure of short flow, the total volume of short sales over the 5-day period ending on day $t - 1$ is scaled by total trading volume over the same period, thereby reducing potential noise. After skipping one day to alleviate microstructure concerns, returns to equal-weighted buy-and-hold quintile portfolios are estimated for a K-day holding period (K = 1, 3, 5, 10, 20 40, 60 days).[15]

[15] We choose equal weighting for two reasons. First, as Boehmer et al. (2010) highlight, value weighting may bias analysis of the performance of shorted stocks. To the extent that heavily shorted stocks have persistent negative abnormal returns, such stocks receive less weighting in value-weighted portfolios, thereby masking the true performance of short sellers. Second, since panel regressions weight stocks equally by construction, use of equally-weighted portfolios allows consistent interpretation of results. Although equal weighted results are reported throughout the paper, the main tenet of the findings does not change when results are value weighted.

Table 6
Short interest and future stock returns.

	No of stocks	Short interest	Short flow	Size ($m)	B/M	Past 1-month return	Past 6-month return
Panel A: portfolio summary statistics							
Low	40	0.23	14.25	6,782	0.72	1.22	7.66
2	40	0.59	16.39	7,335	0.77	0.75	3.30
3	39	1.26	18.36	5,083	0.76	−0.46	−2.24
4	40	2.36	19.84	5,418	0.74	−0.12	−2.86
High	40	6.62	21.69	2,708	0.73	−0.79	−6.98

Panel B: Future K-day holding period returns (expressed on a per-month basis)

	Raw returns							Risk-adjusted returns						
	$K=1$	$K=3$	$K=5$	$K=10$	$K=20$	$K=40$	$K=60$	$K=1$	$K=3$	$K=5$	$K=10$	$K=20$	$K=40$	$K=60$
Low	1.72**	1.85**	1.94**	2.10**	2.07**	2.02**	1.79**	0.87**	0.95**	1.02**	1.17**	1.13**	1.09**	0.89**
2	0.68	0.84	0.83	0.77	0.70	0.77	1.03	−0.07	0.11	0.10	0.07	0.01	0.06	0.27
3	0.09	0.22	0.27	0.14	0.10	0.09	0.15	−0.25	−0.10	−0.06	−0.20	−0.26	−0.28	−0.24
4	0.29	0.29	0.24	0.39	0.44	0.49	0.53	0.08	0.06	−0.01	0.12	0.13	0.12	0.10
High	0.31	0.32	0.31	0.25	0.22	0.21	0.16	0.02	0.02	0.01	−0.06	−0.08	−0.12	−0.20
Low–high	1.41**	1.53*	1.63*	1.86**	1.86**	1.81**	1.63**	0.85*	0.93*	1.01*	1.23**	1.21*	1.20*	1.10*

Each day t, the sample comprises all stocks that were members of the S&P/ASX200 index in the prior month. Short interest (*SI*) is calculated as the cumulative quantity of short positions on day $t-4$, scaled by total number of shares outstanding. Each day stocks are assigned to quintile portfolios sorted on short interest. After skipping one day, equal-weighted portfolio returns are calculated over a K-day holding period (K = 1, 3, 5, 10, 20, 40, 60 days). The portfolio sorting procedure is repeated each day generating a series of K overlapping portfolios, which are then averaged to give the daily return to the portfolio. The sample period spans 3 January 2012 through 30 June 2014 (629 days). To facilitate comparison across holding periods of varying lengths, the table reports portfolio returns on a per month basis. Statistical inference utilizes Newey–West standard errors, where the number of lags is the length of the holding period. Risk-adjusted returns are based on the Fama–French three-factor model, augmented with momentum and contrarian factors. Portfolio characteristics (*SF*, *SI*, size, BM, 1-month return and 6-month return) are the time series mean of the daily cross-sectional means. Size is market capitalization in millions. BM is the stock's book-to-market ratio. A stock's day-t 1-month and 6-month prior return are calculated up to day $t-1$. *, **, *** denote statistical significance at 10%, 5% and 1% levels respectively.

This portfolio sorting approach is repeated each day, giving rise to a series of K overlapping portfolios at any given point in time. In the spirit of Jegadeesh and Titman (1993), the daily portfolio return is the average across the K overlapping portfolios. All statistical inference utilizes Newey and West (1987) standard errors to correct for autocorrelation, where the number of lags is the length of the holding period. The final sample is a time series of 622 daily returns to quintile portfolios formed according to *SF* and *SI*, spanning 12 January 2012 to 30 June 2014. Tables 5 and 6 report the characteristics of and returns to quintile portfolios formed according to *SF* and *SI* respectively.

Table 5 Panel A depicts the key characteristics of stocks in each *SF* quintile. There is substantial cross-sectional variation in short flow, ranging from 9.17% for the most-lightly shorted quintile to 34.22% for the most-heavily shorted quintile. *SI* also increases monotonically across the *SF* quintiles, consistent with positive correlation between the two metrics ($\rho = +0.27$). Naturally, to the extent that *SF* and *SI* are correlated, portfolio analysis sorted on a single metric may struggle to differentiate the unique influence of each metric. This possibility is re-visited shortly. The most striking pattern in Table 5 is the negative relation between average *SF* and prior 6-month stock performance, consistent the intuition that short sellers engage in technical trading strategies.

While stocks in the Low *SF* quintile have the lowest mean market cap ($2.745 bn), caution is warranted when inferring the direction of the relation between short-selling activity and firm size. In fact, Table 6 suggests that the smaller stocks in our sample have the highest levels of *SI*. The Australian equity market is characterized by a handful of mega-cap stocks (banks and resource stocks) which may unduly influence the cross-sectional means reported in Table 5. We formally test the relation between short-selling activity and firm size using panel regressions with stock and day fixed effects. The findings (not explicitly tabulated) confirm a significant negative relation between firm size and each of *SF* and ln (*SI*). At face value, this finding might suggest that controlling for size effects in returns will be paramount. However, this is again tempered by the fact that our sample is confined to the S&P/ASX200 constituents. While there is a significant and well-documented size premium in the population of Australian equities, there is no detectable size effect within the top 500 stocks (see Gray, 2014). Nonetheless, known risk factors are accommodated shortly using common asset-pricing models.

To assess the predictive ability of information embedded in *SF*, Table 5 Panel B reports raw and risk-adjusted returns to quintile portfolios over a range of holding periods. Risk-adjusted returns are proxied by the intercept from a Fama and French (1993) three-factor model augmented with risk factors formed on prior 1-month and prior 6-month momentum. To facilitate comparison across holding periods of different lengths, all returns are scaled to approximate a one-month return. At each horizon, raw returns decrease near monotonically as the level of short flow increases. The return differential between the most-lightly and most-heavily shorted portfolios is strictly positive and consistently around 150–170 basis points per month out to 20 days, then drops sharply to 107 (89) basis points for 40-day (60-day) holding period. Statistically, the information content of *SF* for future returns does not extend beyond 20 days. Similar findings apply at the risk-adjusted level. The difference in risk-adjusted alphas are in the vicinity of 140–160 basis points per month and statistically significant out to a 20-day horizon, then drop to a statistically insignificant 94 (76) bps for 40-day (60-day) horizons.

In a similar vein to Table 5, Table 6 reports the characteristics of and returns to quintile portfolios formed according to short interest. By construction, average *SI* increases across quintiles (from 0.23% to 6.62% of shares outstanding), yet the association is far from linear. While the level of short interest for Quintiles 1–4 is modest, it is substantially higher for Quintile 5 consistent with severe positive skewness in the distribution of *SI* across sample stocks (see Table 1). Consistent with short sellers engaging in momentum trading, the level of short interest is inversely proportional to past performance measured over both 1-month and 6-month horizons. There is very little difference in size across the *SI* quintiles, with the exception that the most-heavily shorted quintile contains noticeably smaller stocks.[16]

Table 6 Panel B presents strong evidence that *SI* embeds important information for future stock returns. With respect to raw returns, the average differential between lightly-shorted and

[16] As noted earlier, untabulated panel regressions using stock and day fixed effects confirm a significant negative relation between ln(*SI*) and firm size.

Table 7
Relation between short-selling metrics and future returns.

Panel A: short flow		Future 1-day return			Future 10-day return		
		Losers	Neutral	Winners	Losers	Neutral	Winners
Low shorts	Observations	5,033	14,457	5,316	4,794	14,248	5,429
	Percentage	20.29%	58.28%	21.43%	19.59%	58.22%	22.19%
Medium shorts	Observations	14,590	45,083	14,646	14,389	44,809	14,131
	Percentage	19.63%	60.66%	19.71%	19.62%	61.11%	19.27%
High shorts	Observations	5,132	14,756	4,918	5,288	14,272	4,911
	Percentage	20.69%	59.49%	19.83%	21.61%	58.32%	20.07%
		Future 20-day Return			Future 60-day Return		
		Losers	Neutral	Winners	Losers	Neutral	Winners
Low shorts	Observations	4,664	13,916	5,466	4,553	13,172	4,677
	Percentage	19.40%	57.87%	22.73%	20.32%	58.80%	20.88%
Medium shorts	Observations	14,267	44,011	13,838	12,844	41,295	13,078
	Percentage	19.78%	61.03%	19.19%	19.11%	61.44%	19.46%
High shorts	Observations	5,114	14,190	4,742	5,005	12,750	4,647
	Percentage	21.27%	59.01%	19.72%	22.34%	56.91%	20.74%
Panel B: short interest		Future 1-day Return			Future 10-day Return		
		Losers	Neutral	Winners	Losers	Neutral	Winners
Low shorts	Observations	3,958	16,314	4,534	3,352	16,704	4,415
	Percentage	15.96%	65.77%	18.28%	13.70%	68.26%	18.04%
Medium shorts	Observations	15,033	44,409	14,877	14,934	43,820	14,575
	Percentage	20.23%	59.75%	20.02%	20.37%	59.76%	19.88%
High shorts	Observations	5,764	13,573	5,469	6,185	12,805	5,481
	Percentage	23.24%	54.72%	22.05%	25.27%	52.33%	22.40%
		Future 20-day Return			Future 60-day Return		
		Losers	Neutral	Winners	Losers	Neutral	Winners
Low shorts	Observations	3,113	16,544	4,389	2,664	15,395	4,343
	Percentage	12.95%	68.80%	18.25%	11.89%	68.72%	19.39%
Medium shorts	Observations	14,741	43,103	14,272	13,735	40,191	13,291
	Percentage	20.44%	59.77%	19.79%	20.43%	59.79%	19.77%
High shorts	Observations	6,191	12,470	5,385	6,003	11,631	4,768
	Percentage	25.75%	51.86%	22.39%	26.80%	51.92%	21.28%

Each day t, stocks are sorted into three groups according to their future K-day return over the period $[t, t + K]$. The top and bottom quintiles are classified Winners and Losers, while the middle three quintiles are labeled Neutral. Stocks are then sorted into three groups according to their most-recently observed short-selling metric (Low, Medium, High Shorts). The table allows a comparison of the number of stock-day observations and observed frequencies to the expected frequency under the null hypothesis that there is no relation between short-selling activity and future stock returns.

heavily-shorted stocks is positive and, unlike the case for *SF*, statistically significant for *all* holding periods considered. The magnitude is in the vicinity of 140–190 basis points per month, which is economically significant. There is no apparent monotonicity in returns across *SI* quintiles. However, as was the case with *SF*, the average returns to Quintile 1 stand out for being large and significant without exception. This is consistent with Boehmer et al.'s (2010) finding of positive information in stocks with low short interest, providing further support for the notion that short sellers are adept at relative valuations. Adjusting for risk factors, the return differential declines to around 85–120 basis points per month, yet the overall findings remain intact. Unlike the case of *SF*, there is no noticeable decline in returns beyond the 20-day horizon.

Two aspects of Tables 5 and 6 warrant further discussion. First, a large proportion of the return differential between extreme short-selling quintiles derives from the positive return to the lightly-shorted portfolio. The cross-sectional variation in average returns between the extreme quintiles can be viewed as a measure of the importance and relevance of the information content embedded in the short-selling metric. Similar to our findings in Tables 5 and 6, Boehmer et al. (2008) and Boehmer et al. (2010) also propose that short sellers are highly skilled at relative valuations. In addition to identifying overvalued stocks to short, they are also adept at avoiding undervalued stocks. As such, the relative absence of short-selling activity in itself is a useful (positive) information signal over a stock's future prospects.

The second notable aspect of Tables 5 and 6 is that, contrary to intuition, the most-heavily shorted quintile generates a positive, albeit statistically insignificant, average return over all horizons. Notwithstanding our focus on cross-sectional variation between the extreme short-selling quintiles, one possible explanation is that the modest time horizon of our study coincides with a sustained bull market. Fig. 1 demonstrates that the S&P/ASX200 index rose just over 30%, from 4101 in January 2012 to 5396 in June 2014. In terms of profiting from their information and relative valuation skills, short traders (with the benefit of hindsight) would have been better served by simply entering long leveraged (margined) positions in quintile 1 stocks. However, to the extent that their trading (and lack thereof) reflects genuine information and valuation skills, it is plausible that short positions will contribute more to the return differential in different market states.

A further explanation may lie in outliers. With approximately 40 stocks per portfolio, if one or more heavily-shorted stocks subsequently generate a large positive return, this may drive the small positive average return reported for the heavily-shorted quintile. To explore this possibility, we perform a double-sorting procedure designed to mitigate the influence of return outliers. First, at each time t, stocks are sorted into three groups based on their K-day future return over the period $[t, t + K]$. The top and bottom quintiles are classified Winners and Losers respectively, while the middle three quintiles are regarded as Neutral. Second, using quintiles in a similar fashion, stocks are sorted into three groups according to their most-recently observed short-selling metric (Low, Medium and High Shorts). To assess the relative valuation skills of short sellers, we compare the proportion of stocks across the resulting 3×3 grid to the expected frequencies under the null that short-selling activity is unrelated to future returns. Table 7 presents the results.

Pearson chi-square tests (not explicitly shown) reject the null that future returns and short selling are independent. This is the case for all holding periods and for both *SF* and *SI* metrics. There are several key insights to short sellers' relative valuation skills. Consider, for example, *SI* and future 10-day returns. Table 7 reports that 25.27% of High Shorts are subsequent Losers. Against an expected frequency of 20% under the null of independence, this suggests that short sellers are proficient at identifying Losers. However, short sellers also 'misfire', with 22.40% of High Shorts ultimately being Winners. While these false positives are less frequent than correct positives (a *z*-test confirms that the difference of 2.87% is significant at the 1% level), they occur with sufficient frequency to induce the positive (albeit statistically insignificant) average return to the highly-shorted quintile in Table 6.

Further, while 18.04% of the Low Shorts are subsequent Winners, only 13.70% are subsequent Losers (again against an expectation of 20%). The 4.34% difference in the proportions is statistically significant ($z = 7.06$, $p < 0.001$). Noting that the long-short strategy in Tables 5 and 6 enters long positions in Low Shorts, the fact that a higher proportion of such stocks are subsequent Winners drives the significant positive average returns to the long end of the strategy. For longer holding periods, the findings in Table 7 are similar yet more pronounced. Qualitatively similar findings obtain with respect to *SF* (up to a 20-day holding period consistent with Table 5). Overall, this analysis suggests that short sellers are good at relative valuation in the sense that they make fewer Type II errors (false negatives) than Type I errors (false positives).

To summarize the results, there is evidence that both *SF* and *SI* convey important information regarding future stock returns. The key difference appears to be the horizon over which the information is relevant. The information content in *SF* is useful over the short-term, peaking at a holding horizon of 10 days. In contrast, the return predictability of *SI* is pervasive out to at least 60 days. These horizons effects are highly consistent with the findings in Section 4 regarding the nature and source of information likely to manifest in each metric. Having documented that *SF* embeds impending news announcements and short-term technical trading, it is intuitive that its relevance for future returns is short lived. In contrast, by capturing fundamental mispricing, the information content of *SI* is likely to generate predictive ability for future returns over the extended time horizons necessary for fundamentals to revert to fair values.

5.2. Regression analysis

Tables 5 and 6 document a number of distinct patterns across portfolios in key characteristics (most noticeably firm size and prior momentum). Accordingly, in addition to an analysis of raw returns, Section 5.1 also estimates risk-adjusted returns to portfolios to control for risk factors associated with these characteristics. A common alternate approach to controlling for characteristics is to construct double (or triple) sorted portfolios using the short selling metric and one (or more) other characteristics. For two obvious reasons, we do not pursue this approach. First, given the modest sample size in the cross section, using multiple sorts will generate portfolios with an unacceptably low number of stocks. Second, double sorts only control for a single additional characteristic at a time. As noted above, our short selling portfolios exhibit patterns in multiple characteristics.

In order to simultaneously control for multiple characteristics, a regression framework is adopted. Using data at the individual stock level, future returns are regressed against short selling metrics, along with various control variables. Specifically, we estimate the following panel regression:

$$R_{i,t+K} = \alpha + \beta_1 SF_{i,t} + \beta_2 SI_{i,t} + \sum_{j=3}^{10} \beta_j X_{j-2,t} + \varepsilon_{i,t+K} \quad (1)$$

The dependent variable $R_{i,t+K}$ is the *K*-day holding period return on stock *i* (after skipping one day following the release of the short selling data). To facilitate comparison across holding periods of different length, the *K*-day return is scaled to reflect a per-month return. $SF_{i,t}$ and $SI_{i,t}$ are stock *i*'s short flow and short interest respectively observable at time *t* as previously defined. Given the positive skewness in short interest noted above, the natural log of *SI* is taken to mitigate the potential bias of influential observations.

A number of control variables are employed (denoted with a generic *X* in model 1). $SIZE_{i,t}$ and $BM_{i,t}$ are stock *i*'s market capitalization and book-to-market ratio respectively. $VOL_{i,t}$ is the realized volatility of stock *i*'s daily returns over the prior six months. $TURN_{i,t}$ is stock *i*'s total trading volume over the prior six months, scaled by the number of shares outstanding. To control for potential contrarian and momentum effects documented in Tables 5 and 6, $PRIOR1_{i,t}$ and $PRIOR6_{i,t}$ are the prior 1-month and 6-month returns to stock *i*. These variables are measured up to the point at which the five-day cumulation of short volume commences for estimation of $SF_{i,t}$.

The final two variables control for potential contemporaneous associations. Whereas model (1) tests a predictive association between short selling activity and future returns, it is conceivable that the association is contemporaneous (for example, heavy short selling drives down stock prices). In such a case, to the extent that returns are autocorrelated, the apparent association between short selling and future returns may be the result of an omitted correlated variable. To accommodate this possibility, model (1) includes stock *i*'s return over the 5-day period during which short flow is estimated ($R5_{i,t}$). Similarly, the change in short interest over the period for which future *K*-day returns $\Delta SI_{i,t}$ controls for the possibility that returns are autocorrelated and there is a contemporaneous association between short selling and returns.

Table 8 presents summary statistics for the independent variables used in model (1). In addition to short interest, a severe right skew is also obvious in the distribution of stock size, turnover and, to a lesser extent, book-to-market and volatility. To mitigate the potential influence of outliers, the natural log of each of these variables is used in model (1).[17] Return-based variables also exhibit occasional extreme positive and negative observations. As such, the prior return variables ($PRIOR1_{i,t}$ and $PRIOR6_{i,t}$), the formation-period return (*R5*) and the *K*-day holding period return (i.e., the dependent variable) are winsorized at the 2.5/97.5 percentiles. Similarly, the change in short interest over the *K*-day holding period (ΔSI) is also winsorized. While the persistence of short interest results in mean and median ΔSI close to zero with a very tight interquartile range, the sample contains a number of extreme observations. Notwithstanding the intuition above that extreme changes in short interest are likely to be relevant to future returns, winsorization at the 2.5/97.5 percentiles is designed to ensure the findings are not driven by a handful of extreme observations. Finally, the correlation matrix between independent variables (not reported) raises no concerns that multicollinearity is problematic. The highest pairwise correlations arise between ln(size) and ln(volatility) (−0.60), prior

[17] No log transformation is performed on short flow (*SF*), which has only a slight positive skew. Nonetheless, robustness analysis (not reported) shows that the results are virtually unchanged when ln(*SF*) is used as the independent variable.

Table 8
Summary statistics for panel regression variables.

	Mean	Std dev	Min	5th	25th	Median	75th	95th	Max
SF (%)	20.83	9.04	3.33	8.06	14.38	19.74	26.15	37.37	53.05
SI (%)	2.62	3.13	0.03	0.15	0.54	1.45	3.50	9.36	18.83
Δ*SI* (%)	0.04	0.56	−1.36	−0.98	−0.18	0.02	0.25	1.11	1.47
SIZE	6,117	14,762	271	430	872	1,682	4,440	28,170	114,409
BM	0.70	0.47	0.03	0.13	0.36	0.62	0.98	1.47	3.26
VOL (%)	34.96	17.19	12.41	16.69	22.74	30.08	42.44	69.49	114.70
TURN	0.50	0.29	0.11	0.19	0.33	0.43	0.59	1.04	2.22
R5 (%)	0.14	4.05	−9.21	−7.26	−2.04	0.19	2.35	7.34	9.34
PRIOR1 (%)	0.50	8.51	−19.32	−15.33	−4.09	0.83	5.40	15.12	18.85
PRIOR6 (%)	3.14	21.41	−46.37	−38.39	−9.28	5.60	16.82	37.39	44.59

The sample period spans 3 January 2012 through 30 June 2014. Each day *t*, the sample comprises all stocks that were members of the S&P/ASX200 index in the prior month. A stock's short interest ratio (*SI*) is calculated as the cumulative quantity of short positions on day $t-4$, scaled by total number of shares outstanding. Short flow (*SF*) is the total short flow over the 5-day period ending on day $t-1$, scaled by total trading volume over the same period. *SIZE* is the stock's market capitalization ($m). *BM* is the stock's book-to-market ratio. *VOL* is the stock's realized volatility of returns over the past 6 months. *TURN* is the stock's total trading volume over the past 6 months, scaled by shares outstanding. *R5* is the stock's cumulative return over the 5-day window used to estimate *SF*. *PRIOR1* and *PRIOR6* are cumulative stock returns over the past one and 6 months respectively. Δ*SI* is the stock's change in short interest over the period for which future *K*-day returns are calculated.

Table 9
Panel regressions of future raw returns against short-selling metrics.

		SF	SI	ΔSI	SIZE	BM	VOL	TURN	R5	PRIOR1	PRIOR6
1-day	Model 1	−4.59**		−18.91	−2.66*	1.83	−2.61**	0.96	−10.31	1.72	−6.24***
	Model 2		−0.61***	−39.64	−2.87*	2.02	−2.66**	1.21*	−11.29	1.91	−6.75***
	Model 3	−3.53**	−0.51**	−30.40	−2.85*	2.03	−2.69**	1.21*	−10.93	1.97	−6.79***
3-day	Model 1	−3.70**		78.46	−3.43**	1.40	−1.99**	0.71	−4.83	2.95	−7.17***
	Model 2		−0.64***	58.47	−3.65**	1.61	−2.06**	0.99	−5.69	3.18	−7.75***
	Model 3	−2.52*	−0.57**	65.11	−3.65**	1.62	−2.08**	0.99	−5.42	3.22	−7.77***
5-day	Model 1	−3.19**		49.92	−3.61**	1.41	−1.96**	0.60	−4.47	3.46	−7.49***
	Model 2		−0.62***	31.15	−3.83***	1.62	−2.03**	0.87	−5.15	3.67	−8.06***
	Model 3	−2.06	−0.56**	35.92	−3.83***	1.62	−2.04**	0.88	−4.94	3.71	−8.08***
10-day	Model 1	−3.44**		−8.84	−4.74***	1.11	−1.99**	0.33	−8.00**	3.57*	−8.29***
	Model 2		−0.57**	−23.77	−4.93***	1.28	−2.02**	0.58	−8.53**	3.73*	−8.79***
	Model 3	−2.44**	−0.50**	−20.13	−4.93***	1.29	−2.04***	0.58	−8.26**	3.78*	−8.81***
20-day	Model 1	−2.55**		−81.37**	−5.00***	1.18	−2.64***	0.15	−7.42***	3.18**	−8.97***
	Model 2		−0.58**	−93.51***	−5.24***	1.34	−2.65***	0.40	−7.89***	3.47**	−9.51***
	Model 3	−1.64	−0.54**	−92.07***	−5.24***	1.35	−2.66***	0.40	−7.70***	3.51**	−9.53***
40-day	Model 1	−0.91		−81.34***	−4.78***	1.22	−2.62***	0.06	−8.17***	0.76	−9.35***
	Model 2		−0.60***	−92.01***	−5.08***	1.39	−2.63***	0.34	−8.42***	0.98	−9.95***
	Model 3	0.07	−0.61***	−92.04***	−5.08***	1.39	−2.63***	0.34	−8.43***	0.98	−9.95***
60-day	Model 1	−0.34		−67.17***	−5.06***	0.95	−2.27**	−0.04	−9.23***	−0.61	−8.96***
	Model 2		−0.57***	−76.66***	−5.34***	1.11	−2.26**	0.20	−9.61***	−0.43	−9.53***
	Model 3	0.59	−0.58***	−76.86***	−5.33***	1.11	−2.25**	0.20	−9.68***	−0.45	−9.52***

Future raw returns over *K*-day periods (*K* = 1, 3, 5, 10, 20, 40, 60) are regressed on currently-observable values of short flow (*SF*), short interest (*SI*) and control variables. ΔSI measures the change in short interest ratios over the *K*-day holding period. *SIZE* and *BM* are a stock's market capitalization and book-to-market ratio respectively. *VOL* is the realized volatility of a stock's daily returns over the prior six months. *TURN* is total trading volume over the prior six months, scaled by the number of shares outstanding. *PRIOR1* and *PRIOR6* are the prior 1-month and 6-month returns. These variables are measured up to the beginning of the reference period over which *SF* is computed. *R5* is individual stock return over the reference period in which *SF* is computed. Log transformations are employed on *SI*, *SIZE*, *BM* and *TURN*. *PRIOR1*, *PRIOR6*, *R5*, Δ*SI* and the *K*-day holding period return are winsorized at the 2.5/97.5 percentiles. For each holding period *K*, three specifications of the regression (1) are reported, depending on which of the short metrics are included as explanatory variables: *SF* only (Model 1), *SI* only (Model 2) and both *SF* and *SI* (Model 3). The regressions are estimated with fixed stock and day effects, and standard errors are clustered by both stock and day. The reported coefficients are scaled by 100. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels respectively.

1-month and prior 6-month momentum (0.40), and ln(turnover) and ln(volatility) (0.41). Importantly, the correlation between *SF* and ln (*SI*) is a modest 0.35.

Tables 8 and 9 report the estimates for panel regression (1) with the dependent variable being raw and risk-adjusted returns respectively. Results for seven holding horizons are reported (*K* = 1, 3, 5, 10, 20, 40 and 60 days). In each table, three specifications of model (1) are estimated. The first (second) specification has short flow (short interest) as explanatory variable along with control variables. To examine their unique predictive ability, the third specification includes both metrics. Stock and day fixed effects are included in all specifications and all statistical inference is based on standard errors clustered by both stock and day.

Table 9 reports that, after controlling for stock characteristics, both *SF* and *SI* predict returns over immediate horizons. For holding periods up to 10 days, the estimated coefficients on the metrics are negative and significant when they are employed as an explanatory variable on their own (models 1 and 2) and when they are both included in the regression (model 3). One exception is the 5-day horizon where *SF* is insignificant when combined with *SI* in the regression. Consistent with the univariate portfolio analysis, the regression results indicate that short flow and short interest carry unique information content regarding future returns. However, at the 20-day horizon, the ability of *SF* to predict future returns deteriorates and becomes insignificant when combined with *SI* in the regression. As such, the information content within *SF* appears to be relevant over relatively short horizons. In contrast, *SI* continues to exhibit a significant negative relation with future returns out to 60 days. Table 10 reports similar findings when the dependent variable is the stock's risk-adjusted return.

Table 10
Panel regressions of future risk-adjusted returns against short-selling metrics.

		SF	SI	ΔSI	SIZE	BM	VOL	TURN	R5	PRIOR1	PRIOR6
1-day	Model 1	−5.44***		324.37*	−2.37	1.55	−1.48	0.66	−4.89	2.88	−6.94***
	Model 2		−0.61***	−39.64	−2.87*	2.02	−2.66**	1.21*	−11.29	1.91	−6.75***
	Model 3	−4.55***	−0.41**	313.39*	−2.51*	1.72	−1.54	0.89	−5.59	2.99	−7.36***
3-day	Model 1	−5.11***		286.68***	−3.02**	1.22	−0.94	0.66	3.24	2.54	−7.38***
	Model 2		−0.55**	264.68***	−3.19**	1.38	−0.97	0.90	2.19	2.61	−7.77***
	Model 3	−4.19**	−0.43**	275.71***	−3.17**	1.39	−1.00	0.90	2.62	2.69	−7.81***
5-day	Model 1	−4.22***		190.21***	−3.13**	1.31	−0.94	0.51	1.37	2.39	−7.53***
	Model 2		−0.50**	171.38***	−3.29**	1.45	−0.98	0.74	0.55	2.46	−7.91***
	Model 3	−3.38**	−0.40**	179.20***	−3.28**	1.46	−1.00	0.74	0.91	2.52	−7.94***
10-day	Model 1	−3.58***		66.72**	−3.89***	1.10	−0.81	0.36	−3.47	3.24**	−8.04***
	Model 2		−0.45**	53.68	−4.03***	1.22	−0.82	0.55	−4.01	3.30**	−8.39***
	Model 3	−2.82**	−0.37*	57.89*	−4.03***	1.23	−0.84	0.55	−3.70	3.36**	−8.42***
20-day	Model 1	−2.78**		−35.16	−4.23***	1.26	−1.23	0.47	−3.39*	3.30**	−8.44***
	Model 2		−0.52**	−46.32**	−4.44***	1.40*	−1.23	0.67	−3.89**	3.52**	−8.88***
	Model 3	−1.96*	−0.46**	−44.55*	−4.44***	1.41	−1.25	0.67	−3.67*	3.56**	−8.91***
40-day	Model 1	−1.56*		−62.58***	−3.64***	1.71**	−1.21	0.40	−5.37***	1.49	−8.57***
	Model 2		−0.60***	−73.25***	−3.92***	1.87**	−1.20	0.67	−5.72***	1.67	−9.13***
	Model 3	−0.60	−0.59**	−72.97***	−3.92***	1.87**	−1.21	0.67	−5.65***	1.69	−9.14***
60-day	Model 1	−1.01		−52.43***	−3.84***	1.50*	−1.14	0.38	−5.88***	1.59	−7.98***
	Model 2		−0.57**	−61.81***	−4.11***	1.64**	−1.12	0.61	−6.34***	1.73*	−8.51***
	Model 3	−0.11	−0.56**	−61.78***	−4.11***	1.64**	−1.12	0.61	−6.33***	1.73*	−8.51***

Future risk-adjusted returns over K-day periods (K = 1, 3, 5, 10, 20, 40, 60) are regressed on currently-observable values of short flow (*SF*), short interest (*SI*)and control variables. ΔSI measures the change in short interest ratios over the K-day holding period. Daily risk-adjusted returns are obtained using a five-factor model that augments Fama–French's (1993) three factors with momentum and short term reversal. *SIZE* and *BM* are a stock's market capitalization and book-to-market ratio respectively. *VOL* is the realized volatility of a stock's daily returns over the prior six months. *TURN* is total trading volume over the prior six months, scaled by the number of shares outstanding. *PRIOR1* and *PRIOR6* are the prior 1-month and 6-month returns. These variables are measured up to the beginning of the reference period over which *SF* is computed. *R5* is individual stock return over the reference period in which *SF* is computed. Log transformations are employed on *SI*, *SIZE*, *BM* and *TURN*. *PRIOR1*, *PRIOR6*, *R5*, *ΔSI* and the K-day holding period return are winsorized at the 2.5/97.5 percentiles. For each holding period K, three specifications of the regression (1) are reported, depending on which of the short metrics are included as explanatory variables: *SF* only (Model 1), *SI* only (Model 2) and both *SF* and *SI* (Model 3). The regressions are estimated with fixed stock and day effects, and standard errors are clustered by both stock and day. The reported coefficients are scaled by 100. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels respectively.

Consistent with the notion that the nature and source of information embedded in short metrics differs, *SF* and *SI* exhibit unique explanatory power for alphas up to a 20-day horizon. Moving beyond the immediate horizon, the nature of information pertaining to mispriced fundamentals means that the predictive ability of *SI* extends to longer horizons.

The importance of the information content implied by the degree of predictability is economically significant. To illustrate, consider Model 3 over a 20-day horizon for which both *SF* and *SI* are statistically related to risk-adjusted returns. For a one standard deviation increase in *SF* (0.0904 from Table 8), the estimated coefficient of −1.96 (Table 10) suggests that the risk-adjusted return drops about 18 bps, all else equal. Since ln(*SI*) is used in the regression, the impact by *SI* on alpha depends on the level of *SI*. We consider the impact of one standard deviation increase in *SI* (0.0313) from the median level (0.0145). The estimated coefficient on ln(*SI*) of −0.46 implies that alpha falls by 53 bps, holding other variables constant. Thus, a one standard deviation change in *SI* predicts a change in risk-adjusted return over the next 20 days that is three times greater in magnitude than does one standard deviation change in *SF*.

Several of the control variables employed in the panel regression are important for predicting future returns. One control variable of particular interest is the contemporaneous change in short interest (*ΔSI*). Over short horizons (up to 10 days), an increase in net short selling is associated with a contemporaneous increase in risk-adjusted returns, suggesting short sellers trade against the stock performance. Over longer horizons (20 days and beyond), changes in net short selling are negatively related to contemporaneous returns at raw as well as risk-adjusted levels, suggesting short covering behavior in response to adverse price movements.

To summarize, the empirical findings in Tables 9 and 10 complement the findings of Section 5. Consistent with the notion that the nature of information captured by *SF* and *SI* differs, the regression analysis establishes the unique predictive ability of each metric for future returns. Further, using both portfolio sorts and regression analysis, the horizons over which each metric is relevant for explaining future returns are in accord with our intuition on the likely nature and sources of the information content.

5.3. Robustness analysis

The main findings of the paper are robust to a number of methodological and sampling variations.[18] First, whereas the base results estimate day-t *SF* as the total volume of short sales over the 5-day period ending on day $t-1$, scaled by total trading volume over the same period, the findings are qualitatively unaltered when either a single-day metric is utilized or when the aggregation period is 10 days. Second, the predictive power of 'abnormal' short flow (defined as the percentage difference between the average daily short volume over the past 5 days and the average daily short volume over the preceding 60 days) is similar to the original *SF* metric. Third, rather than scaling short positions by shares outstanding, an alternate approach is to scale by average daily share turnover (Hong et al., 2015). Nonetheless, this days-to-cover ratio predicts future returns in a similar fashion to the baseline *SI*. Fourth, as noted in Appendix A, reporting obligations for short transactions and volume differ for certain option-related short sales, with the potential to overstate the predictive ability of *SI*. However, the baseline findings are robust in a subsample that excludes optionable stocks.

[18] In the interest of brevity, robustness results are not tabulated, but are available from the authors on request.

Table A1
Reporting requirements for exempted naked short sales.

Situation	Description	Transactional reporting	Positional reporting
Prior purchase agreements	The short seller, before the time of the sale, has contracted to buy and is waiting for delivery	Not required	Not required
Giving or writing of exchange traded options	A short position established via writing a call option or buying a put option without holding the underlying	Not required	Not required
Unobtained financial products	The short seller, at the time of the sale, is able to obtain the securities by exercising exchange traded options	Not required	Not required
Exercise of exchange traded options*	Short sales resulting from exercise of a put option or sale of a call option that is later exercised.	Not required	Required
Selling before completing a recall of loaned securities	Short sales by owner of securities placed in an established securities lending program	Not required	Not required
Hedging risk from derivatives market making activities*	Short sales effected by a market maker to hedge their long position, provided that by the end of the day, the market maker must acquire, enter into a contract to acquire, or entered into a securities lending arrangement	Not required	Required
Client facilitation services	Short sales made to a client in response to client's buy order, provided the short seller has an existing business of providing facilitation services, and that they must, at the end of the day, acquire, enter into a contract to acquire, or entered into a securities lending arrangement	Not required	Required
Deferred purchase agreements (DPA)	Short sales effected by a DPA issuer who has received the purchase price and undertakes to deliver the securities at maturity (at least 12 months later)	Not required	Not required

* In these situations, the reporting obligations apply to both naked and covered short sales.

The fifth issue considered is the potential influence of information events on the relation between short-selling activity and future returns. Section 4 documents that short flow reacts to price-relevant announcements. Given that returns will also almost surely respond to news, it is possible that the apparent relation between short selling and future returns is the outcome of news arrival. To control for this possibility, regression (1) is extended with two dummy variables to control for the recent arrival of good and/or bad news. At each time t, the news dummies take a value of one if a price-relevant announcement occurred in the previous five days. The findings suggest that the observed predictability in the base results is robust to controlling for information events. Both metrics continue to exhibit unique predictive ability for future returns, with *SF* relevant only up to a horizon of 20 days.

Finally, we re-examine the evidence in Boehmer et al. (2008) who find that short flow dominates the *change* in short interest in predicting returns. This clarification is important because one may incorrectly interpret their result (see Section 4) as suggesting that short flow dominates the *level* of short interest, a conclusion that our evidence herein does not support. The availability of *SF* and *SI* at the same daily frequency allows a direct comparison of the predictive power of *SF* and change in *SI* over the same 5-day interval. Using a modification of regression (1), we regress future returns on *SF* and change in *SI*. Consistent with Boehmer et al.'s (2008) finding, the former is indeed a significant predictor of future returns whereas the latter is not. However, similar to the base case, *SF* ceases to predict returns at 60-day horizons.

6. Conclusion

The disclosure initiatives of regulators worldwide following the recent financial crisis are a clear indication that there is information content in short-selling activity. While they are often portrayed in a negative light as market manipulators who profit from falling prices, there is an increasing consensus that short sellers are sophisticated investors who trade on superior information and/or valuation skills, thereby enhancing market efficiency.

While researchers are beginning to explore the nature and source of short sellers' information, their endeavours are often constrained by the availability of appropriate data. The current paper benefits from a short-selling disclosure regime recently implemented in Australia that encompasses *both* short volume and position data. Data at the individual stock level is reported to regulators on a daily basis, and then made publicly available with minimal delay. Arguably, this is the most comprehensive and timely reporting of short sales data in the world.

Aided by this unique regulatory environment, this paper studies the nature and source of information embedded in short flow and short interest metrics of short-selling activity. Given the breadth of information sources that potentially motivate short trading, short sellers are likely to be heterogeneous and it is plausible that alternate short metrics capture different facets of the information set. We conjecture that short flow is more likely to capture short-term technical trading and price-relevant news surrounding company announcements, while short interest embeds views about firm fundamentals and associated mispricing.

The empirical findings are broadly consistent with this conjecture. We document a strong association between short flow and a stock's recent returns, indicating short-term contrarian trading. An imbalance between buy and sell orders for a stock also attracts short flow, suggesting that short sellers may voluntarily step in to provide liquidity. This finding is consistent with the results reported by Comerton-Forde et al. (2015) for the US market at intraday horizons. Short flow also captures an anticipation of imminent price-relevant news and the subsequent reaction to the announcement. While this finding is statistically strong, the economic importance is modest. There is little evidence that short interest reflects imminent news. Rather, short interest appears to reflect sentiment – both negative and positive – regarding the longer-horizon prospects of a stock. High (low) levels of short interest are concentrated in over (under) priced stocks. This finding suggests that short sellers exhibit relative valuation skill. In contrast, the empirical tests detect no relationship between short flow and long-horizon mispricing.

In light of the evidence that short flow and short interest capture different aspects of the short sellers' information set, there are natural implications for the association between the alternate metrics and future returns. Given that each metric captures distinct information, short flow and short interest should have unique ability to predict future returns. Further, the horizon over which the predictive ability of each metric presides is expected to reflect the nature of information embedded in the metric. The empirical findings provide strong support for each of these predictions. Multivariate regressions document that, while both short-selling metrics convey unique information for future returns, clear differences exist in the horizon for which the information is relevant.

Consistent with short flow capturing short-term technical trading and price-relevant news/announcements, the unique predictive ability of *SF* is short lived, peaking at 10 days and not extending beyond 20 days. *SI* provides an economically and statistically significant signal for future returns out to horizons of at least 60 days. This longer-horizon relevance is congruent with short interest reflecting sentiment over the mispricing of firm fundamentals that is likely to revert to fair values over horizons beyond the immediate.

Acknowledgement

We gratefully acknowledge the comments of Ekkehart Boehmer, Peter Brooke, Dominique Gehy, Zsuzsa Husár, Patrick Kelly, Angel Zhong and seminar participants at the University of New South Wales, 2012 AsianFA conference, 2014 Monash/Q-Group colloquium, 2015 FMA conference and 2015 JP Morgan Quantference Sydney. In particular, we thank two anonymous referees whose guidance significantly improved the paper. This research was partially supported by funding from a Platypus Asset Management research grant. We also thank the Securities Industry Research Centre of Asia-Pacific and the Australian Securities Exchange for providing access to the Australian Companies Announcement data and AusEquities data.

Appendix A. Disclosure requirements for exempted naked short sales

Certain forms of exempted naked short sales are subject to differential disclosure requirements whereby short interest reporting is required, yet short flow reporting is not. Such exemptions include the exercise of exchange traded options, hedging risk from derivatives market-making activities and client facilitation services. Table A1 summarizes reporting requirements applied to exempted naked short sales as outlined in the ASIC Regulatory Guide 196 dated April 2011.

It is unlikely that these differential reporting requirements will adversely bias the paper's findings. For example, while short sales arising from an option exercise are not reported in short flow, the nature of these trades is mechanical rather than informational. As such, their exemption from reporting should strengthen the information content in short flow. A similar observation applies to the reporting of short sales that are effected by stock brokers facilitating clients' buy orders. As demonstrated in Section 5, the long-horizon predictive ability of short interest far exceeds that of short flow, suggesting that concerns over bias are unfounded. Alternatively, the treatment of short sales resulting from derivative hedging may potentially give rise to stronger return predictability from short interest. Shorting to hedge a derivative position by a derivatives market maker, either a short put or a long call, manifests the option trader's bearish view into the equity market (Figlewski and Webb, 1993). Therefore, inclusion of such short sale in short interest and not short flow strengthens the information content in the former at the expense of the latter. To alleviate this concern, the robustness analysis in Section 5.3 separately examines the set of non-optionable stocks where short sales for hedging derivatives should be minimal. In any case, the type of short sale that gives rise to differential reporting treatments are thought to account for a very small fraction of total shorting activity.

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