Short-sellers and analysts' self-selection in coverage

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Abstract

We examine whether short-sellers mitigate or exacerbate analysts' self-selection in coverage (i.e., covering (forgoing) firms for which they have favorable (unfavorable) information). We measure short-selling potential using lendable shares, and gauge an analyst's self-selection in coverage by the difference between the analyst's initial ratings for her newly-added firms and ratings for her previously-covered firms (McNichols and O'Brien 1997). We find that short-selling potential is negatively related to analysts' self-selection in coverage and this negative relation is concentrated in firms where higher short-selling potential triggers more short-sales. Further instrumental variable tests and analyses of a shock to short-selling potential provide evidence that this negative relation is causal. Additional tests reveal that our results cannot be attributed to short-sellers conveying negative information to analysts or disciplining analysts. Finally, we show that the predictive power of analyst coverage for subsequent stock returns decreases with short-selling potential. Overall, our results suggest that short-sellers mitigate analysts' self-selection in coverage by increasing the trading benefit of analysts' bad news disclosures (Hayes 1998).

Keywords: short-sellers, analysts, self-selection, coverage, trading.

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1. Introduction

Short-sellers have become an increasingly important information intermediary over the past two decades. Extant literature generally finds that short-sellers are informed and their trading enhances market efficiency. However, there is little evidence on how short-sellers affect other information intermediaries. Such evidence is important for better understanding the overall effect of short-sellers on the price discovery process and market efficiency. In this study, we bridge this gap by examining how short-sellers influence financial analysts' self-selection in coverage, i.e., their tendency to cover (forgo) firms for which they have favorable (unfavorable) information.

We focus on analysts' self-selection in coverage for two reasons. First, analysts are an important information intermediary in capital markets, whose research outputs can influence investors' trades and stock prices. Second and more importantly, analysts' self-selection in coverage has important implications for market efficiency. McNichols and O'Brien (1997) propose that self-selection arises when analysts release their information truthfully but choose to do so only when they hold positive information about the future prospects of the firm. They show that this self-selection is manifested in analysts' coverage decisions as a tendency to initiate coverage on firms they view favorably and drop firms they view unfavorably. This leads to a systematically overly optimistic distribution of analysts' consensus ratings and forecasts by censoring the lower tail of the distribution. Because the distorted distribution leads to overly optimistic investor expectations and overpricing of stocks (Hayes and Levine 2000), it is important to understand how short-sellers influence analysts' self-selection in coverage.

Short-sellers can influence analysts' self-selection in two competing ways. On the one hand, Hayes (1998) shows analytically that short-sellers can mitigate analysts' self-selection in coverage by increasing the trading benefit of disclosing bad news. When short-selling is limited and

investors' initial holdings are not sufficiently large, analysts' bad news disclosures generate less trading than their good news disclosures. Thus, when short-selling potential is greater, analysts' bad news disclosures will spur more short-sales and generate more trading commissions, thereby reducing analysts' self-selection in coverage.

However, on the other hand, short-sellers can also exacerbate analysts' self-selection in coverage by magnifying the damage of disclosing bad news on analysts' relationships with firm managers (and thus hurting their chances to gain access to management and help their employers win banking businesses). When short-selling potential is greater, stock prices become more sensitive to negative information (e.g., Grullon et al. 2015; Li and Zhang 2015); thus, analysts' bad news disclosures trigger more rapid, larger price drops, imposing bigger financial and reputational costs on firm managers. Furthermore, with greater short-selling potential, analysts' bad news disclosures can also exert a more negative impact on stock prices by serving as catalysts that propel short-sellers to time their short-selling aggressively (e.g., Lamont and Stein 2004; Curtis and Fargher 2014). Indeed, anecdotal evidence suggests that when stocks are attacked by short-sellers, managers put greater pressure on analysts not to issue unfavorable reports (e.g., Shen 2016; Thomas 2018). Therefore, given these two competing effects, it is an empirical question whether short-sellers mitigate or exacerbate analysts' self-selection in coverage.

Building upon McNichols and O'Brien (1997), we measure the degree of an analyst's self-selection in coverage using the difference between the analyst's initial ratings for newly added firms (added rating, hereafter) and her outstanding ratings for firms she has previously covered (non-added rating, hereafter). The idea behind this measure is that given the significant start-up costs of initiating coverage on a new firm, analysts require more favorable information to add a firm than to keep a previously covered one. As a result, the greater the analysts' self-selection, the

more favorable is their information about a newly added firm relative to that about previously covered ones. Consistent with recent research (e.g., Beneish et al. 2015; Massa et al. 2015), we measure short-selling potential using lendable shares, defined as the fraction of shares outstanding available for lending, which captures the maximum number of shares lendable to short-sellers.

We test our hypotheses using a large sample of 29,759 added ratings from 4,853 analysts benchmarked against the same analysts' non-added ratings over the period of 2004 to 2017. Because our measure of short-selling potential, lendable shares, is correlated with other firm characteristics, we control for various firm characteristics that likely relate to analysts' self-selection in coverage, particularly firm size, institutional ownership, growth and performance. In addition, we also account for any time-invariant firm and analyst characteristics and time trends by including firm, analyst, and year fixed effects.

We find that higher lendable shares are associated with a lower degree of analysts' self-selection in coverage. This negative relation is statistically significant and economically meaningful: our result indicates that a one standard deviation increase in lendable shares is associated with a 13.3% decrease in analysts' self-selection in coverage. This negative relation is consistent with short-sellers mitigating analysts' self-selection in coverage.

We then examine increased trading as a channel through which short-selling potential mitigates analysts' self-selection in coverage. We estimate a firm-specific measure of the sensitivity of short-sale volume to lendable shares, and split the sample firms based on the median sensitivity into the high- and low-sensitivity groups. We find that the negative relation between lendable shares and our self-selection measure is driven by the high-sensitivity group. This result is consistent with short-sellers mitigating analysts' self-selection in coverage by increasing the trading commissions for their negative information releases (Hayes 1998).

Next, we conduct two tests to address the endogeneity of lendable shares. First, we conduct a two-stage least square (2SLS) test using exchange-traded fund (ETF) ownership as an instrument for lendable shares (Massa et al. 2015). ETFs are a major lender in the equity loan market, and their ownership in an individual firm is largely based on a passive, indexing strategy. Thus, changes in ETF ownership provide a source of variation in lendable shares that is exogenous to analysts' self-selection. Note that we control for institutional ownership in both stages of this 2SLS test; thus, our results cannot be driven by our instrument (ETF ownership) simply picking up the institutional ownership effect. Second, we explore the introduction of exchange-traded options as a shock to short-selling potential. Options are an alternative way to short a stock, and the introduction of exchange-traded options reduces short-sale constraints (e.g., Skinner 1990; Danielsen and Sorescu 2001). Further, exchanges' decision to list a firm is primarily determined by the firm's trading volume, price volatility, and market capitalization (Mayhew and Mihov 2004), and unlikely to be affected by analysts' self-selection. Both tests yield consistent evidence that greater short-selling potential mitigates analysts' self-selection in coverage.

Further, we examine and rule out two potential alternative explanations for our findings. The first is that short-sellers lower analysts' added ratings by making more unfavorable news available for the added firms. However, Beneish et al. (2015) show that more lendable shares – our measure of short-selling potential – actually signal good news to the market, because shareholders are more comfortable making their shares available when the stock is less likely to be overvalued. The second explanation is that short-sellers discipline analysts and reduce the additive bias in their added ratings (i.e., issuing ratings that are more optimistic than their true beliefs).

To test these alternative explanations, we conduct three tests. First, we construct an alternative, within-firm measure of self-selection by benchmarking analysts' added ratings against non-added ratings from other analysts for the same firm. If lendable shares of a firm capture short-sellers conveying negative information or disciplining analysts, these informational and disciplinary effects likely apply to all analysts following that firm, predicting no relation between lendable shares and this alternative within-firm measure of self-selection. However, examining this within-firm measure of self-selection yields results similar to the main within-analyst measure.

Second, we conduct a placebo test using coverage initiations likely due to changes in analysts' assignments rather than their own selection. Following McNichols and O'Brien (1997), we identify such initiations as those occurring on dates when the same analysts add at least three other firms or during the first six months of analysts' appearance in IBES. In addition, we also examine a subsample where the initiation firms are previously covered by other analysts from the same brokerage. If our results are driven by short-sellers mitigating analysts' self-selection, we should find weaker or no result in these assignment-related initiations. In contrast, if our results are driven by short-sellers conveying negative information or disciplining analysts' additive optimism, we should find similar result in these assignment-related initiations. In both samples, we find no relation between lendable shares and our self-selection measure.

Third, we examine the relation between lendable shares and the bias and accuracy of analysts' forecasts associated with added ratings relative to forecasts associated with their own non-added ratings. A key feature of analysts' self-selection is that their forecasts reflect their true beliefs about a firm's future prospects. Thus, short-sellers may influence what firms analysts choose to add, but not the bias or accuracy of their forecasts. In contrast, if short-sellers convey more negative information to analysts or reduce their additive biases, short-sellers should reduce

forecast bias and improve forecast accuracy. We examine annual earnings forecasts associated with added ratings and find no significant relation between lendable shares and the bias or accuracy of analysts' forecasts. The results hold when we use either the within-analyst or the within-firm benchmark. Overall, these three tests yield consistent evidence that our findings are unlikely to be driven by the potential information or disciplinary effect of short-sellers.

Finally, we examine the implication of our findings for the return predictability of analyst coverage. An important capital market consequence of analysts' self-selection in coverage is that higher coverage conveys analysts' favorable information and thus is predictive of positive stock returns (Lee and So 2017). If short-sellers mitigate analysts' self-selection in coverage, they will weaken the predictive power of analyst coverage for subsequent returns. This is indeed what we see in our data: the return predictability of abnormal coverage decreases with lendable shares.

Our study adds to our understanding of the role of short-sellers in two ways. First, prior studies examining the influences of short-sellers on market efficiency have focused on short-sellers' own activities, including their trading behaviors (e.g., Desai et al. 2006; Cohen et al. 2007; Drake et al. 2011, 2015) and disclosure of short-theses (e.g., Ljungqvist and Qian 2016). Our study highlights that short-sellers influence price efficiency also by affecting other players' activities – analysts' self-selection. Second, researchers have also examined how short-sellers influence managers' financing and investment decisions (e.g., Grullon et al. 2015; Chang et al. 2019; He and Tian 2016) and disclosure choices (e.g., Li and Zhang 2015; Fang et al. 2016), and auditors' pricing determinations (Hope et al. 2017). We extend this line of research by documenting how short-sellers affect behaviors of financial analysts.

Our study also adds to our understanding of analysts' self-selection. Analysts' tendency to add good-news firms and drop bad-news firms and its implication for stock prices have been well

documented (e.g., McNichols and O'Brien 1997; Hayes and Levine 2000; Das et al. 2006; Lee and So 2017). However, there is little direct evidence on what the economic forces drive analysts' self-selection. We provide the first set of empirical evidence to support Hayes's (1998) theoretical prediction that low short-selling potential plays a fundamental role in driving analysts' self-selection and the return predictability of analyst coverage.[1]

The next section reviews prior literature and develops hypotheses. Sections 3 and 4 describe our design and sample, respectively. Section 5 presents our results. Section 6 concludes.

2 Prior research and hypotheses

2.1 Prior Research

Our study is related to two strands of literature: the literature on the role of short-sellers in capital markets and the literature on analysts' self-selection.

2.1.1 The role of short-sellers

Short-sellers sell stock they borrow from lenders in the equity lending market, seeking to profit from subsequent price declines. A large body of research has been devoted to examining the effects of short-sellers' activities, especially their trading, on information discovery and market efficiency. Researchers generally find that short-sellers possess superior information and their trades expedite information discovery and enhance market efficiency. For example, many studies find that short-sellers can identify overvalued stocks and short-sales are predictive of negative abnormal returns (e.g., Aitken et al. 1998; Dechow et al. 2001; Desai et al. 2002; Diether et al.

[1] In concurrent work, Ke et al. (2018) examine the relation between short-sellers and the quality of analysts' earnings forecasts. They find that higher short-selling potential improves forecast quality by disciplining analysts and improving price efficiency. They do not examine analysts' self-selection. In contrast, we show that short-sellers mitigate analysts' self-selection in coverage by increasing the trading benefit of releasing bad news. We also demonstrate that our findings are not driven by the informational or disciplinary effects of short-sellers.

2009; Beohmer et al. 2010). Other studies show that short-sellers often anticipate and trade upon various bad news events, such as negative earnings surprises (Christophe et al. 2004), rating downgrades (Henry et al. 2015), and restatements (Desai et al. 2006). When they cannot move stock prices by taking sufficient short-positions due to various short-selling constraints, short-sellers can facilitate price discovery by revealing their information, which may propel existing shareholders to sell (Ljungqvist and Qian 2016). Another line of work (e.g., Christophe et al. 2010; Drake et al. 2011; Khan and Lu 2013) documents that short-sellers can be more informed than other market participants such as financial analysts and corporate managers. We extend this literature by examining a new channel through which short-sellers affect the informational efficiency of stock prices – influencing the actions of financial analysts.

Our study is also related to an emerging stream of research on the influences of short-sellers on the behaviors of other market participants. Prior work has mostly focused on firm managers. For example, Grullon et al. (2015) find that the removal of a short-sale constraint (i.e., price test) reduces equity issues and investments by mitigating overvaluation and increasing the risk of bear raids. Massa et al. (2015) show that short-sellers induce managers to sell more shares and accelerate their trading in order to pre-empt the potential competition from short-sellers. Li and Zhang (2015) document that short-selling pressure leads managers to provide less precise bad news disclosures in order to maintain stock prices. One notable exception is Hope et al. (2017), who examine the influence on auditors and find that short-selling pressure leads auditors to charge higher audit fees to compensate for their higher litigation risk and increased audit effort. We add to this stream of research by investigating how short-sellers influence financial analysts.

2.1.2 Analysts' self-selection

Self-selection arises when analysts release their information truthfully only given that they hold positive information about the future prospects of a firm (McNichols and O'Brian 1997). This asymmetric disclosure behavior stems from analysts' asymmetric payoffs from releasing good versus bad news. Hayes (1998) shows analytically that trading commissions play a key role in driving analysts' self-selection. Because short-selling is generally difficult and costly, the amount of selling analysts' bad news disclosures can generate is constrained by their clients' initial holdings. Thus, when the clients' initial holdings are not sufficiently large, the expected trading commissions will be smaller for bad news disclosures than for good news disclosures. Supporting this prediction, Irvine (2004) and Jackson (2005), among others, find that analysts' unfavorable ratings generate significantly less trading than their favorable ratings.

Disclosing bad news also imposes higher costs on analysts by damaging their relationships with firm managers. A good relationship with firm management is crucial for analysts to gain access to the management and help their employers win lucrative banking business. However, because bad news disclosures decrease stock prices and adversely effect on management compensation and careers, releasing bad news damages analysts' relationships with management. Consistent with this notion, Chen and Matsumoto (2006) show that issuing unfavorable (favorable) ratings reduces (increases) analysts' ability to obtain information from management and thus issue more informative ratings. Mayew (2008) documents that issuing favorable ratings gives analysts more opportunities to ask management questions during conference calls, which helps them generate more private information (Mayew et al. 2013).

McNichols and O'Brien (1997) provide evidence of analysts' self-selection in the context of their coverage decisions. Coverage is an important long-term strategic decision made by analysts, and has important impacts on managerial investment and reporting decisions (e.g., Yu

2008; Chen et al. 2015) and firm value (e.g., Bowen et al. 2008; Kelly and Ljunqvist 2012; Li and You 2015). McNichols and O'Brien (1997) predict that analysts add to their coverage portfolios new firms for which they have favorable information and forgo firms for which they have unfavorable information. Consistent with this prediction, they find that analysts' initial ratings for newly added firms are more favorable than their own ratings for firms they have previously covered. They further rule out the possibility that their findings are driven by analysts using strategic, additive forecast bias by finding a positive link between analysts' self-selection and firms' future fundamental performance.[2] They also use analysts' pre-drop ratings as a noisy proxy for analysts' information at the time of dropping coverage, and find that pre-drop ratings are more unfavorable than their own ratings for firms they continue to cover, consistent with analysts dropping a firm when their information becomes sufficiently negative. Overall, their findings provide empirical support for analysts' self-selection in coverage.

Analysts' self-selection in coverage has been shown to have important capital market consequences. First, it leads to a systematically over-optimistic distribution of analysts' ratings and forecasts by censoring the lower tail of the distribution, which in turn leads to over-optimistic investor expectations and overpricing of stocks. For example, McNichols and O'Brien (1997) show that analysts' self-selection in coverage contributes to the pervasive observed analyst over-optimism. Hayes and Levine (2000) estimate the mean of the untruncated distribution of analysts' forecasts using maximum likelihood and find it is less optimistic and more accurate than the mean of the observed, truncated distribution. More importantly, they find that the optimistic bias in the mean of the observed, truncated distribution leads to stock overpricing. Additionally, Scherbina

[2] Ertimur et al. (2011) find that strong buy initiating ratings earn lower long-term returns than strong buy non-initiating ratings, but initiating earnings forecasts are more accurate than non-initiating earnings forecasts. They conclude that conflicts of interest are a dominant source for favorable recommendations.

(2008) uses the proportion of analysts who stop revising forecasts as a proxy for the amount of negative information analysts choose not to disclose, and finds that it predicts future stock underperformance and negative earnings surprises.

Second, due to analysts' self-section in coverage, high analyst coverage conveys analysts' favorable information about firms' prospects. For example, using a relatively small sample of IPOs, Das et al. (2006) find that higher abnormal analyst coverage predicts better stock and financial performance over the subsequent three years. Lee and So (2017) examine the implication of analyst coverage in a much broader cross-section of firms. They decompose analyst coverage into abnormal and expected components, and demonstrate that abnormal coverage has significant predictive power for firms' stock returns and fundamental performance.

While analysts' self-selection in coverage and its capital market implications have been established, there is little empirical evidence on what drives this behavior. We contribute to this literature by studying the role of short-sellers in shaping analysts' self-selection in coverage.

2.2 Hypotheses

Ex ante, it is unclear whether short-sellers will mitigate or exacerbate analysts' self-selection in coverage. On the one hand, the greater presence of short-sellers and thus greater short-selling potential can increase the amount of trading that analysts' bad news disclosures generate, and consequently mitigate the asymmetric payoffs from releasing bad news relative to releasing good news, resulting in less of analysts' self-selection in coverage:

H1A: Short-selling potential is negatively related to analysts' self-selection in coverage, *ceteris paribus*.

On the other hand, greater short-selling potential can also magnify the damage of releasing bad news on analysts' relationships with firm managers. When short-selling potential is greater, analysts' bad news disclosures also have a greater adverse impact on firms' stock prices. Prior research (e.g., Grullon et al. 2015; Li and Zhang 2015) finds that when short-sale constraints are relaxed, stock prices become more sensitive to bad news (but not to good news) in that bad news disclosures trigger a more rapid and larger price drop.

Further, given the risk and cost of short-selling, short-sellers often see bad news disclosures as catalysts and take a "momentum" strategy of timing their short-selling aggressively at tangible negative events.[3] Prior research (e.g., Lamont and Stein 2004; Savor and Gamboa-Cavazos 2011; Curis and Fargher 2014) shows that price declines trigger significantly more short-selling. Because analysts' rating changes constitute one major catalyst for stock trading (Lightspeed 2018), they can trigger greater price drops by propelling short-sellers to short the stock. Indeed, managers could become very upset when analysts align with short-sellers.[4] Thus, by increasing the damage of releasing bad news on management relationships, greater short-selling potential increases the asymmetric payoffs from releasing bad news relative to releasing good news, resulting in more of analysts' self-selection in coverage:

H1B: Short-selling potential is positively related to analysts' self-selection in coverage, *ceteris paribus*.

[3] For example, as Steve Cohen, hedge fund manager of SAC Capital Advisors, describes in this interview that "A basic principle in going short is that there has to be a catalyst." This is because "when you go short, the risk is open-ended." To avoid the disastrous scenario that the prices of shorted stock remain unchanged or even go higher, short-sellers usually follow such a so-called "catalyst principle." (https://billionaireinvestor.wordpress.com/2013/06/04/short-selling-requires-a-catalyst/).

[4] For instance, the CEO of Cleveland-Cliffs (NYSE: CLF) publicly warned pessimistic analysts at a conference call that "you are messing with the wrong guy." See Cleveland-Cliffs, Inc. (CLF) CEO Lourenco Goncalves on Q3 2018 Results – Earnings call transcript (https://seekingalpha.com/article/4212862-cleveland-cliffs-inc-clf-ceo-lourenco-goncalves-q3-2018-results-earnings-call-transcript).

3. Research design

3.1 Measures of analysts' self-selection in coverage and short-selling potential

Building upon McNichols and O'Brien's (1997) findings, we gauge the degree of an analyst's self-selection in coverage using the difference in favorableness between the analyst's added ratings (i.e., initial ratings for newly added firms) and her own non-added ratings (i.e., ratings for firms she has previously covered) (denoted *SelfSelect*). To quantify rating favorableness, we code buys as 1, holds as 0, and sells as -1.[5] As discussed above, because of the significant start-up costs of adding a new firm, analysts require more favorable information to add a new firm to their coverage portfolios than to maintain their coverage of previously covered firms. When an analyst's self-selection is greater, the incremental amount of favorable information she requires for adding a new firm than for keeping a previously covered firm will be greater, resulting in greater incremental favorableness of her added ratings relative to her non-added ratings.[6]

Short-sellers need to borrow shares in the equity loan market to sell short, so the lendable supply of securities represents a major factor that shapes short-selling potential. Thus, consistent with recent research (e.g., Beneish et al. 2015; Massa et al. 2015), we measure short-selling potential using lendable shares (denoted *LendShare*), defined as the average daily ratio of shares available for lending to total shares outstanding in the month prior to the added ratings.

[5] Because most brokerage houses switched to a three-tier rating system (i.e., buy, hold, and sell) after 2002 (Kadan et al. 2009), we convert the small proportion of recommendations based on the five-tire system to the three-tier system by coding strong buy as buy and strong sell as sell. However, none of our inferences are altered if we use -2 for strong sells, -1 for sells, 0 for holds, +1 for buys, and +2 for strong buys (untabulated).

[6] We do not use the difference between analysts' ratings for firms they drop and their ratings for firms they continue to cover to measure self-selection because analysts typically do not issue ratings when they drop coverage and thus we cannot observe analysts' information at the point they drop a firm (McNichols and O'Brien 1997).

3.2 Regression model

To test our hypotheses, we examine the relation between lendable shares and analysts' self-selection in coverage using the following model:

$$SelfSelect = \alpha_1 LendShare + Controls + Year + Firm + Analyst \quad (1)$$

where *SelfSelect* and *LendShare* are our measures of analysts' self-selection in coverage and short-selling potential, respectively, as defined above. A negative (positive) coefficient on *LendShare* would indicate a negative (positive) relation between short-selling potential and analysts' self-selection in coverage, providing evidence in support of H1A (H1B).

Controls refer to our controls of firm and broker characteristics that affect analysts' self-selection in coverage (see the Appendix for detailed definitions). First, we include firm size (*Size*) and institutional ownership (*IO*) to control for the demand from analysts' brokerage firms and institutional clients for covering a firm. Controlling for this demand is important because analysts are likely to have less discretion in covering larger firms and firms with more institutional investors and thus exhibit less self-selection in coverage of these firms. Further, the inclusion of *IO* also controls for the disciplinary effect institutional investors exert on analysts (Ljungqvist et al. 2007).

Second, we include firms' recent financial and return performances (*ROA* and *PriorRet*), book-to-market ratios (*BTM*), and leverage (*Leverage*) to control for the influences of firms' past performance, growth options, and distress risks on analysts' coverage decisions. Third, we include brokerage size (*BrokSize*) to control for the influences of brokerage resources and reputation on analysts' coverage decisions (Brown et al. 2016). Finally, we include analyst and firm fixed effects to account for any time-invariant analyst and firm characteristics, and year fixed effects to account for any time trends.

4. Sample and descriptive statistics

We obtain stock recommendation data from IBES, lendable shares data from IHS Markit, and financial and price data from the Compustat and CRSP, respectively. Our sample period is from 2004 to 2017.[7] We start with retaining all recommendations on IBES during our sample period. We identify added ratings as the first rating an analyst issues for a firm. We exclude the first ratings that are issued within the first 180 days after the analyst's first appearance in IBES or issued on a date when the analyst adds more than four firms on that day, because these coverage initiations are more likely to reflect brokers' assignments rather than analysts' selection (McNichols and O'Brien 1997). Because our measure of self-selection in coverage benchmarks added ratings against the same analyst's non-added ratings, we require each added rating to have at least one outstanding rating issued by the same analyst in the two years prior to the added rating for firms she has previously covered.[8]

We measure lendable shares using data from IHS Markit, a comprehensive dataset covering more than USD 16 trillion in global securities from 20,000 institutional funds and over three million intraday transactions. After requiring non-missing lendable shares data from Markit Data Explorer and financial and price data needed for measuring our control variables from the Compustat/CRSP, our sample contains 29,759 added ratings. Table 1 shows that our sample is

[7] We have access to Markit data from May 2002 to September 2017. However, the coverage in early years is not as complete as in later years. Consistent with prior research (e.g., Beneish et al. 2015), we start the sample in 2004. However, our results hold if our sample starts in 2003, 2005, 2006, or 2007 (untabulated).

[8] We use the example of JP Morgan analyst Mark Moskowitz (AMASKCD = 106330) to illustrate the way we measure analysts' self-selection in coverage (*SelfSelect*). On September 9, 2009, he added STEC Inc. (IBES ticker = SPTH) into his portfolio with a buy recommendation. Since this initiation was made neither in his first 180 days in IBES (as his first recommendation was made on March 29, 2004), nor with three other initiations on the same day, we identify this initiation as an added rating. We also identify the following five outstanding non-added ratings issued within the past two years and reviewed after September 9, 2009 on firms he had covered previously: a sell on DELL (February 5, 2009), a hold on EMLX (April 21, 2009), a sell on QLGC (March 27, 2008), a hold on SEAA (April 8, 2009), and a hold on WDC (April 8, 2009). We calculate *SelfSelect* = 1 – 1/5*((-1) + 0 + (-1) + 0 + 0) = 1.4.

relatively evenly distributed across the fourteen sample years, with slightly more ratings in 2005 (8.96% of the sample) and fewer ratings in 2008 (5.63%) and 2017 (4.63%).

Table 2 Panel A reports the descriptive statistics for all the variables in Equation (1). The mean (median) of *SelfSelect* is 0.167 (0.250), confirming the finding of McNichols and O'Brien (1997) that analysts issue significantly more favorable ratings for newly-added firms than for previously-covered firms. The mean (median) of *LendShare* is 0.160 (0.148), which is comparable to the number of 0.174 (0.166) reported by Beneish et al. (2015). The mean (median) of *Size* is 13.94 (13.85), *IO* 0.550 (0.628), *Leverage* 0.519 (0.496), *BTM* 0.423 (0.347), *ROA* -0.002 (0.009), *BrokSize* 3.335 (3.367), and *PriorRet* 0.103 (0.062).

Panel B reports the Pearson and Spearman correlations among these variables. The Pearson correlation between *SelfSelect* and *LendShare* is significantly negative (-0.08; $p < 0.05$), consistent with H1A. In addition, *SelfSelect* is negatively correlated with *Size, IO, BTM,* and *ROA*, and positively correlated with *BrokSize* and *PriorRet.* Its correlation with *Leverage* is insignificant. The Spearman rank correlations are largely consistent with the Pearson correlations.

5. Results

5.1 Regression tests of the hypotheses

Table 3 presents the results of estimating Equation (1). We report results including only year fixed effects in Column (1), year and firm fixed effects in Column (2), year and analyst fixed effects in Column (3) and all three types of fixed effects in Column (4). We cluster standard errors by both firm and analyst.

We find that the coefficient on *LendShare* is significantly negative at the 0.05 level across all four columns. The results are relatively stable with different types of fixed effects: the

coefficients on *LendShare* range from -0.115 to -0.218, and the *t-statistics* range from -2.10 to -2.55. Further, this relation is statistically significant and economically meaningful. For instance, the result after including analyst, firm, and year fixed effects in Column (4) indicates that a one standard deviation increase in lendable shares is associated with a decrease of 0.0223 (i.e., 0.123 * 0.289) in analysts' self-selection, which represents 13.3% of its unconditional mean of 0.167. These results support H1A and are consistent with higher short-selling potential mitigating analysts' self-selection in coverage.

With respect to control variables, we find that analysts' self-selection in coverage is generally lower for firms with larger size and higher institutional ownership, suggesting that analysts indeed have less discretion in covering larger firms and firms with more institutional investors. In addition, self-selection is higher for firms with a lower book-to-market ratio, higher ROA, and higher prior return, confirming that analysts are likely to initiate coverage with more favorable ratings on firms with better growth opportunities and superior past performance.

5.2 Tests of increased trading as the channel

If higher short-selling potential reduces analysts' self-selection by increasing the trading commissions for their unfavorable ratings (Hayes 1998), we should expect the negative relation between *SelfSelect* and *LendShare* in Table 3 to be stronger among firms where an increase in lendable shares leads to a greater increase in short-sales that analysts can generate.

To test this prediction, we first construct a firm-specific measure of the sensitivity of short-sale volume to lendable shares by running firm-specific regressions of the monthly average daily ratio of short volume to total volume (*ShortVol*) on lendable shares, controlling for firm size, book-to-market, ROA, and leverage. We collect daily short-sale transaction data from 2009 (when the

data became available) to 2017 from the Financial Industry Regulatory Authority (FINRA) website and aggregate all transactions to the firm-day level. We require each firm to have at least 10 observations. The average firm-specific coefficient on lendable shares in this regression, which captures the firm-specific sensitivity of short-sales to lendable shares, is significant positive (0.01, t = 2.21), indicating that higher lendable shares are generally associated with more short-sales. However, this sensitivity also varies greatly across firms, with the average being 0.394 for the top half of its distribution and -0.378 for the bottom half. [9]

We then split the sample firms based on the median sensitivity into the high- and low-sensitivity groups, and examine how the relation between *SelfSelect* and *LendShare* varies between the two groups. Table 4 reports the results of estimating Equation (1) for the low- and high-sensitivity groups separately. We find that the estimated coefficient on *LendShare* is negative and significant (-0.313, t = -2.22) for the high-sensitivity group, but insignificant (-0.111, t = -0.88) for the low-sensitivity sample. These results indicate that our main findings in Table 3 are concentrated in firms with a higher sensitivity of short-sales to lendable shares. In other words, our results hold only among firms where an increase in lendable shares allows analysts to generate more trading commissions through short-sales. These results are consistent with higher short-selling potential mitigates analysts' self-selection by increasing the trading commissions they can earn by releasing negative information (Hayes 1998).

[9] In untabulated tests we further validate that our sensitivity measure captures the effect of lendable shares on short-sales analysts can generate from releasing negative information. More specifically, we measure abnormal short-sales during the three-day window surrounding analysts' rating downgrades as the average daily percentage of short volume in total trading volume during a three-day window surrounding analysts' rating downgrades minus the average daily percentage in the 50 trading days beginning from 60 trading days prior to the downgrade date (e.g., Bagwell 1997). We find that moving from the bottom to top lendable shares decile, the abnormal short-sales triggered by analysts' downgrades increases by 1.6 percentage points, equivalent to more than a 10% increase from the average percentage of short volume in total trading volume in our sample (15.6%).

5.3 Identification tests

The endogeneity of lendable shares raises concerns about correlated omitted variable and reserve causality problems. While our inclusion of various firm and broker characteristics and firm, analyst, and year fixed effects help mitigate some of the concerns, we conduct two identification tests to further address this endogeneity problem and provide evidence on the causal relation.

First, we use exchange traded fund (ETF) ownership as an instrument for lendable shares (Massa et al. 2015). ETFs are a major lender in the equity loan market, and their ownership in a firm is largely based on a passive, indexing strategy that is not information-based. Thus, changes in ETF ownership provide a source of variation in lendable shares that is arguably exogenous to analysts' coverage decisions.

Table 5 presents a two-stage least squares (2SLS) analysis of Equation (1) using ETF ownership (i.e., *ETFOWN*, defined as the percentage of ETF ownership in total shares outstanding at the quarter-end prior to the added rating) as the instrument.[10] Column (1) reports the first-stage results of regressing the endogenous variable (*LendShare*) on the instrumental variable (*ETFOWN*) and all controls and fixed effects in Equation (1). As expected, *LendShare* is highly positively related to *ETFOWN* (0.463, $t = 14.27$), and the first-stage model has very large explanatory power (85.9%).[11] Column (2) reports the results of the second stage, where the endogenous variable

[10] To identify ETFs, we first follow prior studies (e.g., Da and Shive 2018) and apply the following filters to CRSP Survivor-Bias-Free Fund database: (1) CRSP stock share code is 73; (2) etf_flag is "F" (i.e., ETF); (3) lipper_obj_cd is "EQ" (i.e., Equity); (4) we remove funds investing in international markets: those with lipper_obj_cd as 'CH', 'DL', 'EM', 'EU', 'GFS', 'GH', 'GIF', 'GL', 'GNR', 'GRE', 'GTK', 'GX', 'IF', 'INR', 'IRE', 'IS', 'JA', 'LT', 'PC', 'XJ', 'AGM'; and (5) we manually check fund names and remove funds with "global," "international," or a particular non-US region/country in the fund names. Then we use both CRSP and Thomson Reuters mutual fund holding databases to identify each ETF's holdings and then aggregate them to the firm-quarter level. The results are similar if we use the mutual fund holding data only from CRSP or only from Thomson Reuters (untabulated).

[11] The Cragg-Donald Wald F-statistic is 667, much higher than the rule of thumb threshold of 10, rejecting the weak instrument hypothesis.

(*LendShare*) in Equation (1) is replaced by its predicted value from the first stage. We find that the coefficient on *LendShare* continues to be significantly negative (-1.679; t = -3.49).

Second, we explore the introduction of exchange-traded options as an exogenous shock to short-selling potential. In addition to shorting a stock directly, investors can trade on negative information in the option market by buying put options and writing call options (Figlewski and Webb 1993). Prior research (e.g., Skinner 1990; Danielsen and Sorescu 2001) documents that the introduction of option trading results in a significant reduction in short-sale constraints. Relatedly, Engelberg et al. (2018) show that option availability reduces short-selling risk. Further, the exchanges' decision to list a firm is largely determined by the firm's trading volume, price volatility, and market capitalization (Mayhew and Mihov 2004), and is arguably exogenous to analysts' coverage decisions.

We use data from OptionMetrics to identify the option induction year as the year in which the first equity option of a stock was traded. We identify 3,470 option introductions over our sample period of 2004 to 2017. We compare changes in analysts' self-selection in coverage (*SelfSelect*) from the three years before (i.e., the pre-introduction period) to the three years after (i.e., the post-introduction period) the year of option introductions. We match each added rating for the test firms with an added rating in the same year for a control firm, defined as the firm in the same Fama-French 48 industry with the closest market cap but no option introduction within four years before or after the focal added rating. In this standard difference-in-difference design, the variable *TreatRec* equals one for treatment added ratings and zero for matched added ratings, and the variable *OptionIntro* equals one (zero) for the added ratings made after (before) the option introduction. The variable of interest is the interaction term: *OptionIntro*×*TreatRec*.

Table 6 presents regression results, in which we regress *SelfSelect* on *TreatRec*, *OptionIntro*, *OptionIntro*×*TreatRec*, and all controls and fixed effects in Equation (1). As shown in Column (1), the coefficient on *OptionIntro*×*TreatRec* is significantly negative (-0.093, t =-3.15), indicating a decrease in the analysts' self-selection in coverage after the option introduction for the test firms relative to the matched control firms.

To ensure that this pattern does not merely reflect some time trends, we conduct two placebo tests using years -3 and +3 (year 0 refers to the introduction year) as the pseudo-event years. As reported in Columns (2) and (3) of Table 6, we find no such pattern in either placebo tests – the coefficients on *OptionIntro*×*TreatRec* are positive and insignificant (0.028, t = 0.70 and 0.014, t = 0.52). Taken together, these results suggest that the option introduction mitigates analysts' self-selection (i.e., tendency to add good news firms and forgo bad news firms).

Overall, both the instrumental variable test and the difference-in-differences analysis of the option introduction as a shock to short-selling potential suggest that our findings are unlikely to be driven by the endogeneity of lendable shares. They provide evidence that short-sellers have a causal effect in mitigating analysts' self-selection in coverage.[12]

5.4 Tests of alternative explanations

In this subsection, we examine two potential explanations for our findings. The first is based on the informational effect of short-sellers (i.e., short-sellers lower analysts' ratings by

[12] We considered but did not use the Reg SHO pilot program as an identification strategy because the short-term nature of the pilot program makes it an inappropriate test for analyst coverage, which is a long-term decision. Specifically, the pilot program was initially scheduled for one year from May 2, 2005 to April 28, 2006. Just a few days before the scheduled end, on April 20, 2006, the SEC issued "SEC Release No. 34-53684" to extend the terminate date to August 7, 2007. Thus, for most of time in this pilot program, analysts are likely to expect the pilot program to end within one year. However, coverage is a long-term decision made by analysts. In our sample, once an analyst adds a firm to her portfolio, she keeps covering it for an average of about three years. Therefore, given this mismatch between the horizon of this pilot program and that of analysts' coverage decisions, analysts are less likely to significantly change their coverage in response to the implementation of this pilot program.

making more bad news available). The second is based on the disciplinary effect of short-sellers (i.e., short-sellers discipline analysts and reduce their intentional optimistic bias). Regarding the first information-based explanation, it is important to note that our measure of short-selling potential, lendable shares, has been shown to be related to more good news, not bad news. Beneish et al. (2015) find that more lendable shares convey good news to the market, because shareholders are more comfortable making their shares available for lending when the stock is less likely to be overvalued. To examine these two explanations, we conduct three additional sets of analyses.

5.4.1 Examining an alternative, within-firm measure of self-selection

As analysts' self-selection is an analyst-level construct, our main self-selection measure (*SelfSelect*) is a within-analyst measure (i.e., benchmarking an analyst's added ratings for newly added firms against her outstanding non-added ratings for her previously covered firms). To test the two alternative explanations, we construct an alternative, within-firm self-selection measure, *SelfSelect_WithinFirm*, defined as the difference between an analyst's added rating for a newly added firm and the outstanding non-added ratings by other analysts covering this same firm (McNichols and O'Brien 1997). Examining this within-firm self-selection measure helps us to rule out the two alternative explanations because the informational and disciplinary effects of short-sellers of a firm likely apply to all analysts following this same firm. More specifically, if short-sellers convey negative information about a firm or discipline analysts covering the firm, these informational and disciplinary effects should apply to all analysts who follow it, and thus we should find no relation between lendable shares and this alternative within-firm measure of self-selection. In contrast, if short-sellers mitigate analysts' self-selection in coverage, this effect applies to only the analyst who initiate coverage on the firm, thus we should continue to find a negative relation between lendable shares and the alternative within-firm self-selection measure.

Table 7 presents the results of estimating Equation (1) using *SelfSelect_WithinFirm* as the dependent variable. Similar to our main results using the within-analyst measure (*SelfSelect*), we continue to find a significantly negative coefficient on *LendShare* (-0.251; t = -2.27). This result is consistent with our self-selection hypothesis but inconsistent with the alternative explanations.

5.4.2 Placebo tests using assignment-based initiations

Analyst coverage reflects both analysts' choices and their brokerage firms' assignments. As discussed in Section 4, given our focus on analysts' self-selection, we examine coverage initiations that are more likely to reflect analysts' choices, and exclude those that are likely to reflect brokers' assignments, including the first ratings that are issued within the first 180 days after the analyst's first appearance in IBES or issued on a date when the analyst adds more than four firms (i.e., the "original" ratings as in McNichols and O'Brien (1997)). However, these original ratings provide a placebo test that helps us to rule out the alternative explanations. If our findings are driven by short-sellers mitigating self-selection, we expect to find weaker or no results for these assignment-rated ratings that are less likely to reflect analysts' choices. In contrast, if our findings are driven by short-sellers conveying negative information or disciplining analysts, we expect to find similar results for these assignment-rated initiations.

Table 8 presents this placebo test using both the within-analyst (*SelfSelect*) (Panel A) and within-firm (*SelfSelect_WithinFirm*) (Panel B) measures of self-selection. Because most of these assignment-based ratings are on the first set of firms an analyst adds to her portfolio, only a small sample of 1,595 assignment-based ratings (from 779 analysts on 1,251 firms) has at least one outstanding rating on previously covered firms at the time of initiation, which we require to construct the within-analyst self-selection measure. Column (1) in Panel A reports the result of estimating Equation (1) using this sample of assignment-rated initiations. Because most firms and

analysts have only one observation in this sample, we exclude firm and analyst fixed effects in this estimation. We find that the coefficient of *LendShare* is positive and insignificant (0.112, $t = 0.40$).

To ensure that the results in Column (1) are not driven by our small sample size, we create 500 random samples, each containing 1,595 observations, drawing from our main sample used in Table 3. We estimate Equation (1) using these random samples, and report the mean coefficients in Column (2). We find that the mean coefficient on *LendShare* remains negative and significantly different from zero, indicating that the result in Column (1) is not driven by its small sample size.

To more reliably identify assignment-related initiations, we further confine the sample to 512 added ratings on firms that were previously covered by *different* analysts from the same broker in the past three years. We repeat the analyses for Columns (1) and (2) using this smaller sample and report the results in Columns (3) and (4), respectively. Results are similar to those reported in Columns (1) and (2).

Panel B repeats the analyses in Pane A using the within-firm self-selection measure (*SelfSelect_WithinFirm*). The sample size of the assignment-related ratings is much larger because we require the outstanding non-added ratings from other analysts covering the same firm as the benchmark. Our inferences are the same to those in Panel A.

Overall, the placebo tests show that our main finding holds for coverage initiations that reflect analysts' choices, but not for initiations that reflect brokers' assignments. These results provide support for our self-selection hypothesis, but are inconsistent with the alternative, information- or discipline-based explanations.

5.4.3 Examining analysts' forecast biases and errors

Finally, we examine the bias and accuracy of earnings forecasts associated with added ratings. If short-sellers convey negative information or discipline analysts, they should mitigate

analysts' forecast biases and enhance their forecast accuracy, and thus we expect lendable shares to be negatively related to analysts' forecast biases and errors. In contrast, under the self-selection hypothesis, as analysts reveal their true beliefs, lendable shares should not be negatively related to analysts' forecast biases or errors.

We extract from IBES the annual earnings forecasts associated with added ratings (i.e., issued on the same day or the day before/after from the same analyst), and calculate forecast bias (error) as the signed (unsigned) difference between actual and analysts' forecasted EPS, scaled by the closing price the day before the forecast. Similar to our *SelfSelect* measure, we benchmark the bias (error) of the forecast associated with an added rating against the average bias (error) of the forecasts associated with outstanding non-added ratings on other firms by the same analyst. As shown in Panel A of Table 9, we find no evidence that lendable shares are related to the bias or error of analysts' forecasts associated with their added ratings. Panel B reports similar results from a similar within-firm measure (i.e., benchmarking against the average bias (error) of the forecasts associated with the same firm's outstanding non-added ratings from other analysts).

In sum, the results from examining a within-firm self-selection measure, the placebo test using coverage initiations likely reflecting brokers' assignments, and testing the bias and error of analysts' forecasts associated with added ratings consistently suggest that our results are unlikely to be driven by the alternative, information- or discipline-based explanations. They provide additional evidence in support of our self-selection hypothesis.

5.5 Tests of the return predictability of analyst coverage

An important implication of analyst-selection in coverage is that analyst coverage conveys valuable information on firms' future prospects. Lee and So (2017) document that abnormal

analyst coverage predicts stock returns in the subsequent month. Thus, if higher short-selling potential mitigates analysts' self-selection in coverage, then the return predictability of abnormal coverage should decease with lendable shares.

Following Lee and So (2017), we decompose analyst coverage into an expected component based on observable firm characteristics and an abnormal component that reflects analysts' private information.[13] We then regress the raw return in the subsequent month on the decile ranks of lendable shares at the current month-end (*R_LendShare*), the decile ranks of abnormal analyst coverage at the current month-end (*R_AbCoverage*), and their interactions. To facilitate interpretation, we transform the decile ranks into ranging from 0 to 1. The coefficient of interest is the interaction term, which captures the difference in the return predictability of abnormal coverage between the top and bottom lendable share deciles. A negative coefficient would be consistent with higher short-selling potential weakening the return predictability of coverage. Columns (1) and (2) report the results without and with controlling for Fama-French three factors (*EXMKT*, *SMB*, and *HML*) and the momentum factor (*UMD*).

As shown in Column (1), the estimated coefficient on *R_AbCoverage* is 0.006 (t = 2.20), indicating a return spread of 0.6% between the top-bottom decile of abnormal coverage for the bottom decile of lendable shares. The estimated coefficient on the interaction, *R_AbCoverage* × *R_LendShare* is -0.009 (t =2.19), indicating that the spread between top-bottom decile of abnormal coverage decreases by 0.9% moving from the bottom to top decile of lendable shares. Column (2) reports similar results when we control for Fama-French three factors (*EXMKT*, *SMB*, and *HML*)

[13] More specifically, as in Lee and So (2017), we estimate a cross-sectional monthly regression of analyst coverage (i.e., the number of unique earnings forecasts summed across all analysts and all forecast fiscal periods in the past 90 days) on firm size, share turnover (i.e., trading volume in the past 12 months scaled by shares outstanding at the end of the month), and return momentum (i.e., cumulative market adjusted return in the past 12 months). We extract the regression residuals as abnormal coverage.

and the momentum factor (*UMD*). Overall, these results provide evidence that higher short-selling potential reduces the predictive power of analyst coverage for subsequent returns by mitigating analysts' self-selection in coverage.

6. Conclusion

We examine how short-sellers influence analysts' self-selection in coverage. Building upon McNichols and O'Brien's (1997) findings, we measure an analyst's self-selection as the difference between her initial ratings for newly added firms and her outstanding ratings for the firms she has previously covered. Using lendable shares to gauge short-selling potential, we find that short-selling potential is negatively related to analysts' self-selection in coverage, and that this negative relation is concentrated in firms where short-sales are more sensitive to lendable shares. Further, analyses using ETF ownership as an instrumental variable and the introduction of option trading as an exogenous shock to short-selling potential yield evidence that the negative effect of short-selling potential on analysts' self-selection in coverage is causal. Additionally, tests of the return predictability of analyst overage show that the predictive power of coverage for subsequent stock returns decreases with short-selling potential.

We further test and rule out two alternative explanations based on the informational and disciplinary effects of short-sellers. Specifically, we find that (1) our results continue to hold if we measure analysts' self-selection by benchmarking against outstanding non-added ratings from other analysts covering the *same* firm, (2) as a placebo test, our results disappear when we test assignment-based initiations that are unlikely to reflect analysts' choices, and (3) short-selling potential is unrelated to the bias or error of analysts' earnings forecasts that are associated with their initiations.

Overall, these findings provide empirical evidence in support of Hayes's (1998) theoretical prediction that short-sellers mitigate analysts' self-selection in coverage decisions by increasing the trading benefit of disclosing bad news. Our study adds to our understanding of the role of short-sellers in capital markets. We identify a new mechanism through which short-sellers enhance price discovery and the market efficiency, and document new evidence on the influences of short-sellers on behaviors of an important group of information intermediaries in capital markets. Our study also contributes to our understanding of analysts' self-selection behavior by proving new evidence that low short-selling potential is a fundamental driver of analysts' self-selection.

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Appendix A: Variable Definitions

Variables	Definitions
Bias	Bias of annual EPS forecasts associated with added ratings minus the average bias of such forecasts associated with the same analyst's outstanding non-added ratings on other firms. Bias is calculated as the signed difference between actual and EPS forecast, scaled by the closing price of the trading date prior to the forecast.
Bias_WithinFirm	Bias of annual EPS forecasts associated with added ratings minus the average bias of such forecasts associated with the same firm's outstanding non-added ratings by other analysts. Bias is calculated as the signed difference between actual and EPS forecast, scaled by the closing price of the trading date prior to the forecast.
BTM	Book-to-market ratio in the latest fiscal quarter end prior to the recommendation.
BrokSize	Natural log of the number of IBES analysts in a brokerage house in the year of recommendation.
ETFOWN	The percentage of ETF ownership in total shares outstanding in the latest fiscal quarter prior to the recommendation.
Error	Error of annual EPS associated with added ratings minus the average error of such forecasts associated with the same analyst's outstanding non-added ratings on other firms. Error is calculated as the unsigned difference between actual and EPS forecast, scaled by the closing price of the trading date prior to the forecast.
Error _WithinFirm	Error of annual EPS associated with added ratings minus the average error of such forecasts associated with the same firm's outstanding non-added ratings by other analysts. Error is calculated as the unsigned difference between actual and EPS forecast, scaled by the closing price of the trading date prior to the forecast.
EXMKT	The monthly contemporaneous excess market return, obtained from Kenneth French's website.
HML	The monthly book-to-market factor obtained from Kenneth French's website.
IO	The percentage of institutional ownership in total shares outstanding in the latest fiscal quarter prior to the recommendation.
LendShare	The average daily ratio of lendable shares to total shares outstanding in the calendar month prior to the recommendation.
Leverage	Total liability divided by total assets in the latest fiscal quarter end prior to the recommendation.
PostOption	One for treatment ratings (and their matched ratings) issued in the three years after the year of option introduction and zero for treatment ratings (and their

	matched ratings) issued in the three years before the year of option introduction.
PriorRet	Buy-and-hold return in the six months ending on the day prior to the date of recommendation.
ROA	Return on assets (net income/total assets) in the latest fiscal quarter end prior to the recommendation.
R_AbCoverage	The decile rank of the abnormal total analyst coverage, which is the residual of a cross-sectional monthly regression in which we regress analyst coverage (i.e., the number of unique earnings forecasts summed across all analysts and all forecast fiscal periods in the past 90 days) on firm size, share turnover (i.e., trading volume in the past 12 months scaled by shares outstanding at the end of the month), and return momentum (i.e., cumulative market adjusted return in the past 12 months) (Lee and So 2017). To facilitate interpretation, we transform the decile rank to make it range from 0 to 1.
R_LendShare	The decile rank of monthly lendable shares, which is defined as the average daily ratio of lendable shares to total shares outstanding in the calendar month. To facilitate interpretation, we transform the decile rank to make it range from 0 to 1.
SelfSelect	Added ratings minus the same analyst's outstanding non-added ratings on other firms. We code buy, hold and sell ratings as -1, 0 and 1, respectively.
SelfSelect _WithinFirm	Added ratings minus the same firm's outstanding non-added ratings by other analysts. We code buy, hold and sell ratings as -1, 0 and 1, respectively.
Sensitivity	The coefficient of *LendShare* in a firm-specific regression where we regress *ShortVol* on *LendShare* controlling for firm size, book-to-market ratio, ROA, and leverage. We require each firm to have at least 10 observations.
Size	Natural log of market cap in the end of month prior to the recommendation.
ShortVol	The average daily percentage of short volume in total trading volume in the calendar month.
SMB	The monthly size factor (*SMB*) obtained from Kenneth French's website.
TreatRec	One for treatment added ratings and zero for matched control added ratings. We match each added rating with another added rating in the same year on a Fama-French 48 industry peer with closest market cap and with option introduction at least four years earlier or later than the added rating.
UMD	The monthly momentum factor obtained from Kenneth French's website.

Table 1

Sample distribution by year

Year (1)	Number of observations (2)	Percentage of observations (3)	Accumulative percentage of observations (4)
2004	2,533	8.51%	8.51%
2005	2,665	8.96%	17.47%
2006	2,605	8.75%	26.22%
2007	2,274	7.64%	33.86%
2008	1,675	5.63%	39.49%
2009	1,988	6.68%	46.17%
2010	1,877	6.31%	52.48%
2011	2,100	7.06%	59.53%
2012	2,089	7.02%	66.55%
2013	2,168	7.29%	73.84%
2014	2,267	7.62%	81.46%
2015	2,205	7.41%	88.87%
2016	1,936	6.51%	95.37%
2017	1,377	4.63%	100%
Total	29,759	100%	

This table presents, by year (Column (1)), the number of observations (Column (2)), the percentage of observations (Column (3)), and the accumulative percentage of observations (Column (4)) in our full sample.

Table 2

Descriptive statistics and correlations

Panel A: Summary statistics

	Statistics (N = 29,759)				
Variables	Mean	25th	Median	75th	S.T.D
SelfSelect	0.167	-0.250	0.250	0.600	0.621
LendShare	0.160	0.041	0.148	0.260	0.123
Size	13.94	12.84	13.85	14.91	1.579
IO	0.550	0.190	0.628	0.862	0.382
Leverage	0.519	0.296	0.496	0.697	0.339
BTM	0.423	0.184	0.347	0.588	0.423
ROA	-0.002	-0.002	0.009	0.022	0.055
BrokSize	3.335	2.708	3.367	4.111	1.008
PriorRet	0.103	-0.098	0.062	0.244	0.346

Panel B: Pearson's and Spearman's correlations

	1	2	3	4	5	6	7	8	9
1. SelfSelect		***-0.08***	***-0.09***	***-0.08***	***-0.02***	***-0.04***	***-0.04***	***0.02***	***0.05***
2. LendShare	***-0.08***		***0.36***	***0.57***	***0.04***	***0.11***	***0.18***	***-0.06***	0.00
3. Size	***-0.08***	***0.33***		***0.25***	***0.17***	***-0.12***	***0.31***	***0.10***	***0.11***
4. IO	***-0.08***	***0.56***	***0.24***		***0.01***	***-0.07***	***0.18***	***-0.10***	***0.03***
5. Leverage	-0.01	0.00	***0.09***	-0.01		-0.01	***-0.09***	***0.06***	***0.01***
6. BTM	***-0.03***	***0.08***	***-0.11***	***-0.07***	***-0.09***		***-0.09***	***-0.04***	***-0.14***
7. ROA	***-0.05***	***0.19***	***0.32***	***0.15***	***-0.02***	***0.07***		***0.02***	***0.10***
8. BrokSize	***0.02***	***-0.05***	***0.06***	***-0.08***	***0.03***	***-0.04***	***0.05***		***0.01***
9. PriorRet	***0.05***	***-0.03***	***0.06***	***0.01***	***-0.02***	***-0.14***	***0.02***	0.00	

This table presents descriptive statistics (Panel A) of and correlations (Panel B) among variables used in the main analyses. Panel A presents the variable mean, 25th percentile, median, 75th percentile, and standard deviation of variables used in the main analyses. Panel B presents the Pearson correlations (below the diagonal) and Spearman's rank correlations (above the diagonal) among variables used in the main analyses. Correlations in bold and italics are significant at the 5% level. All variables are as defined in the Appendix A.

Table 3

The relation between lendable shares and analysts' self-selection in coverage

Dep var = SelfSelect	(1)	(2)	(3)	(4)
LendShare	-0.137**	-0.218**	-0.115**	-0.181**
	(-2.55)	(-2.51)	(-2.10)	(-2.11)
Size	-0.027***	0.002	-0.024***	-0.006
	(-7.46)	(0.14)	(-6.20)	(-0.50)
IO	-0.046***	-0.075***	-0.060***	-0.063**
	(-3.09)	(-2.78)	(-3.89)	(-2.32)
Leverage	-0.012	0.007	0.023	0.044
	(-0.93)	(0.24)	(1.60)	(1.54)
BTM	-0.038***	-0.063**	-0.009	-0.043*
	(-2.83)	(-2.40)	(-0.60)	(-1.82)
ROA	-0.077	0.336**	0.179**	0.359***
	(-0.88)	(2.39)	(2.05)	(2.66)
BrokSize	0.008	0.005	-0.013	-0.015
	(1.00)	(0.74)	(-1.15)	(-1.34)
PriorRet	0.108***	0.071***	0.087***	0.063***
	(8.66)	(5.22)	(7.08)	(4.58)
Year	Y	Y	Y	Y
Firm	N	Y	N	Y
Analyst	N	N	Y	Y
Constant	0.569***	0.220	0.576***	0.351**
	(11.06)	(1.29)	(9.33)	(2.09)
Observations	29,759	28,741	28,736	27,651
Adjusted R^2	0.019	0.065	0.157	0.196

This table reports the results of examining the relation between lendable shares and analysts' self-selection in coverage. In addition to all control variables, Column (1) only includes year fixed effects, Column (2) includes year and firm fixed effects, Column (3) includes year and analyst fixed effects, and Column (4) includes year, analyst, and firm fixed effects. Two-tailed *p*-values based on standard errors clustered by firm and analyst are reported in parentheses. All variables are as defined in the Appendix A. ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4

Tests of increased trading as a channel through which short-sellers mitigate analysts' self-selection in coverage

Dep var = SelfSelect	Lower-than-median *Sensitivity* (1)	Higher-than-median *Sensitivity* (2)
LendShare (α_1)	-0.111	-0.313**
	(-0.88)	(-2.22)
Size	-0.006	0.017
	(-0.32)	(0.97)
IO	-0.025	-0.079*
	(-0.55)	(-1.71)
Leverage	0.160***	0.040
	(2.89)	(0.83)
BTM	-0.007	-0.062*
	(-0.20)	(-1.68)
ROA	0.366	0.222
	(1.58)	(1.14)
BrokSize	-0.013	-0.032*
	(-0.77)	(-1.89)
PriorRet	0.080***	0.050**
	(3.53)	(2.34)
Year	Y	Y
Firm	Y	Y
Analyst	Y	Y
Constant	0.222	0.138
	(0.89)	(0.52)
Observations	11,137	11,484
Adjusted R^2	0.210	0.186
α_1: Col (1) = Col (2)	*p*-value (2-tailed) = 0.061	

This table presents evidence that short trading is one channel through which short-sellers mitigate analysts' self-selection in coverage. We define *Sensitivity* as the sensitivity of monthly average proportion of daily short volume in total trading volume to lendable shares, measured as the firm-specific coefficient in a model regressing *ShortVol* on *LendShare* by firm, controlling for firm size, book to market, ROA, and leverage. We require each firm to have at least 10 observations. Columns (1) and (2) present the relation between *LendShare* and analysts' self-selection in analyst coverage for firms with lower-than-median and with higher-than-median *Sensitivity*, respectively.
All controls are included but not tabulated. Two-tailed *p*-values based on standard errors clustered by firm and analyst are reported in parentheses. All variables are as defined in the Appendix A. ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 5

Two-stage Least Square tests using ETF ownership as an instrumental variable for lendable shares

	1st Stage	2nd Stage
Dep var =	*LendShare*	*SelfSelect*
	(1)	(2)
ETFOWN	0.463***	
	(14.27)	
LendShare		-1.679***
		(-3.49)
Size	0.017***	0.034**
	(10.62)	(2.13)
IO	0.126***	0.137*
	(15.85)	(1.92)
Leverage	-0.000	0.059*
	(-0.04)	(1.86)
BTM	0.007**	-0.030
	(2.39)	(-1.16)
ROA	0.032*	0.307**
	(1.86)	(2.00)
BrokSize	0.001	-0.010
	(0.73)	(-0.79)
PriorRet	-0.013***	0.036**
	(-8.77)	(2.16)
Year	Y	Y
Firm	Y	Y
Analyst	Y	Y
Constant	-0.146***	-0.053
	(-6.26)	(-0.26)
Observations	22,609	22,609
Adjusted R^2	0.859	0.211

This table presents two-stage least square (2SLS) results using *ETFOWN* as an instrumental variable for lendable shares (*LendShare*). Column (1) reports the first-stage regression results of the endogenous variable (*LendShare*) on instrumental variable (*ETFOWN*) and controls in Equation (1). Column (2) reports the results of the second-stage estimation of Equation (1).
All controls are included but not tabulated. Two-tailed *p*-values based on standard errors clustered by firm and analyst are reported in parentheses. All variables are as defined in the Appendix A. ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 6

Tests using the introduction of option trading as an exogenous shock to short-selling potential

Dep var = SelfSelect	Year[-3, -1] vs. Year [1, 3] (1)	Placebo tests: Year[-6, -4] vs. Year [-2, 0] (2)	Placebo tests: Year[0, 2] vs. Year [4, 6] (3)
PostOption	0.003	-0.009	-0.027**
	(0.25)	(-0.37)	(-2.14)
TreatRec	0.093**	0.026	0.011
	(2.56)	(0.91)	(0.44)
PostOption × TreatRec	-0.093***	0.028	0.014
	(-3.15)	(0.70)	(0.52)
Size	0.005	-0.043*	-0.024
	(0.28)	(-1.81)	(-1.62)
IO	-0.080*	-0.185***	-0.081**
	(-1.65)	(-2.92)	(-2.38)
Leverage	0.020	0.123**	-0.016
	(0.38)	(2.07)	(-0.45)
BTM	-0.014	-0.031	-0.063
	(-0.93)	(-0.63)	(-1.36)
ROA	0.155	0.589**	0.522**
	(0.74)	(2.51)	(2.47)
BrokSize	-0.019	-0.012	-0.001
	(-1.06)	(-0.62)	(-0.10)
PriorRet	0.086***	0.047*	0.096***
	(3.91)	(1.69)	(4.82)
Year	Y	Y	Y
Analyst	Y	Y	Y
Firm	Y	Y	Y
Constant	0.186	0.812**	0.548**
	(0.81)	(2.42)	(2.52)
Observations	16,760	13,935	24,922
Adjusted R^2	0.556	0.742	0.549

This table examines the analysts' self-selection around the introduction of option trading. For each added rating, we identify a matched added rating which is given in the same year and to the firm in the same Fama-French 48 industry with the closest market cap prior to recommendation. Column (1) presents how analysts' self-selection differs between the three years prior to the year of option introduction and the three years after. Columns (2) and (3) present two sets of placebo tests. The first test uses year -3 as the pseudo-event year and compare analysts' self-selection between years [-6, -4] and years [-2, 0] (with year 0 being the actual option introduction year). The second test uses year 3 as the pseudo-event year and compare analysts' self-selection between years [0, 2] and years [4, 6].
All controls are included but not tabulated. Two-tailed *p*-values based on standard errors clustered by firm and analyst are reported in parentheses. All variables are as defined in the Appendix A. ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 7

Measuring analysts' self-selection with other analysts' outstanding recommendations on the same firm

Dep var = SelfSelect_WithinFirm	(1)
LendShare	-0.251**
	(-2.27)
Controls	Y
Year	Y
Firm	Y
Analyst	Y
Constant	Y
Observations	20,388
Adjusted R^2	0.172

This table reports the results of Equation (1) using an alternative approach to gauge analysts' self-selection: the difference between added ratings and outstanding non-added ratings on the same firm by other analysts.
Two-tailed *p*-values based on standard errors clustered by firm and analyst are reported in parentheses. All variables are as defined in the Appendix A. ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 8

Lendable shares and initiations unlikely due to analysts' self-selection

Panel A: Benchmark against the same analysts' ratings on previously-covered firms

Dep var = SelfSelect	All *Original* ratings	500 random sample of *added* ratings	*Original* ratings on firms covered by the broker in the past three years	500 random sample of *added* ratings
	(1)	(2)	(3)	(4)
LendShare	0.112	-0.142	-0.071	-0.144
	(0.40)	(-16.6)	(-0.13)	(-10.5)
Controls	Y	Y	Y	Y
Year	Y	Y	Y	Y
Firm	N	N	N	N
Analyst	N	N	N	N
Constant	Y	Y	Y	Y
Observations	1,595	1,595	512	512
Adjusted R^2	0.018	0.019	0.017	0.018

Panel B: Benchmark against on the same firms' ratings by other analysts

Dep var = SelfSelect_WithinFirm	All *Original* ratings	All *Original* ratings	*Original* ratings on firms covered by the broker in the past three years	500 random sample of *added* ratings
	(1)	(2)	(3)	(4)
LendShare	-0.103	0.005	0.011	-0.130
	(-0.57)	(0.27)	(0.73)	(-34.67)
Controls	Y	Y	Y	Y
Year	Y	Y	Y	Y
Firm	Y	N	N	N
Analyst	Y	N	N	N
Constant	Y	Y	Y	Y
Observations	13,063	16,750	5,726	5,726
Adjusted R^2	0.113	0.010	0.005	0.019

This table reports the results of Equation (1) by focusing on assignment-based *original* initiations unlikely due to analysts' self-selection. Following McNichols and O'Brien (1997), we define *original* ratings as (1) initiations made by analysts who enter into IBES less than 6 months ago, and (2) initiations made on the same day by the same analyst with at least three other initiations.

In Panel A, we benchmark *original* ratings against the same analysts' outstanding non-added ratings on other firms. Column (1) ((3)) presents results based on all *original* ratings (*original* ratings on firms covered by the broker in the past three years). Column (2) ((4)) presents results based on the mean of 500 random samples of *added* ratings with the same sample size as in Column (1) ((3)).

In Panel B, we benchmark against on the same firms' outstanding non-added ratings by other analysts. Column (1)

((2)) presents results based on all *original* ratings by including all controls and year, firm, and analyst fixed effects (only year fixed effects). Column (3) presents results based on *original* ratings on firms covered by the broker in the past three years. Column (4) presents results based on the mean of 500 random samples of *added* ratings with the same sample size as in Column (3).
Two-tailed *p*-values based on standard errors clustered by firm and analyst are reported in parentheses. All variables are as defined in the Appendix A. ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 9

The EPS forecast quality and short-selling potential

Panel A: Adjusted by the mean of the same analysts' forecasts on other firms

Dep var =	*Bias*	*Error*
	(1)	(2)
LendShare	0.034	-0.036
	(0.76)	(-1.52)
Controls	Y	Y
Year	Y	Y
Firm	Y	Y
Analyst	Y	Y
Constant	0.125	0.147***
	(1.32)	(2.86)
Observations	14,931	14,671
Adjusted R^2	0.322	0.596

Panel B: Adjusted by the mean of other analysts' forecasts on the same firm

Dep var =	*Bias_WithinFirm*	*Error_WithinFirm*
	(1)	(2)
LendShare	-0.016	0.001
	(-1.18)	(0.07)
Controls	Y	Y
Year	Y	Y
Firm	Y	Y
Analyst	Y	Y
Constant	0.032	0.004
	(1.03)	(0.16)
Observations	8,838	8,835
Adjusted R^2	0.232	0.288

This table reports the relation between lendable shares and the biases (Column (1)) and errors (Column (2)) of analysts' annual EPS forecasts associated with added ratings. In Panel A, we adjust variables of interest (i.e., bias and error of the upcoming annual EPS forecasts) by the latest annual EPS forecasts associated with the same analysts' outstanding non-added ratings on other stocks. In Panel B, we adjust variables of interest by the latest annual EPS forecasts associated with the same stock's outstanding non-added ratings by other analysts. Biases (errors) are calculated as the signed (unsigned) differences between actual and forecasted EPS scaled by the closing price of the trading date prior to the recommendation.

Two-tailed *p*-values based on standard errors clustered by firm and analyst are reported in parentheses. All variables are as defined in the Appendix A. ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 10

Lendable shares and the return predictability of abnormal analyst coverage

Dep var = Returns$_{t+1}$	(1)	(2)
R_AbCoverage$_t$	0.006**	0.005*
	(2.20)	(1.95)
R_LendShare$_t$	0.004	0.004
	(1.58)	(1.46)
R_AbCoverage$_t$ × R_LendShare$_t$	-0.009**	-0.008**
	(-2.19)	(-2.47)
EXMKT$_{t+1}$		1.050***
		(40.66)
SMB$_{t+1}$		0.797***
		(21.47)
HML$_{t+1}$		0.022
		(0.52)
UMD$_{t+1}$		-0.153***
		(-5.32)
Constant	0.009**	-0.000
	(2.32)	(-0.26)
Observations	514,603	514,603
Adjusted R^2	0.000	0.131

This table reports the relation between the return predictability of abnormal analyst coverage and lendable shares. In Column (1) we regress the raw next-month returns on the decile ranks of lendable shares, the decile ranks of abnormal analyst coverage, and their interactions, without any control variables. In Column (2) we also control for risk factors in a four-factor model, including monthly contemporaneous excess market return (*EXMKT*), the monthly premium of the size factor (*SMB*), monthly premium of the book-to-market factor (*HML*), and the monthly premium on winners minus losers (*UMD*). These four factors are obtained from Kenneth French's website. ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.