



## Essays in Finance

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## *Essais en Finance*

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## **Introduction**

The three chapters of this study focus on information in the financial markets, and how this is used and diffused by market participants. The first article shows that investors observe prices and extract signals from them, leading to cross-asset learning and spillover effects in prices and liquidity between assets. The second article studies the securities lending market using a novel, hand-collected dataset. I show that mutual funds react to short selling demand through the securities lending market, and that active funds reduce their holdings of stocks that are borrowed from them. In the final article, we study how securities loans are allocated within mutual fund families.

In the first article of this thesis, joint with Daniel Schmidt, we study the extent of cross-asset learning in financial markets by examining spillover effects around mutual fund fire sales. We find that the well-documented impact-reversal pattern for the returns of fire sale stocks (e.g., Coval and Stafford, 2007) spills over onto the stock returns of economic peers with a magnitude that is around one fifth of the original effect. These spillovers extend to liquidity and are not explained by common funding shocks or the hedging activity of liquidity providers. We conclude that they represent information spillovers due to learning from prices, thus identifying cross-asset learning as an important driver for the commonality in returns and liquidity.

The second article studies the market for lending and borrowing securities in the United States. I find that by making securities available for borrowing, mutual funds acquire information about short selling, which they exploit for trading. Funds with discretion in their investment choices re-balance their portfolios away from borrowed stocks, avoiding capital losses on stocks with decreasing prices. Funds also trade more aggressively on stocks with stronger signals. Finally, active funds charge lower lending fees than passive funds, consistent with funds paying for the information with lower fees.

In the third article, joint with Daniel Schmidt, we study the allocation of securities loans within mutual fund families. Using a novel dataset on fund level stock lending, we show that U.S. mutual fund families, first, are more likely to enable index funds to lend securities than active funds. Second, we show that this also holds at the security level: index funds are allocated more securities loans than comparable active funds. We also find no robust evidence that mutual fund families would strategically allocate securities loans to funds that prior literature has found to be more “valuable” to the families.

## Résumé en français

Les trois chapitres de cette thèse portent sur l'information dans les marchés financiers, et sur la manière dont elle est utilisée et diffusée par les acteurs du marché. Le premier article révèle que les investisseurs observent les prix de marché et en extraient des signaux informatifs, ce qui a pour conséquence, d'une part, un effet d'apprentissage par le biais des prix d'un actif à l'autre, et d'autre part, des répercussions sur les prix et la liquidité entre les actifs. Le deuxième article étudie le marché des prêts de titres en utilisant un nouvel ensemble de données collectées manuellement à partir des rapports exigés par le régulateur des marchés financiers américain. Cet article tend à démontrer que les fonds communs de placement réagissent à la demande de vente à découvert sur le marché des prêts de titres, et que les fonds actifs réduisent leurs investissements dans les actions qui leur sont empruntées. Le dernier article analyse la répartition des prêts de titres au sein des familles de fonds communs de placement.

Dans le premier article de cette thèse, en collaboration avec le professeur Daniel Schmidt, nous étudions dans quelle mesure il existe un effet d'apprentissage entre actifs sur la base de leurs prix sur les marchés financiers. Nous examinons pour cela les effets de contagion autour des ventes forcées des fonds communs de placement. Nous constatons que la tendance d'inversion d'impact sur les rendements des actions subissant des ventes forcées (bien documentée dans littérature, par exemple par Coval et Stafford, 2007) se répercute sur les rendements des actions des pairs économiques avec une ampleur d'environ un cinquième de l'effet initial. Ces retombées s'étendent à la liquidité et ne s'expliquent pas par les chocs de financement courants des entreprises concernées ou par l'activité de couverture des fournisseurs de liquidité sur les marchés. Nous concluons qu'elles représentent des retombées d'information dues à l'apprentissage basé sur les prix, ce qui permet d'identifier que l'effet d'apprentissage croisé est un moteur important des variations conjointes des rendements et de la liquidité.

Le deuxième article étudie le marché des prêts et des emprunts de titres aux États-Unis. Je constate qu'en rendant les titres disponibles pour l'emprunt, les fonds communs de placement acquièrent de l'information sur la demande de vente à découvert, qu'ils exploitent dans leurs transactions sur les marchés financiers. Les fonds qui disposent d'une certaine latitude dans leurs choix d'investissement réallouent les actifs de leurs portefeuilles en réduisant leurs investissements dans les actions empruntées. Ces fonds évitent ainsi les pertes en capital sur les actions dont le prix est en baisse en exploitant l'information liée à la demande de prêt d'actifs. Les fonds vendent également de manière plus agressive les actions dont les signaux sont plus forts. En revanche, je ne trouve pas d'évidence empirique que les fonds indiciels (passifs) vendent ou achètent stratégiquement les actions qui leur

sont empruntées. Les fonds indiciels peuvent ainsi être perçus comme des meilleurs “fournisseurs d’actifs” sur les marchés car ils semblent être plus stables dans leurs offres d’actifs à emprunter et moins opportuniste que les fonds actifs. Enfin, les fonds actifs facturent des frais de prêt moins élevés que les fonds passifs, ce qui est en ligne avec une compensation via l’information extraite, expliquant ces frais moins élevés.

Dans le troisième article, également rédigé avec professeur Daniel Schmidt, nous étudions la répartition des prêts de titres au sein des familles de fonds communs de placement. En utilisant un nouvel ensemble de données américaines sur les prêts de titres au niveau des fonds, nous montrons, tout d'abord, que les familles de fonds communs de placement sont plus susceptibles de permettre aux fonds indiciels passifs de prêter des titres que les fonds actifs. Nous établissons ensuite que cette observation reste valide au niveau des actifs financiers : les fonds indiciels se voient attribuer plus de prêts de titres que les fonds actifs comparables. Enfin, nous ne trouverons pas d’indications que les familles de fonds communs de placement attribuent stratégiquement des prêts de titres à des fonds identifiés comme plus "précieux" pour les familles par la littérature existante.

# Learning from Noise? Price and Liquidity Spillovers around Mutual Fund Fire Sales

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June 1, 2019

## ABSTRACT

We study the extent of cross-asset learning in financial markets by examining spillover effects around mutual fund fire sales. We find that the well-documented impact-reversal pattern for the returns of fire sale stocks (e.g., Coval and Stafford, 2007) spills over onto the stock returns of economic peers with a magnitude that is around one fifth of the original effect. These spillovers extend to liquidity and are not explained by common funding shocks or the hedging activity of liquidity providers. We conclude that they represent information spillovers due to learning from prices, thus identifying cross-asset learning as an important driver for the commonality in returns and liquidity.

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Do investors learn from stock prices, and do they try to extract information about one stock from the price movements of other stocks? These questions are important as they pertain to the information efficiency of stock prices as well as to the comovement in returns and liquidity. They also relate to standard theory, most of which assumes rational expectations, and builds on the premise that investors rationally condition their expectations on *all* relevant price signals.<sup>1</sup> However, learning from prices is unlikely to be perfect: given the sheer number of potentially relevant price signals, perfect learning from prices would amount to solving a tremendous filtering problem likely to overwhelm even the most sophisticated investors.<sup>2</sup> Moreover, by responding to price signals, investors are bound to make mistakes: occasionally, an investor will misinterpret a noise shock to be a fundamental signal, causing her to wrongly update her beliefs.

In this paper, we study whether investors learn from prices of—and thus occasionally from *noise* in—economically related peer stocks. Identifying learning from prices is challenging because the econometrician does not observe all the information that reaches investors, whether it stems from newswires, analyst reports, internet chat rooms or even word-of-mouth. For example, if two stocks fall at the same time, the econometrician cannot tell whether this happened because both stocks responded to some common (unobserved) signal, or because investors learnt about one stock from the price of the other. We overcome

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<sup>1</sup> Rational learning from prices has been first formalized in the seminal models of Grossman (1976), Hellwig (1980), Grossman and Stiglitz (1980), and Admati (1985). These models have seen hundreds, if not thousands, of adaptations over time—commonly referred to as the noisy rational expectations equilibrium (NREE) literature.

<sup>2</sup> Consistent with imperfect learning from prices, observed levels of trading activity suggest the presence of large disagreement among market participants; see, for instance, Harris and Raviv (1993), Kandel and Pearson (1995), and Hong and Stein (2007).

this problem by isolating stock price movements where it becomes clear *ex post* that investors have “made mistakes” and updated on noise. Specifically, we consider price movements that turn out to be price pressure effects triggered by mutual fund fire sales (Coval and Stafford, 2007), and which therefore revert over time—indicating that the fundamentals of affected firms remain unchanged. Hence, there is no fundamental news that can explain a potential spillover.<sup>3</sup>

We then ask whether the price pressure effects for these fire sale stocks spill over to their close economic peers, which we identify from the text-based network industry classification (TNIC) developed by Hoberg and Phillips (2010a; 2015). Indeed, when investors learn from prices and are not able to see through the non-fundamental reason of the price drop in the fire sale stock,<sup>4</sup> they should downgrade their expectations about its peers.<sup>5</sup> Over time, investors become aware of the mispricing induced by the fire sale, and the prices of both stocks should revert. Hence, we expect to find a similar impact-reversal pattern for the peers of fire sale stocks. Put differently, models with rational learning entail that, occasionally, investors make mistakes and update on noise. We argue that, due to the omitted variable

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<sup>3</sup> In line with prior work exploiting flow-induced trading pressure (e.g., Edmans et al., 2012; Hau and Lai, 2013; Ali et al., 2011; Dessaint et al., 2016), we focus on fire sales as opposed to “fire purchases”. The argument is that mutual funds are under strong pressure to sell stock positions if outflows deplete their cash reserves, while they have arguably more discretion to time their stock purchases after receiving inflows.

<sup>4</sup> Given that fund flow and holdings data comes online with a reporting lag of up to two quarters (e.g., Coval and Stafford, 2007; Frazzini and Lamont, 2008), most investors are only able to observe the fire sale with a delay. Indeed, if this were not the case, one would expect more liquidity providers to enter so that the price drop upon the fire sale would be significantly reduced in the first place.

<sup>5</sup> We expect a downgrade if negative news for one firm constitutes negative news for the other firm. For firms competing in the same product market (which will be affected by the same demand shocks), this should be true on average. Below, we also present cross-sectional results in which we differentiate between peers for which this is more or less likely to be the case.

problem described above, it is exactly in this case that we can hope to identify learning from prices.

Figure 2 illustrates the main finding of our paper: the impact-reversal patterns from fire sales spill over to peer firms that do not experience fire sales themselves. In the quarter where a mutual fund fire sale hits a firm (Panel A), its economic peers experience a stock price drop that is approximately one fifth of the fire sale effect (Panel B). Both the fire sale and the peer effect reverse over subsequent quarters, confirming the non-fundamental nature of the fire sale shock. We consider several explanations for these findings—including common funding shocks, reverse causality and cross-asset hedging by liquidity-providing arbitrageurs—and conclude that they are most consistent with the “learning channel” posited by multi-asset rational expectation models. Consistent with this interpretation, we find that the price spillover effect is stronger when cross-asset learning is more important —i.e., when public information about peer stocks is scarce (e.g., small firms, firms with low analyst coverage, or high analyst forecast errors), when peer stocks exhibit a high turnover-volatility correlation (a model-implied measure of the extent to which investors condition on prices; see Banerjee, 2011) and for peers that are more closely related to the fire sale firm.

One crucial element for the learning story is the *lack of public information* regarding the non-fundamental nature of the fire sale stock. This observation leads us to conduct a placebo experiment by testing for spillover effects of another well-known price pressure effect for which such information is available—S&P 500 index additions (Harris and Gurel, 1986; Shleifer, 1986; Beneish and Whaley, 1996; Lynch and Mendenhall, 1997). Though the literature does not quite agree on whether the run-up in prices of newly added stocks reflects

pure price pressure or also direct benefits of the index inclusion (such as increased investor awareness; see, e.g., Wurgler and Zhuravskaya, 2002; Denis et al., 2003; Chen et al., 2004; Patel and Welch, 2016), the fact that additions are publicly observed means there should be less uncertainty about the value implications for peer stocks. We indeed find that the peers of added stocks exhibit an economically weaker and mostly insignificant spillover effect. This confirms that the lack of public information surrounding fire sales is key to understanding the return spillover effect that we document.

Finally, we test whether, in addition to the price spillover, there is also evidence of a liquidity spillover from fire sale stocks to their peers. Indeed, we clarify with a standard NREE model based on Admati (1985) that such a liquidity spillover is a unique prediction of the cross-asset learning channel. The intuition is that the fire sale, by reducing the informativeness of the price signal, increases the uncertainty about peer firms, making investors more reluctant to provide liquidity. Consistent with this intuition, we document that fire sale firms see a strong dry-up in liquidity, which similarly spills over to peer firms.

Our identification rests on the assumption that mutual fund fire sales are exogenous to affected stocks. While ours is not the only paper making this assumption, we acknowledge that the endogeneity of fire sales is of particular concern in the context of identifying spillover effects. To be precise, there are two layers of endogeneity. First, distressed funds may selectively sell stocks about which they have negative information (see Huang et al., 2016). To the extent that this information also pertains to industry peers, we may see a simultaneous price drop for fire sale stocks and their peers. Second, we may face a reverse causality when industry distress triggers outflows from funds heavily invested in that

industry. To immunize our approach against the first concern, we follow Edmans et al. (2012) and identify fire sales based on “hypothetical sales” imputed from a proportional downscaling of a fund’s previous portfolio holdings (rather than using their actual sales).<sup>6</sup> To deal with the second concern, we verify in numerous robustness checks that our results are not driven by broad industry trends or funds whose outflows are likely to be caused by industry distress. As we discuss in detail below, the observed return reversal within 1-2 years is further evidence against the reverse causality argument as industry cycles evolve at a more glacial pace (Hoberg and Phillips, 2010b).

Our paper contributes to several strands of research. First, we speak to the literature on comovement and spillovers in asset markets. There is strong evidence for commonality in returns and liquidity (Pindyck and Rotemberg, 1993; Chordia et al., 2000; Hartford and Kaul, 2005; Hasbrouck and Seppi, 2001; Korajczyk and Sadka, 2008). Since these comovements seem excessive relative to the comovement in fundamentals, subsequent research has explored both behavioral explanations (Lee et al., 1991; Bodurtha et al., 1995; Barberis and Shleifer, 2003; Barberis et al., 2005) and financial friction-based explanations (Greenwood, 2005; Andrade et al., 2008; Greenwood and Thesmar, 2011; Anton and Polk, 2014; Koch et al., 2016). Another, more closely related branch of the literature focuses on informed order flow as a source of return comovement (Boulatov et al., 2013; Pasquariello and Vega, 2015).

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<sup>6</sup> In Internet Appendix B.3, we present evidence supporting the view that the fire sale events based on the Edmans et al. (2012) approach are indeed immune to stock selection concerns. Specifically, we show that abnormal short interest, which Huang et al. (2016) find to have strong predictive power for whether *actual* fire sales exhibit a reversal or not, does not have any bite in our context. That is, fire sales identified as in Edmans et al. (2012) exhibit a similarly strong price drop and reversal regardless of whether short interest is high or low. In Internet Appendix B.4, we show that we find a qualitatively similar price spillover effect if we define fire sales based on the “pressure” measure of Coval and Stafford (2007). While potentially confounded by selection concerns, this measure has the advantage that its variation is solely driven by flow-induced fund trades as opposed to contemporaneous price or volume effects (Wardlaw, 2018).

While these papers make inroads into establishing cross-asset information flows as an important driver of comovement, they are unable to control for *all* information arrivals that may explain the joint dynamics in order flow and returns. As such, there remains the possibility that returns comove not because investors learn from order flow, but because of information shocks that drive both returns and order flows. We sidestep this problem by considering fire sales as a quasi-natural experiment to cleanly identify learning from prices across stocks. In doing so, we document that investors occasionally update on noise, thereby identifying a *learning-based* spillover mechanism that contributes to the rich co-variation in returns and liquidity.<sup>7</sup>

Second, we add to the literature on learning in financial markets. While there is a large body of theory on information asymmetry and learning from prices (e.g., Hellwig, 1980; Grossman and Stiglitz, 1980; Wang, 1993), clean empirical tests of primitive predictions from these models remain rare, because investors' information sets are difficult to observe and highly endogenous. One exception is Kelly and Ljungqvist (2012) who exploit exogenous variation in analyst coverage to study how shocks to information asymmetry affect firm valuations. Another, more closely related paper is Banerjee (2011) who solves a dynamic noisy rational expectations model to derive predictions about investors' use of information contained in prices, which he then goes on to test in the data. While the evidence is more consistent with learning from prices, his approach is based on studying correlations and does not consider

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<sup>7</sup> These findings further relate to an old literature showing that firm-specific or market-wide news explain a surprisingly low fraction of the variation in stock returns (Roll, 1988; Cutler et al., 1989; see Boudoukh et al., 2015, for a more recent analysis). Our results suggest a new way for understanding this apparent puzzle. Specifically, we document how cross-asset learning leads to the propagation of noise shocks among economically-related stocks.

learning across stocks. We contribute by applying an empirical design that allows to identify whether and how much investors learn from the stock prices of peer firms. This enables us to directly confirm a basic assumption from rational expectation models with multiple price signals (Admati, 1985; Caballé and Krishnan, 1994; Kodres and Pritsker, 2002; Veldkamp 2006; Bernardt and Taub, 2008). Our results also complement the evidence in Cohen and Frazzini (2008) and Menzly and Ozbas (2010): while their results show that investors learn too little across stocks, ours imply that they sometimes “learn too much” by updating on noise.

Third, we contribute to the literature on mutual fund trading pressure. Coval and Stafford (2007) show that the trading behavior of mutual funds with extreme outflows lead to price pressure effects for affected stocks.<sup>8</sup> Since mutual fund flows can be treated as largely exogenous from the perspective of affected stocks,<sup>9</sup> subsequent research has exploited fire sales to shed light on the real effects of stock price changes on corporate outcomes such as takeover activity (Edmans et al., 2012), investment and employment (Hau and Lai, 2013), opportunistic option grant timing and insider purchases (Ali et al., 2011), and seasoned equity offerings (Khan et al., 2012).<sup>10</sup> Related to our work, Dessaint et al. (2016) show that

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<sup>8</sup> In the international context, Jotikasthira et al. (2012) find that flow shocks to funds domiciled in developed markets affect their asset allocations abroad and thereby transmit to emerging markets. Falato et al. (2016) provide evidence for fire sale spillovers in fixed income markets.

<sup>9</sup> This identifying assumption is supported by the fact that the price pressure effect reverses over subsequent quarters, proving that the fundamentals of affected stocks are unchanged on average. See the robustness section for more discussion on this point.

<sup>10</sup> The evidence on option grant timing, insider trading and SEOs suggests that at least some managers of fire sale firms are aware of the temporary mispricing induced by the fire sale. This finding is in line with the vast literature on the market timing ability of firm managers (e.g., Baker and Wurgler, 2002).

peer firms of fire sale stocks cut investment, consistent with these managers learning from stock prices but failing to filter out the noise induced by fund selling pressure. Instead of looking at corporate outcomes, we study *price* and *liquidity spillovers* between fire sale stocks and their economic peers. In our view, documenting these spillovers is important as it provides clean evidence for the importance of the learning channel—the bedrock of the rational expectations literature—in driving the commonality in returns and liquidity.

The remainder of this paper is organized as follows. Section I lays out the hypotheses tested in this paper. Section II describes the data and methodology. Section III presents the main results on return spillovers, including a cross-sectional analysis and numerous robustness checks. Section IV provides additional evidence in favor of the cross-asset learning channel. Section V concludes.

## **I. Hypotheses**

### *A. Cross-asset Learning*

We draw on multi-asset models with learning from prices to develop our predictions about the *informational spillover* effects of mutual fund fire sales. These predictions are derived in Internet Appendix A using a standard NREE model in the spirit of Admati (1985); here we focus on providing their intuitions. The first prediction concerns a *price spillover effect*: under asymmetric information, the price of the fire sale stock serves as a signal about fundamentally-related peer firms. Rational learning then entails that, unless investors perfectly understand that a price drop in the fire sale stock is caused by noise, they interpret the price drop as representing bad news for peer stocks, causing peers' stock prices to weaken as well. In terms of the model, the fire sale represents an unobserved (positive)

shock to the supply of one stock, which pushes down the equilibrium price of both the fire sale stock and its peer. Over time, investors figure out that the reason for the price drop was non-fundamental and prices revert. Hence, models with cross-asset learning (e.g., Admati, 1985; Caballé and Krishnan, 1994; Veldkamp 2006; Boulatov et al., 2013; Pasquariello and Vega, 2015; Cespa and Foucault, 2014; Asriyan et al., 2016) unequivocally predict that the impact-reversal pattern observed for fire sale firms should spill over to peer firms. Intuitively, such a spillover should be stronger for stocks for which the available public information is scarce because then investors need to rely more on the stock price signals of economic peers.

The second prediction is about a *liquidity spillover effect*, and arises when the fire sale impairs the price informativeness of the fire sale stock.<sup>11</sup> In the model, this can be seen by assuming that a fire sale, in addition to being a large supply shock realization, also causes an increase in the standard deviation of expected supply shocks. Such an increase reduces the signal-to-noise ratio in the fire sale price and thereby raises the overall uncertainty faced by market participants, causing them to withdraw their liquidity from economically-related peer firms. Thus, we expect peer firms to suffer from a temporary deterioration in liquidity around the fire sale. To sum up, we expect cross-asset learning to lead to price and liquidity

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<sup>11</sup> There are at least three reasons for why a fire sale may reduce the price informativeness of the fire sale stock: First, even in the absence of adverse selection (as in Cespa and Foucault, 2014), an extreme noise realization in one period may cause risk-averse market makers to update their expectations about future noise trader risk, to which they respond by decreasing liquidity, thereby rendering the price less informative. Second, when market makers are uncertain whether informed traders are present, a large unexpected trade (as from a fire sale) may cause them to update this probability, leading them to demand a higher price impact (e.g., Easley and O'Hara, 1992; Avery and Zemsky, 1998; Banerjee and Green, 2015). Third, fire sale shocks may hurt informed arbitrageurs, causing them to trade less aggressively in the fire sale stock and thereby rendering its price less informationally-efficient (Dow and Han, 2016).

spillovers between fire sale stocks and their economic peers. We call this the *information spillover hypothesis*.

#### *B. Alternative Spillover Channels*

Clearly, there are alternative explanations for the existence of spillover effects. For instance, spillover effects between two assets can be triggered by financially-constrained arbitrageurs that are trading in both (Kyle and Xiong, 2001; Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009). As these traders suffer losses in one asset, they may be forced (e.g., because of margin calls) to exit their positions in the other asset. Such a contagion effect fits well with anecdotal evidence from prominent fire sale crises such as the collapse of the hedge fund LTCM in 1998. It is further consistent with empirical evidence that stocks with common owners (Anton and Polk, 2014) or different owners with common shocks (Greenwood and Thesmar, 2011) exhibit comovement over and above what can be explained by fundamentals. This *funding shock channel* could presumably also explain a joint liquidity dry-up, although it has a harder time to rationalize why stocks in a weaker information environment would systematically be more affected than those with stronger public information. To address the possibility that return spillovers are explained by common funding shocks, we control for a rich set of proxies intended to capture common ownership and common flow shocks.<sup>12</sup>

Another explanation for a spillover-like return pattern concerns the activity of liquidity-providing arbitrageurs. Such arbitrageurs buy shares from distressed sellers and hedge their

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<sup>12</sup> These controls also help to counter the empirical concern that the peer effect could be driven by small-scale fire sales in disguise.

positions by selling peer stocks.<sup>13</sup> If they do so in droves and demand curves are downward-sloping, peer stocks could see a somewhat smaller price pressure effect themselves (Greenwood, 2005; Andrade et al., 2008; Lou et al., 2013). Such an effect naturally arises in models featuring risk-averse investors that trade correlated stocks in equilibrium (and it is also present in our model; see Internet Appendix A). We deal with this *cross-asset hedging channel* in several ways. First, we construct a proxy for the intensity of cross-asset hedging that we use as a control in our empirical tests. Second, we note (and show in our model) that this explanation is inconsistent with the presence of a liquidity spillover effect (see also Cespa and Foucault, 2014) and does not predict cross-sectional differences in return spillovers across peers (assuming they are equally good for hedging). Finally, we conduct a placebo experiment by looking at another instance of price pressure—S&P 500 index addition events—for which there should be little uncertainty about the value implications for peer firms. Hence, any spillover that we document in this context cannot come from learning and—by comparing it to the spillover intensity in fire sales—allows us to assess the relative importance of cross-asset learning vis-à-vis cross-asset hedging.

Empirically, one key challenge is to distinguish spillover effects—where movements in one stock *cause* movements in another—from comovement driven by other unobserved factors like common economic trends. We argue that we can overcome this challenge by studying spillovers triggered by idiosyncratic fire sale shocks. One important concern, however, is

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<sup>13</sup> Another possibility is front-running: when some arbitrageurs anticipate the fire sale, they can short-sell the fire sale stock and cover their shorts by buying from distressed funds (indirect evidence for front-running by hedge funds is documented in Chen et al., 2008). When arbitrageurs engaging in front-running want to hedge their positions, they may similarly sell peer stocks at the time of the fire sale.

*reverse causality*: it may be that fire sales, rather than causing spillover effects, are themselves caused by industry distress and the simultaneous stock price decline among industry stocks. While we defer a detailed discussion of this potential concern to the robustness section, we note here that the reverse causality story does not predict a swift return reversal as industry distress should arguably persist over several quarters if not years (e.g., Hoberg and Phillips, 2010b).

## **II. Data and Methodology**

Stock market data is obtained from CRSP; mutual fund returns and monthly total net asset (TNA) values come from the CRSP mutual fund database; and quarterly mutual fund holdings are gathered from the Thomson Reuters S12 holdings data. We start from the sample of all common stocks (share codes 10 or 11) with an end-of-quarter price above one dollar and at least 10 non-missing daily returns in a quarter. For each stock, we calculate a measure of hypothetical selling pressure by “fire sale funds” as in Edmans et al. (2012).<sup>14</sup> A detailed description of the construction of their measure is provided in Appendix B. Here, we only provide its intuition. Following their example, we exclude sector funds (third letter of CRSP objective code equal to “S”)—as they could suffer from reverse causality—and drop all international, municipal, bond and metal funds (investment objective codes 1, 5, 6, 8). For each fire sale fund, defined as a mutual fund with quarterly outflows exceeding 5% of TNA, we calculate the imputed dollar selling volume for each portfolio stock if the fund had just downscaled his pre-existing portfolio. We then aggregate the imputed selling pressure of all

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<sup>14</sup> In Internet Appendix B.4, we show that we obtain qualitatively similar results when we instead identify fire sale events based on the “pressure” measure defined in Coval and Stafford (2007).

fire sale funds at the stock level, scale by total trading volume, and call this variable *mfflow*. Following Edmans et al. (2012), we say that a fire sale event (defined at the stock-quarter level) occurs when *mfflow* is in the lowest decile.

It is important to note that this approach shuts down endogeneity concerns coming from the choice of stocks being sold. Indeed, distressed mutual funds may actively sell the stocks that they are the least optimistic about—implying that their actual sell decisions contain information. The use of imputed sells circumvents this issue as imputed sells by construction do not reflect an active choice by the fund manager. In Internet Appendix B.3, we present evidence consistent with this conclusion. Specifically, we show there that a stock’s abnormal short interest, which Huang et al. (2016) find to predict whether a stock actually sold in a fire sale exhibits a price reversal or not, does not have any predictive power with the Edmans et al. (2012) methodology.

We identify the economic peers of fire sale stocks using the Text-based Network Industry Classification (TNIC) developed by Hoberg and Phillips (2010a; 2015). This data covers the period from 1996 to 2013 and is based on a textual analysis of the product description section contained in annual 10-K reports that must be filed with the SEC. For each year, Hoberg and Phillips (2015) compute firm-by-firm pairwise similarity scores based on the number of words that two firms share in their product market descriptions. They then define two firms to be economic peers if their similarity score exceeds a pre-specified minimum threshold. Compared to standard industry classifications (such as SIC and NAICS), TNIC

offers a finer and arguably more accurate description of peer firm relatedness.<sup>15</sup> This turns out to be important for our analysis—indeed, we confirm below that the spillovers to TNIC peers obtain even after controlling for common industry trends (see subsection III.C).

To ensure that any spillover effect we document is not confounded by another fire sale event, we do not consider a peer when it has itself experienced a fire sale in the preceding or succeeding 8 quarters. In addition, we focus on the 10 closest economic peers (based on the product similarity score) for each fire sale event as we expect cross-asset learning and thus potential spillovers to be the strongest for those firms.<sup>16</sup>

Fire sale events tend to cluster. For example, conditional on having a fire sale, a firm has a 61% (69%) probability of experiencing another fire sale over the subsequent four (eight) quarters, while unconditionally the probability of having a fire sale over a four (eight) quarter period is only 21% (30%). To deal with this clustering of fire sale events, we conduct a multivariate panel analysis that allows to isolate the return effects of overlapping fire sales.<sup>17</sup> Specifically, we run regressions of the following type:

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<sup>15</sup> In addition to being finer, TNIC data has three important features that make it more accurate than standard industry classifications: First, TNIC peer definitions are time-varying and can thus account for changes to the industry landscape. Second, by basing the classification on product descriptions (rather than, say, production processes), TNIC may be better able to capture product market competition where firms are exposed to common demand shocks. Finally, TNIC peer definitions are not forced to be transitive, meaning that each firm can have a different set of peers.

<sup>16</sup> We still find a statistically significant (albeit slightly weaker) spillover effect for returns when we include all peers (instead of only the top 10). This is not surprising as the majority of fire sale stocks has no more than a dozen of associated peer stocks. We nonetheless prefer to include this filter so as to not give a disproportionate weight to a small number of fire sale firms that are linked with hundreds of peer firms.

<sup>17</sup> In Internet Appendix B.1, we also report results from a classic event study approach. These results also exhibit an impact-reversal pattern for peer firms, but due to event clustering there is more pre-event drift and the reversal is more protracted.

$$y_{it} = \alpha_i + \alpha_t + \sum_{\tau=-16}^{16} \beta_{\tau} \times FS_{it-\tau} + \sum_{\tau=-16}^{16} \delta_{\tau} \times PEER_{it-\tau} + \gamma' X_{it-1} + \varepsilon_{it} \quad (1)$$

where  $y_{it}$  is a dependent variable of interest,  $\alpha_i$  and  $\alpha_t$  are firm and quarter fixed effects,  $FS_{it-\tau}$  and  $PEER_{it-\tau}$  are a set of dummy variables that flag fire sale firms and their peers in event time, and  $X_{it-1}$  is a vector of pre-specified control variables. To see how this works, consider the case where firm A has a fire sale in the first quarter of 2008, implying that  $FS_{A2008Q1} = 1$ . If firm B is a peer to fire sale stock A (and does not have a fire sale itself), then  $PEER_{B2008Q1} = 1$ . The specification further includes 32 dummies that flag the 16 preceding and succeeding quarters for the two event firms. For example, the dummies  $FS_{A2008Q1-1}$  and  $PEER_{B2008Q1-1}$  take the value one in the fourth quarter of 2007 for firm A and B, respectively. Importantly, if firm A had another fire sale in, say, the first quarter of 2007, then  $FS_{A2008Q1}$  and  $FS_{A2007Q1+4}$  would be one at the same time, ensuring that any reversal from the preceding fire sale does not confound the estimation of the second fire sale effect. In this way, our panel specification allows us to isolate the evolution in  $y_{it}$  for fire sale and peer events in event-time. Standard errors are double-clustered at the firm and quarter level.

For our multivariate analyses, we gather a host of firm-specific control variables from a variety of sources: accounting data comes from Compustat; the number of analysts following a stock is taken from I/B/E/S; institutional holdings data are from CDS Spectrum (S34); and quarterly measures of the probability of informed trading (PIN; Easley et al., 1996) are

downloaded from Professor Stephen Brown’s website.<sup>18</sup> Table I reports descriptive statistics and Appendix A provides detailed variable descriptions for the control variables used in this study. Our final dataset spans the period from 1996 to 2013 and includes 31,403 fire sale events as well as 66,696 associated peer events. Figure 1 shows how these events spread out over time. While the number of events fluctuates quite a bit, there is no apparent trend or an indication that events are concentrated in one particular period.

[Include Table I about here.]

### III. Return Spillover

#### A. Baseline Results

In this section, we study the effect of fire sales on the stock returns of their peers. Specifically, Table II shows the results from estimating equation (1) for the cumulated quarterly return as the dependent variable. For each specification, we show fire sale and peer event-time dummies next to each other to facilitate the comparison.<sup>19</sup> First, we note that the fire sale dummies display the typical impact-reversal pattern. In the fire sale quarter, affected stocks shed 7-8% of their value, which they partly recover over the subsequent 8 quarters. The magnitude of this effect is close to what has been found in the literature (Coval and Stafford, 2007; Edmans et al., 2012; Dessaint et al., 2016). It is also remarkably consistent across different specifications, showing that the results obtain after controlling for a host of accounting variables (column 2), ownership measures (column 3), fund flow proxies

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<sup>18</sup> Available at: <http://scholar.rhsmith.umd.edu/sbrown/pin-data>. These PIN measures are estimated using the Venter and de Jongh (2004) model.

<sup>19</sup> For brevity, we only report results for event-time dummies  $-2 \leq \tau \leq 8$ . The other event-time dummies are mostly insignificant.

(column 4), or all of these combined (column 6). The key result of this table is that the dummy for peer firms in the event quarter ( $t = 0$ ) indicates a drop in returns of about 1.5%. This amounts to approximately one fifth of the original fire sale effect (e.g., in column 1,  $\sim 1.5\%/7.5\%$ ), which is a reasonable magnitude for a spillover effect.<sup>20</sup> Like the fire sale effect, this drop in peer returns remains stable and highly statistically significant across specifications. We further find that this return spillover completely reverses within four quarters.<sup>21</sup> For example, in column 1, the cumulated reversal over four quarters equals 1.6% and is significant at the 5%-level. The existence of the reversal confirms that the stock price drop for peer firms is not caused by fundamental news. Rather, it suggests that investors become aware of the non-fundamental reason for the price drop in the fire sale stock and reevaluate their initial negative assessment for peer firms.

[Include Table II about here.]

We emphasize that the return spillover effect obtains after controlling for an array of potentially confounding factors. The inclusion of firm and quarter fixed effects, for instance, ensures that our results are not driven by unobserved (fixed) firm characteristics or market-

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<sup>20</sup> When observing a drop in the stock price of a peer firm, investors will not be sure whether this price drop reflects fundamentals or noise. For mixed prior beliefs about the unconditional probabilities of fundamental and non-fundamental shocks, it is natural to expect an update which is a fraction of the original price shock.

<sup>21</sup> Interestingly, the reversal for peer firms occurs somewhat faster than the reversal for fire sale stocks, as the latter have not fully reversed after even 8 quarters. While explaining the slow reversal for fire sale firms is outside the scope of this paper, we note that our finding that the peer effect reverts faster is consistent with recent explanations that focus on the role of adverse selection risk surrounding fire sales (Dow and Han, 2016; Huang et al., 2016). According to this argument, there is substantial uncertainty about which stocks are sold by fire sale funds: on the one hand, fire sale funds may sell their most liquid positions to mitigate price impact (in which case trading on the reversal should be profitable). On the other hand, they may sell stocks about which they are particularly pessimistic (in which case the reversal may never materialize). Given this uncertainty, investors may be reluctant to bid up the fire sale stock even after they become aware of the fire sale, thereby explaining why the price reversal for fire sale stocks is more protracted than the one for peer stocks.

wide trends. Nor is the effect explained by standard accounting controls, analyst coverage or institutional ownership.<sup>22</sup> Given our identifying assumption that fire sales occur for reasons outside of affected firms, it is actually reassuring to observe that the return spillover effect is unaffected by the inclusion of these controls. Finally, we note that both the spillover and reversal are robust to controlling for the mutual fund selling pressure in peer firms (columns 4-6).<sup>23</sup> This suggests that the return spillover we document is not driven by peer firms experiencing distressed selling themselves, a point which we belabor further in the robustness section.

One slightly worrying aspect of Table II is that returns of fire sale stocks already show a small but significant reduction one quarter prior to the fire sale event. This could be indicative of reverse causality: some stocks experience distress and this makes investors to pull out of funds heavily invested in these stocks. While we tackle this concern in the robustness section, we acknowledge that it is difficult to rule this out completely. We note, however, that reverse causality cannot explain the entirety of our findings. In particular, it is hard to explain the return reversal without resorting to price pressures triggered by fire-selling mutual funds. Thus, even if some fire sales have been caused by negative fundamentals, the fire sale events themselves cause an impact-reversal pattern, which we show to be spilling over to peer firms (that do not experience a fire sale themselves). In other words, potential endogeneity

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<sup>22</sup> The coefficient estimates for these control variables mostly have the expected sign: small firms, more-levered firms, firms with fewer analysts, and firms with a lower market-to-book ratio have higher quarterly returns.

<sup>23</sup> The coefficient on the *mfflow* variable is significantly positive as expected, suggesting that higher mutual fund selling pressure (i.e., a more negative *mfflow*) triggers lower returns. The flow measure for non-fire sale mutual funds (*mfflow\_complement*) is not significant.

concerns notwithstanding, the fact that we observe a return shock and its *reversal* for both fire sale stocks and their peers constitutes strong evidence in favor of a spillover mechanism.

## *B. Cross-sectional Tests*

In this subsection, we provide results for two types of cross-sectional tests. First, we study whether the return spillover effect is stronger for peers for which alternative sources of public information are scarce—i.e., when a rational learner would need to place a larger weight on the fire sale stock. Second, we examine whether the spillover is stronger when the peer is more closely related to the fire sale stock—i.e., when the stock price of the fire sale firm should be a more informative signal. As our aim is to study how the spillover effect is mediated by peer characteristics, we focus on the peer firm sample for this analysis.<sup>24</sup>

### *B.1. Sample Splits by Firm Characteristics*

Panel A of Table III shows results for sample splits based on several proxies of a stock's information quality. In our first test, reported in columns 1 and 2, we split peer firms by their size (measured by total assets). The literature routinely finds that small stocks are less efficient and more often mispriced (Lee et al., 1991; Hong et al., 2000; Hou and Moskowitz, 2005). In addition, big stocks are known to lead small stocks in terms of price discovery (e.g., Lo and MacKinlay, 1990; and Hou, 2007). Thus, when conditioning on publicly available prices, investors of small firms should put a lower weight on their own stock and a higher weight on other stocks. As such, small stocks should respond more strongly to a fire sale

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<sup>24</sup> Specifically, we drop all firm-quarter observations surrounding fire sale events within 8 quarters. When we do not drop fire sale firms, we find that some firm characteristics—in particular the absence of an investment grade credit rating—are associated with a stronger fire sale effect. In any case, our results for peer firms are unchanged regardless of whether we include fire sale stocks or not.

hitting one of its peers. The results confirm this intuition: at 2.4%, the spillover effect for small peers is almost twice as large as the one for large peers (1.3%). As shown at the bottom of the table, this difference is statistically significant at the 5% level.

[Include Table III about here.]

Next, we investigate the effect of having an investment grade credit rating. Rating agencies have been found to provide valuable information for stock market investors (Holthausen and Leftwich, 1986) and firms with an investment grade rating should thus be deemed safer than those with a speculative grade rating or no rating at all. We therefore expect a lower return spillover effect for investment grade firms. Columns 3 and 4 of Table III, Panel A indeed show that the spillover effect for non-investment grade firms (i.e., unrated or speculative grade firms) is more than three times larger than the one for investment grade ones—a highly significant difference. In columns 5 and 6, we split peer firms by S&P 500 index membership. Index members are widely recognized and receive more attention by the public media (Chang et al., 2014), which should make their prices more efficient. Consistent with this intuition, we find that the return spillover for S&P 500 members is only half as large as for non-members. This difference is again statistically significant.

Finally, we use financial analyst data to measure a stock's information environment more directly. We start by splitting the sample based on the number of analysts following a firm. The literature finds that analysts provide valuable information to investors and reduce information asymmetry in the market (Brennan and Subrahmanyam, 1995; Womack, 1996; Barber et al., 2001; Gleason and Lee, 2003; Loh and Stulz, 2011; Kelly and Ljungqvist, 2012). Consistently, we find that the return spillover effect is more than twice as large for peer

stocks with below-median analyst following (column 7) compared to those with above-median analyst following (column 8). With a  $t$ -statistic of 1.9, this difference is marginally significant. For our last test, we compute stocks' average (absolute) forecast error (AFE) based on one-year-ahead EPS forecasts over the previous five years. The idea is that stocks with a low AFE have more precise public information and investors should thus place a lower weight on stock prices of their peers (Dessaint et al., 2016). The results shown in columns 9 and 10 confirm this intuition: whereas the spillover effect for stocks with low AFE is 1.2%, it rises to 2.4% for stocks with above-median AFE—again a statistically significant difference.

### *B.2. Cross-sectional Tests by Relationship Characteristics*

In Panel B of Table III, we investigate whether the spillover is stronger for *closer* peers of fire sale firms, or for peers connected to more severe fire sales. To this end, we estimate equation (1) after categorizing peer stocks into groups based on different relationship characteristics between them and their respective fire sale stocks, and separately including different sets of event-time dummy variables for each peer category.<sup>25</sup> We begin by examining whether the return spillover effect is stronger for peers of fire sale firms that experience a larger return drop in the quarter of the fire sale. Specification 1 of Panel B shows that, as expected, the return spillover is larger and highly statistically significant for more severe fire sales, whereas it is insignificant for less severe ones.<sup>26</sup>

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<sup>25</sup> We have to proceed in this way rather than conducting sample splits because the fire sale-peer relationship characteristics are only defined for the peers of fire sale firms and not for the control stocks.

<sup>26</sup> Less severe fire sales exhibit a return of (only) -1% on average; it is thus not surprising that the return spillover onto peers is not significant for this group.

The second relationship characteristic we consider is the similarity score assigned to each firm pair in the TNIC data, which allows us to group peers according to their proximity to the fire sale firm. A higher similarity score means that the peer is a closer rival of the fire sale firm in the sense that they offer more similar products, and we thus expect the return spillover effect to be stronger in this case. The results shown in specification 2 of Panel B confirm this intuition: peers with an above-median similarity score exhibit a price spillover that is three times as strong as the one for peers with below-median similarity score. The difference is strongly statistically significant.

Next, we investigate whether the spillover effect varies with the number of peers of a given fire sale firm. The idea is that the average spillover effect may be weaker when there are many peers, because then the price drop of the fire sale firm is only one out of many available price signals. The results for specification 3 in Panel B are in line with this expectation. For fire sales with ten or more peers, the average spillover effect is 1.7%, compared to 2.1% for fire sales with less than ten peers. This difference is, however, not statistically significant.

Our results so far show that, on average, negative returns for fire sale firms are considered bad news for their peers. In our third cross-sectional test, we study whether there is variation among peers along this dimension. To this end, we estimate return correlations between fire sale firms and their peers (using 8 quarters of daily return data prior to the fire sale). Intuitively, we expect the return spillover effect to be stronger for peers that have a higher return correlation with the fire sale stock. As shown in specification 4 of Panel B, this intuition is clearly borne out in the data: peers with an above-median return correlation to the fire sale stock see a spillover effect of 2.8%, whereas peers with below-median return

correlation only see a price drop of 1.2%. This difference is statistically significant. In principle, bad news about the fire sale stock could even be good news for some peers. We therefore explore the relation between return spillovers and return correlations in more detail. Specifically, in Figure 3, we report the estimated return spillover effects that we obtain when we group peers into quintiles. In the lowest quintile, the spillover effect is still negative, but close to zero and statistically insignificant. In this group, the average return correlation is low but still positive. It thus seems to be difficult to identify peer firms which unconditionally benefit from bad news to one of its product-market competitors. Figure 3 further shows that the return spillover effect rises (almost) monotonically across quintiles. Hence, the stronger the prior return correlation, the stronger the return spillover from the fire sale stock onto its peer.

In our last cross-sectional test, we examine whether the return spillover effect is stronger for peer stocks with a larger turnover-volatility correlation. Banerjee (2011) shows that this correlation may serve as a proxy for the extent to which investors condition on prices. In his model, a low correlation between share turnover and volatility is consistent with investors being oblivious to information contained in prices, whereas a high correlation obtains when investors condition on prices. We therefore group peers based on the turnover-volatility correlation (estimated using daily stock market data over the 8 quarters prior to the fire sale). As predicted by Banerjee (2011), we find that the return spillover effect is significantly larger for peer stocks with an above-median turnover-volatility correlation.

In summary, this subsection shows that return spillovers are stronger (1) for peers whose own prices are less efficient and (2) for peers that are more closely related to fire sale firms.

Overall, these results offer strong support for the information spillover hypothesis. Finally, we acknowledge that there is little evidence that stocks with a larger spillover also display a stronger return reversal. This is likely explained by a loss in statistical power, as returns cumulated over a 1-2 year period tend to be quite volatile. We note, however, that while being statistically insignificant, reversals are typically of the same economic magnitude than those found in Table II and we can never reject the hypothesis of there being a full reversal within four quarters (unreported).

### *C. Robustness*

In this subsection, we examine the robustness of the return spillover. Because many of the control variables used below cannot be defined for fire sale stocks, we exclude all stock-quarter observations within eight quarters of a fire sale. Consequently, we also drop the fire sale dummies from the regressions. The results are shown in Table IV. For comparison, we report in specification 1 of this table the return spillover effect that obtains in this setting if we include all the controls from before. Not surprisingly, the results closely resemble those reported in Table II.<sup>27</sup>

[Include Table IV about here.]

The first alternative explanation we consider is liquidity provision. Even in a world without asymmetric information, price pressure effects arise when market makers are averse to deviating from their target inventory (e.g., Ho and Stoll, 1981; Grossman and Miller, 1988).

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<sup>27</sup> The only difference is that the return reversal is now only marginally significant. However, this is solely explained from the loss in power that comes with the reduction of the sample size (due to the exclusion of all stock-quarter observations surrounding fire sales) as, in terms of economic magnitude, the return reversal continues to completely offset the return spillover effect.

When there is a drop in stock prices due to a fire sale, arbitrageurs have an incentive to provide liquidity to the fire-selling funds, and they may want to hedge their positions by selling peer stocks. If enough arbitrageurs hedge their exposure to fire sale stocks, this could explain why peer stocks also see a small price pressure effect themselves. Our first argument against this alternative explanation draws on the rational learning model that we present in Internet Appendix A. Specifically, we show there that, while both cross-asset learning and cross-asset hedging give rise to price spillovers, only cross-asset learning can also explain the presence of a simultaneous liquidity spillover.<sup>28</sup> Thus, evidence for liquidity spillovers to peer stocks—which we present in subsection IV.C below—favors our learning interpretation over cross-asset hedging.

We now employ two proxies to deal with this concern empirically. Our first proxy is designed to capture liquidity provision by current owners of peer stocks. Indeed, these investors are natural liquidity providers to fire-selling funds as they can buy from them at fire sale prices and hedge their purchases by selling peer stocks without needing to sell short—a trade that promises to return the fire sale discount in expectation.<sup>29</sup> The *liquidity provision* proxy measures the extent by which current peer stock owners enter this arbitrage trade. Specifically, for each stock, we calculate the minimum of the dollar selling volume by its current owners and their corresponding buy volume in fire sale stocks, and scale this by the

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<sup>28</sup> In Cespa and Foucault (2014), hedging by cross-market arbitrageurs even dampens the liquidity spillover as these arbitrageurs absorb part of the selling pressure by distressed funds, thereby mitigating the shock to the price informativeness of the fire sale stock.

<sup>29</sup> In addition to saving the short-lending fee, they may also be more informed about peer stocks compared to other potential liquidity providers, enabling them to guess better the non-fundamental nature of the fire sale shock.

stock's market capitalization. Our second proxy is short interest, i.e. the number of shares on loan as a fraction of the number of shares outstanding, and captures liquidity provision (and corresponding hedging activity) by non-owners of peers stocks. Specifications 2 and 3 of Table IV show the results when we include these proxies as control variables. In both cases, we obtain significantly negative coefficients, consistent with cross-asset hedging having some price impact: more liquidity provision by current owners or short sellers is associated with lower returns for peer stocks. Nonetheless, the return spillover effect (i.e., the coefficient of the *PEER* dummy for  $t = 0$ ) is hardly affected and remains strongly significant.<sup>30</sup> Hence, the drop in the stock price observed for peer firms does not seem to be explained by liquidity provision.<sup>31</sup>

Next, we explore whether peer firms themselves experience mutual fund selling pressure which causes the impact-reversal pattern in their stock returns. Note, however, that this selling pressure could not have been very large, as we require a peer firm *not* to have had a fire sale itself within eight quarters. Nevertheless, since the impact-reversal pattern for peer firms is only one fifth of the fire sale effect, it is conceivable that it was triggered by a small-scale fire sale. In our main specification from Table II, we deal with this concern by including a stock's own *mfflow* as a control variable. The *mfflow* measure turns out to be non-normal and highly skewed, however (see Table I). As a robustness check, we therefore replace it by

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<sup>30</sup> The liquidity provision proxy has a median of 0 and never exceeds 1%. Thus, it appears as if the current owners of peer stocks do not provide much liquidity to fire sale funds, explaining why the price spillover effect is virtually unchanged when we include this control.

<sup>31</sup> The return spillover effect is unlikely to be explained by liquidity providers' short-selling activity for yet another reason. Indeed, if the return spillover comes from the selling pressure induced by short sales, we would expect it to be stronger for peers that are easy to short. In fact, we find the opposite since the return spillover effect is weaker for large stocks and stocks that are member of the S&P 500 (e.g., Saffi and Sigurdson, 2011).

a set of dummy variables that flag different *mfflow* deciles. In different tests, we also control for the fraction of the stock owned by fire sale funds (labeled *fire sale stock share*) and for the portfolio fraction of fire sale stocks held by the mutual funds owning the stock (labeled *fire sale fund share*). Specifications 4 to 6 of Table IV report that the price spillover effect is not affected by any of these changes. We conclude that it is unlikely that the impact-reversal pattern for peer firms is due to forced selling by distressed mutual funds.

We next discuss the possibility that the return spillover effect is explained by a corporate investment channel. Indeed, Dessaint et al. (2016) find that peer firms temporarily curb their investment around mutual fund fire sales. If this cut in investment is tracked or anticipated by investors, this could explain why they discount the shares. To mitigate this concern, we directly control for peer firms' capital expenditures (scaled by the stock of PPE at the end of the previous quarter), obtained from the Compustat quarterly files, in column 7. While the capex control garners a negative significant coefficient (suggesting that higher capex leads to lower returns), its economic magnitude is small, explaining why the return spillover effect is not much affected. This rules out the corporate investment channel as an alternative explanation.

Next, we consider reverse causality: it could be that negative fundamentals about an industry trigger outflows from mutual funds heavily invested in that industry, which forces them to liquidate part of their assets at fire sale prices. The worry is that the drop in returns for peer firms reflects the negative fundamentals instead of being caused by an information spillover channel like we claim. As noted above, the quick reversal of the peer effect is clearly inconsistent with this explanation. We now strengthen this conclusion by showing that the

return spillover effect is robust to controlling for industry trends through the inclusion of industry-quarter fixed effects.<sup>32</sup> The results in the last column of Table IV confirm that the impact-reversal pattern for both fire-sale stocks and their close economic peers is hardly affected by this change. We conclude that the return spillover result is not explained by industry distress.

Finally, we verify that the return spillover result is robust to measuring returns in different ways. Note first that, although we use raw returns for our main spillover tests in Table II, the inclusion of time fixed effects means that we are always neutralizing general market trends. In other words, it is effectively as if we were using market-adjusted returns. In column 8 of Table IV, we further show that the spillover effect survives the inclusion of industry-time fixed effects. This implies that the spillover effect is robust to using industry-adjusted returns. In Internet Appendix B.2, we confirm that we get very similar results if we use different variants of risk-adjusted returns: benchmark-adjusted returns as recommended by Daniel et al. (1997), CAPM-alphas, Fama and French (1993) 3-factor alphas, Carhart (1997) 4-factor alpha, or Fama and French (2014) 5-factor alphas. Indeed, for all these measures, we obtain significant fire sale and peer spillover effects that revert over time.<sup>33</sup> Thus, common risk factors do not explain the impact-reversal patterns that we observe.

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<sup>32</sup> We use the Fama-French 48 industry classification.

<sup>33</sup> For Carhart 4-factor and Fama-French 5-factor alphas, the return reversal for peer firms fails to be statistically significant. However, economically the reversal almost fully offsets the peer spillover effect and we can never reject the null that there was a complete return reversal.

## IV. Additional Evidence

### A. *Placebo*

The “learning channel” explanation for the return spillover of fire sales relies on the presence of uncertainty: investors cannot be sure that the price decline in a fire sale stock is not due to fundamentals and therefore discount its peer firms. In other words, if we were to identify price pressure effects whose causes are well understood by the market, there should be no learning and thus no learning-based spillover. We argue that S&P 500 index additions are ideally suited for this type of placebo experiment.<sup>34</sup> Indeed, the literature finds that stocks that are announced to become a member of the S&P 500 index experience a strong run-up in returns (Harris and Gurel, 1986; Shleifer, 1986; Beneish and Whaley, 1996; Lynch and Mendenhall, 1997; Chen et al., 2004), commonly attributed to the forced buying by passive index funds tracking the S&P 500.<sup>35</sup> While there is no agreement in the literature as to whether this run-up completely or only partially reverses after the addition becomes effective,<sup>36</sup> the crucial feature for us is that the public announcement of the addition should remove any uncertainty regarding the value implications for peer firms. As such, we don’t

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<sup>34</sup> We focus on index additions rather than index deletions because the latter are often confounded by corporate events such as mergers, takeovers, spinoffs, or immanent bankruptcies (Barberis et al., 2005; Patel and Welch, 2016) and tend to be associated with smaller or even insignificant price effects (Lynch and Mendenhall, 1997; Chen et al., 2004; Patel and Welch, 2016).

<sup>35</sup> Consistent with this interpretation, the run-up in returns has been increasing over time concomitant to the growth of passive investment.

<sup>36</sup> It is thus not clear whether the run-up constitutes a pure price pressure effect or also something else. For instance, Denis et al. (2003) show that newly added stocks see a rise in analysts’ earnings forecasts as well as realized earnings and Chen et al. (2004) document evidence of increasing investor awareness in line with the Merton (1987) model. The literature agrees, however, that price pressure is part of the explanation (see, for instance, Lynch and Mendenhall, 1997; Chen et al., 2004, and Chang et al., 2014). Moreover, as documented by Patel and Welch (2016), index additions post 2000 have seen stronger price reversals and are thus more consistent with a price pressure effect.

expect a return spillover due to cross-asset learning for S&P 500 index addition events, even though the run-up in returns is almost as large in (absolute) magnitude as the fire sale effect.

To identify the inclusion effect as well as any potential spillover, we run panel regressions similar to specification (1) but at daily frequency and where the fire sale dummies are replaced by “addition (AD) dummies” that flag the days surrounding an index addition event, defined as the day when a stock’s addition to the S&P 500 index becomes effective according to the Compustat index constituents database. Our sample includes 247 index addition events and 2,502 corresponding peer events over the sample period 1996 to 2013.<sup>37</sup> The peer dummies now flag the economic peers of newly added stocks in event-time and we employ the same battery of controls from before. All regressions include firm and day fixed effects and standard errors are double-clustered at the firm and day level.<sup>38</sup>

[Include Table V about here.]

The results are reported in Table V and visualized in Figure 4. For the added stocks, we find a statistically significant and economically sizable run-up in returns setting in about five days prior to the effective index addition. This is consistent with previous literature (Beneish and Whaley, 1996; Lynch and Mendenhall, 1997; Chen et al., 2004) and reflects the fact that S&P typically announces the index change roughly five days before it becomes effective (Beneish and Whaley, 1996). Column 1 shows, for instance, that added stocks rise by 5.6% over the

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<sup>37</sup> We again focus on the top ten peers excluding all firms that become S&P 500 index members themselves within one year of the respective addition event.

<sup>38</sup> In Internet Appendix B.1, we report similar results using an event study methodology.

eight trading days before the effective date of the addition ( $t=0$ ) and see their returns partly reversed thereafter (see also Figure 4, Panel A). Looking at the peers of added stocks, we find that there is only a weak spillover of this price pressure effect. For instance, in the specification without controls (column 1), peer stocks have an insignificant cumulated abnormal return of only 0.5% over the eight days before the addition (see also Figure 4, Panel B).<sup>39</sup> When all controls are added (column 6), this figure remains small and insignificant. Economically, the spillover to peers is less than 10% when compared to the size of the addition effect, which contrasts with a spillover of about 20% that we found for fire sales (see Section III.A). This suggests that roughly one half of the return spillover for mutual fund fire sales is due to cross-asset learning, whereas the other half is likely explained by cross-asset hedging (and is thus present in both settings). We therefore establish that information spillovers contribute to return comovements over and above what can be explained by cross-asset liquidity provision alone.

### *B. Liquidity Spillovers*

To the extent that fire sales reduce the price informativeness of fire sale stocks, models with learning from prices predict that peer stocks should see a deterioration in liquidity (e.g., Admati, 1985; Cespa and Foucault, 2014). Such a decrease in the price informativeness of fire sale stocks could occur for several reasons. First, the selling pressure by fire sale funds may lead to the perception of higher noise trader risk, for which risk-averse market makers

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<sup>39</sup> If anything, Figure 4, Panel B, shows slowly increasing returns for peer stocks *after* the addition event. This may reflect the existence of a common upward trend underlying all stocks in that industry. After all, stocks that are added to the S&P 500 have been growing in the past and this may be also true for their peers.

would demand higher compensation (e.g., Ho and Stoll, 1981; Grossman and Miller, 1988). Second, when there is uncertainty about whether informed traders are present, a large unexpected fire sale may lead to an update of this probability, causing market makers to increase price impact to protect themselves against the perceived increase in adverse selection (e.g., Easley and O'Hara, 1992). Finally, it is possible that the price drop in fire sale stocks hurts informed arbitrageurs, who in response trade less aggressively, thereby rendering the stock price less efficient (Dow and Han, 2016). Whatever the cause, once price informativeness falls, liquidity providers in peer stocks face higher uncertainty and respond by curbing their liquidity provision. Importantly, this liquidity spillover is a side effect of cross-asset learning—alternative spillover channels such as cross-asset hedging do not make such a prediction.<sup>40</sup>

[Include Table VI about here.]

In this subsection we test whether mutual fund selling pressure hurts the liquidity of fire sale stocks and their peers. To this end, we estimate equation (1) for four different liquidity proxies: bid-ask spreads, the logarithm of the Amihud illiquidity ratio (Amihud, 2002), the probability of informed trading (PIN, Easley et al., 1996), and share turnover. Table VI, Panels A to D, show the results. The first thing to notice is that there is strong evidence for a dry-up in liquidity for fire sale firms with all four liquidity measures. For instance, bid-ask spreads go up by roughly 15-18 basis points (Panel A), representing an increase of 10% relative to the unconditional mean, and remain elevated for about four quarters after the fire sale. For

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<sup>40</sup> See our model in Internet Appendix A for more discussion on this point.

PIN, the increase is smaller with about 4-5% (Panel C) but still statistically significant. For the logarithm of Amihud (Panel B) and share turnover (Panel D), the decrease in liquidity is even larger, but we acknowledge that these results have a mechanical touch to them, as fire sale events are defined as events where funds' selling pressure is large relative to the stock's trading volume (see Appendix B). Overall, the evidence for a deterioration in liquidity is nonetheless overwhelming.

Table VI also shows that the dry-up in liquidity spills over to the economic peers of fire sale firms. Indeed, the event-time dummy for peer firms is at least marginally significant for all four measures of liquidity in the quarter of the fire sale. In terms of magnitude, the liquidity spillover represents between one tenth (for turnover) to one third (for bid-ask spreads) of the original fire sale effect. All these effects disappear after at most two quarters (not shown for brevity), proving that the shock to the liquidity of peer stocks is only temporary. These results are consistent with models of rational learning, which predict that market makers react to the decreased price informativeness of the fire sale stock by curbing back their liquidity provision in peer firms. Indeed, we demonstrate in Internet Appendix A that such a liquidity spillover effect is a unique prediction of cross-asset learning and cannot be explained by alternative spillover channels such as the hedging activity by liquidity-providing arbitrageurs.

## **V. Conclusion**

In this paper we test and confirm a basic tenet of the large literature on trading under asymmetric information—the assumption that investors can and do learn from prices. We test this conjecture in the context of mutual fund fire sales, which have been found to trigger

substantial price pressure effects (Coval and Stafford, 2007). We argue that, when the fire sale occurs, investors are at first unsure whether the price decline is caused by forced selling or negative news about fundamentals. Thus, if investors learn from prices, they should update their expectations of close economic peers. Over time, the non-fundamental nature of the price decline becomes apparent and investors return to their initial expectations. Consistent with this learning channel, we find that the impact-reversal pattern for fire sale stocks spills over onto the stock prices of economic peers. It is precisely the non-fundamental nature of the fire sale shock that helps our identification, as it ensures that this return spillover onto peer firms cannot be explained by investors reacting to new information common to many stocks.

Additional results corroborate the learning channel interpretation. First, the return spillover effect is stronger (1) for peers in a weaker information environment (i.e., smaller stocks, unrated stocks, stocks with fewer analysts, and stocks with larger forecast errors) and (2) for peers that are more closely related to the fire sale firm (i.e., peers with a higher TNIC similarity score or a higher return correlation)—consistent with rational learners placing a larger weight on the stock price of fire sale firms in such cases. Second, we show that another type of price pressure—the S&P 500 index addition effect—leads to a weaker return spillover, consistent with cross-asset learning being less important when the ultimate cause of the price pressure is widely understood by market participants. Finally, we find evidence of a liquidity spillover to peer firms. These findings support recent theory showing how cross-asset learning leads to an interdependence of the informational efficiency across stocks (Cespa and Foucault, 2014).

Apart from identifying learning from prices, these results have broader implications for our understanding of return and liquidity comovements in the stock market. They show that, as investors try to solve the massive filtering problem posed by a stock market in which every price is a potential signal for any other, they occasionally make mistakes and update on noise. Thus, the very fact that investors engage in cross-asset learning causes spillover effects that contribute to the documented comovement in returns and liquidity (e.g., Pindyck and Rotemberg, 1993; Chordia et al., 2000). Future research on the sources of commonalities in returns and liquidity should take this cross-asset learning channel into account.

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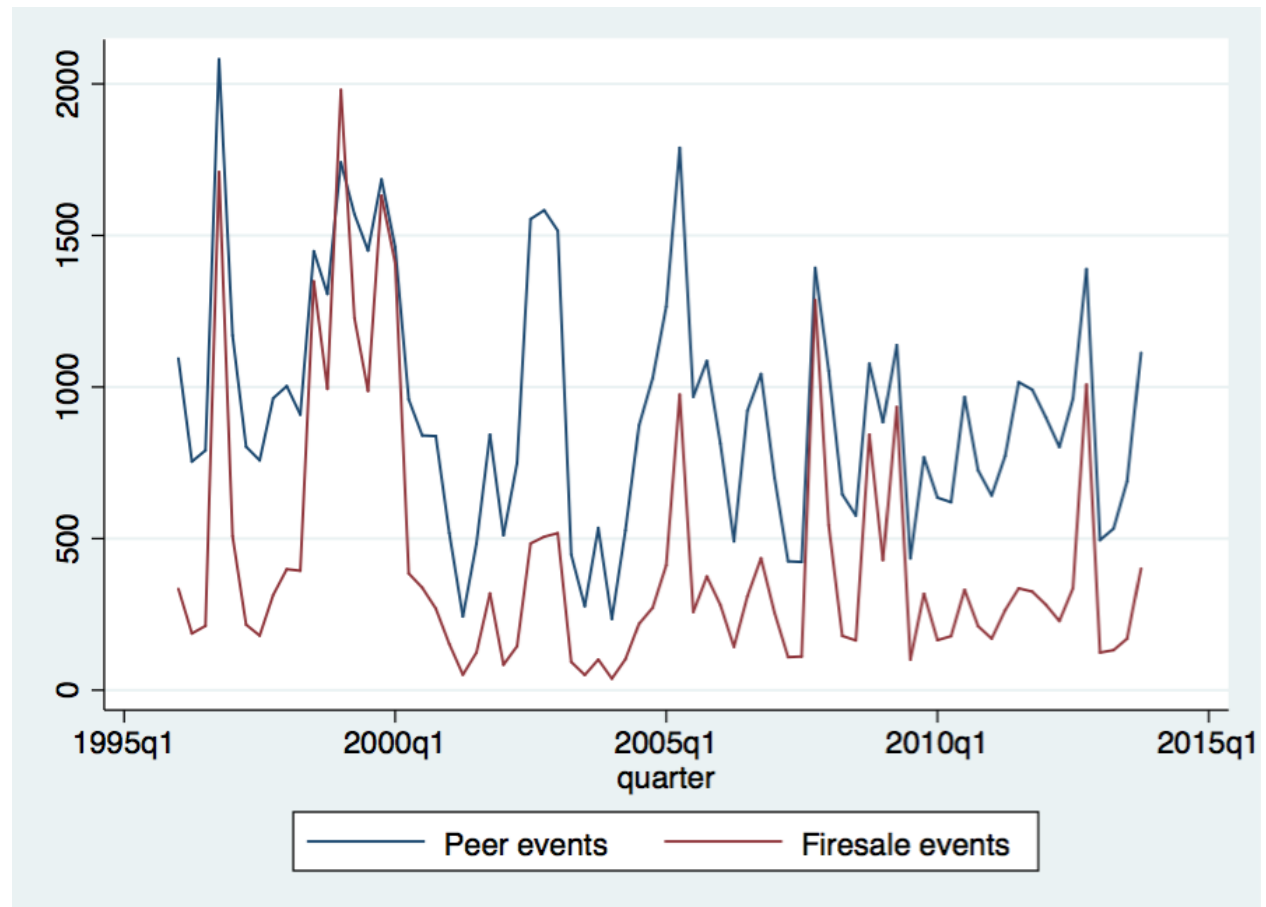
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**Figure 1: Number of Fire Sale and Peer Events over time**

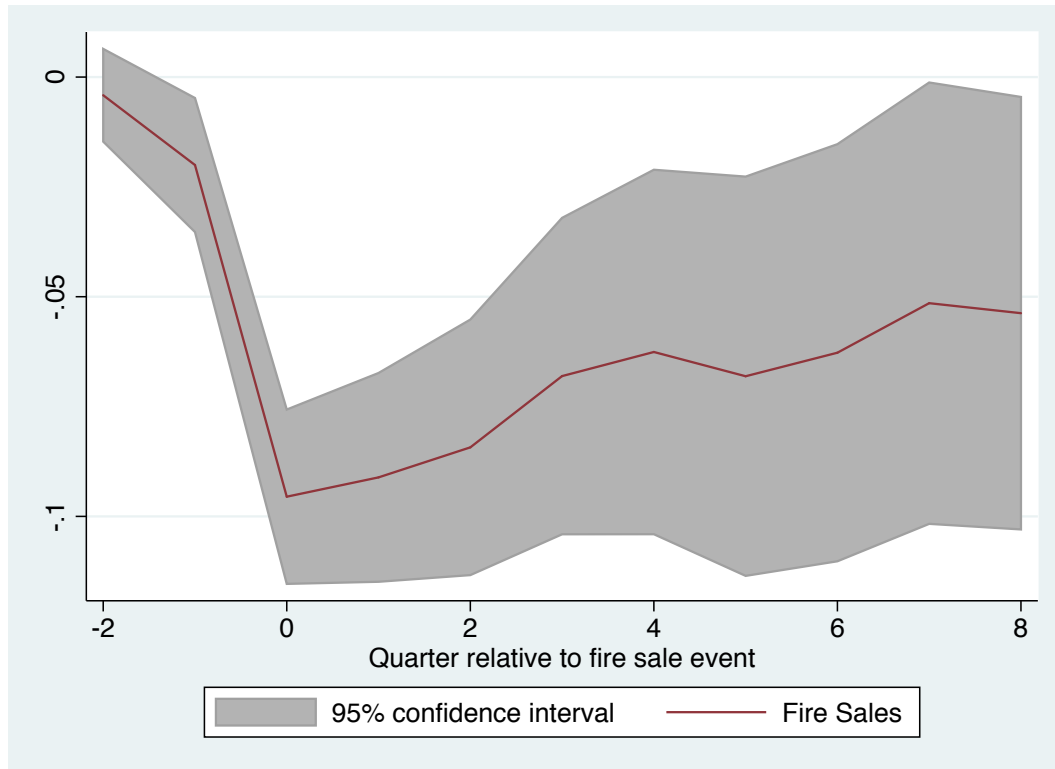
This figure shows the number of fire sale and peer events over our sample period from 1996 to 2013. Fire sale events are defined as in Edmans et al. (2012) [and explained in Appendix B]. For each fire sale event, we define as peer events the ten closest economic peers (according to the TNIC similarity score developed by Hoberg and Philips, 2010a, 2015) that are not undergoing a fire sale themselves in the preceding or succeeding eight quarters.



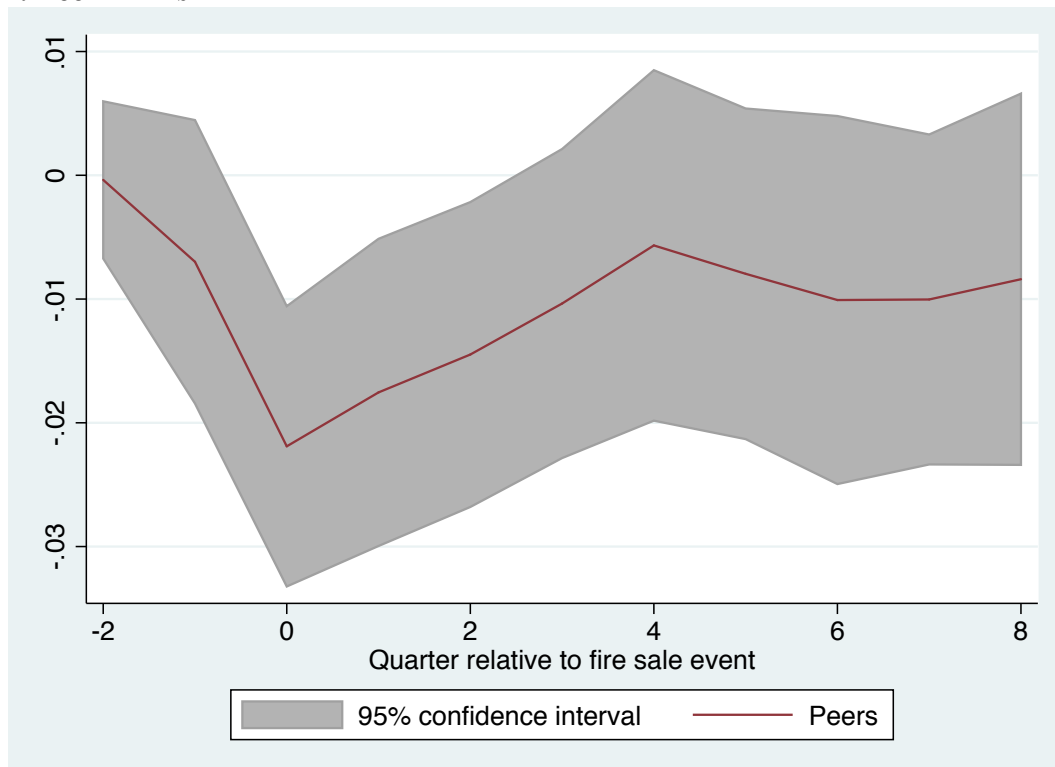
## Figure 2: Event-time Returns for Fire Sale and Peer Firms

This figure shows returns for fire sale firms (Panel A) and peer firms (Panel B) in event-time (where 0 is the quarter of the fire sale). These graphs are based on the cumulated coefficient estimates of the fire sale and peer dummies shown in Table II, column 1. The grey band around the cumulated returns represents the 95%-confidence interval.

### Panel A: Fire Sale Firms

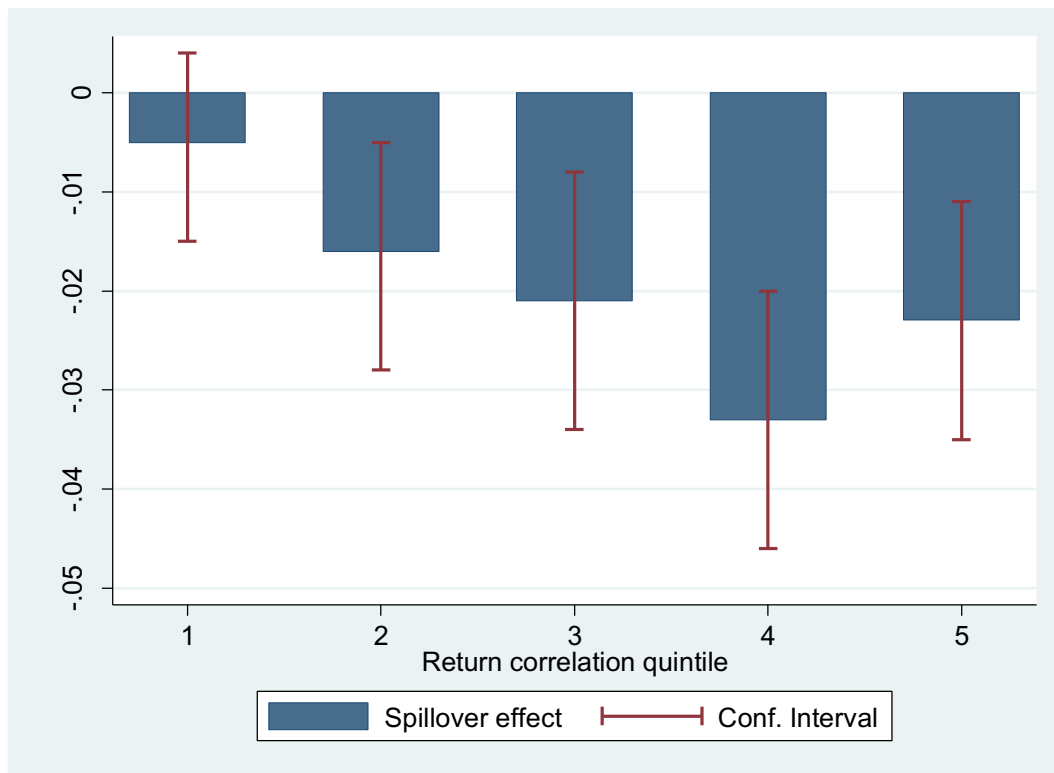


### Panel B: Peer Firms



### Figure 3: Return Spillover Effect for Peer Firms by Return Correlation

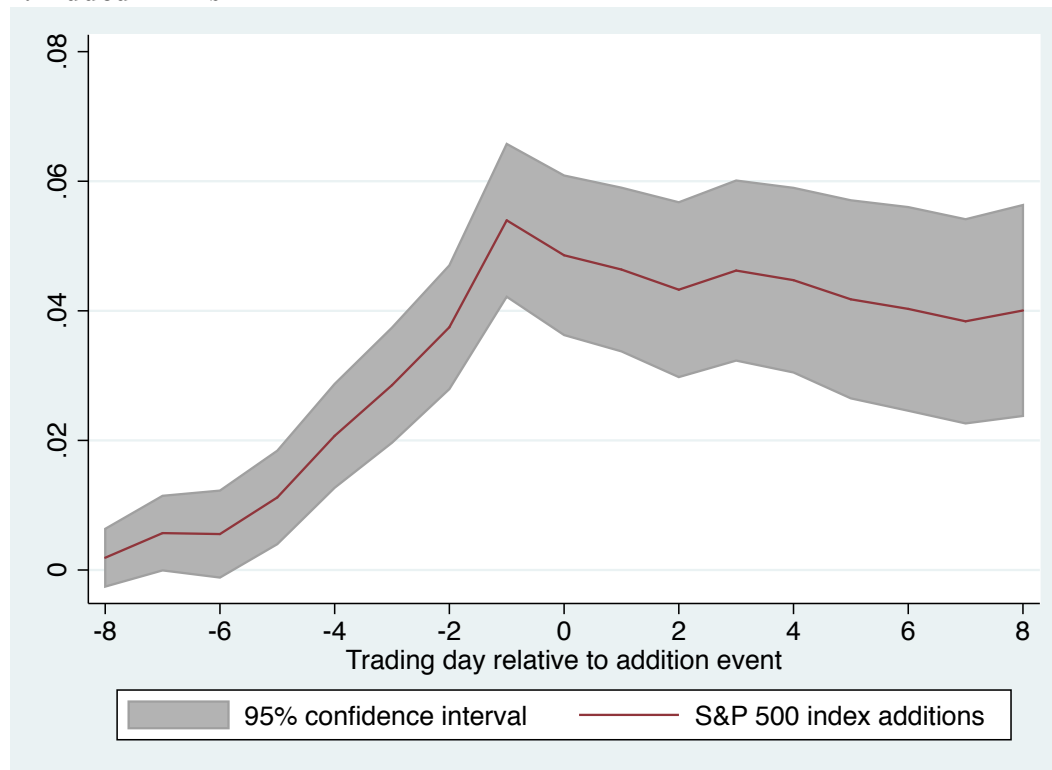
This figure shows the return spillover effect for quintiles of peer firms grouped by their prior return correlation with the fire sale stock. Return correlations are computed using daily stock returns over the 8 quarters prior to the fire sale. The spillover effects are then obtained by estimating equation (1) after replacing the peer dummy variable with five dummy variables for each return correlation quintile. The red lines represent the 95%-confidence intervals based on the standard errors of these estimated dummy coefficients.



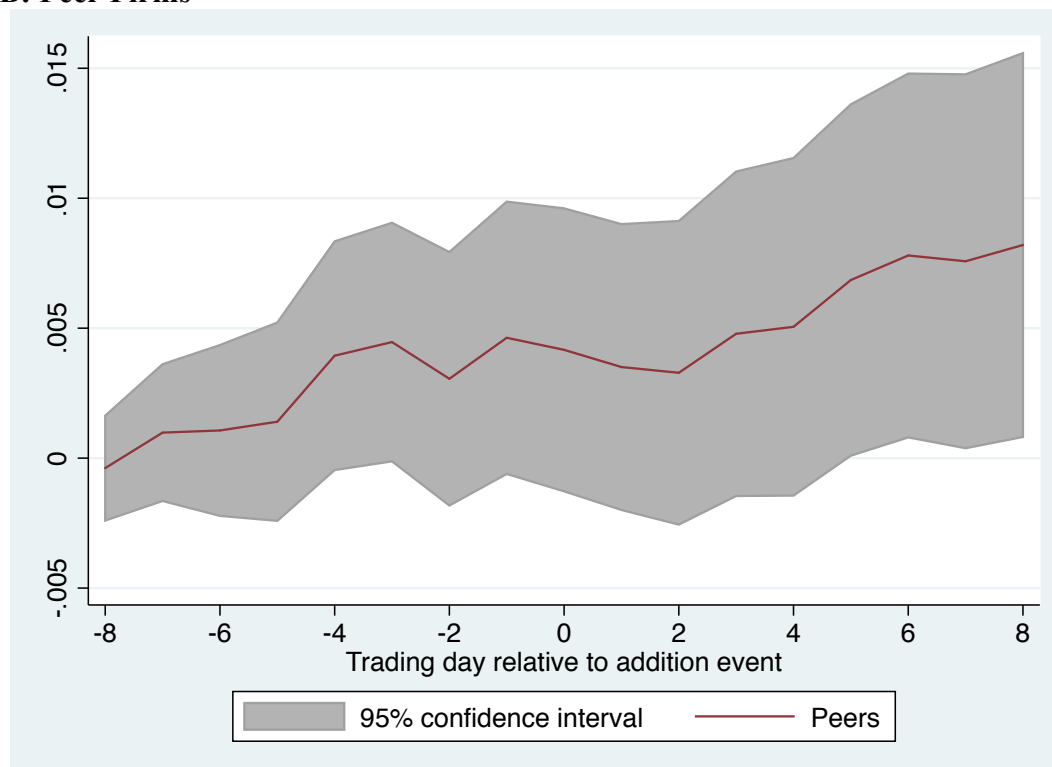
#### Figure 4: Event-time Returns for S&P 500 Index Additions and Peer Firms

This figure shows returns for firms added to the S&P 500 index (Panel A) and their peers (Panel B) in event-time (where 0 is the day when the index addition becomes effective). These graphs are based on the cumulated coefficient estimates of the addition and peer dummies shown in Table V, column 1. The grey band around the cumulated returns represents the 95%-confidence interval.

##### Panel A: Added Firms



##### Panel B: Peer Firms



**Table I: Descriptive Statistics**

This table shows descriptive statistics for the main dependent and control variables used in this study. *N* indicates the number of non-missing observations at the stock-quarter level over our sample period (after dropping non-common shares [i.e., retaining only CRSP share codes 10 and 11], stocks with an end-of-quarter price below \$1, and stocks with less than 10 daily non-missing return observations in a quarter). Return is the compounded quarterly return. Bid-ask spread is defined as the average daily relative bid-ask spread (multiplied by 100). Log Amihud is defined as the natural logarithm of the average ratio of absolute returns over dollar volume scaled by one million. PIN is the probability of informed trading (Easley et al., 1996) estimated at quarterly frequency. Turnover is defined as the total dollar volume in the quarter divided by the market capitalization at the end of the previous quarter. Log turnover is the natural logarithm of one plus turnover. Total assets and return on assets are those reported for the end of the previous fiscal year. Log total assets is the natural logarithm of total assets. Leverage is the ratio of long-term debt and current liabilities over stockholders' equity (at the end of the previous fiscal year). Log leverage is the natural logarithm of one plus leverage. Market-to-book is the ratio of the stock's market value at the end of the previous quarter over the stockholders' equity. Investment (speculative) grade is a dummy variable that indicates whether a firm's long-term debt has an investment grade (speculative grade) rating given by S&P. The remaining fraction of stock-quarter observation does not have a long-term bond rating. Num. analysts is the number of analysts following a stock at the end of the previous quarter. Log analysts is the natural logarithm of one plus the number of analysts. Mutual fund ownership is the fraction of shares outstanding owned by open-ended mutual funds at the end of the previous quarter. Institutional ownership is the fraction of shares outstanding owned by institutional investors at the end of the previous quarter. Mfflow is the selling pressure by mutual funds experiencing a fire sale as defined in Edmans et al. (2012). Mfflow complement is the difference between mutual fund trading pressure by all mutual funds and the selling pressure by fire-selling mutual funds. All variables are winsorized at the 0.5% level on both sides.

				Quantiles		
	<i>N</i>	Mean	S.D.	0.25	Median	0.75
<i>Dependent variables:</i>						
Return	353,146	0.04	0.29	-0.12	0.02	0.15
Bid-ask spread	352,528	2.18	3.19	0.23	1.06	2.83
Log Amihud	353,138	-3.23	3.38	-5.83	-3.34	-0.63
PIN	271,492	0.21	0.12	0.12	0.18	0.28
Turnover	342,933	0.43	0.55	0.11	0.25	0.54
<i>Control variables:</i>						
Total assets	349,785	3,641.55	15,236.01	75.94	324.97	1,355.04
Leverage	348,278	0.9	3.17	0.02	0.37	1.05
Investment grade	353,146	0.13	0.33	0	0	0
Speculative grade	353,146	0.11	0.32	0	0	0
Market-to-book	349,780	3.52	9.08	1.11	1.89	3.47
Return on assets	349,222	-0.04	0.35	-0.02	0.02	0.06
Num. analysts	353,146	5.04	6.33	0	3	7
Mutual fund ownership	353,146	0.16	0.14	0.03	0.13	0.26
Inst. ownership	353,146	0.43	0.31	0.15	0.4	0.7
Mfflow	326,122	-0.01	0.06	-0.01	0	0
Mfflow complement	326,122	0.09	5.53	0	0.01	0.02

**Table II: Return Spillover Effect**

This table reports results from estimating equation (1) at the stock-quarter level. The dependent variable is the quarterly return. The main independent variables are FS and PEER dummies that flag fire sale events and peers for fire sale events, respectively. For example, the FS( $t=4$ ) dummy equals one when the given firm experienced a fire sale 4 quarters ago and the PEER( $t=4$ ) dummy equals one for all peer firms of a firm that experienced a fire sale 4 quarters ago (and that did not themselves experience a fire sale in the previous or subsequent 8 quarters). All regressions include dummies from  $t=-16$  to  $t=16$ ; for brevity we only show the coefficients for  $t=-2$  to  $t=8$ . Firm and quarter fixed effects are included in all specifications. In specification 2, additional firm-level controls are included (logarithm of total assets, logarithm of leverage, investment grade dummy, speculative grade dummy, market-to-book ratio, return on assets, logarithm of number of analysts). In specification 3, ownership controls are included (mutual fund ownership, institutional ownership). In specification 4, mutual fund flow controls are included (separately for fire sale funds and others). In specification 5, ownership and flow controls are included. In specification 6, firm-level, ownership and flow controls are included. All variables are defined in Appendix A. Standard errors are double-clustered at the firm and quarter level.  $t$ -statistics are reported below coefficient estimates in parentheses. At the bottom of the table, we report the sum of the FS and PEER dummy coefficients for windows [1, 4] and [1, 8], respectively, together with the corresponding  $t$ -statistic for the cumulated return reversal. \*, \*\*, \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels.

Event-time	(1)		(2)		(3)		(4)		(5)		(6)	
	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER
$t = -2$	-0.004 (-0.77)	-0.000 (-0.14)	-0.003 (-0.61)	-0.001 (-0.34)	-0.001 (-0.14)	-0.000 (-0.15)	-0.004 (-0.82)	-0.001 (-0.38)	-0.001 (-0.16)	-0.001 (-0.38)	-0.002 (-0.46)	-0.002 (-0.59)
$t = -1$	-0.016** (-2.27)	-0.006 (-1.52)	-0.015** (-2.22)	-0.005 (-1.28)	-0.012* (-1.74)	-0.007 (-1.57)	-0.016** (-2.14)	-0.005 (-1.30)	-0.012 (-1.64)	-0.006 (-1.34)	-0.013* (-1.94)	-0.005 (-1.19)
$t = 0$	-0.076*** (-8.58)	-0.015*** (-3.58)	-0.074*** (-8.53)	-0.015*** (-3.46)	-0.071*** (-8.14)	-0.016*** (-3.75)	-0.071*** (-9.08)	-0.013*** (-3.25)	-0.067*** (-8.66)	-0.014*** (-3.52)	-0.068*** (-8.94)	-0.014*** (-3.33)
$t = 1$	0.004 (0.71)	0.004 (1.42)	0.004 (0.62)	0.005 (1.60)	0.007 (1.21)	0.004 (1.43)	0.005 (0.82)	0.006* (1.91)	0.008 (1.31)	0.006* (1.91)	0.005 (0.88)	0.006* (1.98)
$t = 2$	0.007 (1.10)	0.003 (0.91)	0.007 (1.16)	0.004 (1.24)	0.009 (1.49)	0.003 (1.04)	0.007 (1.12)	0.003 (0.85)	0.009 (1.50)	0.003 (0.96)	0.008 (1.26)	0.004 (1.05)
$t = 3$	0.016* (1.69)	0.004 (1.00)	0.015 (1.66)	0.005 (1.20)	0.018* (1.89)	0.005 (1.12)	0.015 (1.53)	0.004 (0.86)	0.017* (1.71)	0.004 (0.96)	0.015 (1.56)	0.004 (1.03)
$t = 4$	0.005 (0.82)	0.005 (1.23)	0.005 (0.73)	0.005 (1.49)	0.007 (1.08)	0.005 (1.37)	0.008 (1.23)	0.006 (1.46)	0.010 (1.50)	0.006 (1.62)	0.007 (1.17)	0.006 (1.63)
$t = 5$	-0.006 (-0.85)	-0.002 (-0.61)	-0.006 (-0.95)	-0.001 (-0.24)	-0.004 (-0.65)	-0.002 (-0.46)	-0.006 (-0.90)	-0.003 (-0.68)	-0.004 (-0.70)	-0.002 (-0.52)	-0.006 (-0.91)	-0.001 (-0.29)
$t = 6$	0.005 (1.09)	-0.002 (-0.48)	0.005 (1.03)	-0.001 (-0.12)	0.007 (1.39)	-0.002 (-0.37)	0.006 (1.21)	-0.002 (-0.54)	0.007 (1.49)	-0.002 (-0.43)	0.006 (1.24)	-0.001 (-0.19)
$t = 7$	0.011 (1.49)	0.000 (0.06)	0.011 (1.51)	0.001 (0.32)	0.013* (1.69)	0.001 (0.30)	0.011 (1.49)	0.000 (0.12)	0.013* (1.68)	0.001 (0.38)	0.012 (1.55)	0.001 (0.41)
$t = 8$	-0.002 (-0.37)	0.002 (0.51)	-0.003 (-0.51)	0.003 (0.84)	-0.001 (-0.16)	0.002 (0.79)	-0.003 (-0.39)	0.001 (0.44)	-0.002 (-0.22)	0.002 (0.74)	-0.003 (-0.43)	0.003 (0.90)

(continued on next page)

	(1)	(2)	(3)	(4)	(5)	(6)						
<i>(continued from previous page)</i>												
Log total assets		-0.058*** (-10.36)				-0.054*** (-9.21)						
Log leverage		0.045*** (8.61)				0.040*** (7.49)						
IG rating		-0.009* (-1.71)				-0.010 (-1.81)						
SG rating		-0.002 (-0.58)				-0.000 (-0.00)						
Market-to-book		-3.308*** (-6.90)				-3.071*** (-5.79)						
Return on assets		-0.003 (-0.54)				-0.004 (-0.64)						
Log analysts		-0.031*** (-9.70)				-0.021*** (-7.29)						
MF ownership			-0.085*** (-3.54)		-0.084*** (-3.43)	-0.013 (-0.3)						
Inst. ownership			-0.162*** (-9.82)		-0.173*** (-10.02)	-0.103*** (-6.51)						
Mfflow				0.078** (2.43)	0.071** (2.29)	0.073** (2.23)						
Mfflow compl.				-0.000 (-0.91)	-0.000 (-0.95)	-0.000 (-1.01)						
<i>N</i>	352,870	340,084	352,870	325,817	325,817	315,293						
adj. <i>R</i> <sup>2</sup>	0.153	0.170	0.160	0.163	0.172	0.182						
Firm & qtr. f.e.	Yes	Yes	Yes	Yes	Yes	Yes						
Reversal [1, 4]	0.033** (2.01)	0.016** (2.25)	0.031** (2.02)	0.019*** (2.67)	0.042** (2.56)	0.018** (2.45)	0.035** (2.17)	0.018** (2.37)	0.044*** (2.72)	0.019** (2.55)	0.035** (2.35)	0.019** (2.63)
Reversal [1, 8]	0.042* (1.89)	0.014* (1.69)	0.038* (1.83)	0.021** (2.50)	0.056** (2.53)	0.017** (2.21)	0.044** (1.99)	0.015* (1.75)	0.058** (2.61)	0.019** (2.24)	0.044** (2.15)	0.022** (2.43)

### Table III: Cross-sectional tests for Return Spillover Effect

This table reports results from estimating regressions of quarterly returns on PEER dummies that flag peers for fire sale events. For example, the  $PEER(t=4)$  dummy equals one for all peer firms of a firm that experienced a fire sale 4 quarters ago (and that did not themselves experience a fire sale in the previous or subsequent 8 quarters). All regressions include dummies from  $t=-16$  to  $t=16$ ; for brevity we only show the coefficients for  $t=-2$  to  $t=8$ . Firm and quarter fixed effects are included in all specifications. To focus on how the return spillover effect varies across different firm and fire sale-peer relationship characteristics, stock-quarter observations with fire sales in the preceding or succeeding eight quarters are excluded. Panel A shows results for sample splits: In columns 1 and 2, stocks are split along the median of firms' total assets. In columns 3 and 4, stocks are split into firms with an investment grade rating and others. In columns 5 and 6, stocks are split for whether they are a constituent of the S&P 500 index or not. In columns 7 and 8, stocks are split along the median of analyst coverage. In columns 9 and 10, stocks are split along the median of analysts' average forecast error. Panel B shows cross-sectional tests for different fire sale-peer relationship characteristics. Since these characteristics are defined only for peer stocks in relation to the fire sale stocks to which they are linked, these tests cannot take the form of a sample split. Rather, peers are grouped based on a specific fire sale-peer relationship characteristic and then different sets of event-time dummies are included for each peer group in the same regression. In specification 1, peers are categorized into two groups based on the severity of the fire sale effect (in terms of the drop in raw return for the associated fire sale stock). In specification 2, peers are categorized into two groups based on the peer score given in the TNIC data. In specification 3, peers are categorized into two groups based on whether they are linked with a fire sale stock that has less or more than ten peers. In specification 4, peers are categorized into two groups based on their return correlation with the fire stock to which they are linked. In specification 5, peers are categorized into two groups based on the turnover-volatility correlation of their stock returns. [Banerjee (2011) shows that investors in stocks with a high turnover-volatility correlation condition on prices more.] The return correlation between peer and fire sale stocks as well as the turnover-volatility correlation of peer stocks are estimated using daily return data in the 8 quarters prior to the fire sale. All variables are defined in Appendix A. Standard errors are double-clustered at the firm and quarter level.  $t$ -statistics are reported below coefficient estimates in parentheses. For each sample split, we report the  $t$ -statistic of the difference in the  $PEER(t=0)$  coefficient. At the bottom of the table, we further report the sum of the PEER dummy coefficients for windows  $[1, 4]$  and  $[1, 8]$ , respectively, together with the corresponding  $t$ -statistic for the cumulated return reversal. \*, \*\*, \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels.

Panel A: Sample splits by firm characteristics

	Firm size		Rating		S&P 500 member		Analyst coverage		Average forecast error	
	Small	Large	Other	IG	No	Yes	Low	High	High	Low
Event-time	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	PEER	PEER	PEER	PEER	PEER	PEER	PEER	PEER	PEER	PEER
t = -2	-0.000	-0.000	-0.000	0.000	-0.000	0.001	0.000	-0.002	0.004	-0.005
	(-0.02)	(-0.02)	(-0.01)	(0.15)	(-0.00)	(0.15)	(0.09)	(-0.57)	(0.89)	(-1.20)
t = -1	-0.010	-0.004	-0.009	-0.004	-0.009	-0.005	-0.009	-0.009**	-0.007	-0.012**
	(-1.33)	(-1.33)	(-1.54)	(-1.44)	(-1.51)	(-1.48)	(-1.30)	(-2.23)	(-1.22)	(-2.39)
t = 0	-0.024***	-0.013***	-0.021***	-0.006**	-0.020***	-0.009***	-0.025***	-0.015***	-0.024***	-0.012***
	(-3.81)	(-3.84)	(-4.25)	(-2.06)	(-4.24)	(-2.74)	(-4.36)	(-3.96)	(-4.20)	(-2.95)
t = 1	-0.002	0.000	0.000	-0.001	-0.000	0.002	0.002	-0.001	0.002	0.000
	(-0.40)	(0.12)	(0.01)	(-0.42)	(-0.08)	(0.53)	(0.48)	(-0.23)	(0.53)	(0.11)
t = 2	0.000	0.002	0.002	0.002	0.002	0.001	-0.003	0.003	-0.001	0.005
	(0.07)	(0.58)	(0.48)	(0.61)	(0.46)	(0.39)	(-0.62)	(0.99)	(-0.21)	(1.20)
t = 3	0.002	0.002	0.004	-0.000	0.004	0.001	0.007	0.001	0.002	-0.002
	(0.32)	(0.57)	(0.84)	(-0.13)	(0.78)	(0.25)	(1.27)	(0.36)	(0.48)	(-0.38)
t = 4	0.005	0.006	0.006	0.002	0.006	0.006	0.007	0.006*	0.007	0.008*
	(0.72)	(1.53)	(1.36)	(0.66)	(1.26)	(1.31)	(1.41)	(1.87)	(1.32)	(1.97)
t = 5	0.003	-0.004	-0.002	-0.003	-0.002	-0.004	0.001	-0.007*	-0.003	-0.010**
	(0.45)	(-1.08)	(-0.42)	(-0.89)	(-0.41)	(-1.18)	(0.28)	(-1.96)	(-0.70)	(-2.40)
t = 6	-0.000	0.003	-0.000	0.001	0.001	0.002	-0.000	0.001	-0.003	0.005
	(-0.03)	(0.77)	(-0.00)	(0.42)	(0.14)	(0.61)	(-0.02)	(0.21)	(-0.69)	(1.03)
t = 7	0.005	0.000	0.002	-0.002	0.003	-0.001	0.001	0.003	-0.002	0.004
	(0.91)	(0.07)	(0.51)	(-0.55)	(0.71)	(-0.33)	(0.12)	(0.99)	(-0.37)	(1.02)
t = 8	-0.001	0.003	0.001	0.002	0.001	0.004	-0.002	0.003	0.006	0.001
	(-0.14)	(0.98)	(0.27)	(0.57)	(0.19)	(1.17)	(-0.62)	(0.97)	(1.32)	(0.15)
t-statistic of difference	2.06**		2.71***		2.61**		1.93*		2.50**	
N	89,957	90,175	163,461	25,260	164,587	24,166	103,736	84,014	57,393	57,255
adj. R <sup>2</sup>	0.144	0.199	0.144	0.279	0.141	0.278	0.125	0.232	0.169	0.191
Firm & quart. f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reversal [1, 4]	0.005	0.010	0.012	0.002	0.011	0.010	0.014	0.010	0.010	0.011
	(0.44)	(1.39)	(1.30)	(0.38)	(1.19)	(1.34)	(1.41)	(1.28)	(1.10)	(1.26)
Reversal [1, 8]	0.011	0.012	0.013	0.000	0.013	0.011	0.014	0.010	0.008	0.011
	(0.86)	(1.43)	(1.19)	(0.06)	(1.22)	(1.31)	(1.46)	(0.96)	(0.64)	(0.89)

Panel B: Cross-sectional tests by peer relationship characteristics

	Severity of fire sale		Peerscore		# Peers		Return correlation		Volume-volatility correlation	
	Small	Large	Small	Large	$\geq 10$	$< 10$	Low	High	Low	High
	(1)		(2)		(3)		(4)		(5)	
Event-time	PEER	PEER	PEER	PEER	PEER	PEER	PEER	PEER	PEER	PEER
t = -2	0.002 (0.61)	0.001 (0.20)	0.002 (0.60)	-0.001 (-0.23)	-0.000 (-0.06)	0.001 (0.16)	0.004 (0.90)	-0.003 (-0.72)	-0.001 (-0.15)	0.002 (0.52)
t = -1	0.000 (0.01)	-0.017* (-1.79)	-0.007* (-1.80)	-0.009 (-1.26)	-0.007 (-1.47)	-0.011* (-1.82)	-0.002 (-0.40)	-0.015** (-2.41)	-0.009 (-1.34)	-0.007 (-1.58)
t = 0	0.005 (0.94)	-0.047*** (-5.85)	-0.010** (-2.63)	-0.030*** (-4.53)	-0.017*** (-3.56)	-0.021*** (-4.49)	-0.012** (-2.60)	-0.028*** (-4.95)	-0.015*** (-3.06)	-0.022*** (-5.11)
t = 1	0.002 (0.43)	-0.001 (-0.24)	-0.001 (-0.29)	0.002 (0.43)	-0.000 (-0.05)	0.001 (0.20)	0.002 (0.51)	-0.001 (-0.31)	-0.002 (-0.61)	0.003 (0.79)
t = 2	-0.002 (-0.71)	0.006 (0.93)	0.000 (0.06)	0.004 (0.85)	0.005 (1.28)	-0.004 (-0.97)	0.003 (0.92)	0.003 (0.67)	0.005 (1.29)	0.000 (0.11)
t = 3	-0.004 (-1.18)	0.013* (1.87)	0.001 (0.20)	0.008 (1.29)	0.004 (0.92)	0.002 (0.38)	0.004 (0.94)	0.004 (0.73)	0.004 (0.72)	0.005 (1.05)
t = 4	0.004 (1.02)	0.006 (0.89)	0.004 (1.25)	0.006 (1.22)	0.007* (1.67)	0.002 (0.43)	0.009** (2.04)	-0.001 (-0.21)	0.007* (1.85)	0.002 (0.49)
t = 5	-0.001 (-0.28)	-0.004 (-0.70)	-0.001 (-0.18)	-0.005 (-1.07)	-0.004 (-0.91)	0.002 (0.33)	-0.001 (-0.21)	-0.002 (-0.49)	-0.004 (-0.86)	-0.000 (-0.03)
t = 6	0.003 (0.88)	-0.004 (-0.62)	-0.000 (-0.10)	0.001 (0.23)	0.001 (0.28)	-0.002 (-0.50)	-0.002 (-0.53)	0.003 (0.63)	0.003 (0.63)	-0.004 (-0.76)
t = 7	-0.004 (-0.93)	0.009 (1.51)	0.003 (0.88)	0.003 (0.52)	-0.001 (-0.19)	0.009** (2.02)	0.004 (0.82)	0.005 (1.14)	0.008* (1.72)	-0.000 (-0.02)
t = 8	-0.005 (-1.08)	0.007 (1.28)	0.001 (0.49)	0.002 (0.56)	0.001 (0.22)	0.003 (0.76)	0.004 (1.07)	0.004 (0.88)	0.001 (0.28)	0.006 (1.36)
t-statistic of difference	4.92***		3.44***		1.11		2.89***		1.81*	
N	188,776		188,776		188,776		188,776		188,776	
adj. $R^2$	0.150		0.147		0.147		0.147		0.147	
Firm & quart. f.e.	Yes		Yes		Yes		Yes		Yes	
Reversal [1, 4]	-0.001 (-0.08)	0.023 (1.64)	0.004 (0.64)	0.020 (1.90)	0.017 (1.70)	0.001 (0.10)	0.019 (1.80)	0.004 (0.47)	0.014 (1.53)	0.010 (1.27)
Reversal [1, 8]	-0.007 (-0.93)	0.031 (1.65)	0.008 (0.92)	0.021 (1.66)	0.014 (1.24)	0.012 (0.87)	0.024 (2.01)	0.014 (0.98)	0.022 (2.02)	0.012 (1.27)

**Table IV: Robustness of Return Spillover Effect**

This table reports results from estimating a reduced variant of equation (1) at the stock-quarter level. Specifically, stock-quarter observations with a fire sale in the preceding or succeeding eight quarters are excluded and the main independent variables are PEER dummies that flag peers for fire sale events. For example, the PEER( $t=4$ ) dummy equals one for all peer firms of a firm that experienced a fire sale 4 quarters ago (and that did not themselves experience a fire sale in the previous or subsequent 8 quarters). The dependent variable is the quarterly return. All regressions include dummies from  $t=-16$  to  $t=16$ ; for brevity we only show the coefficients for  $t=-2$  to  $t=8$ . All regressions include firm-level controls (logarithm of total assets, logarithm of leverage, investment grade dummy, speculative grade dummy, market-to-book ratio, return on assets, logarithm of number of analysts), ownership controls (mutual fund ownership, institutional ownership), mutual fund flow controls (separately for fire sale funds and others) and fixed effects as specified at the bottom of the table. Specification 1 reports the return spillover effect when all baseline controls are included. In specification 2, the liquidity provision proxy is added as an additional control variable. In specification 3, short interest is added as an additional control variable. In specification 4, dummies for different mutual fund flow deciles (separately for fire sale funds and others) are used instead of the continuous fund flow variables. In specification 5, the fire sale stock share is added as an additional control variable. In column 6, the fire sale fund share is added as an additional control variable. In specification 7, capx is added as an additional control variable (for visibility, the capx coefficient is multiplied by 1,000). In specification 8, industry $\times$ quarter fixed effects (based on the Fama-French 48 industry classification) are used instead of quarter fixed effects. All variables are defined in Appendix A. Standard errors are double-clustered at the firm and quarter level.  $t$ -statistics are reported below coefficient estimates in parentheses. At the bottom of the table, we report the sum of the PEER dummy coefficients for windows [1, 4] and [1, 8], respectively, together with the corresponding  $t$ -statistic for the cumulated return reversal.

\*, \*\*, \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels.

Event-time	(1) PEER	(2) PEER	(3) PEER	(4) PEER	(5) PEER	(6) PEER	(7) PEER	(8) PEER
t = -2	-0.002 (-0.46)	-0.002 (-0.62)	-0.002 (-0.45)	-0.002 (-0.48)	-0.002 (-0.54)	-0.002 (-0.46)	0.000 (0.09)	0.000 (0.17)
t = -1	-0.007 (-1.27)	-0.007 (-1.34)	-0.006 (-1.26)	-0.007 (-1.33)	-0.007 (-1.31)	-0.007 (-1.27)	-0.007 (-1.48)	-0.003 (-0.97)
t = 0	-0.016*** (-3.74)	-0.015*** (-3.67)	-0.016*** (-3.74)	-0.015*** (-3.73)	-0.016*** (-3.80)	-0.016*** (-3.76)	-0.014*** (-3.80)	-0.009*** (-3.62)
t = 1	0.002 (0.61)	0.004 (1.25)	0.002 (0.60)	0.002 (0.79)	0.002 (0.55)	0.002 (0.60)	-0.000 (-0.14)	-0.001 (-0.50)
t = 2	0.002 (0.67)	0.004 (1.20)	0.002 (0.68)	0.003 (0.98)	0.002 (0.66)	0.002 (0.67)	0.002 (0.56)	-0.001 (-0.55)
t = 3	0.003 (0.87)	0.005 (1.18)	0.003 (0.87)	0.004 (1.11)	0.003 (0.84)	0.003 (0.87)	0.002 (0.61)	0.001 (0.47)
t = 4	0.008** (2.04)	0.008** (2.14)	0.008** (2.04)	0.008** (2.22)	0.007** (2.00)	0.008** (2.04)	0.007* (1.97)	0.005* (1.92)
t = 5	-0.002 (-0.51)	-0.002 (-0.47)	-0.002 (-0.50)	-0.001 (-0.33)	-0.002 (-0.56)	-0.002 (-0.51)	-0.000 (-0.05)	0.000 (0.09)
t = 6	0.002 (0.49)	0.002 (0.42)	0.002 (0.51)	0.003 (0.71)	0.002 (0.58)	0.002 (0.49)	0.002 (0.55)	0.001 (0.42)
t = 7	0.004 (1.09)	0.004 (1.11)	0.004 (1.10)	0.005 (1.36)	0.004 (1.12)	0.004 (1.09)	0.005 (1.64)	0.004 (1.66)
t = 8	0.001 (0.41)	0.001 (0.45)	0.001 (0.44)	0.001 (0.38)	0.001 (0.32)	0.001 (0.41)	-0.000 (-0.02)	-0.001 (-0.24)

(continued on next page)

Event-time	(1) PEER	(2) PEER	(3) PEER	(4) PEER	(5) PEER	(6) PEER	(7) PEER	(8) PEER
<i>(continued from previous page)</i>								
Liquidity provision proxy		-0.022*** (-2.78)						
Short interest			-0.178** (-2.08)					
Fire sale stock share					1.518*** (4.26)			
Fire sale fund share						-0.025 (-0.48)		
CAPX							-0.048** (-2.57)	
<i>N</i>	156,891	149,241	156,891	156,891	156,891	156,891	141,186	156,846
adj. <i>R</i> <sup>2</sup>	0.195	0.198	0.195	0.211	0.198	0.195	0.215	0.263
Firm & qtr. f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Firm & ind×qtr f.e.	No	No	No	No	No	No	No	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flow controls	Yes	Yes	Yes	Yes*	Yes	Yes	Yes	Yes
Reversal [1, 4]	0.015* (1.80)	0.020** (2.47)	0.015* (1.81)	0.018** (2.19)	0.015* (1.76)	0.015* (1.80)	0.010 (1.36)	0.004 (0.88)
Reversal [1, 8]	0.020* (1.84)	0.025** (2.34)	0.020* (1.88)	0.025** (2.33)	0.020* (1.81)	0.020* (1.84)	0.017 (1.60)	0.009 (1.28)

**Table V: Placebo Test for S&P 500 Index Additions**

This table reports results from estimating regressions in the spirit of equation (1) at the stock-day level. The dependent variable is the daily return. The main independent variables are AD and PEER dummies that flag S&P 500 index addition events and peers for these addition events, respectively. For example, the FS( $t=4$ ) dummy equals one when the given firm experienced a fire sale 4 quarters ago and the PEER( $t=4$ ) dummy equals one for all peer firms of a firm that experienced a fire sale 4 quarters ago (and that did not themselves experience a fire sale in the previous or subsequent 8 quarters). All regressions include dummies from  $t=-25$  to  $t=25$ ; for brevity we only show the coefficients for  $t=-8$  to  $t=8$ . Firm and day fixed effects are included in all specifications. In specification 2, additional firm-level controls are included (logarithm of total assets, logarithm of leverage, investment grade dummy, speculative grade dummy, market-to-book ratio, return on assets, logarithm of number of analysts). In specification 3, ownership controls are included (mutual fund ownership, institutional ownership). In specification 4, mutual fund flow controls are included (separately for fire sale funds and others). In specification 5, ownership and flow controls are included. In specification 6, firm-level, ownership and flow controls are included. All variables are defined in Appendix A. Standard errors are double-clustered at the firm and day level.  $t$ -statistics are reported below coefficient estimates in parentheses. At the bottom of the table, we report the sum of the AD and PEER dummy coefficients for windows  $[-4, -1]$  and  $[-8, -1]$ , respectively, together with the corresponding  $t$ -statistic for the cumulated price pressure effect. \*, \*\*, \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels.

Event-time	(1)		(2)		(3)		(4)		(5)		(6)	
	AD	PEER	AD	PEER	AD	PEER	AD	PEER	AD	PEER	AD	PEER
$t = -8$	0.002 (0.85)	-0.000 (-0.24)	0.003 (1.01)	-0.001 (-0.43)	0.002 (0.88)	-0.000 (-0.22)	0.002 (0.86)	-0.000 (-0.12)	0.003 (0.89)	-0.000 (-0.10)	0.003 (1.04)	-0.000 (-0.27)
$t = -7$	0.003 (1.62)	0.001 (0.91)	0.004* (1.90)	0.001 (0.88)	0.003 (1.65)	0.002 (0.92)	0.003 (1.55)	0.001 (0.79)	0.003 (1.58)	0.001 (0.81)	0.004* (1.87)	0.001 (0.78)
$t = -6$	-0.000 (-0.21)	-0.000 (-0.15)	-0.000 (-0.09)	-0.000 (-0.13)	-0.000 (-0.18)	-0.000 (-0.13)	-0.001 (-0.22)	-0.000 (-0.13)	-0.000 (-0.19)	-0.000 (-0.11)	-0.000 (-0.09)	-0.000 (-0.04)
$t = -5$	0.006*** (2.81)	0.001 (0.46)	0.006*** (2.93)	0.001 (0.58)	0.006*** (2.84)	0.001 (0.47)	0.006*** (2.66)	0.000 (0.28)	0.006*** (2.69)	0.000 (0.31)	0.006*** (2.79)	0.001 (0.47)
$t = -4$	0.009*** (3.61)	0.003 (1.49)	0.010*** (3.70)	0.003 (1.64)	0.010*** (3.63)	0.003 (1.50)	0.010*** (3.60)	0.002 (1.35)	0.010*** (3.62)	0.002 (1.37)	0.010*** (3.70)	0.003 (1.50)
$t = -3$	0.008*** (2.92)	-0.000 (-0.06)	0.008*** (3.08)	-0.000 (-0.05)	0.008*** (2.96)	-0.000 (-0.05)	0.008*** (2.87)	-0.000 (-0.01)	0.008*** (2.90)	0.000 (0.00)	0.008*** (3.04)	-0.000 (-0.03)
$t = -2$	0.010*** (4.20)	-0.001 (-0.63)	0.010*** (4.33)	-0.000 (-0.36)	0.010*** (4.22)	-0.001 (-0.61)	0.010*** (4.15)	-0.001 (-0.59)	0.010*** (4.17)	-0.001 (-0.56)	0.010*** (4.30)	-0.001 (-0.40)
$t = -1$	0.017*** (5.31)	0.002 (1.66)	0.017*** (5.20)	0.002 (1.33)	0.018*** (5.32)	0.002* (1.68)	0.017*** (5.15)	0.002* (1.67)	0.017*** (5.16)	0.002* (1.69)	0.017*** (5.05)	0.002 (1.33)
<i>(continued on next page)</i>												

Event-time	(1)		(2)		(3)		(4)		(5)		(6)	
	AD	PEER	AD	PEER	AD	PEER	AD	PEER	AD	PEER	AD	PEER
<i>(continued from previous page)</i>												
t = 0	-0.006*** (-2.72)	-0.001 (-0.99)	-0.006** (-2.57)	-0.002 (-1.15)	-0.006*** (-2.71)	-0.001 (-0.97)	-0.006*** (-2.83)	-0.002 (-1.11)	-0.006*** (-2.83)	-0.002 (-1.09)	-0.006*** (-2.68)	-0.002 (-1.20)
t = 1	-0.003 (-1.66)	-0.001 (-0.73)	-0.003 (-1.61)	-0.001 (-0.63)	-0.003 (-1.65)	-0.001 (-0.71)	-0.003 (-1.65)	-0.001 (-0.87)	-0.003 (-1.64)	-0.001 (-0.85)	-0.003 (-1.59)	-0.001 (-0.82)
t = 2	-0.005** (-2.05)	-0.002 (-1.32)	-0.005** (-2.13)	-0.001 (-1.09)	-0.005** (-2.04)	-0.002 (-1.30)	-0.005* (-1.97)	-0.002 (-1.33)	-0.005* (-1.96)	-0.002 (-1.30)	-0.005** (-2.03)	-0.001 (-1.03)
t = 3	0.001 (0.53)	-0.000 (-0.16)	0.001 (0.68)	-0.000 (-0.22)	0.001 (0.54)	-0.000 (-0.13)	0.001 (0.55)	-0.000 (-0.30)	0.001 (0.55)	-0.000 (-0.27)	0.001 (0.71)	-0.000 (-0.32)
t = 4	-0.002 (-0.95)	0.000 (0.35)	-0.001 (-0.63)	0.000 (0.27)	-0.002 (-0.94)	0.000 (0.38)	-0.002 (-0.99)	0.000 (0.45)	-0.002 (-0.99)	0.000 (0.48)	-0.001 (-0.65)	0.000 (0.39)
t = 5	-0.004 (-1.65)	0.001 (0.90)	-0.003 (-1.49)	0.001 (0.88)	-0.004 (-1.65)	0.001 (0.92)	-0.004* (-1.81)	0.001 (0.90)	-0.004* (-1.81)	0.001 (0.92)	-0.004 (-1.65)	0.001 (0.88)
t = 6	-0.001 (-0.73)	0.001 (1.00)	-0.001 (-0.60)	0.001 (1.07)	-0.001 (-0.72)	0.001 (1.02)	-0.001 (-0.78)	0.001 (0.99)	-0.001 (-0.78)	0.001 (1.02)	-0.001 (-0.64)	0.001 (1.12)
t = 7	-0.001 (-0.42)	0.001 (0.33)	-0.001 (-0.35)	0.000 (0.22)	-0.001 (-0.41)	0.001 (0.35)	-0.001 (-0.42)	0.001 (0.46)	-0.001 (-0.42)	0.001 (0.48)	-0.001 (-0.35)	0.001 (0.35)
t = 8	0.002 (0.89)	0.001 (0.39)	0.002 (0.84)	0.000 (0.15)	0.002 (0.89)	0.001 (0.41)	0.002 (0.96)	0.001 (0.49)	0.002 (0.96)	0.001 (0.52)	0.002 (0.91)	0.000 (0.26)
N	17,739,694		17,035,338		17,739,694		15,953,631		15,953,631		15,442,302	
adj. R <sup>2</sup>	0.002		0.003		0.002		0.003		0.003		0.093	
Firm & date f.e.	Yes		Yes		Yes		Yes		Yes		Yes	
Firm controls	No		Yes		No		No		No		Yes	
Own. Controls	No		No		Yes		No		Yes		Yes	
Flow controls	No		No		No		Yes		Yes		Yes	
Run-up [-4, -1]	0.044*** (8.12)	0.004 (1.34)	0.045*** (8.24)	0.004 (1.44)	0.045*** (8.16)	0.004 (1.37)	0.044*** (7.96)	0.004 (1.34)	0.044*** (7.98)	0.004 (1.38)	0.045*** (8.10)	0.004 (1.37)
Run-up [-8, -1]	0.056*** (7.34)	0.005 (1.63)	0.058*** (7.68)	0.006 (1.66)	0.056*** (7.40)	0.005* (1.69)	0.055*** (7.19)	0.005 (1.49)	0.055*** (7.24)	0.005 (1.57)	0.057*** (7.55)	0.005 (1.54)

**Table VI: Liquidity Spillover Effect**

This table reports results from estimating equation (1) at the stock-quarter level. In Panel A, the dependent variable is the average bid-ask spread (multiplied by 100). In Panel B, the dependent variable is the natural logarithm of the average Amihud ratio (scaled by 1,000,000). In Panel C, the dependent variable is the Probability of Informed Trading (PIN) estimated at quarterly frequency. In Panel D, the dependent variable is the natural logarithm of share turnover. The main independent variables are FS and PEER dummies that flag fire sale events and peers for fire sale events, respectively. For example, the FS( $t=0$ ) dummy equals one when the given firm experienced a fire sale in a given quarter and the PEER( $t=0$ ) dummy equals one for all peer firms of a firm that experienced a fire sale in that quarter (and that did not themselves experience a fire sale in the previous or subsequent 8 quarters). All regressions include dummies from  $t=-16$  to  $t=16$ ; for brevity we only show the coefficients for  $t=0$ . Firm and quarter fixed effects are included in all specifications. In specification 2, additional firm-level controls are included (logarithm of total assets, logarithm of leverage, investment grade dummy, speculative grade dummy, market-to-book ratio, return on assets, logarithm of number of analysts). In specification 3, ownership controls are included (mutual fund ownership, institutional ownership). In specification 4, mutual fund flow controls are included (separately for fire sale funds and others). In specification 5, ownership and flow controls are included. In specification 6, firm-level, ownership and flow controls are included. All variables are defined in Appendix A. Standard errors are double-clustered at the firm and quarter level.  $T$ -statistics are reported below coefficient estimates in parentheses. \*, \*\*, \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels.

**Panel A: Bid-ask spreads**

	(1)		(2)		(3)		(4)		(5)		(6)	
Event-time	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER
$t = 0$	0.154*** (3.63)	0.043* (1.94)	0.160*** (3.88)	0.039* (1.91)	0.173*** (4.02)	0.039* (1.74)	0.156*** (3.00)	0.081*** (5.29)	0.176*** (3.37)	0.075*** (4.94)	0.152*** (3.01)	0.068*** (4.88)
$N$	352,250		339,481		352,250		325,224		325,224		314,711	
adj. $R^2$	0.677		0.689		0.679		0.663		0.666		0.677	
Firm & quart. f.e.	Yes		Yes		Yes		Yes		Yes		Yes	
Firm controls	No		Yes		No		No		No		Yes	
Own. controls	No		No		Yes		No		Yes		Yes	
Flow controls	No		No		No		Yes		Yes		Yes	

**Panel B: Log Amihud**

	(1)		(2)		(3)		(4)		(5)		(6)	
Event-time	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER
$t = 0$	0.311*** (8.45)	0.084*** (5.25)	0.331*** (9.94)	0.075*** (5.94)	0.407*** (11.89)	0.069*** (4.68)	0.305*** (8.47)	0.096*** (5.84)	0.391*** (11.56)	0.077*** (4.97)	0.352*** (11.04)	0.065*** (5.12)
$N$	352,863		340,078		352,863		325,817		325,817		315,293	
adj. $R^2$	0.863		0.903		0.884		0.858		0.881		0.905	
Firm & quart. f.e.	Yes		Yes		Yes		Yes		Yes		Yes	
Firm controls	No		Yes		No		No		No		Yes	
Own. controls	No		No		Yes		No		Yes		Yes	
Flow controls	No		No		No		Yes		Yes		Yes	

Panel C: PIN

	(1)		(2)		(3)		(4)		(5)		(6)	
Event-time	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER
t = 0	0.009*** (5.00)	0.002** (2.20)	0.010*** (5.47)	0.002** (2.48)	0.013*** (7.39)	0.002** (2.02)	0.008*** (4.26)	0.002** (2.23)	0.011*** (6.48)	0.002* (1.91)	0.009*** (5.79)	0.001* (1.78)
N	271,148		262,086		271,148		256,029		256,029		247,998	
adj. R <sup>2</sup>	0.574		0.601		0.588		0.576		0.592		0.609	
Firm & quart. f.e.	Yes		Yes		Yes		Yes		Yes		Yes	
Firm controls	No		Yes		No		No		No		Yes	
Own. controls	No		No		Yes		No		Yes		Yes	
Flow controls	No		No		No		Yes		Yes		Yes	

Panel D: Log turnover

	(1)		(2)		(3)		(4)		(5)		(6)	
Event-time	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER
t = 0	-0.318*** (-19.31)	-0.032*** (-3.91)	-0.317*** (-19.63)	-0.031*** (-4.00)	-0.351*** (-22.59)	-0.027*** (-3.40)	-0.286*** (-17.50)	-0.034*** (-4.20)	-0.316*** (-20.59)	-0.028*** (-3.55)	-0.307*** (-20.34)	-0.028*** (-3.58)
N	342,642		330,256		342,642		316,221		316,221		306,062	
adj. R <sup>2</sup>	0.671		0.687		0.686		0.673		0.690		0.698	
Firm & quart. f.e.	Yes		Yes		Yes		Yes		Yes		Yes	
Firm controls	No		Yes		No		No		No		Yes	
Own. controls	No		No		Yes		No		Yes		Yes	
Flow controls	No		No		No		Yes		Yes		Yes	

## Appendix A: Definition of Variables

Variable name	Source	Definition
Return	CRSP	Quarterly compounded return.
Bid-ask spread	CRSP	Difference between closing bid and ask prices, divided by the mid-price. Daily observations averaged quarterly.
Log Amihud	CRSP	Natural logarithm of the average ratio of absolute returns over dollar volume multiplied by one million.
PIN	Stephen Brown	Probability of informed trading (Easley et al., 1996) estimated at quarterly frequency. Data available at: <a href="http://scholar.rhsmith.umd.edu/sbrown/pin-data">http://scholar.rhsmith.umd.edu/sbrown/pin-data</a>
Turnover	CRSP	Turnover is the total dollar volume in the quarter divided by the market capitalization at the end of the previous quarter.
Log turnover	CRSP	Log turnover is the natural logarithm of one plus turnover.
S&P 500 member	CRSP	Dummy equal to one if the stock is a current constituent of the S&P 500 index.
Total assets	Compustat	Total assets from the previous fiscal year.
Log total assets	Compustat	Log total assets is the logarithm of total assets from the previous fiscal year.
Leverage	Compustat	Leverage is the ratio of long-term debt and current liabilities over stockholders' equity at the end of the previous fiscal year.
Log leverage	Compustat	Log leverage is the natural logarithm of one plus leverage.
Investment grade	Compustat	Investment (speculative) grade is a dummy variable that indicates whether a firm's long-term debt has an investment grade (speculative grade) rating given by Standard&Poors.
Speculative grade	Compustat	
Market-to-book	Compustat	Market-to-book is the ratio of the stock's market capitalization at the end of the previous quarter over the stockholders' equity.
Return on assets	Compustat	Return on assets as reported for the previous fiscal year.
Num. analysts	I/B/E/S	Num. analysts is the number of analysts following a stock and/or issuing recommendations at the end of the previous quarter.
Log analysts	I/B/E/S	Log analysts is the natural logarithm of one plus the number of analysts.
Average absolute forecast error	I/B/E/S	Absolute forecast error for analysts' one year ahead EPS forecasts averaged over the previous five fiscal years.
Mutual fund ownership	Thomson Reuters S12	Mutual fund ownership is the fraction of shares outstanding owned by open-ended mutual funds at the end of the previous quarter.
Inst. ownership	Thomson Reuters S34	Institutional ownership is the fraction of shares outstanding owned by institutional investors at the end of the previous quarter.
Mfflow	S12 / CRSP MF database	<i>Mfflow</i> is the selling pressure by mutual funds experiencing a fire sale as defined in Edmans et al. (2012). See Appendix B for details.
Mfflow complement	S12 / CRSP MF database	<i>Mfflow complement</i> is the difference between mutual fund trading pressure by all mutual funds and the selling pressure by fire-selling mutual funds. See Appendix B for details.
Liquidity provision proxy	S12 / CRSP MF database	For each stock, we calculate the aggregated dollar selling volume in that stock by its current fund owners and their simultaneous aggregate dollar buy volume in peer stocks experiencing a fire sale. We then take the minimum of those two numbers to measure liquidity provision by current owners to fire sale funds. The measure is not defined for fire sale stocks. Because values are very small, we multiply the measure by 1,000,000 for better visibility.
Short interest	Compustat	We average the number of shares held short each month (obtained from the Supplemental Short Interest file) in a given quarter, and scale by the total number of shares outstanding.
Fire sale fund share	S12 / CRSP MF database	Fraction of holdings by current owners invested in fire sale stocks. The measure is not defined for fire sale stocks.
Fire sale stock share		Fraction of shares outstanding owned by fire sale funds (i.e., funds with flow < -5%). The measure is not defined for fire sale stocks.

## Appendix B: Construction of the Edmans et al. (2012) Mfflow measure

We compute the mutual fund selling pressure proxy for each stock as in Edmans et al. (2012). The same approach is also used in Dessaint et al. (2016). We start from the sample of open-ended U.S. equity mutual funds contained in the CRSP Mutual Fund Database. We exclude sector funds (third letter of CRSP objective code equal to “S”)—as they could suffer from reverse causality—and drop all international, municipal, bond and metal funds (investment objective codes 1, 5, 6, 8).

For all remaining funds, we find monthly total net assets ( $TNA$ ) and returns ( $ret$ ). We then compute

$$flow_{j,t} = \frac{(TNA_{j,t} - (1 + ret_{t,j}) * TNA_{j,t-1})}{TNA_{j,t-1}}$$

at quarterly frequency and construct the *mfflow* measure as

$$mfflow_{i,t} = \sum_{j=1}^M flow_{j,t} * \frac{shares_{i,j,t-1} * prc_{i,t-1}}{vol_{i,t}}$$

using only the funds  $j$  which have  $flow < -5\%$  (called “fire sale funds”).  $shares_{i,j,t-1}$  is the number of shares of company  $i$  owned by fund  $j$  in quarter  $t-1$ . ( $shares_{i,j,t-1} * prc_{i,t-1}$ ) gives the total value of investment held in company  $i$  by fund  $j$  in quarter  $t-1$ .  $flow_{j,t} * (shares_{i,j,t-1} * prc_{i,t-1})$  gives the “hypothetical” selling volume (in dollars) by fire sale fund  $j$ . We then sum this hypothetical selling volume over all fire sale funds and scale by trading volume (in dollars) to obtain the *mfflow* measure. Finally, we designate stock-quarter observations in the bottom decile of *mfflow* as “fire sale” events.

Using “hypothetical” rather than actual sales immunizes our approach against selection concerns stemming from funds’ endogenous decisions to sell particular portfolio stocks as opposed to others (Huang et al., 2016). Scaling by dollar volume singles out fire sale events where mutual funds’ selling pressure makes up a large fraction of the overall trading volume, ensuring a large price impact.

Finally, as a control variable, we also construct *mfflow complement* $_{i,t}$  as the sum of hypothetical fund sales (and/or purchases) over mutual funds with  $flow > -5\%$  (non-fire sale funds).

# Securities Lending and Trading by Active and Passive Funds\*

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[\[link to the most recent version\]](#)

## Abstract

I study the market for lending and borrowing securities in the United States. I find that by making securities available for borrowing, mutual funds acquire information about short selling, which they exploit for trading. Funds with discretion in their investment choices re-balance their portfolios away from borrowed stocks, avoiding capital losses on stocks with decreasing prices. Funds also trade more aggressively on stocks with stronger signals. Finally, active funds charge lower lending fees than passive funds, consistent with funds paying for the information with lower fees.

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# 1 Introduction

At the end of 2018, U.S. mutual funds had \$695 billion of outstanding securities loans, representing over 80% of all outstanding short interest.<sup>[1]</sup> The funds earned more than \$2 billion in lending fees during the year, with 28% of active funds and 61% of index funds lending some of their portfolio securities.<sup>[2]</sup> Besides lending fees, lender funds also gain real-time information about short selling in the borrowed stocks. The information is possibly valuable given that short interest has been shown to predict stock price declines.<sup>[3]</sup> This raises the question of whether fund-level borrowing contains information, and whether lender funds exploit this information for trading.

This article is, to the best of my knowledge, the first to use stock-loan level data to study the securities lending practices of U.S. mutual funds. The key finding is that funds use the information they gain from stock lending to rebalance their portfolios away from stocks that are borrowed. In addition, stock loans predict negative future returns that do not revert even twelve calendar quarters after the loan, confirming that the stock loans are a valuable trading signal. Additionally, I find the rebalancing by active funds to be profitable: compared to similar funds, lender funds gain about 18% of the value of the position in the stock by rebalancing away from the borrowed stocks. Finally, I find that active funds charge lower lending fees than passive funds, a result that cannot be explained by differences in loan risk. This is consistent with active funds “buying” information from the borrowers by charging lower lending fees.

I use regulatory filings submitted to the SEC to construct a novel dataset on securities lending by around 3,500 U.S. mutual funds belonging to a sample of the largest mutual fund families. The final dataset contains about 23,000 fund-quarter and 456,000 fund-

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<sup>1</sup>The total value of short interest on 31.12.2018 was \$855 billion. Source: Compustat supplemental short interest file.

<sup>2</sup>Data collected from SEC N-CEN filings.

<sup>3</sup>See, for example, Rapach, Ringgenberg, and Zhou (2016).

stock-quarter observations from 2001 to 2017. Most importantly, the data identify, for each fund, the list of securities that are at least partially on loan. This enables me to study in detail the securities lending and trading practices of mutual funds: specifically, whether funds trade the stocks that are borrowed from them. The data also contain multiple fund-level variables on securities lending: the value of securities on loan, the securities lending collateral held by the fund, as well as the fee income the fund earned from securities lending.

My main hypothesis is that lender funds gain information about short-selling on borrowed stocks, and then use this signal to rebalance away from those stocks. This hypothesis rests on two assumptions. First, borrowing a stock indicates short-selling. Short sellers must borrow the stocks they sell to deliver them to the buyer by the settlement date. There are other reasons to borrow a stock, such as borrowing to vote. However, they are unlikely to be major drivers of borrowing demand, as both the regulation that governs securities loans from mutual funds and many fund issuers' lending policies dictate that the funds must participate in any "material votes" in the borrowed stocks, as these may affect the value of the underlying investments.

The second assumption is that funds can trade on that information. This assumption clearly holds only to the extent that funds have discretion in their holdings and portfolio allocation. To deal with this issue, I classify mutual funds into two categories according to the degree of discretion they have in their portfolio allocations: active funds and index funds. For the purposes of this study, I consider non-index funds as "active"; these funds have few restrictions and can trade on information to improve performance relative to their benchmarks. Instead, index funds have relatively little discretion in their portfolio allocations as they must hold securities within their target index, and can therefore not tilt their holdings aggressively away from borrowed stocks.

To test the main hypothesis, I first investigate whether funds react to stock borrowing

by balancing their portfolio holdings away from borrowed stocks. I do this by regressing fund portfolio weights in stocks on a loan dummy and its leads and lags. The coefficients of the loan dummies provide an estimate of the intensity of rebalancing by lender funds around stock loans. There are, however, potential confounding factors that drive portfolio rebalancing, such as news or other signals observed also by non-lenders. I control for these effects by performing a quasi-difference-in-differences analysis and by including various fixed effects and controls.

Using a large panel regression setting, I find that lender funds with discretion in their portfolio holdings – i.e., active funds – trade in response to the borrowing of a stock. These funds reduce their weight in borrowed stocks by about 2 percentage points compared to similar non-lender funds in the five quarters that follow a loan. Index funds show no statistically significant deviation from similar non-lenders either before or after a stock is borrowed.

Second, I study whether mutual funds’ trading in reaction to the borrowing of a stock is profitable. I examine the returns of the stocks that are lent by each fund type, as well as cross-sectional differences in the returns of borrowed stocks. I find that stock prices decline on average 10% in the eight quarters following a loan from a mutual fund. This finding not only resonates with prior research on short interest and price predictability, but also provides evidence that loan-level signals are valuable. Moreover, stocks for which active funds undertake more rebalancing tend to experience lower returns. I estimate that funds gain about 18% of the initial value of the position by avoiding losses compared to similar funds by reducing their holdings in borrowed stocks.

I find additional evidence consistent with mutual funds trading on the information acquired through stock lending. Funds that have more latitude to trade on the information they gain from borrowers, i.e., active funds, earn lower lending fees. I find no evidence that the lower fees reflect lower risk in lending programs: there is no difference across

fund types in the collateral levels held by lenders. Moreover, mutual funds' loan counterparties are predominantly the final borrowers' prime brokers, that are generally creditworthy. Additionally, as the loans are collateralized at over 100%, securities lending incurs little risk.<sup>4</sup>

Finally, passive funds may be seen as natural lenders, as they have stable and transparent portfolios and little flexibility in their investment choices. As a result, passive funds are less likely to take advantage of short sellers' information or to "front run" them, so short sellers might therefore prefer passive lenders. In support of this idea, I find that 63% of passive funds participate in the lending market compared to 48% of active funds. The fraction of portfolio value on loan for passive funds is also up to three times higher than active funds. However, the variation of this measure within fund issuers is not statistically significant, indicating that there is issuer-level variation in engagement in securities lending. This is also supported by both documentary and anecdotal evidence<sup>5</sup> indicating that issuer-level strategies may affect the quantity and type of securities offered on loan, and whether funds engage in "quantity lending" (pushing as large a share of their holdings as possible) or "quality lending" (lending only high-fee securities).

This article contributes to several strands of literature, including those on the market for lending securities and the role mutual funds hold in the securities lending market. Several studies document the rising importance of lending fee revenues in mutual funds' business model, sometimes at the expense of portfolio returns (Blocher and Whaley 2016; Johnson and Weitzner 2019). Instead, I focus on another, indirect, source of revenues associated with stock lending. I present new evidence that lending funds gain information from borrowers and trade profitably on it. I also present evidence that passive funds

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<sup>4</sup>A lender collateralized at, for example, 102% will incur losses only if the security on loan increases by over 2% within a day and the borrower reneges on the loan, as in this case the collateral will not cover the repurchase of the security at market price. This is further supported by evidence in the N-CEN filings, where *no* lender funds indicate having incurred losses from their securities lending practices.

<sup>5</sup>See, for example, <https://personal.vanguard.com/pdf/ISGSL.pdf> (accessed on 09.10.2019).

earn considerably higher fees from lending than active funds, which is consistent with the latter paying for information with lower lending fees.

Another strand of literature relates to short selling and short selling risk. Engelberg, Reed, and Ringgenberg (2017) show that short selling risk in the form of higher lending fees or unexpected recalls impacts short selling activity negatively, and thus lowers price efficiency. D’Avolio (2002) shows that expensive-to-borrow stocks and recalls are rare on average, but that their incidence increases in the divergence of opinion among investors, and Saffi and Sigurdsson (2011) show that lending supply has a significant positive impact on price efficiency. Kolasinski, Reed, and Ringgenberg (2013) show that stock lending fees are largely insensitive to demand shocks when demand is moderate, but at high demand levels positive shocks lead to significantly higher fees. I contribute to this literature in multiple ways. First, I show that mutual funds are the dominant source of lendable shares, with their outstanding loans covering more than 80% of the total value of short interest. Second, I show that although active funds lend securities, their subsequent portfolio rebalancing implies a lower lending supply by them. Instead, passive funds do not rebalance their portfolios away from the stocks they lend, which suggests that they can act to stabilise lending supply. Their presence may, therefore, contribute positively to the incentives to short sell, thus improving price efficiency.

This article also relates to the literature on passive investment and Exchange Traded Funds (ETFs), where several papers have studied ETFs’ impact on, e.g., stock comovement (see for example Da and Shive (2018)); volatility (see for example Ben-David, Franzoni, and Moussawi (2017)); liquidity (Hegde and McDermott (2004); Richie and Madura (2007); Hamm (2014)); or how they enable a short seller to create a “synthetic short” in hard-to-borrow underlying stocks (see Li and Zhu (2017)). I contribute to this strand of literature by showing that passive funds can contribute to price efficiency by lowering the indirect costs of short selling, and by stabilizing stock lending supply.

The paper proceeds as follows: Section 2 presents the regulations on securities lending by mutual funds. Section 3 details the hypotheses to be tested. Section 4 describes the data and reports descriptive statistics. Section 5 presents the main tests and results. Section 6 presents additional evidence in support of the hypotheses. Section 7 concludes.

## 2 Securities lending market

### 2.1 Regulatory framework

The regulatory framework governing securities lending by funds regulated under the Investment Companies Act of 1940 – which covers most US mutual funds and ETFs – is set in a series of no-action letters between the SEC and fund management companies.<sup>6</sup> The current rules stipulate that funds (1) may lend at most one third of their total assets, (2) must receive collateral at least equal to 100% of the value of investments on loan, (3) must be able to terminate the loan at any time, and (4) should earn a reasonable return on the loan. Additionally, funds should invest cash collateral in securities that offer maximum liquidity and a reasonable return. In practice, collateral is nearly always invested in money market funds or directly in T-bills. The ability to terminate the loans at will essentially means that the loans are overnight and rolled over daily until either party ends the loans. This is a major difference compared to repurchase agreements, which are generally for a fixed maturity.

Even though the lenders pass on the shares and the attached voting rights to the borrower, both the loaned securities and the collateral are recorded in the holdings and balance sheet of a lender fund.

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<sup>6</sup>SEC “no-action letters” can be requested to certify that e.g., a product or service does not constitute a violation of securities law that the SEC would pursue enforcement action against the requester.

Most funds cite the regulatory maximum of one third of total assets as their upper limit on lending, even despite lending much less. One exception to this are State Street SPDR funds, that say they “may lend up to 40% of the value of the fund’s net assets, in line with industry standards and below the regulatory limit of 50%.”<sup>7</sup> The 50% limit referred to by State Street takes into account the fact that the collateral that borrowers post is included in the assets of the lenders, so even with no excess collateral (i.e. collateralization at 100% of the loan value) the fund can lend 50% of its *net* assets, as this then represents only 1/3 of the *total* assets of the fund.

The lending activity itself is generally performed by one of three parties: the custodian that holds the fund’s securities, a third-party lending agent, or by the fund (issuer) itself. In 2019, about 84% of funds had external lending agents, and in about 35% of cases the external lending agent is also the custodian. In total, about 55% of funds had third-party lending agents.<sup>8</sup> Regardless of the identity of the lending agent, it is reasonable to assume that the portfolio managers can get real-time information about any outstanding and newly issued loans, as they should be aware of their actual portfolio holdings, and as loans affect both the total assets of the funds through collateral and the returns of the funds through the lending fees. Moreover, lending fee revenue may, in the case of index funds, impact the tracking error of the fund relative to the index, and thus the funds performance relative to the index. Moreover, as funds identify any outstanding securities loans in regulatory filings, it is clear that this information is available also to the portfolio managers.

Short sellers may not always know what type of lender they face when approaching a lending agent, and prior to engaging the loan. When they approach the internal lending agents of e.g., Blackrock or Vanguard – two of the largest companies that primarily

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<sup>7</sup><https://global.spdrs.com/blog/post/2018/august/a-closer-look-at-securities-lending-and-etfs.html>, accessed on 10.09.2018.

<sup>8</sup>Source: N-CEN filings accessed on SEC Edgar.

issue passive funds – borrowers can be fairly certain that the lender fund is an index fund. They have less such certainty when dealing with third-party lending agents: third-party lending agents such as BBH or State Street handle securities lending for a variety of clients including both active and passive funds. Moreover, most have in place a “queuing” system where all lenders that make a stock available to borrow are placed in a queue in the order of arrival<sup>9</sup>. However, the lending agents may at least informally reveal the type or identity of the lender when negotiating the fee, so as to reassure the borrower e.g., of a lower recall risk or of lesser information leakage. Lenders are also unlikely to know their position in the queue.

## 2.2 Securities lending market structure

A typical securities lending transaction involves four parties. On one side of the transaction, there is the securities lender and its lending agent (who can be either internal or a third-party external agent), and on the other side there is the final borrower and its broker. The lending agent and the broker act as intermediaries between the lender and the borrower, and generally the borrower’s broker commits to finding a lender to enable and settle the borrower’s short positions.

The brokers are generally the largest and most recognised investment banks, and many fund management companies explicitly name the prime brokers that their agents are allowed to lend to in the Master Securities Lending Agreements (MSLAs).

The loans are most often between the lender and the borrower’s broker, who in turn lends the stock further to the ultimate borrower (e.g., a hedge fund). This has two benefits for the lender: the prime brokers are generally much more creditworthy than a typical short seller, and the lenders may not want to reveal its identity or portfolio

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<sup>9</sup>Lending agents may also have other criteria for determining the queue position, such as the size of the available position; larger positions that can fulfil loans on their own are more likely to have higher priority.

holdings to a trader that may trade against it.

Lenders' risks are further mitigated by the order in which collateral and the loan securities are transferred: the borrower posts collateral first, only after which will the lending agent release the securities. The same protections apply when the loans are terminated: the borrower returns the securities, and only then will the lending agent release the collateral. Moreover, loans are always fully collateralised with an average haircut of about 3.5% in the data<sup>10</sup>, and the collateral is adjusted daily to reflect movements in the underlying security. If the borrower reneges on the loan, the lender can simply use the collateral to repurchase the loaned securities on the secondary market.

The broker on the borrower's side does not know who the actual lender is: the lending agent only reveals the identity of the lender to the credit risk department<sup>11</sup> of the prime broker, who contractually must not reveal the lender's identity to the borrower. The lender, on the other hand, knows which prime broker borrows the securities, but does not now know who the ultimate borrower is. While this hides the identity of the borrower from the lender, the position in the borrowed stock is still revealed, as borrowing the stock reveals a short position. If the lender has high confidence that the borrower is informed, the signal he gains from the loan should be valuable and induce him to trade in the same direction as the borrower.

An additional source of protection to the lender comes from the callability of the loan: the lender can at any point in time terminate the loan, and receive the loaned securities back on the settlement date following the recall. This, on the other hand, gives rise to recall risk to the borrower. The borrower or his broker has to find another lender to carry the position. Brokers generally provide a loan "guarantee" to their client: the broker ensures that a client will be able to maintain short positions. If the initial lender

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<sup>10</sup>The "industry standard" and most documents describing lending policies set a minimum haircut or excess collateral of 2%.

<sup>11</sup>The borrower is exposed to credit risk of the lender due to the collateral he posts, and as the value of the collateral is higher than that of the securities he borrows.

recalls the shares, the broker will first try to find another lender, or – if all else fails – buy the security to his own account, and then lend it to the client. This, of course, exposes the broker to risk in the underlying security.

### 3 Hypothesis development

In this section, I outline the hypotheses that I test in this article. The central idea is that by participating in the securities lending market, funds gain real-time information about short selling activity. Portfolio managers decide to make their portfolio holdings available to lend, and a loan signals that a borrower has negative information about the stock, inducing the manager to underweight it in order to reduce downside risk.

A complementary mechanism that leads to the same outcome – funds reducing their holdings of stocks on loan – relies on limited attention by portfolio managers: managers may not actively seek to lend securities to gain information, but more passively make securities available to borrow. A loan then draws the manager’s attention to the stock that is borrowed, in which case the manager pays more attention to other information, such as short interest or analyst reports, about the security.

In either case, the outcome is that the lender fund reduces its holdings of the stock that is borrowed. The first hypothesis that I test is that funds trade on the information they gain from lending:

**Hypothesis 1.** *Lender funds reduce their holdings of the stocks that are borrowed.*

This contributes to pushing down the price to the fundamental value. Moreover, I expect funds to trade more on stocks where they receive a stronger signal, or where they predict more negative returns. This gives rise to the second hypothesis:

**Hypothesis 2.** *Stocks that are rebalanced more by lender funds after an observed loan have more negative returns after the loan.*

This hypothesis is also consistent with mutual funds exerting more price pressure on the stock they trade, i.e., that the effect does not arise through information but through their trading on the underlying.

The short seller may be adversely impacted by the lenders actions in two cases. First, if the lender “front-runs” to trade on the information by selling the stocks that are borrowed or, second, if the lender recalls the loan to trade. The recall risk affects the expected profitability of short selling, as any recalls will force the short seller (or his broker) to either find an alternative lender or close the position. To avoid this, short seller may be willing to pay a higher fee to lenders that are less likely to recall the shares to trade on the information in the first place. This yields the third hypothesis that I test in this article:

**Hypothesis 3.** *Lenders that cannot trade on the information they gain from stock loans earn higher lending fees than lenders that are likely to trade.*

In aggregate, the aim of the tests is to show that funds gain valuable information from lending their portfolio securities to short sellers, and that they use this information to trade. Crucially, I also show that the trading is profitable, i.e., that the prices of stocks on loan decline in the quarters that follow the loan. Additionally, the tests show that trading by lender funds leads to faster convergence in the target stocks.

## 4 Data and variables

### 4.1 Data

The main data sources of this article are mandatory filings that U.S. mutual funds regulated under the Investment Companies Act of 1940 must submit to the SEC. The quarterly N-Q and semi-annual N-CSR filings contain all portfolio holdings as well as

the statements of operations and the statements of assets and liabilities for each fund. In addition, they contain information on the securities lending practices at the fund level – the main focus of this paper: in particular, they identify the securities currently on loan by each fund and the loan collateral aggregated at the fund level. Additionally, in many cases the filings disclose the total dollar amount of outstanding securities loans as well as the fee income earned from securities lending at the fund level.

I hand-collect information for the ten largest mutual fund and ETF issuers in the U.S.<sup>[12]</sup> who together comprise roughly 50% of the total mutual fund market at the end of 2017.<sup>[13][14]</sup>

Additionally, I collect information from N-SAR and N-CEN filings for the universe of U.S. mutual funds. The N-SAR filings contain self-reported descriptive information such as whether the fund is primarily an equity fund, and a self-reported investment style (items 66A and 66B), whether the fund is an index fund (item 69), as well as information on the fund’s investment practices (items 70 A through 70 R). From 2018 onwards, the N-CEN filings replace the N-SAR, and contain some additional more detailed information, such as the identity of the fund’s securities lending agent, and whether the agent is affiliated with the fund issuer.<sup>[15]</sup>

I use CRSP mutual fund data to identify passive funds. If any fund share class is identified as an ETF (index fund) in CRSP, I classify the fund as an ETF (index fund).<sup>[16]</sup>

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<sup>12</sup>Blackrock/iShares, FirstTrust, Wisdomtree, Fidelity, Statestreet/SPDR, Vanguard, VanEck, Dimensional Fund Advisors, Invesco/Powershares, and Franklin Templeton Investments.

<sup>13</sup>CRSP mutual fund holdings.

<sup>14</sup>The data collection from Edgar filings is very labor intensive due to the lack of standardization and consistency in the filings across fund issuers or even within fund issuers over time.

<sup>15</sup>The N-CEN filing also discloses if the fund liquidated any loans, and whether the fund was subject to any “adverse impact” related to the loans, i.e., whether the fund incurred any losses related to the loans; the average monthly value of the securities on loan by the fund; and each fund’s principal brokers and the commissions and trade volume associated with each. For ETFs, I can identify creation and redemption volumes, and the average amounts of cash and in-kind securities included in all creation and redemption transaction during the reporting period, as well as all their authorised participants, i.e., brokers or other traders that are allowed to transact directly with the fund to create and redeem ETF shares against the underlying securities basket.

<sup>16</sup>CRSP groups funds into four categories: no index, index-based, index enhanced, and pure index

The correlation between these measures is about 64%. In the main specifications, I use ETFs as a proxy for passive funds, and active funds as all non-ETF funds. There are non-ETF index funds, although a large share of index mutual funds have at least one ETF share class, which according to the methodology described above effectively classifies them as an ETF. On the other hand, there are also ETFs that are not passive funds (so called “active” or “index enhanced” ETFs). I do not seek to exclude them from the “passive funds” in the sample. This, together with the possible misidentification of non-ETF index funds as active funds, biases any results against finding (1) any effect for active funds, and (2) differing effects for passive and active funds.

Finally, I retain funds that are identified as equity or mixed-strategy funds in CRSP, and drop fixed-income funds. I do not exclude synthetic or derivative-strategy funds, as these often also hold at least some equity securities. I only retain funds that hold US stocks, but I do not require the funds to be exclusively focused on the US market: for example, the SPDR S&P Global Dividend ETF and the Invesco International Growth Fund, which hold both international and US equities, remain in the data.

The final sample that is matched to the CRSP mutual fund database covers the period between Q4 2001 and Q4 2017, and contains about 23,000 fund-quarter observations on lending data, and roughly 456,000 fund-stock-quarter observations for stocks on loan.

## 4.2 Variable construction

I obtain the main variable of interest from the SEC data: the stocks that are at least partially on loan by a fund. I thus get the  $loan_{f,s,t}$  dummy, which indicates at the quarterly frequency that fund  $f$  was lending the stock  $s$  at time  $t$ .

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fund.

The SEC filings also give me fund-level information on the quarter-end securities lending practices of funds: total collateral held against securities loans, the total value of securities on loan, and net asset values ( $collateral_{f,t}, loanvalue_{f,t}, nav_{f,t}$ ) are measured at the fund-quarter level, while securities lending fee income ( $lendingincome_{f,t}$ ) is measured semi-annually. I use these to characterise the magnitude of funds' securities lending activity.

In order to measure the intensity or aggressiveness of funds' lending strategies, I compute multiple variables:  $collateralshare_{f,t}$  is the share of securities lending collateral a fund holds relative to its net assets, while  $lending share_{f,t}$  is the value on loan relative to net assets.  $Numonloan_{f,t}$  is the number of individual securities on loan.  $Numintensity_{f,t}$  is the number of securities on loan ( $numonloan_{f,t}$ ) divided by the total number of holdings, and  $loanintensity_{f,t}$  is the value of securities on loan divided by the total value of holdings in the securities on loan.  $Overcollateral_{f,t}$  measures the overcollateralization or haircut that a lender fund requires from the borrower, and is measured by the ratio of collateral to value on loan. I additionally use these as controls in tests regarding securities lending fees charged by funds.

For the main tests on portfolio rebalancing following lending in Section [5.1](#), I construct a variable to measure a fund's over or underweighting in a stock relative to similar funds. By doing this, I aim to address several factors that could drive the results, such as widely observed news that is available to all investment funds, or stock-specific time-varying effects that impact portfolio allocations, such as index effects. I define the benchmark groups according to fund net asset tercile and CRSP Investment Objective Code (IOC), and compute the quarterly average holding for each stock by funds in each group: for stock  $s$  in time  $t$ , I define the average holding of group  $g$  in stock  $s$  in time  $t$  as

$$\widehat{w_{g,s,t}} = \frac{1}{N_{g,t}} \sum_f w_{f,s,t},$$

where  $N_{g,t}$  is the number of funds in group  $g$  in time  $t$  and  $w_{f,s,t}$  is the holding of fund  $f$  in stock  $s$  in time  $t$ , for each fund  $f$  in group  $g$  in time  $t$ . The overweighting of stock  $s$  by fund  $f$  in time  $t$  is then

$$\Delta w_{f,s,t} = w_{f,s,t} - \widehat{w_{g,s,t}}. \quad (1)$$

The data from mutual fund filings does not directly reveal the lending fees that borrowers pay, but rather the *net fee* that the lender receives after collateral reinvestment income, rebates to the borrower, and the share of income retained by the lending agent. The data thus identify the left hand side of the following equation

$$\begin{aligned} \text{lending income}_{f,t} &= \sum_b [\text{fee paid}_{f,b,t} - \text{rebates}_{f,b,t} - \text{agent fees}_{f,t} + \text{collateral reinv. income}_{f,b,t}] \\ &= \text{fees}_{f,t} - \text{rebates}_{f,t} - \text{agent fees}_{f,t} + \text{collateral reinv. income}_{f,t} \end{aligned}$$

for fund  $f$  and borrower  $b$ . This illustrates that the income a fund earns from securities lending is the sum of the gross fees charged to the borrower and the collateral reinvestment income, less rebates paid to the borrower (from the collateral reinvestment) and fees charged by the lending agent. For most easy-to-borrow stocks, the rebates are positive, meaning that the effective lending fees are low. However, hard-to-borrow stocks have negative rebate rates; the borrower pays the lender a fee in excess of the collateral reinvestment yield.

Rearranging this equation and dividing by the value of securities on loan yields average lending rate charged by the lender:

$$\frac{\text{fees}_{f,t}}{\text{vol}_{f,t}} = \frac{\text{lending income}_{f,t} - \text{collateral reinv. income}_{f,t}}{\text{vol}_{f,t}} + \frac{\text{agent fees}_{f,t} + \text{rebates}_{f,t}}{\text{vol}_{f,t}}$$

My data does not identify the agent fees or rebates paid to the borrower, but I do identify the lending income and the collateral value. I can thus create a proxy for the lending fee by estimating the collateral reinvestment income by multiplying the collateral value by the average contemporaneous money market fund yield.<sup>17</sup> To account for the omission of rebates and agent fees, I include fund issuer fixed effects in all regressions on lending fees and collateral levels. This will account for any systematic differences in agent fees or rebates across fund issuers, and by that address any differences in securities lending strategies. Implicitly, this assumes that the lending agent receives a constant share of lending fee income for any given issuer.

I create the  $\widehat{lendingfee}_{ft}$  proxy by dividing the sum of lending income and collateral reinvestment income by the value of outstanding securities loans, and adjust this for the number of quarters the fund has outstanding securities loans in the half-year period to which the N-CSR report refers to. Finally, I annualise the lending fee rate by multiplying by 2.  $\gamma_{it}$  is the unobserved issuer fixed effect.

$$\widehat{lendingfee}_{f,t} = \frac{lending\ income_{f,t} - col_{f,t} * r_{MMF,t}}{loanvalue_{f,t}} \times \frac{2}{q_{f,t}} \times 2 + \gamma_{it} \quad (2)$$

Collateral yield and lending yield are computed by dividing the lending income by collateral and net assets respectively. The dummy variable  $lending_{f,t}$  is equal to 1 if collateral or value on loan is nonzero, and set to 0 otherwise.

Stock-level variables are computed for each stock at the highest available frequency<sup>18</sup>, and aggregated to the quarterly frequency. Short interest is measured as a fraction of the shares outstanding:  $shortint\_scaled_{s,t} = shortint_{s,t}/shrout_{s,t}$ . Short volume, short interest, and fails to deliver are scaled by shares outstanding, and multiplied by 100.

<sup>17</sup>Almost all securities lending collateral is invested in money market funds or U.S. treasuries.

<sup>18</sup>CRSP, short transactions, and fails to deliver are measured daily; mutual fund flows monthly; and Compustat and securities lending data are measured quarterly.

Market capitalization is computed as the product of CRSP shares outstanding and the closing price. The high-low ratio is computed as  $1/2 \times (high - low)/(high + low)$ , and the bid-ask ratio is computed as  $1/2 \times (ask - bid)/(ask + bid)$  using daily CRSP data and then averaged at the quarterly level for each stock. *Volatility* is the average daily absolute value of return over the quarter. All variable definitions are collected in Appendix [A](#).

### 4.3 Descriptive statistics

Table [1](#) presents descriptive statistics for the funds in the sample.

[TABLE [1](#) HERE]

On average, active funds are significantly larger than passive funds, but earn lower lending fees and lending yields. Overcollateralization is slightly higher for active funds when taking an average, but Table [6](#) shows that this difference disappears when including fund issuer fixed effects. The lending intensity measures show that passive funds lend a much larger share of their portfolio securities (24% vs 8%), and a slightly larger share of the total holdings of the stocks on loan (30% vs 24%). This indicates that passive funds lend both more widely (more stocks) and more intensively (a larger proportion of the lendable supply). The Collateral/NAV and Value on loan/NAV measures show that passive funds lend a larger share of their portfolios (5% vs 2%), and naturally hold more collateral as a result as a share of total net assets (6% vs. 3%). The average short interest for stocks on loan is lower for passive funds (11% vs. 13%). Liquidity variables such as bid-ask spread and high-low ratio are slightly lower for stocks on loan from passive funds than from active funds. There is no difference in the market capitalization of the stocks on loan, on the other hand.

## 5 Empirical analysis

In this section, I test the hypotheses presented in Section 3. I begin by testing whether funds react to the signal they get from stock borrowing – the main result of this article. Then, I show that stock loans predict future stock returns, i.e., that the borrowers are informed. Finally, I show that stock lending fees that funds charge are affected by the funds’ ability to trade on the information.

### 5.1 Trading on lending signals

This section presents the main test and results of this paper. Specifically, I identify the stock loan induced trading by mutual funds by comparing the holdings of funds that have the discretion to underweight the lent stocks to funds that do not have this discretion.

The identification relies on the assumptions that (1) index funds do not deviate from index weights, and that (2) similar funds – as measured by their investment objective, index replication status, and total net assets – only differ in the fact that some funds lend while others do not. In short, I assume that similar funds have access to similar information, and that the lending is relatively exogenous at the fund level. Since stock lending happens through a lending agent (internal or external) it is reasonable to assume that the allocation of a loan is relatively random for funds for any given lending agent.

I run the following regression:

$$\begin{aligned} \Delta w_{f,s,t} = & \sum_{k=-8}^8 \beta_k \text{loan}_{f,s,t+k} + \beta_9 \text{loan}_{f,s,t \geq 9} \\ & + \sum_{k=-8}^8 \gamma_k \text{loan}_{f,s,t+k} \text{Active}_f + \beta_9 \text{loan}_{f,s,t \geq 9} \text{Active}_f + \epsilon_{f,s,t}, \end{aligned} \tag{3}$$

where the dummy  $loan_{f,s,t}$  is equal to one when stock  $s$  is on loan by fund  $f$  at time  $t$ , and the  $Active_f$  dummy is equal to one if fund  $f$  is an active fund. The coefficients  $\beta_k$  on the leads and lags of the  $loan_{f,s,t}$  dummy give the event-time variation in  $\Delta w_{f,s,t}$ . This is the baseline result for passive funds' rebalancing of the stocks that are borrowed at  $t = 0$ . The coefficients  $\gamma_k$  on the interaction of the  $loan_{f,s,t}$  and  $Active_f$  dummies show the trading done by active funds when compared to passive funds. The sum of  $\beta_k$  and  $\gamma_k$  thus shows the total effect for active funds' rebalancing in time  $k$ .

The dependent variable measures the difference in portfolio weight between a lender fund and the average holding of funds in its peer group. The interaction between the leads and lags of the *loan* dummy with the *Active* dummy captures any difference in trading by active lenders with respect to passive funds. The null hypotheses are that passive funds do not trade based on the information they gain from loans, and that there is no difference between passive funds and active funds in the quarters that follow a stock loan.

In the baseline specification, I include stock $\times$ quarter fixed effects. In subsequent specifications I additionally include fund $\times$ stock; fund $\times$ quarter; and fund $\times$ quarter and IOC $\times$ quarter fixed effects. The stock $\times$ quarter fixed effects absorb much unobserved fluctuation and take into account time-varying stock effects such as short interest or stock-specific transitional effects that could affect mutual funds' holdings of the stock. One such factor could be index adjustments or inclusions/deletions, that might impact mutual funds' holdings of the stock. It is important to note that including this fixed effect does not change the coefficients' magnitude or statistical significance.

Table 2 presents the results for the regression. For brevity, I omit coefficients for leads exceeding four periods and lags exceeding six periods. The baseline coefficients (that measure trading by full-replication passive funds) are all close to zero and statistically insignificant. On the other hand, the interaction coefficients for active funds are negative

and highly significant in the two quarters that follow an observed loan. Since other information within the funds can reasonably be expected to be the same for similar funds, this differences-in-differences can be interpreted to indicate trading due to lending. Figure 1 presents the aggregate effects for active and passive funds.<sup>19</sup> The coefficients are statistically zero for passive funds, whereas they are negative and statistically significant for active funds in the five quarters following a loan. This indicates that active funds reduce their holdings of the stocks they lend after the loan when compared to similar funds.

Figure 2b presents the cumulative deviation from the peer group average holding for passive and active funds. The trend for both fund types is flat in the pre-lending period, while it drops sharply for active funds after a stock is borrowed. The cumulative deviation in holdings in the event window is about 2.2% for active funds, and the change occurs in the two quarters following stock loans. For passive funds, although there is an indication of a declining trend after the loan, the deviation from the group average holding becomes statistically significant at the 5% level only five quarters after a loan.

In (unreported) robustness checks, I perform the same analysis using fixed-effects estimation instead of the differencing technique as defined in specification 3 to avoid the overestimation bias concerns raised in Gormley and Matsa (2014).

[TABLE 2 HERE]

A concern is that stock borrowing might coincide with another factor that leads to a subsequent reduction in holdings. One such factor could be an exogenous increase in a fund's position in a stock, which makes the fund more likely to lend the stock (as the fund now has a larger supply of the stock). The fund would then reduce its holdings in the

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<sup>19</sup>The total effect for passive funds is equal to the baseline coefficient, whereas for active funds it is the sum of the baseline coefficient and the marginal effect for active funds.

stock to return to its “target allocation.” In this case, we should observe an increase and a subsequent corresponding decrease in holdings relative to the mean. Indeed, there is a small statistically significant increase in holdings prior to lending. This can, potentially, be attributed to an accumulation effect where a fund does not become a viable lender until it has accumulated a sufficient level of holdings. The decrease relative to the group average holding is considerably larger after the loan, as can be seen from the cumulative effects in Figure 2b. This contradicts the story of a reversal to the mean.

Another concern is that active funds are simply reacting to high short interest, and that lending is just correlated with this. This concern is, however, mitigated in two ways. First, the quasi difference-in-differences regression method address this, as short interest should be available to the same extent to similar funds, regardless of whether they are lending securities or not. If the effects were due to short interest, the diff-in-diff methodology should not show any significant coefficients. Second, the stock $\times$ quarter fixed effects in all regression specifications should eliminate any time-varying effects for stocks, such as changes in short interest.

To further understand the mechanism behind the trading and to see whether this arises from information, I perform a variety of sample splits, where I again regress  $\Delta w_{f,s,t}$  on leads and lags of the lending dummy for the different subsamples. In short, I test whether funds react more to stock borrowing when information is scarce and when borrowing is likely to provide additional information to the lender than when lenders are likely to have more information from other sources. I split the panel in two according to portfolio weight, short interest, market capitalization, S&P 500 index membership, investment grade debt rating, and fund total net assets.

The results from these regressions are presented in Table 3. We see that funds react more aggressively when the borrowed stock has a high portfolio weight. Larger positions have a higher impact on fund returns, and fund managers may, therefore, be more sensitive

to new information about the stocks and more readily adjust the positions, especially in order to avoid losses. The results for short interest show that the level of short interest has little impact on the reaction to the borrowing information. We also see that funds rebalance more heavily away from stocks with high market capitalization and an investment grade rating. This may indicate that fund managers react to information presenting a contrarian view on the borrowed stocks. On the other hand, S&P 500 membership, here proxying for media and analyst attention, has little impact on active funds' reaction to stock borrowing. Finally, smaller funds react more aggressively to new information. This may be due to either smaller absolute position sizes (that are easier to trade), or that smaller funds have less access to other information such as analyst reports.

[TABLE 3 HERE]

The negative and significant coefficient in the interaction of the active lending dummy one quarter after the loan indicates that portfolio managers do, indeed, react to lending more when short interest is higher. This can be interpreted as an attention effect: fund managers may react to short selling, but lending draws their attention to it.

## 5.2 Stock returns

In this section, I show that funds have a strong incentive to trade the securities that they lend, i.e., the information they gain is valuable on average.

First, I test whether a stock loan predicts negative returns in an event study setting. Using both raw and risk-adjusted returns, I plot average returns of stocks going forward from an observed loan by a mutual fund, splitting the stock observations by fund type. In the first test, I use every observed fund-stock-quarter loan observation as an event. This assigns more weight to stocks that are more heavily on loan, and reflects the

average post-loan returns for stocks lent by funds of each type. In the second test, I remove duplicate stock-quarter observations from the data. This essentially assigns equal weight to each stock-loan observation. In the third test, I only use the first fund-stock observation within 4 quarters, i.e., I remove continued loans from the sample and only focus on when a fund first starts lending a stock.

The results are summarised in Figure 3 and Table 4. The aim is to display the forward-looking returns of stocks when a fund first starts lending those stocks. In each panel, the stock lending by mutual funds predicts future negative returns. Panels (a) and (b) show the average post-loan cumulative returns for stocks. Panels (c) and (d) show the return paths for loan events with equal weight assigned to each stock-quarter loan observation, i.e., without overweighting stock-quarter events where multiple funds lend the stock. Panels (e) and (f) display the return paths for the first stock loan event for a fund within four calendar quarters, i.e., where loans present for more than one consecutive quarter are omitted.

For active funds, there is little difference between different subsamples: a stock loan predicts future negative returns of about 10% in the next four quarters. For passive funds, the difference between the full sample and non-duplicate sample (panels (b) and (d)) shows that stocks with truly negative returns are over-represented in the borrowing, as cumulative returns stay negative in panel (b), whereas there is a reversal in panel (d) where duplicate events at the stock-quarter level are dropped.

The first fund-stock loan observations (panels (e) and (f)) display more negative cumulative returns than loans on average. This indicates that the first loan observation – when short sellers first start borrowing/short selling – is the most informative of future returns.

[TABLE 4 HERE]

Next, I test whether more rebalancing by lender funds leads to faster price convergence. I do this by splitting the events into two groups according to the change in the number of shares held by lender funds the three quarters following a loan. I run this test on the number of shares instead of the portfolio weight, as declining prices post-lending would mechanically decrease the portfolio weight of the stocks even if the number of shares remained constant (or even increased). Figure 4 and the last regression specification in panels (a) and (b) of Table 5 summarise the results. The stock-loan events where funds reduce their holdings more (panel (a)) show a much faster convergence to fundamental value: prices reach their bottom after only about two quarters, as opposed to the roughly six quarters for stocks that experience less rebalancing by active funds. This is also an indication that trading by active funds speeds up price convergence induced by short selling, which might contribute to improving price efficiency. It is important to note that the effect is also consistent with the funds trading more aggressively on stocks where the borrowing provides more reliable information.

Passive funds, on the other hand, do not significantly rebalance following stock borrowing, as seen in Section 5.1. This is also reflected in the sample split on rebalancing in panel (b) of Table 5: in the bottom group for change in the number of shares, cumulative returns are not statistically significant from zero after 8 quarters. The group with the highest increase in shares held, on the other hand, experiences large significant negative cumulative returns. This likely arises from reverse causality: index funds follow the index weights, so decreasing prices will force them to increase the number of shares they hold in order to maintain their portfolio weights.

[TABLE 5 HERE]

The remaining columns in table 5 present sample split results on stock returns. I split the stock loan events in two according to proxies for the stocks' information environment

as in Section 5.1. The group with low short interest, low market capitalization, and no investment grade debt rating experience much larger negative returns than stocks in the high groups. S&P 500 index membership (and the higher media and analyst attention it proxies for) predicts higher forward looking returns for both active and passive funds, suggesting that stocks with less attention have less efficient prices. This is consistent with the hypothesis that short sellers bring information to the markets.

### 5.3 Trading ability and lending fees

The final hypotheses states that funds that trade or are able to trade on the information they gain from securities loans charge lower lending fees, and thus compensate the borrowers for the information.

I regress the lending fee proxy from equation 2 on a dummy for passive funds funds:

$$\widehat{lendingfee}_{f,t} = \beta_1 Passive_f + family_g + \epsilon_{ft} \quad (4)$$

The coefficient  $\beta_1$  shows if and how passive funds, on average, earn fees that are different from those of active funds. I include a fund family fixed effect  $family_g$  to take into account differences in lending strategies between fund issuers.<sup>20</sup> As a result, the coefficients  $\beta_1$  and  $\beta_2$  capture the “passive fund” effect *within* an issuer, while neutralising any issuer-level effects on lending fees.

Panel (a) in Table 6 presents the results. The results show that passive funds earn about 2.5% higher lending fees than active funds.

One concern could be that passive funds take on more risk in their lending programs in order to boost returns. One way of doing this would be by placing lower collateral

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<sup>20</sup>As mentioned in the Introduction and Section 2, fund issuers have different lending strategies that can aim to e.g., maximise the lending revenues by lending as much as possible, or at maximising the loan-level lending fee.

requirements, and thereby exposing the investors in the fund to the risk that the borrower does not return the security if its price increases. To test this, I use the same model as in regression [4](#), and regress excess collateral on the ETF and Sampling dummies and their interaction. The results are presented in panel (b) of Table [6](#). We see that the coefficients are very close to 0, and are not statistically significant in any specification.

[TABLE [6](#) HERE]

## 6 Additional evidence

### 6.1 Gains from trading

From sections [5.1](#) and [5.2](#), we see that active funds reduce their holdings of stocks that they lend, and that the prices of these stocks decrease subsequent to lending. From here it can be inferred that funds gain from selling the stocks that are borrowed by avoiding capital losses on them. However, the typical stock on loan by an active fund has a portfolio weight of only about 0.58%, so capturing rebalancing-induced gains at the fund level is difficult due to the small magnitude.<sup>[21](#)</sup>

Instead of focusing on fund-level returns, another way to measure the value of lender funds' information is to calculate how much they benefit from rebalancing their portfolio away from the stock. More precisely, I can compute the magnitude of avoided losses for lender funds at the position level by using the amount of rebalancing relative to peer funds from Section [5.1](#) and the returns of stocks on loan from Section [5.2](#).

I use cumulative rebalancing for each period  $t$   $\sum_{k=0}^t \Delta w_{f,s,k}$ , and multiply by the return of the stock  $r_{s,t}$  in the corresponding quarter to get the per-period gain (relative to peer

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<sup>21</sup>For example, a fund that reduces an average position in a stock by 50%, and avoids losses of 30% on that, would only gain about 9 basis points at the fund level.

funds):  $gain_{f,s,t} = r_{s,t} \times \sum_{k=0}^t \Delta w_{f,s,k}$ . I cumulate this to find the cumulative gains for active funds from the rebalancing:  $cumulative\ gain_{f,s,t} = \sum_{k=0}^t gain_{f,s,t}$ . The values are presented in Table 7. I find that active funds avoid losses of about 11 basis points of portfolio value over the first 8 quarters following a loan for each stock loan position relative to similar peer funds. The effect is small at the fund level, but amounts to roughly 18% of the average position size of a stock on loan (0.106/0.58).

[TABLE 7 HERE]

This in itself shows that the lending-induced trading is both informed and profitable.

## 6.2 Market participation

Passive funds have stable and transparent portfolios, and unlike active funds have little discretion in choosing their investment allocations. Anecdotally, short sellers may prefer them as lenders, as they cannot trade on the information revealed by the borrowing. To this end, I show that passive funds are more likely to participate in the lending market than active funds. This is consistent with the preference for passive funds.

I regress the lending dummy (equal to 1 if the fund lends securities, 0 otherwise) on an ETF dummy in order to compare the two fund types. I control for various portfolio characteristics, as well as time and fund issuer fixed effects. The results are presented in panel (a) of Table 8a. Specification (1) shows that passive funds are, on average, about 16% more likely to lend securities than active funds. Controlling for fund size and management fee, this effect rises to over 23% (specification (2)). In specifications (5)-(8), the ETF dummy measures the within-issuer effect of being a passive fund: indeed, the coefficient is higher than for passive funds on average. This may indicate that fund issuers prefer lending securities through their passive funds instead of through their active funds. This is consistent with the results in Section 5.1, where I show that active

funds sell their holdings of the stocks they lend relative to similar non-lender funds. Fund issuers may prefer to lend from their passive funds, and thus be able to both extract information from borrowers while still being able to trade through their active funds.

[TABLE 8 HERE]

Finally, I study lending by U.S. mutual funds at the intensive margin. This gives us a better understanding of the lending strategies of mutual funds. I regress the value of loans as a share of total assets on an ETF dummy and various controls in the same regression specifications as in Panel (a) of Table 8. Again, in specifications (1)-(4), I show that passive funds lend a larger share of their portfolios than active funds: on average, passive funds lend about 2.5 times more of their portfolio by value than active funds. However, the inclusion of issuer $\times$ quarter fixed effects changes the sign of the coefficient, and renders it negative and significant in specifications (7) and (8). The change when measuring the effect within-issuer instead of as a fund type average indicates, once more, that there are significant issuer level differences in lending strategy.

[TABLE 8 HERE]

## 7 Conclusion

Using a unique novel dataset on securities lending by U.S. mutual funds, I show that a large proportion of U.S. mutual funds lend securities, and that this lending provides funds with not only additional revenue in the form of lending fees, but also valuable information through the lending mechanism. Funds that have greater portfolio allocation discretion – namely active funds – reallocate their portfolios away from stocks that are

borrowed from them. Passive funds do not rebalance their portfolios before or after lending a stock, as they have little incentive to deviate from index weights given that they are evaluated mainly on their tracking error: holding all the component securities of an index in the index weights minimises the pre-fee tracking error.

I also show that stock borrowing predicts future returns for the stocks that are borrowed, and that rebalancing away from those stocks avoids losses of about 18% of the value of the position for the lender funds when compared to similar non-lenders.

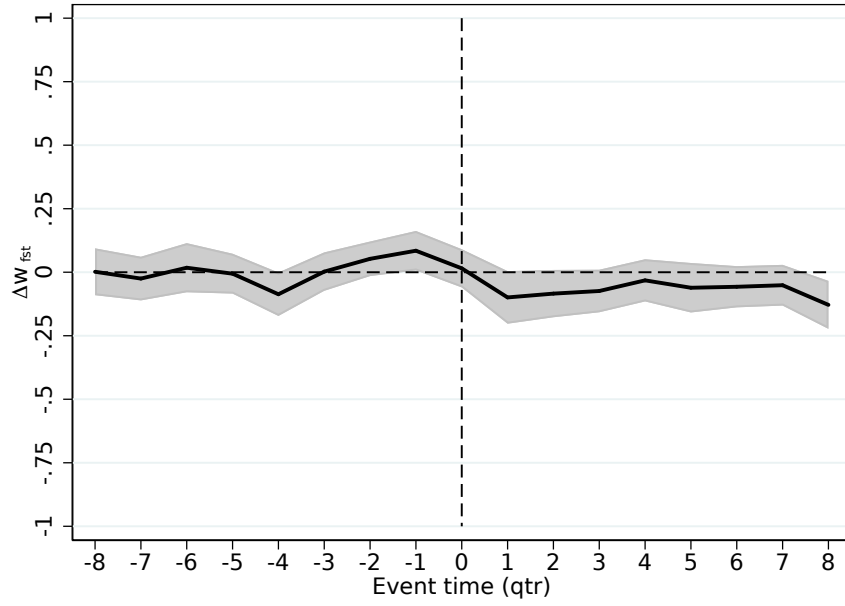
Finally, I find that passive funds gain considerably higher lending revenues than active funds, and that this effect remains when controlling for a variety of portfolio-level characteristics such as short interest and portfolio size. I also show that there is no difference in the collateral requirements between the different fund types, indicating that passive funds do not trade off higher lending fees against lower collateral requirements.

The evidence is consistent with the hypothesis that active funds “buy” information from short sellers by charging them lower lending fees, and then use the acquired information to rebalance their portfolios. These findings shed light on the securities lending and borrowing market as a whole, as well as the securities lending practices of U.S. mutual funds. The results are also of interest to the mutual fund literature, and information acquisition in the financial markets.

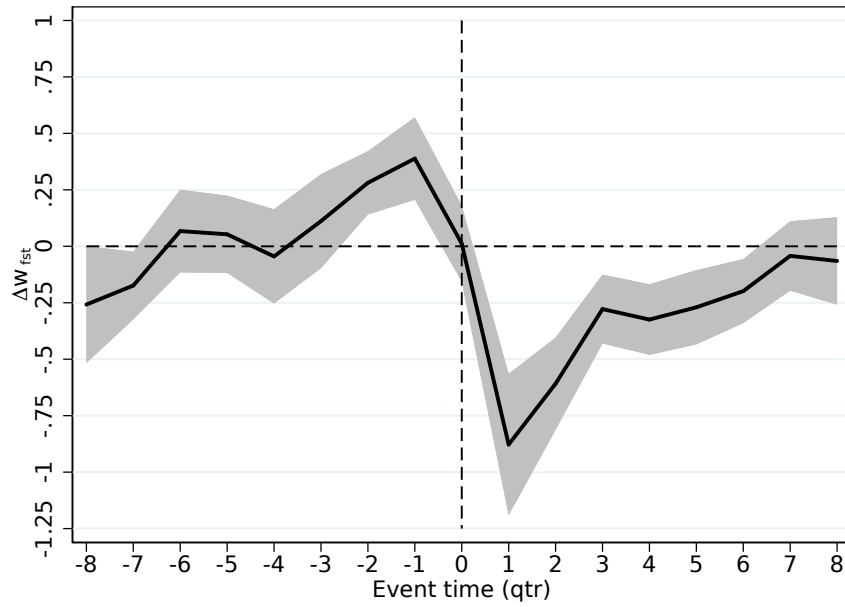
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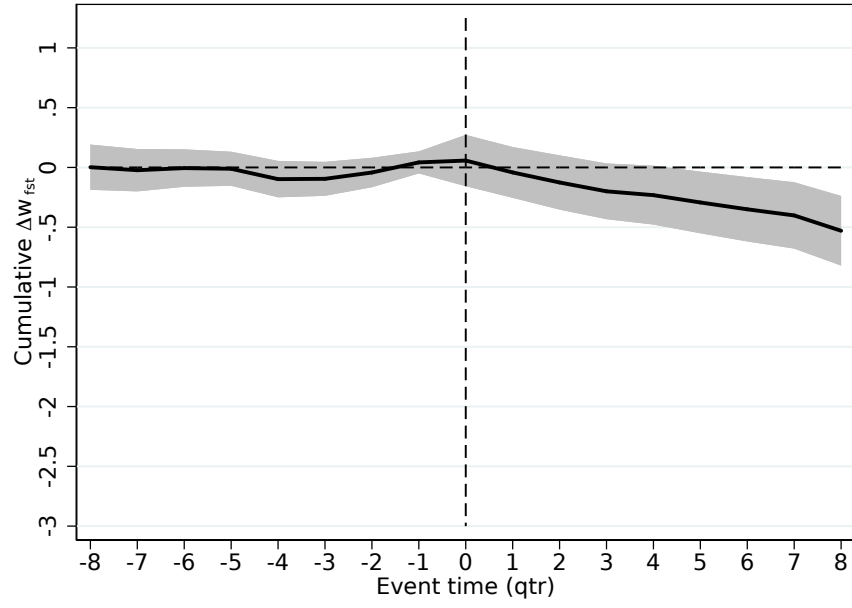
(a) Full-replication passive funds



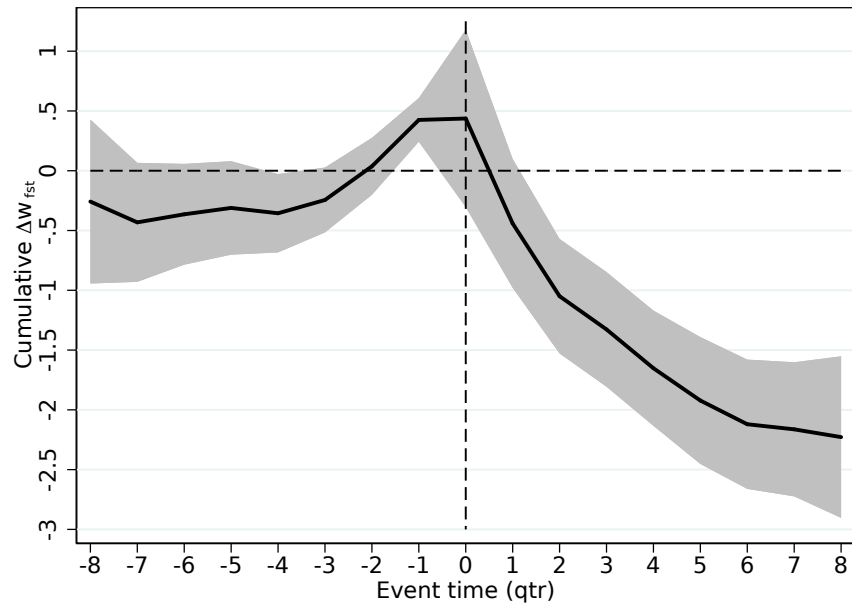
(b) Active funds

Figure 1: Trading – total effects

I regress the deviation from an group-average stock holding for each fund on leads and lags of a stock loan dummy. Figure 1 shows the total effect for passive and active funds. The vertical axis shows deviation from the average holding, and the horizontal axis measures quarters relative to a stock loan.



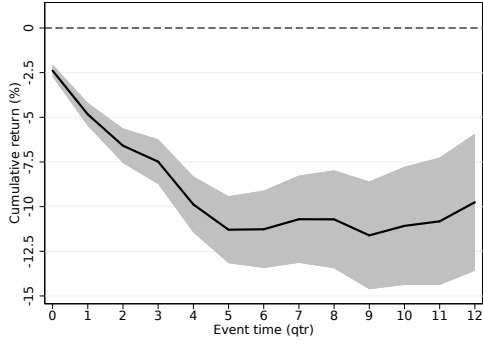
(a) Passive funds



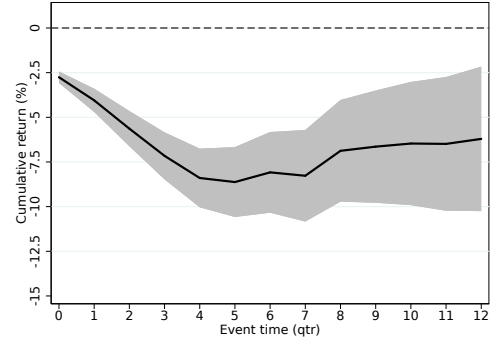
(b) Active funds

Figure 2: Trading – cumulative rebalancing

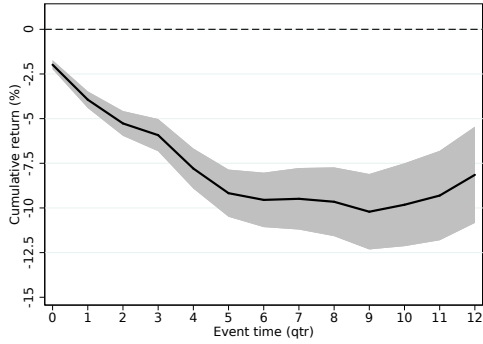
The figure plots the cumulative deviation in portfolio weight from an average of similar funds. The coefficients shown here are the cumulative sum of the coefficients from Figure [1](#)



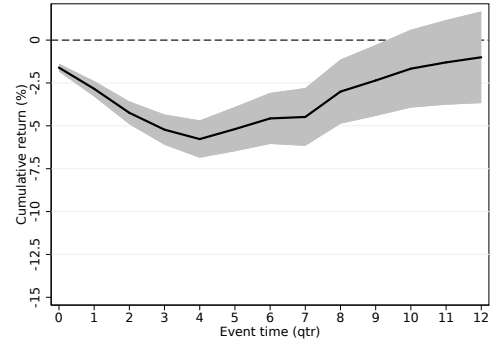
(a) Returns on loan stocks – Active funds.



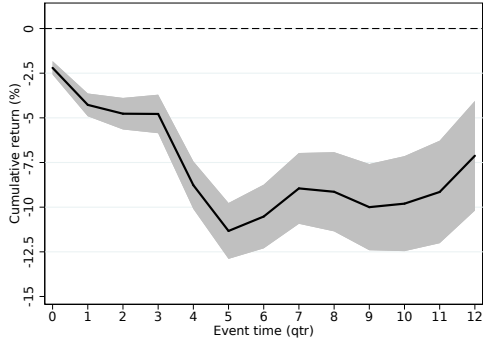
(b) Returns on loan stocks – Passive funds.



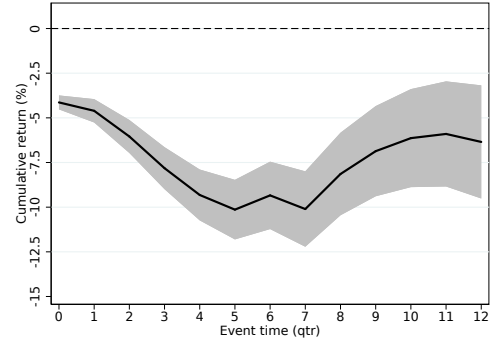
(c) Returns on loan stocks – Active funds (no duplicate events).



(d) Returns on loan stocks – Passive funds (no duplicate events).



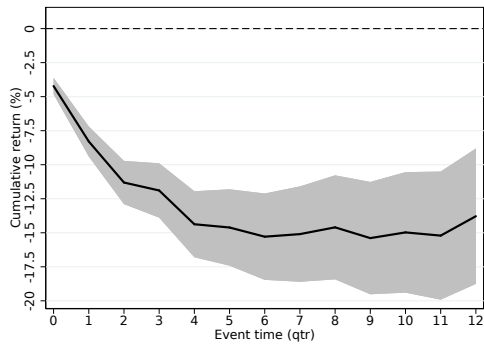
(e) Returns on loan stocks – Active funds (1st loan).



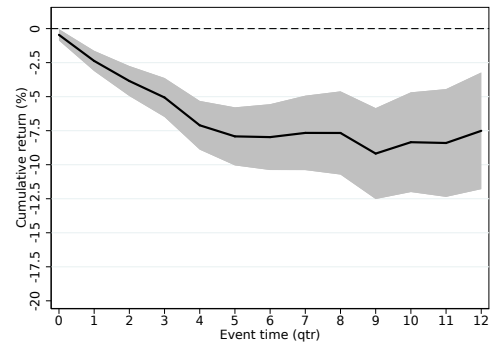
(f) Returns on loan stocks – Passive funds (1st loan).

Figure 3: Stock returns after loans

In this figure, I run an event study on the forward-looking returns of stocks on loan by mutual funds. Panels (a) and (b) depict the average raw returns for stocks on loan by active funds and ETFs respectively. Panels (c) and (d) depict the forward-looking returns of stocks on loan by active and passive funds, focusing on unique loans. In the two panels, I remove duplicate observations, and thereby give all observed loans an equal weight, as opposed to panels (a) and (b) where stocks that are on loan by multiple funds have a higher weight. In panels (e) and (f), I only look at the first loan observation by a fund within four calendar quarters, and thus drop repeat loans by funds.



(a) Returns on stocks with high sales.



(b) Returns on stocks with low sales.

Figure 4: Stock returns and rebalancing

In this figure, I focus on stock loans by active funds. I perform a forward-looking event study on the returns of stocks on loan by active funds, splitting all loan observations according to the rebalancing activity in the stock in the two calendar quarters following an observed loan. While not causal, the result is consistent with the idea that active fund trading contributes to pushing down stock prices to their fundamental level. The difference between panels (a) and (b) shows that the stocks that active funds trade more away from (where the rebalancing is more negative), decrease faster than the stocks where active funds trade less aggressively.

Table 1: Summary statistics on securities lending by investment funds.

	Active		Passive		(Passive - Active)	
	mean	sd	mean	sd	b	t
NAV (M-USD)	5480.97	11517.58	2575.34	8780.25	-2905.63***	(-20.84)
Lending fee	1.08	5.15	2.06	4.71	0.98***	(6.31)
Lending yield	0.01	0.02	0.02	0.04	0.01***	(8.03)
Overcollateralization	4.80	6.83	4.40	5.98	-0.41*	(-2.36)
Lend intensity: $N_L/N_H$	7.57	13.77	23.97	39.83	16.40***	(31.29)
Lending intensity: Vol/TS	23.83	29.07	30.40	34.89	6.57***	(10.77)
Avg. position (pct)	1.00	1.40	1.63	2.40	0.63***	(22.70)
Avg. position in loans (pct)	0.58	0.80	0.91	1.74	0.33***	(12.50)
Collateral/NAV	1.22	2.92	3.63	6.11	2.41***	(38.30)
Collateral/NAV for lenders	2.62	3.83	5.73	6.89	3.12***	(32.20)
VOL/NAV	0.92	2.34	2.65	5.38	1.73***	(25.27)
VOL/NAV for lenders	2.00	3.13	5.15	6.63	3.15***	(25.82)
Loan Avg.Shortint.	13.15	6.22	11.33	6.49	-1.82***	(-14.00)
Loan Avg.Bid-Ask	0.16	0.18	0.13	0.15	-0.03***	(-8.76)
Loan Avg.Hi-Lo	4.03	1.84	3.71	1.90	-0.32***	(-8.44)
Loan Avg.Mcap.	6281.39	14593.14	6553.39	12951.81	272.00	(0.95)
Observations	10138		12128		22266	

This table presents summary statistics on Active and Passive funds in the SEC Edgar lending fund sample. All variables except Net asset Value and Loan Avg.Mcap. are in percentage points.

Table 2: Portfolio rebalancing around stock lending

	(1)	(2)	(3)	(4)
Passive				
-2	0.00 (1.52)	0.00** (2.32)	0.00** (2.37)	0.00* (1.90)
-1	0.00** (2.14)	0.00** (2.33)	0.00** (2.30)	0.00** (2.00)
0	0.00 (0.40)	-0.00 (-0.35)	-0.00 (-1.03)	-0.00 (-1.05)
1	-0.00* (-1.88)	-0.00 (-1.23)	-0.00*** (-2.91)	-0.00*** (-3.71)
2	-0.00* (-1.77)	-0.00 (-0.89)	-0.00*** (-3.35)	-0.00*** (-3.58)
3	-0.00* (-1.73)	-0.00 (-0.87)	-0.00 (-1.48)	-0.00 (-1.28)
4	-0.00 (-0.76)	0.00** (2.41)	-0.00 (-0.69)	-0.00 (-1.31)
5	-0.00 (-1.23)	-0.00 (-0.00)	0.00 (0.49)	0.00 (0.24)
6	-0.00 (-1.38)	0.00 (1.30)	-0.00** (-1.99)	-0.00* (-1.77)
Active				
-2	0.00*** (2.76)	0.00*** (2.83)	0.00*** (2.71)	0.00*** (2.68)
-1	0.00** (2.25)	0.00** (2.53)	0.01*** (4.18)	0.01*** (3.97)
0	-0.00 (-0.04)	0.00 (0.20)	-0.00 (-0.05)	-0.00 (-0.08)
1	-0.01*** (-4.67)	-0.01*** (-3.80)	-0.00*** (-3.57)	-0.01*** (-3.28)
2	-0.01*** (-4.64)	-0.00*** (-3.51)	-0.00* (-1.67)	-0.00** (-2.22)
3	-0.00** (-2.29)	-0.00 (-1.25)	-0.00 (-1.60)	-0.00* (-1.93)
4	-0.00*** (-3.28)	-0.00*** (-3.54)	-0.00* (-1.68)	-0.00* (-1.66)
5	-0.00** (-2.16)	-0.00** (-2.12)	-0.00* (-1.82)	-0.00* (-1.91)
6	-0.00* (-1.78)	-0.00** (-2.22)	-0.00 (-1.26)	-0.00* (-1.79)
Stock $\times$ Quarter FE	Yes	Yes	Yes	Yes
Stock $\times$ Fund	No	Yes	No	No
Fund $\times$ Quarter FE	No	No	Yes	Yes
IOC $\times$ quarter	No	No	No	Yes
Observations	33508879	32916920	33497052	30550455
Adjusted $R^2$	-0.005	0.048	0.270	0.258

The dependent variable  $\Delta w_{f,s,t}$  measures the difference in portfolio weight between a fund and the fund group average, computed for active and passive funds in each Investment Objective Code and Total Asset group. The leads and lags of the lending dummy measure the deviation from the group average portfolio weight for the stock in event time relative to an observed stock loan. Each specification includes stock  $\times$  quarter fixed effects. Specifications (3), (4), (5) additionally include fund $\times$ stock, fund $\times$ quarter and fund $\times$ quarter and IOC $\times$ quarter fixed effects, respectively. For brevity, the table only reports leads up to four quarters and lags up to six quarters. The regression specification has leads and lags up to eight quarters. Standard errors are clustered at the stock and fund level.

Table 3: Cross-sectional variation in trading

	Portfolio weight		Short interest		Past returns		Market capitalization		S&P 500 member		Investment grade	
	Low	High	Low	High	Low	High	Low	High	No	Yes	No	Yes
Passive												
-2	-0.001** (-2.31)	0.003* (1.85)	0.002 (0.59)	0.000 (0.47)	-0.000 (-0.14)	0.001 (0.70)	0.000 (0.25)	0.000 (0.01)	0.001 (0.66)	0.001 (0.45)	0.001 (0.34)	0.001 (1.12)
-1	-0.000 (-1.11)	0.002 (1.20)	0.001 (0.43)	0.001 (1.11)	0.000 (0.22)	0.001 (1.11)	0.001 (1.16)	0.002 (0.78)	0.000 (0.49)	0.002 (0.72)	-0.002 (-0.60)	0.001* (1.67)
0	-0.000 (-0.49)	-0.002 (-1.41)	0.001 (0.22)	0.000 (0.11)	0.000 (0.13)	0.000 (0.03)	-0.000 (-0.43)	0.000 (0.08)	-0.000 (-0.18)	-0.000 (-0.15)	0.001 (0.25)	0.001 (1.11)
1	-0.000 (-0.70)	-0.004** (-2.51)	-0.000 (-0.14)	-0.001 (-1.56)	-0.000 (-0.27)	-0.001 (-1.60)	-0.001 (-1.35)	-0.004* (-1.80)	-0.001 (-0.67)	-0.003 (-1.33)	-0.003 (-1.07)	-0.001* (-1.75)
2	-0.000 (-0.68)	-0.003 (-1.58)	-0.001 (-0.30)	-0.001 (-1.12)	-0.000 (-0.13)	-0.001 (-1.17)	-0.001* (-1.71)	-0.000 (-0.19)	-0.001 (-1.34)	-0.001 (-0.46)	0.002 (0.52)	-0.002*** (-2.64)
3	-0.001 (-1.33)	-0.002 (-1.18)	-0.002 (-0.70)	-0.001 (-0.72)	-0.000 (-0.51)	-0.001 (-0.87)	-0.001 (-0.89)	-0.001 (-0.48)	-0.001 (-0.71)	-0.001 (-0.32)	-0.002 (-0.58)	-0.000 (-0.38)
4	-0.000 (-1.22)	-0.002 (-1.08)	-0.000 (-0.02)	-0.000 (-0.43)	0.000 (0.44)	-0.000 (-0.42)	-0.000 (-0.60)	-0.001 (-0.33)	-0.000 (-0.17)	-0.001 (-0.22)	-0.000 (-0.11)	0.000 (0.14)
Active												
-2	0.003*** (4.69)	0.004 (1.33)	-0.001 (-0.36)	0.003** (2.48)	0.000 (0.48)	0.003** (2.18)	0.003*** (2.67)	0.001 (0.27)	0.002 (1.58)	0.003 (0.87)	-0.003 (-0.38)	0.002* (1.81)
-1	0.002*** (4.13)	0.011*** (3.97)	0.002 (0.57)	0.003*** (2.87)	0.000 (0.09)	0.004*** (3.15)	0.002** (2.22)	0.001 (0.34)	0.004*** (3.19)	0.004 (1.13)	0.011* (1.69)	0.002** (2.12)
0	0.001*** (3.11)	0.003 (1.04)	-0.000 (-0.06)	0.000 (0.08)	-0.000 (-0.10)	0.000 (0.18)	-0.000 (-0.22)	-0.005 (-1.42)	0.001 (0.62)	0.001 (0.39)	-0.003 (-0.43)	-0.000 (-0.34)
1	-0.001** (-2.48)	-0.023*** (-8.59)	-0.006* (-1.69)	-0.008*** (-7.42)	-0.001 (-1.27)	-0.010*** (-7.59)	-0.005*** (-5.65)	-0.006* (-1.84)	-0.008*** (-6.23)	-0.013*** (-3.80)	-0.018** (-2.57)	-0.006*** (-5.54)
2	-0.000 (-0.46)	-0.015*** (-5.01)	-0.005 (-1.24)	-0.005*** (-4.56)	-0.001 (-0.70)	-0.007*** (-4.88)	-0.004*** (-3.64)	-0.004 (-1.14)	-0.006*** (-4.17)	-0.009** (-2.36)	-0.015** (-2.04)	-0.004*** (-3.35)
3	0.001 (1.17)	-0.006* (-1.90)	-0.001 (-0.13)	-0.002* (-1.77)	0.000 (0.36)	-0.003** (-1.96)	-0.002 (-1.53)	-0.008** (-2.37)	-0.002 (-1.38)	-0.009** (-2.29)	0.004 (0.48)	-0.003** (-2.31)
4	-0.000 (-0.13)	-0.008** (-2.34)	-0.002 (-0.41)	-0.003** (-2.41)	-0.001 (-0.72)	-0.004** (-2.44)	-0.002* (-1.67)	-0.002 (-0.47)	-0.003* (-1.66)	-0.008* (-1.94)	0.000 (0.04)	-0.004*** (-2.68)
Observations	16230296	17245635	8853818	24379642	3427370	29806090	14705419	8618054	14930078	11700568	6309442	15470526
Adjusted $R^2$	0.118	0.002	-0.010	-0.003	-0.030	-0.002	-0.006	0.001	-0.008	0.000	-0.028	-0.012

The dependent variable  $\Delta w_{f,s,t}$  measures the difference in portfolio weights between a fund and the fund group average, computed for active and passive funds in each Investment Objective Code and Total Asset group. The leads and lags of the lending dummy measure the deviation from the group average portfolio weight for the stock in event time relative to and observed stock loan. This table presents results from sample split regressions, where I divide the sample in high and low information groups, with the aim of testing whether lender funds react to stock borrowing more when information is scarce or if the borrowing might bring in information that is not yet incorporated in prices. I split the data in two groups according to portfolio weight, short interest, market capitalization, S&P 500 index membership, investment grade debt rating, and fund net assets. Each specification includes stock  $\times$  quarter fixed effects. For brevity, the table only reports leads from two periods before the event up to four periods after. The regression specification has leads and lags up to eight quarters.

Table 4: Stock returns after borrowing from mutual funds

	(1)		(2)		(3)		(4)	
	Active	Passive	Active	Passive	Active	Passive	Active	Passive
0	-0.02*** (-13.72)	-0.03*** (-16.75)	-0.02*** (-8.27)	-0.02*** (-2.96)	-0.02*** (-15.51)	-0.02*** (-13.68)	-0.02*** (-11.47)	-0.04*** (-20.73)
1	-0.02*** (-13.03)	-0.01*** (-7.02)	-0.02*** (-8.76)	-0.01 (-1.23)	-0.02*** (-14.77)	-0.01*** (-9.68)	-0.02*** (-10.37)	-0.00** (-2.41)
2	-0.02*** (-9.10)	-0.02*** (-8.48)	-0.02*** (-5.99)	-0.01 (-1.63)	-0.01*** (-9.71)	-0.01*** (-10.96)	-0.00** (-2.33)	-0.01*** (-6.87)
3	-0.01*** (-4.83)	-0.02*** (-8.10)	-0.01*** (-3.12)	-0.01 (-1.63)	-0.01*** (-4.91)	-0.01*** (-7.58)	-0.00 (-0.07)	-0.02*** (-8.57)
4	-0.02*** (-12.09)	-0.01*** (-6.59)	-0.02*** (-8.33)	-0.01 (-1.33)	-0.02*** (-13.33)	-0.01*** (-4.32)	-0.04*** (-17.41)	-0.01*** (-6.88)
5	-0.01*** (-6.96)	-0.00 (-1.20)	-0.01*** (-5.29)	0.00 (0.04)	-0.01*** (-10.25)	0.01*** (4.47)	-0.03*** (-11.43)	-0.01*** (-3.71)
6	0.00 (0.13)	0.01*** (2.90)	0.00 (0.47)	0.01 (1.13)	-0.00*** (-2.74)	0.01*** (4.80)	0.01*** (3.78)	0.01*** (3.82)
7	0.01*** (2.82)	-0.00 (-0.98)	0.01** (2.52)	0.00 (0.08)	0.00 (0.44)	0.00 (0.66)	0.02*** (7.39)	-0.01*** (-3.66)
8	-0.00 (-0.03)	0.01*** (7.32)	0.00 (0.33)	0.02** (2.44)	-0.00 (-1.17)	0.01*** (11.25)	-0.00 (-0.83)	0.02*** (9.01)
9	-0.01*** (-4.46)	0.00 (1.18)	-0.01*** (-3.22)	0.00 (0.71)	-0.01*** (-3.94)	0.01*** (4.84)	-0.01*** (-3.81)	0.01*** (5.37)
10	0.01** (2.49)	0.00 (0.87)	0.01** (2.55)	0.00 (0.64)	0.00*** (2.59)	0.01*** (5.01)	0.00 (0.83)	0.01*** (3.25)
11	0.00 (1.28)	-0.00 (-0.11)	0.00 (1.35)	0.00 (0.33)	0.01*** (3.59)	0.00*** (2.65)	0.01*** (2.92)	0.00 (1.14)
12	0.01*** (5.05)	0.00 (1.34)	0.01*** (4.71)	0.01 (0.80)	0.01*** (7.78)	0.00** (2.08)	0.02*** (8.24)	-0.00** (-1.98)
Shortinterest			-0.01 (-0.54)	-0.03 (-0.36)				
Observations	1846603	2680589	1846603	2680589	683272	705692	859730	895517
Adjusted $R^2$	0.002	0.002	0.002	0.002	0.001	0.001	0.003	0.003

This table presents the results from event study regressions on the stocks borrowed from active and passive mutual funds. The aim of the event study is to show that stock borrowing from mutual funds contains information, and that funds can as a result profitably trade the stocks that are borrowed without relying on other information. The dependent variable is quarterly stock returns. Specification (1) includes all observed stock loans. Specification (2) only retains non-duplicate observations at the stock-quarter level, i.e., equal-weights all stock loans. Specification (3) retains first loan observations at the fund-stock level, and drops all stock loans that occur within 4 quarters of a previous stock loan observation. Standard errors are clustered at the stock level.

Table 5: Cross-sectional variation in stock returns

## (a) Active funds

	Short interest		Market capitalization		S&P 500 member		Investment grade		Change in shares	
	Low	High	Low	High	No	Yes	No	Yes	Low	High
0	-0.03*** (-7.04)	-0.02*** (-11.28)	-0.06*** (-15.25)	-0.01*** (-5.18)	-0.00** (-2.42)	0.00 (0.63)	-0.03*** (-11.91)	-0.00 (-0.70)	-0.04*** (-13.69)	-0.00** (-2.15)
1	-0.03*** (-6.49)	-0.02*** (-11.05)	-0.06*** (-15.53)	-0.01*** (-4.91)	-0.01*** (-5.21)	0.02*** (3.83)	-0.03*** (-12.34)	0.01** (2.22)	-0.04*** (-12.07)	-0.02*** (-8.11)
2	-0.02*** (-4.60)	-0.02*** (-7.83)	-0.06*** (-13.29)	-0.00 (-0.31)	0.00 (0.17)	0.02*** (5.34)	-0.02*** (-8.66)	0.00 (1.51)	-0.03*** (-8.80)	-0.01*** (-5.83)
3	-0.01*** (-3.39)	-0.01*** (-3.85)	-0.04*** (-9.61)	0.00* (1.88)	-0.00 (-0.57)	0.02*** (6.69)	-0.01*** (-5.57)	0.02*** (5.75)	-0.01* (-1.74)	-0.01*** (-4.73)
4	-0.02*** (-4.60)	-0.02*** (-11.07)	-0.06*** (-12.53)	-0.01*** (-5.22)	-0.01*** (-4.79)	0.00 (1.21)	-0.03*** (-12.90)	-0.00* (-1.71)	-0.02*** (-7.24)	-0.02*** (-7.54)
Observations	305548	1535110	504371	1336287	1309308	196421	1002273	234552	723756	867497
Adjusted $R^2$	0.002	0.002	0.008	0.001	0.001	0.008	0.004	0.005	0.004	0.001

## (b) Passive funds

	Short interest		Market capitalization		S&P 500 member		Investment grade		Change in shares	
	Low	High	Low	High	No	Yes	No	Yes	Low	High
0	-0.03*** (-6.71)	-0.03*** (-14.85)	-0.06*** (-17.95)	-0.02*** (-10.28)	-0.01*** (-7.88)	-0.00 (-0.27)	-0.03*** (-15.37)	-0.00 (-0.09)	-0.03*** (-13.03)	-0.03*** (-11.38)
1	-0.03*** (-4.94)	-0.01*** (-5.34)	-0.06*** (-14.08)	0.00 (0.73)	-0.00** (-2.31)	0.01** (2.29)	-0.01*** (-5.12)	0.01*** (3.91)	-0.00 (-0.74)	-0.02*** (-8.74)
2	-0.02*** (-3.55)	-0.02*** (-7.71)	-0.07*** (-13.81)	-0.00 (-1.13)	-0.01** (-2.50)	0.01*** (2.69)	-0.02*** (-7.52)	0.01*** (4.19)	0.01*** (4.60)	-0.03*** (-10.91)
3	-0.02*** (-4.18)	-0.01*** (-7.15)	-0.07*** (-13.73)	-0.00 (-0.35)	-0.01*** (-3.51)	0.01** (2.18)	-0.02*** (-8.83)	0.01*** (4.94)	0.00 (1.00)	-0.03*** (-10.05)
4	-0.02*** (-3.40)	-0.01*** (-5.78)	-0.05*** (-9.83)	-0.00 (-0.91)	-0.01*** (-2.63)	0.01*** (2.77)	-0.02*** (-7.67)	0.01*** (5.41)	-0.00 (-0.93)	-0.02*** (-6.92)
Observations	309284	2362231	569770	2101745	2003980	318322	1349954	337991	996437	1560044
Adjusted $R^2$	0.002	0.002	0.010	0.002	0.001	0.006	0.003	0.013	0.002	0.003

This table presents cross sectional variation in the returns of borrowed stocks. I split stocks in two groups according to their information environment according to their short interest, market capitalization, S&P 500 index membership, and investment grade debt rating by Standard & Poors, and perform the same event study regression as in specification (1) in Table 4. Additionally, I split the sample according to the change in number of shares held by each fund type in order to proxy for the trading activity by funds. The dependent variable is quarterly stock return of the borrowed stocks. For brevity, the table only reports event time up to four quarters after the event. Standard errors are clustered at the stock level.

Table 6: Lending fees and collaterals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Lendingfee	Lendingfee	Lendingfee	Lendingfee	Overcollateral	Overcollateral	Overcollateral	Overcollateral
Passive	2.669*** (8.00)	2.616*** (8.71)	2.892*** (9.40)	2.272*** (7.23)	-0.478 (-1.64)	-0.480 (-1.60)	-0.311 (-0.98)	-0.183 (-0.62)
ln(NAV)		-0.077** (-2.26)		-0.050 (-1.32)		-0.299*** (-6.99)		-0.218*** (-5.07)
Lending intensity: VoL/TS			-0.007*** (-2.71)	-0.004 (-1.58)			-0.011*** (-3.52)	-0.012*** (-3.82)
Loan ln(Shortint.)				0.330*** (2.94)				-0.956*** (-7.70)
Loan ln(Mkt cap)				-0.616*** (-9.85)				-1.221*** (-17.34)
Lend intensity: $N_L/N_H$				-0.009*** (-2.99)				-0.002 (-0.67)
Observations	4207	4191	3928	3325	6135	6107	5675	4755
Adjusted $R^2$	0.143	0.326	0.333	0.414	0.079	0.097	0.095	0.171

The dependent variable in columns (1)-(4) is the lending fee proxy computed according to Equation 2. The dependent variable in columns (5)-(8) is overcollateralization. The control variables are log total net assets, log average market capitalization of the stocks on loan, and log average short interest of the stocks on loan. I also include two measures of lending intensity in the regressions: the share of stocks in the portfolio at least partially on loan, and the share of total holdings of loan stocks that is lent. Each specification includes a fund issuer fixed effect to address heterogeneity in lending strategy between fund issuers.

Table 7: Gains from rebalancing – Active funds

Event time	Cumulative rebalancing (%)	Stock return (%)	Cumulative gain (bp)
0	0.4	-2.4	-0.9
1	-0.5	-2.4	0.2
2	-1.1	-1.8	2.1
3	-1.3	-0.1	3.3
4	-1.6	-2.4	7.2
5	-1.9	-1.4	9.9
6	-2.1	0.0	9.8
7	-2.1	0.6	8.6
8	-2.1	0.0	10.6

This table computes returns to lending-induced rebalancing, using the results from Sections 5.1 and 5.2. The returns are computed as the cumulative rebalancing from event time 0 to time  $t$  multiplied by the stock return in quarter  $t$  and cumulated over time. The cumulative gain from rebalancing measures the profit from rebalancing the position relative to similar non-lender funds that do not rebalance: for two funds that hold the same stock, this measures how much better the lender fund does when it rebalances away from the stock relative to the competitor fund. In short, lender funds avoid about 10.6 basis points of losses of portfolio value in the position. This amounts to about 18% of the value of the position (average position size is about 0.58%).

Table 8: Lending market participation

(a) Lending market participation – Extensive margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Passive	0.146*** (22.76)	0.230*** (35.57)	-0.000 (-0.01)	0.089*** (12.52)	0.341*** (25.00)	0.373*** (28.02)	0.082*** (5.99)	0.117*** (8.67)
ln(TNA)		0.058*** (43.21)		0.063*** (41.02)		0.051*** (37.03)		0.044*** (30.10)
Mgmt fee		0.047*** (11.92)		0.017*** (4.25)		0.049*** (13.38)		0.021*** (5.84)
Portf. ln(Mkt cap)			0.032*** (17.12)	0.016*** (8.88)			0.016*** (9.73)	0.008*** (4.92)
Portf. Avg.Shortinterest			0.004*** (4.52)	0.001 (0.51)			0.004*** (5.38)	0.002*** (2.81)
Portf. Avg.Bid-Ask			0.345*** (3.43)	0.416*** (4.31)			0.800*** (9.40)	0.767*** (9.21)
Portf. Avg.Dollar vol.			9.819*** (10.03)	12.563*** (13.16)			15.645*** (18.93)	16.560*** (20.22)
Constant	0.464*** (98.48)	0.044*** (4.20)	0.213*** (10.48)	-0.099*** (-4.70)				
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Issuer $\times$ Quarter FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	23147	22950	18974	18818	23147	22950	18974	18818
Adjusted $R^2$	0.072	0.152	0.086	0.162	0.247	0.298	0.364	0.396

(b) Lending market participation – Intensive margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Passive	3.263*** (21.47)	2.354*** (14.07)	2.415*** (17.12)	1.739*** (11.20)	-0.209 (-0.88)	-0.241 (-0.99)	-0.617*** (-2.90)	-0.766*** (-3.48)
ln(TNA)		-0.562*** (-17.06)		-0.451*** (-14.44)		-0.115*** (-3.42)		-0.038 (-1.21)
Mgmt fee		1.528*** (5.98)		0.661*** (2.73)		0.249 (0.97)		-0.576*** (-2.37)
Portf. ln(Mkt cap)			-0.761*** (-18.28)	-0.623*** (-14.85)			-0.552*** (-14.96)	-0.554*** (-14.65)
Portf. Avg.Shortinterest			0.103*** (5.12)	0.122*** (6.17)			0.123*** (7.06)	0.125*** (7.13)
Portf. Avg.Bid-Ask			13.668*** (6.06)	14.622*** (6.60)			14.174*** (7.19)	14.343*** (7.27)
Portf. Avg.Dollar vol.			313.354*** (15.79)	296.946*** (15.20)			306.988*** (17.43)	305.997*** (17.38)
Constant	1.972*** (16.71)	5.880*** (18.25)	6.337*** (12.95)	8.300*** (15.60)				
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Issuer $\times$ Quarter FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	6525	6525	6369	6369	6525	6525	6369	6369
Adjusted $R^2$	0.096	0.143	0.250	0.275	0.313	0.314	0.440	0.441

The dependent variable in panel (a) is a dummy that is equal to 1 if a fund lends securities, and 0 otherwise. In panel (b), the dependent variable is the proportion of assets on loan. The two variables measure lending at the extensive margin and the intensive margin. Specifications (1-4) include quarter fixed effects, and specifications (5)-(8) include quarter and fund issuer fixed effects. The aim of the quarter fixed effects is to capture unobserved time-varying lending market fluctuations, while the issuer fixed effects addresses fund-issuer level differences in lending strategy.

## Appendix

### A Variables

Variable	Description	Data source
$passive_{f,t}$	Passive fund dummy variable	SEC and CRSP
$nav_{f,t}$	Net asset value at quarter end	SEC (N-Q, N-CSR) and CRSP
$loanvalue_{f,t}$	Value on loan: dollar value of outstanding securities loans at the quarter end	SEC: N-Q, N-CSR
$collateral_{f,t}$	Collateral: dollar value of collateral held at quarter end	SEC: N-Q & N-CSR
$income_{f,t}$	Dollar value of securities lending income earned in the quarter of half-year period	SEC: N-CSR
$collateralshare_{f,t}$	Share of collateral of total net assets. $collateralshare_{f,t} = collateral_{f,t}/nav_{f,t}$	SEC: N-Q, N-CSR
$lendshare_{f,t}$	Share of net assets on loan. $lendshare_{f,t} = loanvalue_{f,t}/nav_{f,t}$	SEC: N-Q & N-CSR
$overcollateral_{f,t}$	Overcollateralization at quarter end. $overcollateral_{f,t} = collateral_{f,t}/loanvalue_{f,t} - 1$	SEC: N-Q, N-CSR
$lendingfee_{f,t}$	Proxy for average lending fee earned by lender funds. $\frac{lending\ income_{f,t} - col_{f,t} * r_{MMF,t}}{loanvalue_{f,t}} \times \frac{2}{q_{f,t}} \times 2 + \gamma_{it}$	SEC: N-Q, N-CSR
$colyield_{f,t}$	Yield on collateral. $colyield_{f,t} = income_{f,t}/collateral_{f,t} - 1$	SEC: N-Q, N-CSR
$lendyield_{f,t}$	Yield on lending. $lendyield_{f,t} = income_{f,t}/nav_{f,t} - 1$	SEC: N-Q, N-CSR
$numonloan_{f,t}$	Number of individual stocks on loan at quarter end.	SEC: N-Q, N-CSR
$numintensity_{f,t}$	$numintensity_{f,t} = numonloan_{f,t}/(Number\ of\ securities\ in\ portfolio)_{f,t}$	SEC: N-Q, N-CSR
$loanintensity_{f,t}$	$loanintensity_{f,t} = loanvalue_{f,t}/(Total\ holding\ of\ stocks\ on\ loan)_{f,t}$	SEC: N-Q, N-CSR
$lending_{f,t}$	Dummy variable indicating that $collateral_{f,t}$ or $loanvalue_{f,t}$ is greater than zero.	SEC: N-Q, N-CSR
$MIC_f$	Morningstar Investment Category. Describes the investment objective of the fund.	Morningstar
$IOC_f$	CRSP Investment Objective Code	CRSP
$active_{f,t}$	Indicator variable set to 1 if the fund is not an ETF	CRSP
$SP500_{s,t}$	Member of the S&P 500 index	Compustat
$Invgrade_{s,t}$	Investment grade rating by Standard & Poors	Compustat
$\widehat{weight}_{f,s,t}$	Fund-category and net asset tercile level average holding for each stock.	CRSP
$\Delta w_{i,j,t}$	Fund-level over/underweighting in a stock. $deviation_{i,j,t} = weight_{i,j,t} - \widehat{weight}_{i,j,t}$	CRSP

# Strategic allocation of stock lending profits

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## Abstract

This article studies the allocation of securities loans within mutual fund families. Using a novel dataset on fund level stock lending, we show that U.S. mutual fund families, first, are more likely to enable index funds to lend securities than active funds. Second, we show that this also holds at the security level: index funds are allocated more securities loans than comparable active funds. We also find no robust evidence that mutual fund families would strategically allocate securities loans to funds that prior literature has found to be more “valuable” to the families.

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# 1 Introduction

This article studies whether mutual fund management companies strategically allocate securities loans and the affiliated profits between funds in the family. The rationale for this article is a series of empirical observations about mutual fund management fees, lending market participation, lending income, and short interest. First, in the past two decades, average expense ratios of both active and passive mutual funds have decreased by more than 30%, as is illustrated in Figure [1](#). The decline has, to some extent, been offset by economies of scale and rising assets under management, as well as a probable decrease in the marginal cost of money management thanks to computerisation. It is, however, difficult to imagine that money managers have not sought to offset the lost revenues through other sources. Indeed, many of them have strengthened their securities lending programs in order to offset some of the lost fee revenues.<sup>[1](#)</sup>

Additionally, an increasing number of both active and passive mutual funds participate in the securities lending market (see Figure [2](#)). Since the primary reason to borrow securities is short selling (as short sellers must borrow securities to settle the trades), the short selling market sets the limits for securities lending. And since aggregate borrowing demand from short sellers is a small fraction of the total holdings of funds that can participate in the stock lending market,<sup>[2](#)</sup> the question of how securities loans are allocated arises. In short, more funds are willing to lend securities than can lend securities.

This article asks whether fund families strategically allocate securities loans between their funds, potentially giving preferential treatment to some funds over others in order to boost these funds' returns by channeling loans and lending revenues to them. This has multiple implications for both mutual fund investors and stock borrowers and lenders.

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<sup>1</sup>“As margins are squeezed, asset managers are turning to securities lending to lower the cost of running funds.” Financial Times – Fund groups challenged over securities lending practices, May 11, 2019.

<sup>2</sup>See Figure [3](#).

Stock borrowers may end up paying higher fees to borrow securities if supply is artificially restricted, possibly leading to less incentives to short sell and produce information for the financial markets. Moreover, funds that are prevented from lending securities will have lower returns due to forgoing the lending revenues. This, in turn, will lead to lost returns to the investors in the funds that are prevented from participating. This is of particular importance given that the contribution of securities lending income to fund revenues and returns has increased significantly especially for passive funds.<sup>3</sup> For index funds, stock lending also contributes to minimizing tracking error relative to the target index.

We use a dataset first presented in [Honkanen \(2020\)](#) to study securities lending at the fund-stock level. The dataset identifies all stocks on loan for U.S. active and passive funds issued by a sample of the ten largest mutual fund issuers for the time period from 2001 to 2017. To our knowledge, this is the first time loan-level data has been used to answer questions about the allocation of securities loans. The loan-level data enables us to examine the allocation of securities loans and the associated profits in much higher detail than prior studies that have relied on fund-level lending indicators or proprietary sample data.<sup>4</sup>

Our empirical strategy is based on, first, disproving the premise that securities loans are allocated fairly and equitably within fund families, and second, identifying the characteristics that drive the likelihood of loan allocation to a fund. Most fund issuers and their securities lending agents state that any lendable supply is placed in a queue in the order of lender level utilization rate, independent of fund size, revenue splits, or other characteristics.<sup>5</sup> If this claim holds, the only driver of lending likelihood is the value of

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<sup>3</sup>[Blocher and Whaley \(2016\)](#)

<sup>4</sup>See, for example, [Blocher and Whaley \(2016\)](#); [Evans, Porras Prado, and Zambrana \(2019\)](#); [Aggarwal, Saffi, and Sturgess \(2016\)](#).

<sup>5</sup>See [U.S. Securities and Exchange Commission \(2011\)](#): “The primary factor in determining which investor received the next loan opportunity was each investor’s percentage of shares it had out on loan, known as the utilisation rate.”

stock-level holdings, as it affects the frequency at which a fund is at the top of the queue and how long it stays there.

On a more fundamental level, if fund families seek to maximize the performance of all funds in the family, they should allow all of their funds to participate in the securities lending market. Given that the loans are always more than fully collateralized, the lending activity carries relatively little risk to the lenders and will in expectation bring revenue to any fund that is allocated a loan. Thus, observing that fund families prohibit some funds from lending while allowing others to do so indicates that some funds may receive preferential treatment in having access to this additional revenue source. At the stock loan level, if loans are allocated through a queue system, the main driver of the probability of lending should be the value of the holding.

For this identification methodology to hold, it must be that funds that lend securities make their whole portfolios available to borrow without systematically selecting specific stocks to make available or not. This is supported by observing Securities Lending Agreements that funds file with the SEC. Typical securities lending agreements contain phrases such as *“All of the Fund’s securities held by State Street as trustee or custodian shall be subject to this securities lending program and constitute Available Securities hereunder, except those securities, which the Fund or the Investment Manager specifically identifies herein as not being Available Securities.”*<sup>6</sup> Fund managers, once they opt in, thus participate with all their holdings unless they expressly exclude specific securities by informing the securities lending agent in writing. Moreover, it seems implausible that fund managers would systematically choose not to lend some securities, as this would be against the interests of the investors in the fund. Arguments such as not wanting to support short selling in specific securities are, on their own, inconsistent given the width of the securities lending market and the scant probability that the withdrawal of one

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<sup>6</sup>Securities lending agreement between Lattice Strategies Trust and State Street Bank and Trust. [len](#) (2020).

lender could bear an impact on traders' ability to enter short positions. One exception to this may be the proxy votes. Lender funds must participate in any "material votes", and may therefore at times be forced to exclude some securities from their lending programs. This is, however, orthogonal to the fund, fund manager or fund family, and should thus not affect the results.

First, we show that index funds are considerably more likely to be allowed to lend securities. Similarly, this result also holds at the fund-stock level. Index funds within fund families are more likely to be allocated individual loans than similar active funds holding the same security at the same point in time, even when controlling for fund strategies.

Second, our paper is also interesting for what we do not find. In particular, mutual fund families do not appear to be allocating stock lending revenues to high-value active funds (e.g., funds with a high expense ratio). This would result from fund families giving preferential treatment to funds that are more valuable to the fund issuer. This is in contrast with, e.g., [Gaspar, Massa, and Matos \(2006\)](#), where the authors find that fund families readily transfer performance from low-value funds to high-value funds within the family. In short, the relatively discretionary allocation of securities lending revenues within fund families does not display evidence of similar favoritism. The differences, similarly, are not fully explained by fund bylaws not allowing stock lending. This explanation would indicate that fund families disallow lending from certain funds, only allowing the champions to lend stocks, and thereby mechanically forcing all stock lending gains to only those funds.

The absence of a rule or bylaw-based explanation for the allocation of stock lending profits suggests the presence of soft rules within the fund families that drive loan allocation and profits toward certain funds over others.

These findings have clear regulatory implications. The vast majority of mutual funds

share securities lending revenues with the lending agent and the fund family, with the lion's share of the proceeds being allocated to fund investors. However, there is wide heterogeneity in the revenue split proportions across fund families' and across time. Blackrock, for example, retains 25% of all gross securities lending revenues, with the remaining 75% being distributed to the fund, whereas Vanguard returns all of the securities lending proceeds to the fund, net of direct program costs.<sup>7</sup> Favoring some funds over others in the allocation of loans deprives investors in the disfavored funds from lending profits, especially if these funds are also allowed to lend securities and indicate in their prospectuses and bylaws that this is a part of their revenue generation process despite in reality not being allowed to participate in the market due to management company level decisions. Regulators should define best practices and enforce fair allocation guidelines in the stock lending processes. Another way to enable more fair allocation of loans and to improve access to the stock lending market would be to push towards a centralized market for stock lending. This would also improve transparency in the stock lending market, though Huszár and Porras Prado (2019) report adverse effects from the increased transparency.

This article proceeds as follows: Section 2 discusses prior literature and the contribution of the present article. Section 3 presents the hypotheses and the methodology we use to test them. Section 4 introduces the data and presents descriptive statistics, and Section 5 presents the empirical tests. Section 6 concludes.

## 2 Literature

This article relates primarily to the literatures on the microstructure of OTC markets – in this case, the market for lending securities – and the long literature on competition and cooperation within mutual fund families. Brown, Harlow, and Starks (1996) and

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<sup>7</sup>See for example Rowley, J. (Vanguard) 2020, Blackrock 2020

subsequent papers show that mutual fund managers behave as in tournaments, consistent with mutual fund managers being incentivized to outperform their peers. [Gaspar, Massa, and Matos \(2006\)](#) show that mutual fund managers optimize at the family level, transferring performance from low-value funds to high-value funds, and [Bhattacharya, Lee, and Pool \(2013\)](#) find that funds-of-funds invest into affiliated mutual funds when these experience outflows, thus improving their performance and increasing their assets under management. More recently, [Evans, Porras Prado, and Zambrana \(2019\)](#) show evidence consistent with the idea that the degree of cooperation or competition within fund families depends on the incentives fund families give their portfolio managers, leading to more cooperative or competitive cultures.

This article follows the prior literature by trying to establish how fund families allocate securities loans and the affiliated profits between their members funds. In addition to the incentives of fund managers, we also analyze the incentives of the fund management company, which typically retains a proportion of the lending income. A higher share of lending income retained by the management company incentivizes the management company to maximize lending income as a whole and likely to distribute loans more equitably between funds as the performance afforded to individual funds becomes relatively less important. If, on the other hand, the fund management company retains a low share of the lending income, the incentives skew towards allocating loans to the highest-value funds in the family.

[D’Avolio \(2002\)](#) gives an overview of the securities lending market in the U.S., and shows that short sale constraints are increasing in the divergence of opinion of investors in the securities lending market. More recently, [Huszár and Porras Prado \(2019\)](#) discuss the differences between OTC and centralized securities lending markets. [Huszár and Porras Prado \(2019\)](#) show evidence consistent with some investors preferring the OTC market structure due to its opacity. This is also in line with [Honkanen \(2020\)](#), where

the author finds that active mutual funds gain valuable information from the securities lending market and rebalance their holdings away from stocks that they lend. Thus, more transparency in the securities lending market might induce more trading on the private short selling signals, and thereby reduce the information gathering incentives of short sellers.

The present article is, to our knowledge, the first one to study the allocation of securities loans and the microstructure level organization of the U.S. securities lending market. We contribute both to the literature on mutual funds and fund family level allocation of revenues, and to the literature on securities lending and to understanding of the structure of this market.

### **3 Hypothesis and Methodology**

We set out to test whether fund families give preferential treatment to certain funds within the family in allocating stock loans and the related stock lending profits.

We begin with the claim that loans are allocated through a queue system. The industry posits that all loans are allocated fairly from the queue based on either the order of arrival or the utilization rate at the lender-security level. Either of these mechanisms would lead to a random and fair allocation of loans, where the only variable determining the likelihood of loan allocation to a specific fund is the value of the holding. In the first case, as the order of arrival in the queue can be taken as random (as it is unknown to the lenders), a larger holding size means that the fund, once arrived at the top of the queue, spends a longer time at the top of the queue until its lendable supply in a security has been exhausted. In the second case, loans are allocated based on the utilization rate, i.e. the proportion of shares on loan relative to the number of shares held by the specific lender. While in the data from 2001 to 2017 we can not observe the

lender-stock level utilization rate, under the null hypothesis of fair allocation of loans, this is a direct function of the holding value.<sup>8</sup>

Therefore, in either case the only variable that drives the likelihood of lending should be the value of the holdings, and no other characteristics of the fund or its strategy should drive the allocation of loans. However, in order to observe a random allocation of loans at the fund-stock level, we need funds to make all their holdings available to borrow. If some type of funds exclude specific securities from their lending programs, for example because they do not want to support short selling in these stocks, we might falsely conclude that loans are not allocated fairly, despite the true reason for a non-random allocation being a portfolio manager’s active choice not to lend a specific stock.

From discussions with industry practitioners, it seems unlikely that fund managers would be excluding securities from their lending program. First, one reason to exclude securities could be to make short selling harder. It is, however, very unlikely that an individual lender would have any significant impact on the market for borrowing a specific stock due to low market power. Moreover, as short sellers have been documented to be on average informed, it would be irrational for a portfolio manager to discard the signal from the borrowing market.<sup>9</sup> Additionally, if the portfolio manager has a more positive view about the stock, he should be happy to collect the lending fees while still enjoying the upside potential of the security.

The assumption that funds, once they have opted into the lending programs, make all their securities available to borrow is also supported by the securities lending agreements. Typical agreements have phrases such as “all of the Fund’s securities held by State Street as trustee or custodian shall be subject to this securities lending program and constitute Available Securities hereunder, except those securities, which the Fund

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<sup>8</sup>A larger holding size by a fund will result in a lower utilization rate given a loan of a fixed size. If loans are allocated according to utilization rate, the position size is the only determinant of the likelihood of being allocated a loan.

<sup>9</sup>Evans, Ferreira, and Porras Prado 2016; Honkanen 2020.

or the Investment Manager specifically identifies herein as not being Available Securities.” Excluding specific securities from the lending programs thus requires the lenders to specifically identify stocks that they do not want to lend, and inform the lending agent in writing.

While we can not conclusively show that such exclusions never occur, we believe that they are rare and unsystematic. Fund strategy and fund family fixed effects will, additionally, address these concerns if funds that follow a given strategy are more likely to exclude a specific stock from their lending programs. If this is done at the family level, the same will be achieved with the fund family fixed effects.

To show that there is fund-level favoritism within mutual fund families, we will, first, demonstrate that there are factors other than the value of the holding and fund sizes that determine the likelihood of loan allocation. Second, we try to identify the main fund characteristics that drive loan allocation.

We begin by demonstrating that there are differences at the fund level in both the likelihood of being allowed to lend securities and in the likelihood of actually lending securities between funds within a fund family, controlling for fund size and desirability of the securities in the respective funds’ portfolios. Next, we show that this also holds at the stock-level within funds. The stock-level loan allocation between funds in a fund family (or, more specifically, within a lending agent) should only depend on the size of the position, as discussed above. Any statistically significant coefficients on other factors will therefore invalidate the claim of fair and random allocation of loans.

Finally, we also control for the securities lending agent and the revenue split agreement that the funds have with their securities lending agents. The revenue split agreement may have an impact on fund families’ incentives to allocate loans to funds most needing an improvement in performance or to lender funds that maximize the gross securities lending revenues. If the fund family or lending agent retains a larger share of the

securities lending revenues, it has a higher incentive to maximize total lending revenue (and thus its own revenue) rather than to allocate the loans to the fund most needing an external contribution to returns. We thus expect the favoritism to be lower in fund families that retain a larger share of gross lending revenues.

In order to test which funds are allocated the most lost loans and lending revenues, we follow the idea of Gaspar, Massa, and Matos (2006), where fund families allocate performance to the highest value fund. The difference to Gaspar, Massa, and Matos (2006) is that we aim to identify, first, the funds that most benefit from additional revenue, and second, the funds where additional revenue most benefits the fund family. We focus on three factors: fund expense ratio, flow-return sensitivity, and index fund status.

As media articles have noted, funds have been offsetting decreases in expense ratios by increasing their securities lending programs.<sup>10</sup> Moreover, fund families may also lend more from low-expense ratio funds, as these have larger asset bases (as decreased expense ratios contribute to investor flows). Funds whose flows are more sensitive to performance may also be allocated more loans. Lending revenues contribute to returns, and are therefore followed by higher investor flows, increasing assets under management and thus the future management fees collected by the fund company. Index funds have been seen as “better” lenders from the borrowers’ perspective by practitioners, as they have transparent and stable portfolios. Moreover, they also have on average lower management fees, which may increase their propensity to participate in the securities lending market to earn additional revenues both to the fund and the management company.

The null-hypothesis is thus that there is no overall lending strategy – i.e. that all loans and the subsequent revenues are allocated fairly – and that the only factor that should drive loan allocation is the fund level holding size. The alternative hypotheses aim to

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<sup>10</sup>See, for example, Riding (2019): “As margins are squeezed, asset managers are turning to securities lending to lower the cost of running funds.”

disprove this.

## 4 Data

We use a novel dataset that describes the securities lending practices of US mutual funds. The dataset is collected from filings that are U.S. mutual funds regulated under the 1940 Investment Companies Act must file. The fund-level information is collected from N-SAR filings from 2001 to 2017, and contain descriptions on fund strategies. Namely, we are interested in whether a fund is allowed to lend portfolio securities<sup>11</sup> and whether the fund actually lent securities in the time period in question. In particular, whether a fund is allowed to lend portfolio securities is determined at the management company level, and can be a tool to allocate securities lending gains between funds: preventing some funds from lending securities automatically favors other funds, as then they are more likely to be able to lend securities and gain revenues from the activity. We additionally use the self-reported "Equity fund" identifier variable in the SEC data to exclude fixed income funds.

In addition to the fund level data, we also use data on stock level holdings. In particular, using N-Q and N-CSR filings, we know which specific portfolio securities are on loan by each fund. To our knowledge, this is the first article to use these data to study the allocation of securities loans and the microstructure of the securities lending market. This lets us study how loans are allocated at the security level; for example, whether certain funds receive preferential treatment in receiving loans of high-lending fee stocks. The N-Q and N-CSR filings are collected for the ten largest mutual fund issuers, and thus contain a subsample of funds, and identify stocks that are on loan with an indicator variable. We restrict the N-Q and N-CSR sample to 2003Q1 to 2017Q4. For a detailed discussion of the data, please refer to [Honkanen](#) (2020).

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<sup>11</sup>This is set in the fund bylaws.

We use the CRSP mutual fund database to construct a set of control variables for each fund and fund management company. From CRSP, we get fund Total Net Assets, fund flows, age, and returns. For each variable, we create an indicator variable flagging the top decile of funds within a given quarter. We also identify the funds with the highest flow-return sensitivity this way. We measure flow-return sensitivity by estimating the regression  $flow_{ft} = \alpha_f + \beta_f r_{ft-1} + \epsilon_{ft}$  for each fund in the data using the past 36 observations of monthly returns and flows. To identify index funds, we use the self-reported index fund status obtained from SEC filings. We use the CRSP investment objective code as a control for the fund strategy.

We use the Compustat Supplemental Short Interest file to estimate short interest for each individual stock, and compute a portfolio holdings short interest measure for each fund in the data by computing the portfolio level average short interest for each fund in each time period in the data.

The final fund-level dataset has 233,624 observations, and the fund-stock level dataset has 6,611,191 observations. The fund level dataset contains the universe of U.S. mutual funds that can be matched to SEC filings, whereas the fund-stock level dataset is restricted to a subset of the ten largest American mutual fund issuers.

Table [I](#) presents summary statistics at the fund level. First, we see that passive funds are more likely to both be allowed to lend securities (95% vs. 89%), and to lend securities (57% vs. 36%) if it they are allowed. Although the difference in point estimates in the value of lending relative to the overall portfolio is large (0.67% vs 0.01%) it is not statistically significant. This in itself illustrates the large differences and dispersion in lending strategies. The average lending fee is higher for passive funds than for active funds, as is the lending yield (lending income scaled by total assets). The average TNA is nearly a billion U.S. dollars higher for index funds than for active funds, although passive funds are younger and come from younger fund families on average. Index funds

are also more likely to have an affiliated securities lending agent. (46% vs 7%).

The average expense ratio is lower for index funds than for active funds. The total TNA of index funds within their CRSP objective code is considerably lower than that for active funds, though this can be attributed to the lower number of funds within the objective code (72 vs. 569). As a result, the market concentration, as measured by the Herfindahl index based on TNA is also considerably higher for index funds than for active funds (0.23 vs. 0.06).

Table 2 presents stock level descriptive statistics.

## 5 Empirical results

### 5.1 Lending market participation

In this section, we examine whether funds are equally likely to be allowed to lend securities. The null hypothesis in the first step of the analysis is that all funds in the family are equally likely to be allowed to lend securities. Fund families could plausibly claim that all their funds *that are allowed to lend* have perfectly equal access to loan allocation and lending markets, while preventing all but the highest value funds from lending. Differences between fund families may still lead to fund family level heterogeneity in the likelihood of being allowed to lend securities.

In the first regression, we regress a dummy for being allowed to lend ( $islending_{ft}$ ) and a dummy for whether a fund actually lends securities conditional on it being allowed to do so ( $didlend_{ft}$ ) on the main variable of interest: a dummy variable indicating whether a fund is an index fund or not. We include time or fund family  $\times$  time fixed effects in the regressions, and in specifications (3) and (6) include  $\ln TNA$ , the natural logarithm of total net assets.

The results in Table 3 reject the null hypothesis that there does not seem to be any systematic lending strategy. Index funds are generally more likely to be allowed to lend securities than active funds. The same holds, with even stronger effects, at the intensive margin: index funds, if allowed to lend securities, are significantly more likely than active funds to do so. This is, of course, likely to reflect differences in holdings. To address this, in the next section we study loan allocations at the fund-stock level.

## 5.2 Stock-level loan allocation

The previous results at the fund level could be entirely attributed to portfolio holding differences across funds. For instance, if index funds are more likely to hold stocks with a large demand for borrowing, then it is only natural that index funds would appear more likely to lend stocks. In this section, we mitigate this concern with the help of a microscopic analysis at the stock-fund level. In particular, from funds' N-Q and N-CSR filings, we know which stocks from a fund's portfolio are on loan and which ones aren't. Thus, by spanning a fund-stock-quarter panel, we can study whether certain funds are more likely to be allocated a stock loan compared to other funds within the *same fund family* holding the *same stock* at the *same point in time*.

Specifically, we run regressions of the following type:

$$onloan_{fst} = \alpha_{mst} + \alpha_{obj} + x_{ft} + stockown_{fst} + controls_{fst} + \epsilon_{fst} \quad (1)$$

where  $onloan_{fst}$  is a dummy variable indicating whether a given stock  $s$  is on loan by fund  $f$  in quarter  $t$ . Key to our identification are the high-dimensional fixed effects. In particular, by including family-stock-quarter fixed effects ( $\alpha_{mst}$ ), we ensure that we are comparing loan allocations for the same stock in the same quarter across funds within the same fund family. By including fund objective code fixed effects ( $\alpha_{obj}$ ), we further

control for different propensities to lend stocks across fund strategies. As argued above, when lending allocations are fair across funds within the family, we expect a fund’s stock ownership ( $stockown_{fst}$ , defined as the number of shares owned by fund  $f$  in stock  $s$  in quarter  $t$ , divided by the number of shares outstanding of stock  $s$  in quarter  $t$ ) to be the only variable driving lending allocations. As additional controls, we employ the fund’s latest total net assets, its average fund turnover (defined as dollar value of shares traded divided by fund TNA, averaged over the preceding 4 quarters), and the percentage holding change over the previous and the subsequent quarter for the stock in question. Standard errors are double-clustered at the fund and quarter level.

One issue with our specification is that we only observe whether a portfolio stock was actually lent, not whether it was made available by a fund in the first place. Thus, any differences in lending allocations could be driven by certain funds choosing to not supply their stocks rather than the fund family favoring certain type of funds. Luckily for us, the nature of funds’ security lending agreements is such that funds typically make available their entire stock portfolio for lending. Thus, if a fund lends at least one stock position, it is reasonable to assume that the other portfolio stocks were also potentially available for lending (i.e., the fund submitted them to the “queue” at the family-wide lending desk). We therefore restrict our analysis to funds that have at least one stock on loan in a given quarter. This condition effectively excludes all funds that may not have active lending programs in place, or that may have decided to withdraw from the securities lending market for any unobserved reason.

Our first independent variables of interest ( $x_{ft}$ ) is  $indexfund_{ft}$ , a dummy equal to one if fund  $f$  is an index fund and zero otherwise. Next, we check whether funds with a high expense ratio are more or less likely to receive a loan allocation. We thus define  $exp\_ratio\_top10$ , a dummy variable flagging funds with an expense ratio being in the top decile across all funds in a given quarter. Our third variable of interest is  $fr\_sens\_top10$ ,

a dummy variable flagging funds with a flow-performance sensitivity being in the top decile across funds in a given quarter, where flow-performance sensitivity is estimated by regressing fund flows on fund returns over the previous 36 months. Finally, we analyse whether funds with a high year-to-date return are more likely to be granted stock loans. For this we use *ytd\_ret\_top10*, a dummy variable flagging funds with a year-to-date return being in the top decile across all funds in a given quarter, where year-to-date return is defined as the fund’s cumulated return since the preceding January.

Table 4 presents the results. First, consistent with the fund level analysis, we find a positive coefficient for the *indexfund* dummy, indicating that index funds within a fund family are about 4.9% more likely to lend a specific stock than an active fund holding the same stock in the same quarter. The coefficient estimate is very robust to different control variables and fixed effects. Second, the *stockown* dummy is positive and significant in all specifications, showing that the relative portfolio share owned by a fund is a key driver affecting lending allocations. Fund TNA does not affect the likelihood of lending at the stock level. Somewhat surprisingly, the fund’s portfolio turnover garners a positive coefficient. This is, however, likely due to omitted variable bias: funds that manage their portfolios more actively may also be managing their lending programs more actively. Finally, the coefficients on the top decile dummies for year-to-date returns, expense ratio, and flow-return sensitivity are significant. The year-to-date return and flow-return sensitivity dummies are consistent with loans being allocated to the “highest-value” funds within the families. The negative coefficient on the expense ratio top decile dummy suggests that the cheapest funds within their categories are lending the most. This is in line with the hypothesis that funds are offsetting low expense ratios by increasing their lending programs. The variables *f1trade* and *l1trade* that measure stock level position changes in the quarter before and after the loan are both negative and significant, confirming that stock positions that are traded more are lent less.

Table 5 presents regressions where the main independent variable of interest is the dummy that identifies funds with a high year-to-date return. In both specifications, the year-to-date return dummy is interacted with calendar quarter dummies. The hypothesis is that funds may lend more in the last quarter(s) of the year in order to gain an advantage against their peers in fund performance rankings, thereby attracting inflows. Specification (1) shows a bit of evidence that funds with a high year-to-date return are allocated more loans in the second and last quarter of the year. This finding, however, is not robust to including all controls and fund strategy fixed effects.

## 6 Conclusion

This article studies the mechanisms of securities loan allocation within mutual fund families. Using a novel fund-loan level dataset, we show that fund families are considerably more likely to allocate loans in specific securities to index funds within the family. This holds even when controlling for fund characteristics such as expense ratio, fund size, and turnover, as well as characteristics that prior literature has found to drive performance allocation within mutual fund families.

Apart from the effect on index funds, contrary to prior literature, we do not find indication of fund family level decision making in allocating securities lending revenues. This could suggest the performance diversion found in e.g. Gaspar, Massa, and Matos (2006) is due to bilateral quid-pro-quo between individual fund managers rather than fund family level orders or directives. This view is supported by Evans, Porras Prado, and Zambrana (2019), where the authors find that cooperation between fund managers is greatly affected by the incentive scheme in use in the company: incentives that reward family performance more than individual fund performance lead to greater transfers of performance and cross-trading between funds.

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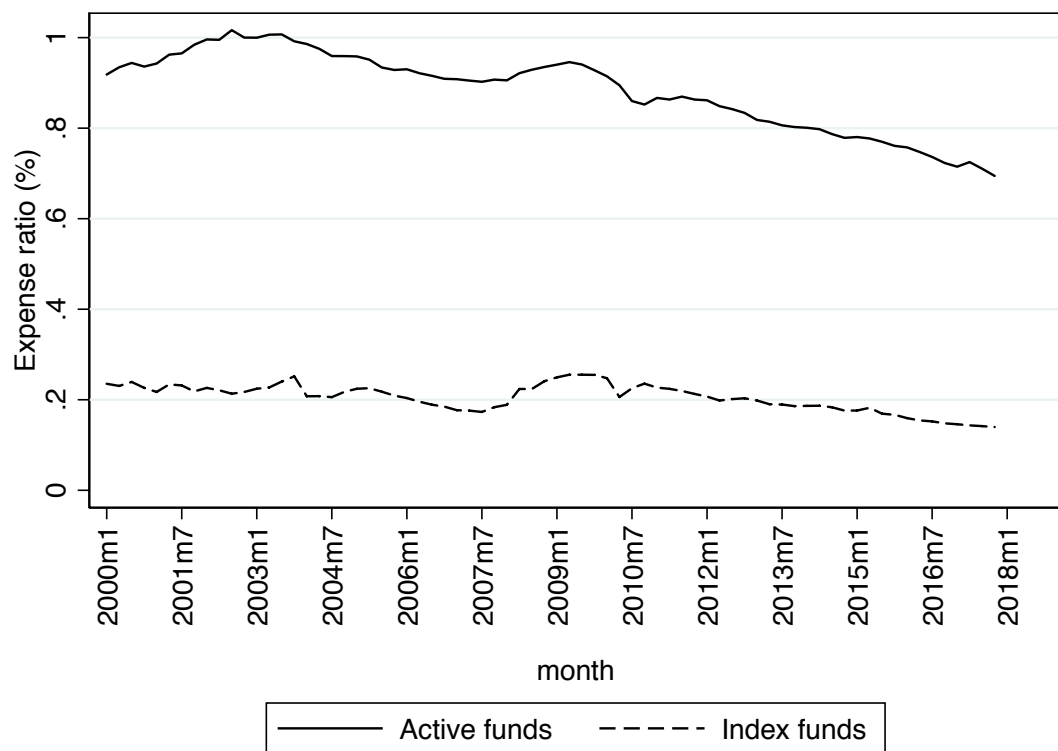


Figure 1: Average expense ratios for equity Active and Index funds from 2000 to 2017.

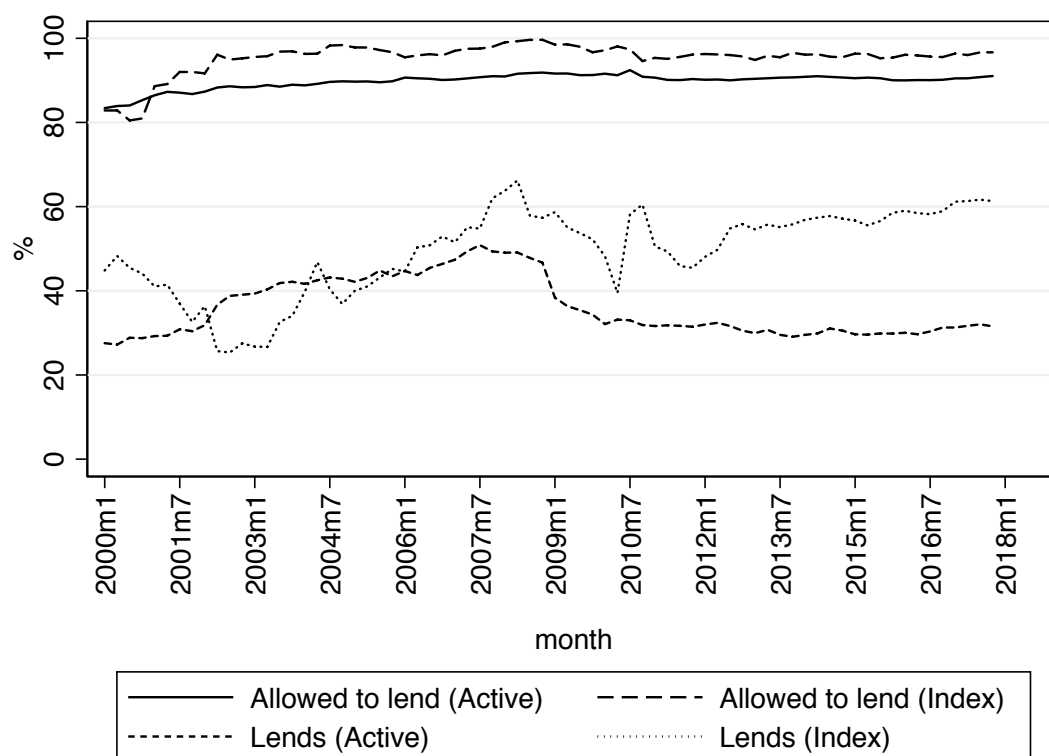


Figure 2: Lending market participation for equity Active and Index funds from 2000 to 2017. The share of funds allowed to lend has remained relatively stable throughout the sample period. The proportion of Index funds actually lending securities (conditional on being allowed to) has increased steadily over time to about 60%, while the proportion of Active funds lending securities has decreased.

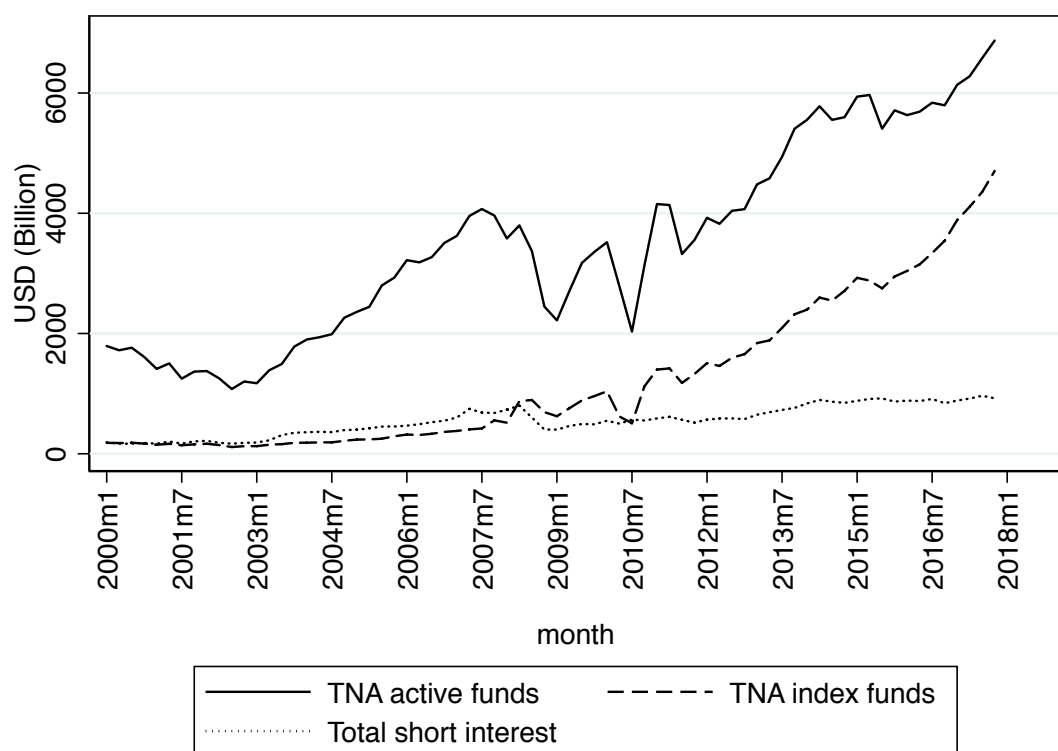


Figure 3: The graph displays the evolution of total net assets of Active and Index funds over the sample period. It also shows the total dollar value of outstanding short interest. Short interest is a small fraction of the total assets of mutual funds throughout the sample.

Table 1: Fund-level summary statistics

	Active		Passive		(Passive - Active)	
	mean	sd	mean	sd	b	t
Lending allowed	0.89	0.31	0.95	0.21	0.07***	(52.41)
Lends securities if allowed	0.36	0.48	0.57	0.50	0.21***	(75.39)
Lending share	0.01	0.05	0.67	33.89	0.65	(1.06)
Avg Lending fee	0.02	0.03	0.02	0.03	0.00***	(4.54)
Lending yield	2.36	5.09	4.04	7.11	1.67***	(9.55)
TNA	1423.58	5756.38	2504.99	16568.56	1081.41***	(13.03)
Fund age	12.80	12.02	7.92	6.22	-4.88***	(-118.51)
Flow-return sensitivity	0.14	0.94	0.24	1.17	0.10***	(15.58)
Expense ratio	0.01	0.01	0.01	0.00	-0.01***	(-154.64)
Fund family age	38.32	27.10	29.91	26.42	-8.40***	(-58.13)
Affiliated seclend agent	0.07	0.25	0.30	0.46	0.23***	(26.79)
Avg. expense ratio in CRSP obj cd	0.01	0.00	0.01	0.00	-0.01***	(-313.64)
Tot. TNA of funds in CRSP obj cd	743021.84	682214.73	157071.04	244206.95	-585950.79***	(-297.71)
Number of funds in CRSP obj cd	569.24	425.90	71.80	78.72	-497.44***	(-475.87)
Herfindal index in CRSP obj cd	0.06	0.10	0.23	0.17	0.17***	(193.84)
Observations	192750		40874		233624	

Table 2: Stock-level summary statistics

	mean	p50	sd	min	p1	p25	p75	p99	max
onloan	0.091	0.000	0.287	0.000	0.000	0.000	0.000	1.000	1.000
ytd_ret_top10	0.093	0.000	0.291	0.000	0.000	0.000	0.000	1.000	1.000
exp_ratio_top10	0.086	0.000	0.281	0.000	0.000	0.000	0.000	1.000	1.000
fr_sens_top10	0.077	0.000	0.266	0.000	0.000	0.000	0.000	1.000	1.000
index fund	0.743	1.000	0.437	0.000	0.000	0.000	1.000	1.000	1.000
stockown	2.931	0.501	5.226	0.000	0.000	0.086	2.816	26.831	26.831
ln_tna	7.595	7.780	2.265	1.589	2.219	5.996	9.201	12.636	12.636
turnover4	0.185	0.064	0.289	-0.129	-0.099	0.026	0.191	1.007	1.021
l1trade	0.208	0.039	0.479	-1.749	-1.631	0.000	0.322	1.000	1.000
fltrade	0.263	0.037	0.488	-0.637	-0.619	0.000	0.442	1.974	2.399
N	3585728								

Table 3: Lending market participation

	(1)	(2)	(3)	(4)	(5)	(6)
	Allowed	Allowed	Allowed	Lends	Lends	Lends
Indexfund	0.070*** (43.00)	0.013*** (7.41)	0.012*** (6.58)	0.219*** (80.03)	0.117*** (34.63)	0.106*** (31.96)
ln_tna			0.007*** (30.43)			0.047*** (102.91)
Quarter FE	Yes	No	No	Yes	No	No
Family $\times$ Quarter FE	No	Yes	Yes	No	Yes	Yes
Observations	230966	216427	215177	207872	196906	195791
Adjusted $R^2$	0.040	0.573	0.574	0.045	0.522	0.549

This table shows results from panel regressions at the fund-level. The dependent variable in columns (1)-(3) is a dummy variable where value 1 indicates that a fund is allowed to lend securities. The dependent variable in columns (4)-(6) is a dummy variable equal to 1 if a fund is allowed to lend securities and lends securities. The specifications in columns (1) and (4) include Quarter fixed effects. Specifications (2)-(3) and (5)-(6) include fund family-quarter fixed effects. The sample is restricted to CRSP mutual funds that can be matched to SEC Edgar N-SAR filings.

Table 4: Stock-loan allocation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Indexfund	0.049*** (4.04)	0.049*** (4.10)	0.042*** (4.20)	0.048*** (4.00)	0.045*** (3.32)	0.046*** (3.36)	0.038*** (3.37)	0.045*** (3.27)
stockown	0.004*** (4.67)	0.004*** (4.65)	0.004*** (4.81)	0.004*** (4.65)	0.004*** (4.69)	0.004*** (4.69)	0.004*** (4.83)	0.004*** (4.69)
ln_tna	0.002 (0.84)	0.002 (0.90)	0.001 (0.62)	0.002 (1.09)	0.001 (0.60)	0.001 (0.60)	0.001 (0.40)	0.001 (0.78)
ma: x(t)= turnover: window(3 1 0)	0.023* (1.90)	0.023* (1.89)	0.022* (1.85)	0.022* (1.84)	0.036*** (2.69)	0.036*** (2.69)	0.035*** (2.68)	0.035** (2.63)
ytd_ret_top10		0.010** (2.24)				0.007* (1.78)		
exp_ratio_top10			-0.026*** (-2.85)				-0.029*** (-2.84)	
fr_sens_top10				0.014** (2.19)				0.014* (1.89)
l1trade					-0.012*** (-4.85)	-0.012*** (-4.92)	-0.012*** (-5.07)	-0.012*** (-4.86)
f1trade					-0.006** (-2.09)	-0.006** (-2.08)	-0.006** (-2.22)	-0.006** (-2.07)
Family $\times$ Stock $\times$ Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
CRSP Obj Cs FE					Y	Y	Y	Y
Observations	3796613	3787251	3796613	3787298	3360555	3355903	3360555	3355915
Adjusted $R^2$	0.514	0.514	0.514	0.514	0.518	0.518	0.518	0.518

This table shows results from panel regressions at the fund-stock-quarter level. The dependent variable is the on loan dummy, a variable that flags observations in which the fund lent out the stock in question during that quarter. The sample is restricted to funds that lent out at least one stock during that quarter. This presumably ensures that the stock positions in our sample were available for lending. All regressions include family-stock-quarter fixed effects, implying that we compare the lending activities for different funds within a given fund family all owning the same stock in a given quarter. Regressions in columns 5 to 8 further include fund objective code fixed effects. The independent variables are defined as follows: *stockown* is the number of shares owned by a given fund in a given stock divided by shares outstanding; *ln\_tna* is the natural logarithm of the funds latest available reported TNA; *turnover4* is the average fund turnover the four preceding quarters, where fund turnover is defined as total dollar holding changes divided by fund TNA; *l1trade* is the percentage change in a fund's position in a given stock over the previous quarter (set to zero if fund *f* did not report holdings in stock *i* for quarter *t*-1); *f1trade* is the percentage change in a fund's position in a given stock over the next quarter (set to zero if fund *f* did not report holdings in stock *i* for quarter *t*+1); *indexfund* is a dummy variable flagging index funds; *exp\_ratio\_top10* is a dummy variable flagging funds with an expense ratio being in the top decile across all funds in a given quarter; *fr\_sens\_top10* is a dummy variable flagging funds with a flow-performance sensitivity being in the top decile across funds in a given quarter, where flow-performance sensitivity is estimated by regression fund flows on fund returns over the previous 36 months; *ytd\_ret\_top10* is a dummy flagging funds with a year-to-date return being in the top decile across all funds in a given quarter, where year-to-date return is defined as the fund's cumulated return since the preceding January. All continuous variables (including those based on which dummy variables are created) are winsorized on both sides at the 1%-level. Standard errors are double-clustered at the fund and quarter level.

Table 5: Stock-loan allocation II

	(1)	(2)
Indexfund	0.049*** (4.10)	0.046*** (3.36)
ytd_ret_qtr1	0.001 (0.22)	0.004 (0.56)
ytd_ret_qtr2	0.013** (2.09)	0.008 (1.60)
ytd_ret_qtr3	0.009 (1.11)	0.007 (0.78)
ytd_ret_qtr4	0.015** (2.51)	0.009 (1.32)
stockown	0.004*** (4.66)	0.004*** (4.69)
ln_tna	0.002 (0.89)	0.001 (0.60)
ma: x(t)= turnover: window(3 1 0)	0.023* (1.89)	0.036*** (2.71)
l1trade		-0.012*** (-4.90)
fltrade		-0.006** (-2.06)
Observations	3787251	3355903
Adjusted $R^2$	0.514	0.518

This table shows results from panel regressions at the fund-stock-quarter level. The dependent variable is the on loan dummy, a variable that flags observations in which the fund lent out the stock in question during that quarter. The sample is restricted to funds that lent out at least one stock during that quarter. This presumably ensures that the stock positions in our sample were available for lending. All regressions include family-stock-quarter fixed effects, implying that we compare the lending activities for different funds within a given fund family all owning the same stock in a given quarter. The independent variables are defined as follows: *stockown* is the number of shares owned by a given fund in a given stock divided by shares outstanding; *ln\_tna* is the natural logarithm of the funds latest available reported TNA; *turnover4* is the average fund turnover the four preceding quarters, where fund turnover is defined as total dollar holding changes divided by fund TNA; *l1trade* is the percentage change in a fund's position in a given stock over the previous quarter (set to zero if fund *f* did not report holdings in stock *i* for quarter *t*-1); *fltrade* is the percentage change in a fund's position in a given stock over the next quarter (set to zero if fund *f* did not report holdings in stock *i* for quarter *t*+1); *indexfund* is a dummy variable flagging index funds; *exp\_ratio\_top10* is a dummy variable flagging funds with an expense ratio being in the top decile across all funds in a given quarter; *fr\_sens\_top10* is a dummy variable flagging funds with a flow-performance sensitivity being in the top decile across funds in a given quarter, where flow-performance sensitivity is estimated by regression fund flows on fund returns over the previous 36 months; *ytd\_ret\_top10* is a dummy flagging funds with a year-to-date return being in the top decile across all funds in a given quarter, where year-to-date return is defined as the fund's cumulated return since the preceding January. All continuous variables (including those based on which dummy variables are created) are winsorized on both sides at the 1%-level. Standard errors are double-clustered at the fund and quarter level.

**Titre :** Essais en Finance

**Mots clés :** fonds d'investissement, information, prêt de titres, vente à découvert

**Résumé** Cette thèse se compose de trois articles. Les deux premiers articles étudient les flux d'informations sur les marchés financiers, et le troisième étudie comment les familles de fonds communs de placement peuvent utiliser des sources de revenus relativement discrétionnaires pour canaliser des bénéfices vers des fonds spécifiques au sein de la famille.

Le premier article, rédigé en collaboration avec Daniel Schmidt, étudie les retombées de prix et de liquidité sur les marchés financiers. En utilisant une expérience quasi-naturelle, nous montrons que les investisseurs observent les prix des actions pour en extraire des signaux, et les utilisent pour effectuer des transactions.

Dans le deuxième article, je montre que les fonds d'investissement acquièrent des informations par le marché des prêts de titres. Je montre que les fonds communs de placement actifs vendent les actions qui leur sont empruntées par des vendeurs à découvert, alors que les fonds indiciels - qui sont interdits de négociation - ne le font pas. D'un autre côté, les fonds indiciels sont en mesure de facturer des frais de prêt de titres plus élevés aux emprunteurs. Je leur attribue le fait qu'ils sont de meilleurs prêteurs dans le sens où ils ne peuvent pas utiliser les informations qu'ils obtiennent pour négocier, et donc tirer des bénéfices des informations des vendeurs à découvert.

Le troisième article, également avec Daniel Schmidt, étudie les politiques des familles de fonds en matière de répartition des prêts de titres et des revenus de prêts entre les fonds membres. Nous montrons que les familles de fonds s'écartent de l'allocation équitable revendiquée, en dirigeant davantage de prêts de titres et de bénéfices de prêts vers les fonds indiciels. Cette conclusion est conforme à la substitution par les fonds des frais de gestion plus faibles par des revenus de prêts de titres plus élevés.

**Title :** Essays in Finance

**Keywords :** mutual funds, information, securities lending, short selling

This thesis consists of three articles. The two first articles study information flows in the financial markets, and the third one studies how mutual fund families may use relatively discretionary income sources to channel profits to specific funds within the family.

The first article, joint with Daniel Schmidt, studies price and liquidity spillovers in financial markets. Using a quasi-natural experiment, we show that investors look at stock prices to extract signals, and use these to trade.

In the second article, I show that mutual fund acquire information through the securities lending market. I show that active mutual funds start selling the stocks that are borrowed from them by short sellers, whereas index funds — that are prohibited from trading — do not. On the other hand, index funds are able to charge higher stock lending fees from the borrowers. I attribute this to them being better lenders in the sense that they can not use the information they gain to trade, and thereby extract profits from the short sellers' information.

The third article, also with Daniel Schmidt, studies fund family level policies in allocating securities loans and lending revenues between member funds. We show that fund families deviate from the claimed fair allocation, directing more securities loans and lending profits to index funds. The finding is in line with funds substituting a lower expense ratio with higher securities lending income.