Tax-loss selling and the January effect revisited:
Evidence from municipal bond closed-end funds and exchange-traded funds

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Abstract

We revisit the tax-loss selling hypothesis as a potential explanation of the well-known January effect in securities markets. We expand the empirical evidence from municipal bond closed-end funds (CEFs) by extending the sample period by almost 20 years and adding exchange-traded funds (ETFs) to the sample. Our updated sample covers the recent growth of municipal bond ETFs and a significant increase in municipal bond trading volume and liquidity. Both developments reduce arbitrage costs and thus are expected to increase tax loss selling in the funds and increase the transmission of price effects to the underlying bonds. We find that the January effect of municipal bond CEFs becomes stronger in more recent years, and show evidence that largely supports the tax-loss hypothesis. We also find some evidence indicating a smaller discrepancy between the abnormal returns of the funds and underlying bonds. For the municipal bond ETFs, we find a smaller January effect that cannot be explained by the tax-loss selling hypothesis.

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1. Introduction

The January effect is the empirical regularity that several categories of securities generate abnormally high returns in January. This is one of the most extensively studied securities market anomalies, and had been documented in many countries and asset classes. Since its first documentation of Rozeff and Kinney (1976), many hypotheses explaining this anomaly have been proposed and tested. Among them, the tax-loss selling hypothesis is perhaps the leading candidate, and has empirical support in the literature (Branch, 1977; Ritter, 1988; Badrinath and Lewellen, 1991; Odean, 1998; Ivkovic, Poterba, and Weisbenner, 2005; Sikes, 2014). The tax-loss selling hypothesis argues that, near year-end, tax-sensitive individual investors sell securities that experience negative returns in order to realize capital loses to reduce taxes. As a result, these securities experience unusually high returns in the subsequent January as they revert to fair value after this selling pressure abates. Other proposed explanations include window dressing, where the selling pressure comes from a motive to remove risky or poorly performing stocks from institutional portfolios before year-end disclosures (Lakonishok et al. 1991; Kang, 2010; Lynch, Puckett, and Yan 2014), time variation in compensation for risk (Sun and Tong, 2010), and various behavioral explanations (Haug and Hirschey, 2006; Doran, Jiang, and Peterson, 2012; Bergsma and Jiang, 2016; Hirshleifer, Jiang, and DiGiovanni, 2020).

A major challenge of empirically testing the tax-loss selling hypothesis is to distinguish between individual investors and institutional investors, as the two types of investors have different sensitivity to taxes, with individual investors thought to be more motivated by tax-loss considerations than institutional investors. Starks, Yong, and Zheng (2006) (hereafter, SYZ) deal with this challenge by studying the return and trading patterns of municipal bond closed-end funds (Muni CEFs), which are predominantly held largely by the most tax-sensitive individual investors. SYZ find that the average January return for Muni CEFs is 2.40% higher than the rest of the year, showing that the January effect is present and surprisingly strong in Muni CEFs. They also document trading behavior that is consistent with the tax-loss selling hypothesis. Higher year-end trading volume and increased sell order imbalances are observed for funds that are "losers" in the current and previous year, and this trading activity is also positively related to the subsequent January return.

In this paper, we build on the analysis of SYZ by expanding both the breadth and length of their sample. SYZ use a sample of 168 Muni CEFs from 1990 to 2000. Our analysis covers 1990 to 2019 and uses 605 Muni CEFs and municipal bond exchange-traded funds (Muni ETFs). Therefore, our sample period adds 19 years of data to the 11 years covered in the original paper. We also build on the SYZ methodology by adding additional tests that allow for the possibility that the relevant holding periods for tax-sensitive investors varies over time.

There are important implications associated with the inclusion of Muni ETFs in our sample, which experienced a significant growth since their first introduction in 2007.[1] According to Simon and Burns (2018a), Muni ETFs grew by 35.4% from 2008 to 2016. As of 2019 (the end of our sample period), the assets under management (AUM) of the Muni ETFs in our sample total $37 billion and comprise 38% of the total AUM of Muni ETFs and CEFs combined. In contrast, the total AUM of Muni CEFs has remained relatively steady at around $60 billion since 2002. ETFs are generally more tax efficient than CEFs. CEFs are usually actively managed, while ETFs are almost all passively managed. The active trading of the underlying CEF portfolios can result in frequent and/or unexpected taxable capital gains distributions. CEFs pass on capital gains taxes to investors through the life of the investment – when the CEF sells a bond with an embedded capital gain, it is a taxable event for the fund's investors. In contrast, capital gains taxes on ETFs are incurred primarily when the ETF shares are sold by investors. Although ETF portfolios are rebalanced in response to inflows and outflows, the ETF creation/redemption process allows ETFs to reduce

[1] The first Muni ETF, iShares National Muni Bond ETF (MUB), was created in September 2007.

the tax basis on their holdings resulting in minimal capital gains distributions.[2] From this perspective, tax-sensitive investors may prefer ETFs over CEFs with similar characteristics, which could lead to stronger tax-loss selling in Muni ETFs. Further, while CEFs are often levered and trade with large premiums and discounts, ETFs are generally unlevered and trade closer to NAV. These factors could combine to reduce volatility and result in fewer tax-loss selling opportunities for ETFs relative to similar CEFs. Finally, the creation-redemption process for ETFs could lead to direct transmission of price pressures from the funds to underlying bonds, a possibility which we discuss below.

By adding 19 years to the original SYZ sample period, we also incorporate the effects of three significant changes in the municipal bond market. First, trading costs have declined significantly. According to Simon and Burns (2018b), the average effective spread of municipal bonds was above 150 basis points in 2005 and dropped to 73 basis points in 2018 – a 51% decline. Second, the retail ownership of municipal bonds has increased. In 2000, only 34% of municipal bonds were hold by individual investors. In 2018, however, 54% of the direct holders of municipal bonds were households, according to MSRB (2019). Finally, ETFs have entered the market and are now a significant portion of the remaining holders of the underlying bonds. Unlike CEFs, ETFs create and redeem fund shares upon demand. This allows them to track their underlying assets more closely by facilitating arbitrage trades when premiums or discounts overcome transaction costs. If tax-loss selling depresses ETF prices below fair value, arbitrage traders can profit by buying shares of the ETF, exchanging them for the underlying bonds, and then selling the bonds. In contrast, a trader hoping to profit from buying an underpriced CEF would likely have to hold the position and wait for its return to fair value, which adds significant risk relative to the comparable ETF trade.[3] This would presumably strengthen the link between the prices of the ETFs and the underlying bonds. These developments in the municipal bond market suggest a need to revisit an interesting finding from SYZ

[2] ETFs capital gains distributions are relatively rare. See https://www.ici.org/pdf/per20-05.pdf.

[3] In principle the risk could be reduced by shorting a correlated security. However, shorting municipal bonds directly is generally not feasible. Correlated Muni ETFs may be available, but given the limited number of products, basis risk is likely to be high. It is also possible that many Muni ETPs tend to be affected by tax-loss selling price pressure simultaneously, which raises the risk of shorting an under-priced hedge.

regarding market efficiency. SYZ report that, although there is a significant January effect in the Muni CEFs, the underlying municipal bonds do not experience the same effect. The decrease in trading costs could reduce frictions sufficiently to induce tax-loss sellers to swap CEF positions with positions in similar bonds. Similarly, the increased retail ownership coupled with lower trading costs could increase direct tax-loss selling in the underlying municipal bond market. And the ETF creation and redemption trades facilitate a new and more efficient arbitrage strategy that can transmit price pressures from the funds to the underlying bonds. Any of these channels could lead to a more pronounced January effect in the underlying bonds in recent years.

The extended sample period in our paper also covers a period that has seen major changes in tax-loss selling practices. Increased competition in the market for retail financial services has led investment advisors to offer tax-loss selling advice more broadly than in the past, especially to investors with smaller accounts. However, the increased use of technology and decreases in trading costs have allowed investors to conduct tax-loss selling on a more frequent basis, possibly mitigating its effects around year-end.

Our results are as follows. SYZ's results fully replicate in our analysis when we limit our sample to the same period, 1990 to 2000. In more recent data, we find that the January effect becomes stronger in Muni CEF raw returns and that the tax-loss hypothesis is still supported by evidence from CEF trading activity. We also find that the January Effect has increased in the underlying bonds while the discrepancy between the abnormal returns of the CEFs and underlying bonds has remained relatively stable over time. This suggests that the increase in the January Effect in the CEFs is driven by NAV returns rather than seasonal changes in fund premiums. For the municipal bond ETFs, we find a smaller January effect that cannot be explained by tax-loss selling in the ETFs, but rather appears to be largely driven by the January effect in the underlying bonds. We also show that the lack of tax loss selling in ETFs is likely explained by less frequent opportunities to realize large losses due to shorter investor holding periods and lower volatility. The effects we document are large relative to the expected returns on municipal bonds, and are likely to be of interest to market participants as well as to academics.

Section 2 provides background on tax-loss selling and reviews recent changes in the related institutional details. Section 3 describes our data and sample selection process. Section 4 presents and interprets our empirical results. Section 5 concludes.

2. Tax-Loss Selling Background

The incentive for tax-loss selling that existed during the SYZ sample period and was described in the earlier literature (see Branch 1977 for example) still exists after various evolutions of the tax code and U.S. market structure. Investors have an incentive to sell securities that have decreased in value to realize capital losses, and these realized capital losses can be used to reduce an investor's tax liability. Tax-loss harvesting is a related practice that includes tax-loss selling in a broader strategy involving reinvestment of the sale proceeds to maintain desired portfolio exposures while avoiding wash-sales. It is difficult to characterize how the strength of the incentive to tax-loss harvest has changed over time, because it is driven by both tax circumstances that are specific to individual investors and tax laws that vary across states and change over time. However, the basic incentive to harvest tax losses has remained unchanged directionally.

There are several developments in the institutional details surrounding tax-loss harvesting practices over the last few decades that may have affected both the intensity and timing of tax-loss selling, however, and their net effects are not clear. Increased competition in the market for retail financial services has created pressure for investment advisors and financial planners to provide additional services, including tax-loss harvesting advice and execution. Tax-loss harvesting is an old practice, but was traditionally a manually intensive process that was not widely offered as a service for investors with small accounts. This increased competition has pressured less sophisticated advisors to offer these services and more sophisticated advisors to offer these services to smaller accounts. While this would seem likely to increase price pressure from tax-loss selling, there is another major development that is potentially offsetting. As tax-loss harvesting has become more popular, advancements in technology and reductions in trading costs have made it more efficient and less expensive. Historically, tax-loss harvesting was thought of as a primarily a year-end activity. This made sense because investors tend to have more certainty about their tax circumstances near year-end, and the cost and effort involved was a deterrent to more frequent tax-loss harvesting. However, technological advances have made it feasible to conduct tax-loss harvesting on an automated or semi-automated basis and much more frequently, and reduced trading costs have made this more cost-effective. Now investors are likely to conduct tax-loss harvesting at more frequent intervals, in response to sales in their portfolio with capital gains to be offset, or in response market declines that generate opportunities to harvest losses which may not persist until year-end. One example is Morgan Stanley's Select UMA program, which offers automated quarterly tax-loss harvesting and additional tax-aware trading strategies that may generate even more frequent trades.[4] Their Access Investing Program also provides automated tax-loss harvesting.[5] Another is Wealthfront, a large robo-advisor, which offers automated daily tax-loss harvesting and presents a whitepaper on their website showing simulations where daily tax-loss harvesting offers large after-tax advantages over annual tax-loss harvesting.[6] If there is a large increase in tax-loss selling by less sophisticated investors and advisors due to competitive pressures, it is likely that year end tax loss selling has increased in intensity over time. Alternately, if the dominant effect is that investors who previously conducted tax loss selling near the year end now use technology to engage in these transactions more frequently, spreading out their effects over the year, it is possible that year end tax loss selling and associated price pressures have decreased. Both factors motivate testing whether the impact of tax-loss selling has changed since the SZY sample period.

3. Data

We obtain a sample of Muni CEFs and ETFs using CRSP and Compustat. We first use the share code in CRSP to select a list of CEFs and ETFs.[7] We next merge CRSP with Compustat and use the fields of company name and business description to select the securities that contain a list of keywords related to

[4] https://advisor.morganstanley.com/lucie.honosutomo/documents/field/l/lu/lucie-honosutomo/Actively-Pursuing-Tax-Alpha.pdf
[5] See https://www.morganstanley.com/what-we-do/wealth-management/access-investing/features
[6] See https://research.wealthfront.com/whitepapers/tax-loss-harvesting/
[7] CEFs are identified by a share code ending with 4. ETFs are identified by a share code of 73.

municipal bonds.[8] Then we manually check each resulting security and, relying on fund sponsor websites and various third party websites such as Morningstar, Bloomberg, and ETF.com, select the ones that indeed invest in municipal bonds. Our final sample consists of 512 Muni CEFs and 93 Muni ETFs that were traded between 1990 and 2019. We focus on four subsamples: (1) Muni CEFs from 1990 to 2000, the SYZ sample period, (2) Muni CEFs from 2001 to 2019 to examine the subsequent years, (3) all Muni ETFs from 2007 to 2019, and (4) Muni CEFs from 2007 to 2019 for comparison with the ETF sample of the same time period.

We obtain price, return, trading volume, and shares outstanding from CRSP. We obtain monthly returns on the Bloomberg Barclays Municipal Bond Index from Bloomberg as a proxy for the return on the underlying municipal bonds.[9]

We also collect trades and quotes data from TAQ, which we use to calculate the buy-sell ratio for each fund in various intervals around the turn-of-the-year period. Our TAQ data is available from 1993 through 2019. We follow Lee and Ready (1991) to assign trades as buyer or seller-initiated.

Figure 1 presents the assets under management (AUM) of Muni CEFs and ETFs through our sample period of 1990 to 2019. Muni CEF AUM shows growth in the early part of the sample and remains relatively stable at around $60 billion for the last decade. In contrasts, we observe a significant growth in Muni ETF AUM since their introduction in 2007. As of 2019, Muni ETF AUM accounts for about 38% of the combined total between Muni CEFs and ETFs.

Table 1 Panel A presents monthly summary statistics for both Muni CEFs and ETFs. Compared to Muni CEFs, ETFs tend to be larger ($387 billion vs. $210 billion mean AUM), more heavily traded (18.7% vs. 3.6% mean monthly turnover), have higher prices ($35.69 vs. $13.31 mean share price). CEF returns

[8] For example: municipal, muni, and tax-exempt.
[9] We obtain both dividend-included and -excluded returns. Following SYZ, we only report results using dividend-excluded returns in this paper. Our results do not change when using dividend-included returns.

are lower (-0.05% vs. 0.12% mean monthly return) and more volatile (0.50% vs. 0.16% monthly return standard deviation).

Table 1 Panel B presents quantiles from the distribution of January-November holding period returns for both fund types. This illustrates the incentives for investors in each fund type to engage in tax-loss selling. The larger the loss an investor faces near the end of the tax year, the more likely they are to sell to realize the loss for tax purposes. Larger losses may be more likely to overcome transaction cost hurdles and increase the chances that the particular fund is selected over other securities in the investor's portfolio to be sold. In each year, we calculate the proportion of funds of each type with calendar year-to-date returns lower than -1%, -5%, and -10% as of the last trading day in November, and report the mean across years. Consistent with the lower and more volatile returns reported for Muni CEFs in Panel A, more CEFs than ETFs have 11-month losses greater than each of the specified thresholds. For example, on average 16.7% CEFs have losses greater than 10%, compared to 1.52% of ETFs. This pattern is somewhat expected considering that Muni CEFs are more likely to use leverage and have more volatile premiums/discounts, but the differences are strikingly large.

4. Empirical results

4.1. The January effect in municipal bond funds

We first test the existence of the January effect in Muni CEFs and ETFs. We calculate the average monthly return across all funds in each subsample for each calendar month. Figure 2 presents the results. For the CEF (1990-2000) subsample, the average January return is 2.39%, and the average return of the other 11 months is -0.30% – the results are very similar to those in SYZ that use the same time period but fewer funds. The results for the two other CEF subsamples indicate that the January effect is at least more economically significant in recent years. In fact, the average January return for the CEF (2007-2019) subsample is 3.32%, as compared to an average return of -0.27% for the other 11 months. The results for ETFs, however, do not show a similarly pronounced January effect.

We further investigate the January effect by estimating three time-series regressions of monthly returns against monthly dummy variables.

$$Return_t = \alpha_1 + \beta_1 MonDummy_t + \varepsilon_t \quad (1)$$

$$Return_t = \alpha_1 + \beta_1 MonDummy_t + \beta_{13} IndexReturn_t + \varepsilon_t \quad (2)$$

$$IndexReturn_t = \alpha_1 + \beta_1 MonDummy_t + \varepsilon_t \quad (3)$$

where *Return* is the average monthly return across all funds in the subsample, *MonDummy* is the dummy that indicates one of the twelve months at a time, and *IndexReturn* is the monthly return of the underlying municipal bond index. The first regression tests whether the January effect is present in raw fund returns. The second regression controls for returns on the index and can be interpreted as an approximate test of whether the January effect exists in fund premium or discount changes. The third tests for the January effect in the underlying bonds and can be interpreted as an approximate test for the presence of the January effect in the funds' NAV returns. These specifications follow the regressions in SYZ, with the exception that we report the December dummy variables separately. We are interested in the December returns because the tax-loss selling explanation for the January effect implies negative returns in the latter part of the year.

Table 2, Panel A presents the results for regression (1). For Muni CEFs, the January effect is stronger in recent years, as the estimated coefficients on *JanDummy* increases from 2.36% in the 1990-2000 period to 3.05% in the 2001-2019 period and to 3.40% in the 2007-2019 period.[10] For Muni ETFs, we observe a January return of 0.79%, which is economically and statistically significant but smaller than that of CEFs. Panel B reports the results for regression (2), which controls for the monthly returns of the underlying municipal bond index. After controlling for the index, we still observe a significant January effect in the CEFs in all subsamples, but not in the ETFs. This finding suggests that either ETFs are more

[10] To test the statistical significance of the change, we run a regression for the full sample period with an indicator variable for the January months pre-2001 and an indicator for the January months post-2001. We find that January returns post-2001 are higher than those pre-2001 and that the difference is statistically significant (Wald-statistic of 18). In a similar regression with a cutoff year of 2007, we also find that the increase in January returns is statistically significant (Wald-statistic of 20.56).

efficient in tracking the value of underlying bonds or that more of the price pressure on the ETFs is transmitted to the underlying bonds. For the SYZ sample period (1990-2000), we observe similar results after controlling for the index return. For the 2001-2019 period, however, the coefficient on *JanDummy* decreases from 3.05% in the raw return regressions to 2.04% after controlling for the index returns. The decrease is even larger for the 2007-2019 period (from 3.40% to 2.12%). This result is consistent with our conjecture that recent developments in the secondary market for municipal bonds have led to tighter integration between the markets for the funds and the underlying bonds. Panel C reports the results for regression (3), where we use the bond index return as the dependent variable. As in SYZ, we do not find evidence of a statistically significant January effect in the underlying bonds in the earlier sample period, although the point estimate of 0.24% is arguably economically significant in this market. In the two later sample periods, the coefficients on *JanDummy* increase to 0.52% and 0.63%, and are strongly significant in the longer 2001-2019 period and marginally significant in the 2007-2019 period. This is also consistent with our conjecture regarding increased integration between the markets for the funds and the underlying bonds. Moreover, the point estimates grow from 0.52% in the 2001-2019 periods to 0.63% in the 2007-2019 period, suggesting greater transmission of price pressures as the bonds become more liquid.

We also report the estimated coefficients for *DecDummy* for all specifications. If the January effect is caused by year-end tax-loss selling, we might expect the selling pressure to cause a low December return. Our results do not confirm this expectation. The coefficients on *DecDummy* are almost all negative but all statistically insignificant for both CEFs and ETFs, and positive but insignificant for the index. We find no evidence consistent with negative price pressure associated with extreme tax loss selling in December. These results do not rule out tax loss selling that occurs earlier or is spread out over longer periods, or modest price pressure that delays price increases until January. We explore these possibilities further below.

4.2. Abnormal January returns and abnormal year-end trading volume

According to the tax-loss selling hypothesis, investors sell losers at the year-end. As such, we expect to observe a positive relation between a fund's abnormal January return and its abnormal year-end trading volume around the end of the prior year. Following SYZ, we use two abnormal volume measures that capture the trading volume around the end of the year. *Turnover* controls for the fund's shares outstanding and *Vol_ratio* controls for the fund's average trading activity before the year-end.

$$Turnover_{it} = \frac{average\ November\ and\ December\ trading\ volume\ of\ fund\ i\ in\ year\ t}{Number\ of\ shares\ outstanding\ for\ fund\ i\ at\ the\ beginning\ of\ year\ t} \quad (4)$$

$$Vol\_ratio_{it} = \frac{average\ November\ and\ December\ trading\ volume\ of\ fund\ i\ in\ year\ t}{average\ February\ to\ October\ trading\ volume\ of\ fund\ i\ in\ year\ t} \quad (5)$$

We use the two abnormal year-end volume measures as alternative explanatory variables and estimate the regression:

$$JanRet_{it} - Ret_{it-1}^{2-10} = \beta_0 + \beta_1 Volume\_measure_{it-1} + \varepsilon_{it} \quad (6)$$

where *JanRet* is the January return and $Ret^{2\text{-}10}$ is the monthly holding period return from February to October in the preceding year. As a result, the dependent variable is the abnormal January return relative to the average return in the previous year. The January effect literature finds that most of the abnormal January return is realized in the beginning of the month. Therefore, we also calculate an alternative January return measure that equals to the holding period return of the first 5 trading days of January.

Table 3 reports the results. For the CEF subsample with the same time period as SYZ, 1990-2000, there is a positive relation between abnormal January return and year-end trading volume, regardless of which return or volume measure we use. These relationships become weaker in more recent periods and disappear for the most recent 2007-2019 period. This result suggests that the trading dynamics around the year-end have changed over time. For the ETF subsample, we fail to find evidence of a significant relationship in any of our specifications. This is consistent with the contemporaneous CEF results.

4.3. Past returns and year-end selling

We further test the tax-loss selling hypothesis by examine whether the year-end trading volume is related to the lagged returns of the funds. According to the hypothesis, funds that experience lower returns are sold by the investors at the year-end, incurring a higher trading volume. Therefore, we expect a negative relation between the year-end volume and the fund performance. Again following SYZ, we estimate the following regression:

$$Volume\_measure_{it} = \beta_0 + \beta_1 Return_{it}^{c} + \beta_2 Return_{it}^{p} + \varepsilon_{it} \quad (7)$$

where $Volume\_measure_{it}$ is measured for the November-December period of the current year, $Return^c$ is the return of the current year and $Return^p$ is the return of the previous year. We calculate current year return as the holding period return of January through October in in the current year, and previous year return as the holding period return of January through December in in the previous year.

The above specification is designed to capture high trading activity due to tax-loss selling by investors with relatively long holding periods, and SYZ shows that returns over these long holding periods had explanatory power for year-end trading activity during their sample period. However, these lagged returns actually proxy for taxable losses over a representative investor's holding period that can be realized upon a sale. It is possible that lagged returns over shorter horizons are now more relevant if there is an increased population of tax-sensitive investors with holder shorting periods.[11] It is also possible that the most relevant lookback horizon varies with turnover, as representative holding period need not remain constant over time. To investigate these possibilities, we repeat these tests using an alternate proxy for a representative investors' relevant return calculated from lagged prices and volumes using a procedure from Grinblatt and Han (2005).[12] More specifically, we use three years of lagged daily prices and volumes to estimate the cost basis or reference price at which the representative investor purchased each fund, and we then calculate the return from that price to the price at the beginning of the period we use to measure year-end trading activity (*RefReturn*). The reference price is a weighted-average of daily closing prices in the measurement period, with higher weights accruing to days with higher volumes traded. Grinblatt and Han (2005) interpret the daily weights as the probability that a share was purchased on that day and still held by the same investor at the end of the measurement period. Our procedure essentially estimates the relevant

[11] We note that the tax code provides incentives to realize both short-term and long-term tax losses.
[12] We use Eq. (9) from Grinblatt and Han (2005) to calculate the reference price.

holding period from the data and allows it to vary over time. For comparability with the SYZ specification, we use *RefReturn* measured at the end of October to explain November-December trading activity. Our modified regression specification is:

$$Volume\_measure_{it-1} = \beta_0 + \beta_1 RefReturn_{it} + \varepsilon_{it} \tag{8}$$

where variables are as defined previously.

Table 4 Panels A and B report the findings using fixed horizon lagged returns. For the early CEF subsample (1990-2000), we observe statistically significant results that are similar to those of SYZ. Regardless of which volume measure is used, we observe negative coefficients for the current year return and the previous year return, consistent with the implication of the tax-loss hypothesis that recent loser funds experience a high trading volume at year-end. For more recent periods, the results indicate that the year-end trading activity is still negatively related to the current year return but the magnitudes of the coefficients drops dramatically. Further, year-end trading activity is now positively related to the previous year return. This could suggest that investors are quicker to capture losses or have shorter holding periods in recent years. In contrast, the regressions in the ETF subsample do not show a significant relationship between year-end trading activity and past fund performance using either activity variable.

Table 4 Panels C and D report the results using the *RefReturn* explanatory variable. Consistent with our results from the fixed horizon lagged returns, both models show a significant negative relationship between year-end trading activity and *RefReturn* for all CEF subsamples. However, the magnitude of the effect again drops dramatically in more recent periods. This suggests that our results from the fixed horizon lagged return models reflect an actual decrease in CEF year end tax-loss selling, rather than a shift in its timing. The results for the ETF subsample show mixed results. *Vol_ratio* shows a pattern similar to the CEF samples, but *Turnover* does not show a negative relation between past fund performance. In both models, it appears that allowing for time variation in the relevant holding period is an improvement over the fixed-horizon approach, particularly in the more recent CEF subsamples. Comparing these results to the similar regressions in Panels A and B, the magnitudes of the coefficients on are *RefReturn* tend to be larger than those on $Return^c$, and are often larger than the sum of the coefficients on $Return^c$ and $Return^p$.

4.4. December and January buy-sell ratios

Another implication of the tax-loss selling hypothesis is that, in addition to a high trading volume, we should also observe a high sell volume relative to buy volume in December for loser funds. Furthermore, in January, loser funds should have a high buy volume relative to sell volume. We use trade and quote data from TAQ to calculate the buy-to-sell ratio for each fund for the turn-of-the-year period (last 5 trading days in December and first 5 trading days in January). Then, following SYZ, we estimate the following regression:

$$Buy\_sell\_ratio_{it} = \beta_0 + \beta_1 Return_{it}^c + \beta_2 Return_{it}^p + \varepsilon_{it} \tag{9}$$

where *Buy_sell_ratio* is the buy-to-sell ratio for either the last 5 trading days in December or the first 5 trading days of January and other variables are as defined previously.

Table 5 presents the results. Again, the CEF (1990-2000) subsample confirms the results of SYZ. December buy-to-sell ratio has a positive relation with past fund performance, while January buy-to-sell ratio has a negative relation with past fund performance, indicating that loser funds experience more sell volume at year-end but more buy volume in January. For more recent periods, the results are consistent with the findings in Table 4 that the relation between year-end trading activity is not significantly related to the previous year return anymore. For the ETF subsample, we do not observe a significant relation between buy-to-sell ratio and past returns at either horizon.

4.5. Return patterns associated with tax-loss selling

In addition to the trading activity tests conducted by SYZ, we also test whether fund-year return patterns are consistent with tax-loss selling. If the tax-loss selling hypothesis explains the January effect, we should expect a fund's January return to be a reversal of price pressure observed near the end of the prior year in the same fund. Further, the price pressure near the prior year end should be driven by a representative investor's return over their holding period. Therefore, the year-end return should be a continuation of the reference period return and the January return should be a reversal of the reference period return. To test these implications, we estimate the following regression:

$$Return_{it} = \beta_0 + \beta_1 RefReturn_{it} + \varepsilon_{it} \tag{10}$$

where $Return_{it}$ is a fund's return in either the fourth quarter or January, and $RefReturn_{it}$ is as defined above.

Table 6 reports the results. For all CEF subsamples, the fourth quarter (January) returns are positively (negatively) related to *RefReturn*, as predicted by the tax-loss selling hypothesis. The relationship is negative and significant for the January returns in all cases and does not appreciably diminish in magnitude in the more recent sample periods. The fourth quarter returns are positively related to *RefReturn*, also as predicted by the tax-loss selling hypothesis, but the effect weakens over time and becomes marginally significant in the most recent sample. We interpret these results as suggesting that tax-loss selling is a major factor in the January effect for muni CEFs, but the actual tax-loss selling is no longer intensely concentrated in the fourth quarter of the year. For the ETF sample, there is no significant effect and the signs of the estimated coefficients are opposite those predicted by the tax-loss selling hypothesis.

5. Conclusion

The January effect has been one of the most widely-studied anomalies in financial markets. In a sample ending in 2000, SYZ show that the January effect is strong in municipal bond closed-end funds and show that it is likely due to tax-loss selling. Since 2000, municipal bonds experienced several important developments that changed the market structure from several perspectives. These include increased trading volume and lower transaction costs in the municipal bond market and the introduction and rapid growth of muni ETFs. In addition to changes in muni market structure, there have also been changes in tax loss harvesting practices. In this paper, we expand on the empirical evidence of SYZ by extending their sample period by almost 20 years and adding muni ETFs to the sample. We examine whether the January effect is still present in these markets and revisit the tax-loss selling hypothesis as a potential explanation. We find that the January effect becomes stronger in Muni CEFs in more recent years and is still consistent with the tax-loss selling hypothesis. We also find some evidence indicating smaller discrepancies between the abnormal returns of the funds and underlying bonds. This is consistent with our hypothesis that increased liquidity in the bond markets has facilitated arbitrage activity that transmits more of the January effect price pressure from the funds to the underlying bonds. For the municipal bond exchange-traded funds, we find a smaller January effect that cannot be explained by the tax-loss selling hypothesis. The January effect in ETFs is explained by the January effect in the underlying bonds, while the January effect in CEFs is significantly larger than that in the bonds. We present evidence showing that there are fewer opportunities for tax-loss selling in ETFs due to less volatile returns and shorter holding periods for ETF investors. We also argue that these results are consistent with the ETF structure facilitating more efficient arbitrage between the funds and the underlying bonds than the CEF structure.

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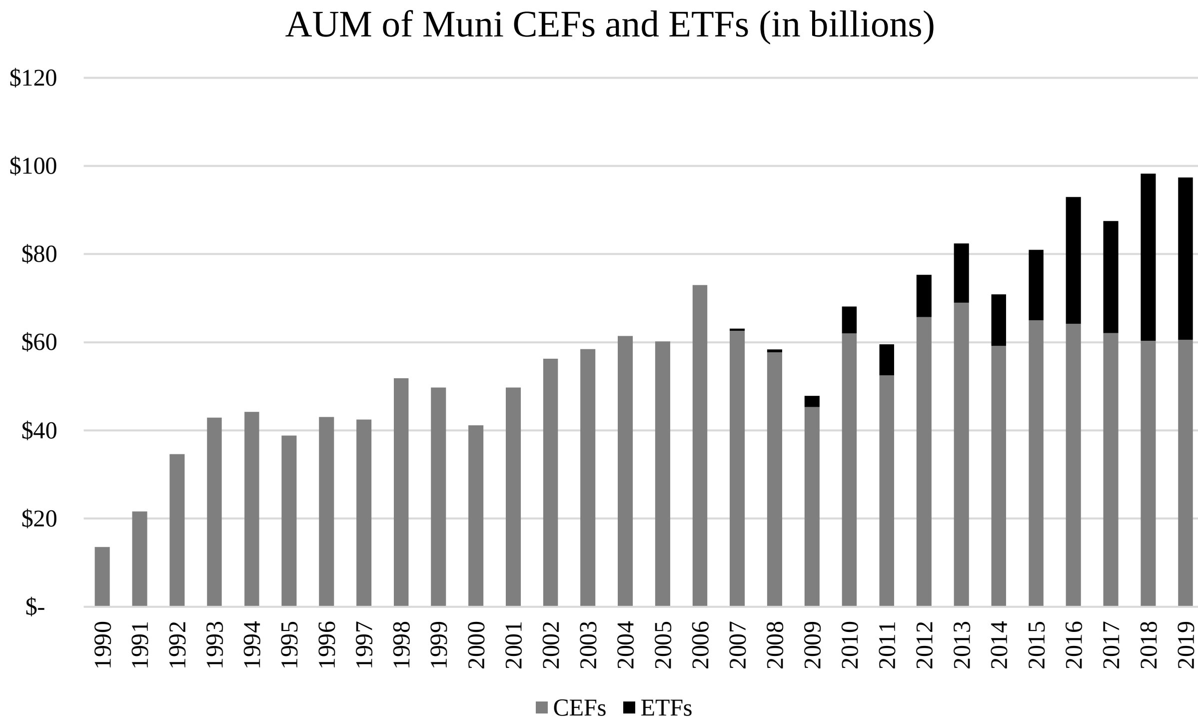

Fig. 1. Assets under management (AUM) of Muni CEFs and ETFs. This figure presents the AUM (in billions) of Muni CEFs and ETFs through our sample period of 1990 to 2019.

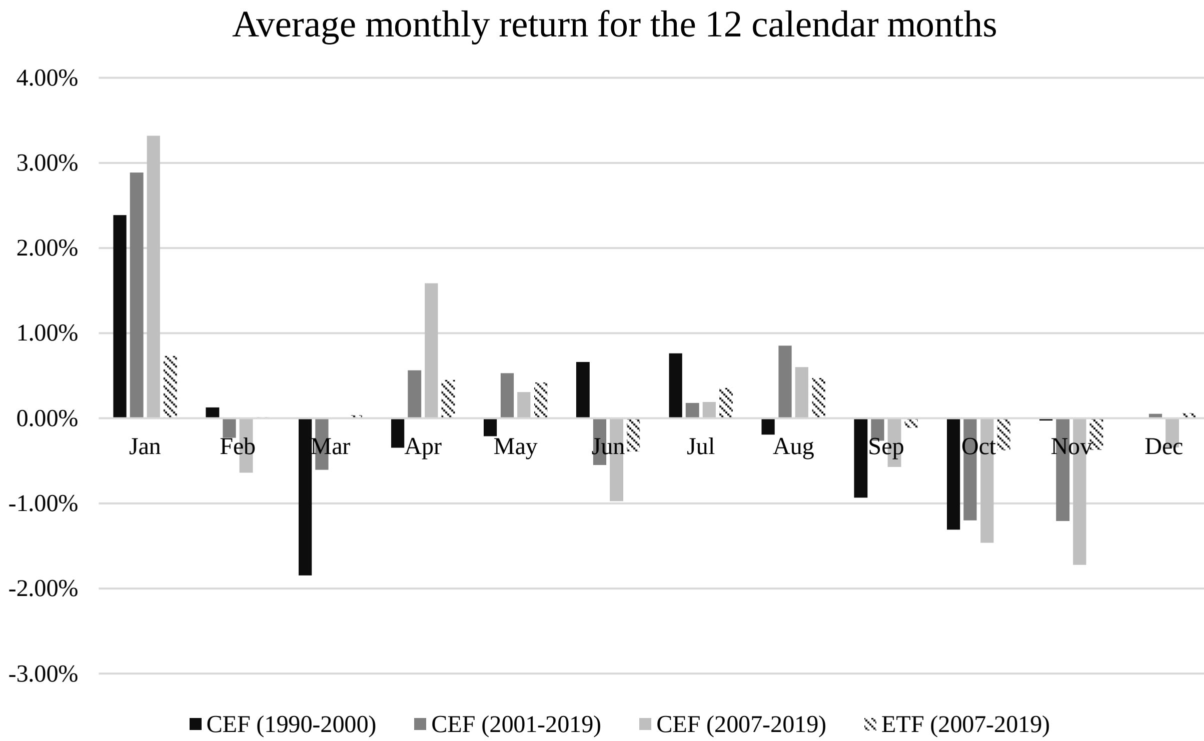

Fig. 2. Average monthly return for the 12 calendar months. This figure shows the average monthly return for the 12 calendar months across all funds in each subsample.

Table 1

Summary statistics

This table presents the summary statistics of our sample of CEFs and ETFs. Panel A shows the mean, median, and standard deviation of fund characteristics. *Monthly turnover* is *monthly share volume* divided by *number of shares outstanding*. Panel B shows the proportion of negative returns. First, for each fund/year we calculate the holding period return from January to November. Then, for each year we calculate the proportion of funds with returns that are below certain negative thresholds (-10%, -5%, and -1%). Finally, we calculate the average proportion through all years in our sample (1990 – 2019).

	CEFs			ETFs		
Panel A: Fund characteristics						
# of securities		512			93	
	Mean	Median	StdDev	Mean	Median	StdDev
Price	13.31	13.70	2.33	35.69	25.66	18.86
Monthly share volume (in thousands)	609	349	694	1,427	207	2,661
Shares outstanding (in thousands)	16,330	10,536	17,565	9,907	1,657	18,082
Monthly turnover	3.60%	3.41%	1.12%	18.69%	17.04%	8.90%
Monthly return	-0.05%	0.05%	0.50%	0.12%	0.09%	0.16%
Assets under management (in millions)	210	134	222	387	60	826
Panel B: Proportion of negative returns						
< -10%		16.70%			1.52%	
< -5%		23.25%			6.12%	
< -1%		35.02%			14.73%	

Table 2

Regressions of monthly returns on calendar month dummies

This table presents the results of three regressions of monthly returns on calendar month dummies.

(1) $Return_t = \alpha_1 + \beta_1 MonDummy_t + \varepsilon_t$

(2) $Return_t = \alpha_1 + \beta_1 MonDummy_t + \beta_{13} IndexReturn_t + \varepsilon_t$

(3) $IndexReturn_t = \alpha_1 + \beta_1 MonDummy_t + \varepsilon_t$

where *Return* is the average monthly return across all funds in the subsample, *MonDummy* is the dummy that indicates one of the twelve months at a time, and *IndexReturn* is the monthly return of the underlying municipal bond index. The table only shows the estimated coefficients and accompanying p-values for the regressions of January and December dummies. All p-values (in parentheses) are based on the Newey-West (1987) adjusted standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Subsamples	1990-2000	2001-2019	2007-2019	2007-2019
Panel A: Regression (1)				
	CEFs			ETFs
JanDummy	2.36%***	3.05%***	3.40%**	0.79%***
	(0.0059)	(0.0015)	(0.0110)	(0.0060)
DecDummy	0.14%	-0.05%	-0.29%	-0.04%
	(0.8224)	(0.9275)	(0.6869)	(0.8992)
Panel B: Regression (2)				
	CEFs			ETFs
JanDummy	2.07%***	2.04%***	2.12%***	0.10%
	(0.0053)	(0.0003)	(0.0039)	(0.4277)
DecDummy	-0.49	-0.25%	-0.42	-0.09%
	(0.3696)	(0.4964)	(0.4062)	(0.1240)
Panel C: Regression (3)				
	Index			
JanDummy	0.24%	0.52%**	0.63%*	
	(0.3983)	(0.0437)	(0.0707)	
DecDummy	0.52%	0.10%	0.06%	
	(0.1345)	(0.6809)	(0.8299)	
# of observations	132	228	156	156

Table 3

Panel regression of January return on volume measures

This table presents the results of the regressions of January return on volume measures.

$$JanRet_{it} - Ret_{it-1}^{2-10} = \beta_0 + \beta_1 Volume\_measure_{it-1} + \varepsilon_{it}$$

where *Janret* is either the monthly January return or the holding period return the first 5 trading days of January, and *volume_measure* is either *turnover* or *vol_ratio*. Coefficients on constants are not reported. All p-values (in parentheses) are based on the panel corrected standard errors, which adjust for contemporaneous correlation, autocorrelation, and heteroskedasticity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	CEFs			ETFs
Subsamples	1990-2000	2001-2019	2007-2019	2007-2019
Panel A: Regression of monthly January return on Turnover				
Turnover	35.59***	3.87	1.33	0.42
	(0.0000)	(0.2029)	(0.5154)	(0.3287)
Panel B: Regression of monthly January return on Vol_ratio				
Vol_ratio	1.89***	0.87***	0.44	0.12
	(0.0000)	(0.0000)	(0.3304)	(0.7248)
Panel C: Regression of first 5 days January return on Turnover				
Turnover	2.73***	0.49	0.28	0.04
	(0.0000)	(0.1307)	(0.4244)	(0.3595)
Panel D: Regression of first 5 days January return on Vol_ratio				
Vol_ratio	0.14***	0.09***	0.06	0.02
	(0.0006)	(0.0000)	(0.3243)	(0.5788)
# of observations	2,343	6,552	3,396	440

Table 4

Panel regression of volume measures on past returns

This table presents the results of the panel regressions with fund fixed effects. Panel A and B report the following regression:

$$Volume\_measure_{it-1} = \beta_0 + \beta_1 Return_{it}^{c} + \beta_2 Return_{it}^{p} + \varepsilon_{it}$$

where *Return*^{c} is the current year return, *Return*^{p} is the previous year return, and *volume_measure* is either *turnover* or *vol_ratio*. Panel C and D report the following regression:

$$Volume\_measure_{it-1} = \beta_0 + \beta_1 RefReturn_{it} + \varepsilon_{it}$$

where *RefReturn* is the reference price return calculated as *(Market price – Reference price)/Reference price* at the end of September. In Panel A and B, the numerator of volume measures is the average trading volume from November to December; in Panel C and D, the numerator of volume measures is the average trading volume in the fourth quarter. Coefficients on firm fixed effects and constants are not reported. All p-values (in parentheses) are based on the panel corrected standard errors, which adjust for contemporaneous correlation, autocorrelation, and heteroskedasticity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Subsamples	CEFs			ETFs
	1990-2000	2001-2019	2007-2019	2007-2019
Panel A: Turnover (Nov. to Dec.) on current and previous year return				
Return^c	-0.1396***	-0.0581***	-0.0555***	1.2412***
	(0.0000)	(0.0000)	(0.0000)	(0.0013)
Return^p	-0.5826***	0.0161***	0.0244***	0.6635***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
# of observations	2,255	6,878	3,679	440
Panel B: Vol_ratio (Nov. to Dec.) on current and previous year return				
Return^c	-5.6122***	-1.0922***	-0.9845***	3.2323***
	(0.0000)	(0.0000)	(0.0000)	(0.0004)
Return^p	-2.1289***	0.5737***	0.7763***	3.1079***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
# of observations	2,255	6,878	3,679	440
Panel C: Turnover (Nov. to Dec.) on reference price return at the end of Oct.				
RefReturn	-0.1643***	-0.0987***	-0.0872***	0.0190
	(0.0000)	(0.0000)	(0.0000)	(0.8022)
# of observations	1,710	6,282	3,312	216
Panel D: Vol_ratio (Nov. to Dec.) on reference price return at the end of Oct.				
RefReturn	-7.0199***	-1.7769***	-1.4290***	-1.7309***
	(0.0000)	(0.0000)	(0.0000)	(0.0022)
# of observations	1,710	6,282	3,312	216

Table 5

Panel regression of buy-to-sell ratio on past returns

This table presents the results of the panel regressions with fund fixed effects. Panel A and B report the following regression:

$$Buy\_sell\_ratio_{it-1} = \beta_0 + \beta_1 Return_{it}^{c} + \beta_2 Return_{it}^{p} + \varepsilon_{it}$$

where *Return*^{c} is the current year return, *Return*^{p} is the previous year return, and *Buy_sell_ratio* is the buy-to-sell ratio for either the last 5 trading days in December or the first 5 trading days of January. Panel C and D report the following regression:

$$Buy\_sell\_ratio_{it-1} = \beta_0 + \beta_1 RefReturn_{it} + \varepsilon_{it}$$

where *RefReturn* is the reference price return calculated as *(Market price – Reference price)/Reference price* at the end of September, and *Buy_sell_ratio* is the buy-to-sell ratio for either the fourth quarter or January. Coefficients on firm fixed effects and constants are not reported. All p-values (in parentheses) are based on the panel corrected standard errors, which adjust for contemporaneous correlation, autocorrelation, and heteroskedasticity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Subsamples	CEFs			ETFs
	1990-2000	2001-2019	2007-2019	2007-2019
Panel A: December last 5-day buy-to-sell ratio on current and previous year return				
Return^c	5.6701***	3.1304*	3.1747	-11.7125
	(0.0000)	(0.0731)	(0.1215)	(0.4382)
Return^p	4.5112***	0.9991	1.0899	13.5036
	(0.0000)	(0.6094)	(0.6266)	(0.5840)
# of observations	2,255	6,878	3,679	440
Panel B: January first 5-day buy-to-sell ratio on current and previous year return				
Return^c	-7.4147***	-3.8445**	-4.4884**	-38.4609
	(0.0000)	(0.0239)	(0.0205)	(0.1419)
Return^p	-5.1841***	-1.1147	-1.1400	-22.3234
	(0.0000)	(0.4414)	(0.4996)	(0.1481)
# of observations	2,255	6,878	3,679	440
Panel C: Fourth Quarter buy-to-sell ratio on reference price return at the end of Sept.				
RefReturn	3.5190***	3.6510***	4.1340**	-3.9908
	(0.0004)	(0.0089)	(0.0222)	(0.7643)
# of observations	1,710	6,282	3,312	216
Panel D: January buy-to-sell ratio on reference price return at the end of Sept.				
RefReturn	-0.6967	-6.3613***	-6.6238***	-12.2121
	(0.1172)	(0.0016)	(0.0062)	(0.3545)
# of observations	1,710	6,282	3,312	216

Table 6

Panel regression of subsequent returns on the reference price return

This table presents the results of the panel regressions with fund fixed effects.

$$Return_{it} = \beta_0 + \beta_1 RefReturn_{it} + \varepsilon_{it}$$

where *Return* is the return of either the fourth quarter or January, and *RefReturn* is the reference price return calculated as *(Market price – Reference price)/Reference price* at the end of September. Coefficients on firm fixed effects and constants are not reported. All p-values (in parentheses) are based on the panel corrected standard errors, which adjust for contemporaneous correlation, autocorrelation, and heteroskedasticity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Subsamples	CEFs			ETFs
	1990-2000	2001-2019	2007-2019	2007-2019
Panel A: Fourth Quarter return on reference price return at the end of Sept.				
RefReturn	0.3872***	0.0792***	0.0357*	-0.0149
	(0.0000)	(0.0000)	(0.0692)	(0.5583)
Panel B: January return on reference price return at the end of Sept.				
RefReturn	-0.3135***	-0.3346***	-0.3141***	0.0101
	(0.0000)	(0. 0000)	(0. 0000)	(0.5993)
# of observations	1,710	6,282	3,312	216