The MOM-TOM effect:
Detecting the market impact of CTA trading

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Abstract

Motivated by the explosive growth in CTA assets under management, in combination with the recent poor performance of many managers in this sector, we explore whether the trend-following trading style employed by many CTAs has become crowded. Explicitly, we test for market impact using the following hypothesis: around the turn of the month (TOM), trend-following (MOM) strategies digest sizeable inflows, causing the managers to trade up their existing positions, thereby pushing prices temporarily in their favor. The main empirical test is whether there is an above average return for MOM strategies on TOM days, which we refer to as the MOM-TOM effect. We found a very strong MOM-TOM effect in the Newedge Trend Index returns, with 90% of cumulative returns since 2000 being realized on the three TOM days. In addition, a replicating strategy we designed to closely track the Newedge Trend Index displayed a strong MOM-TOM effect.

Keywords: momentum, trend following, CTA, managed futures, market impact, calendar effect, crowded trade, market efficiency, trading strategy, hedge fund

JEL codes: G11, G12, G14

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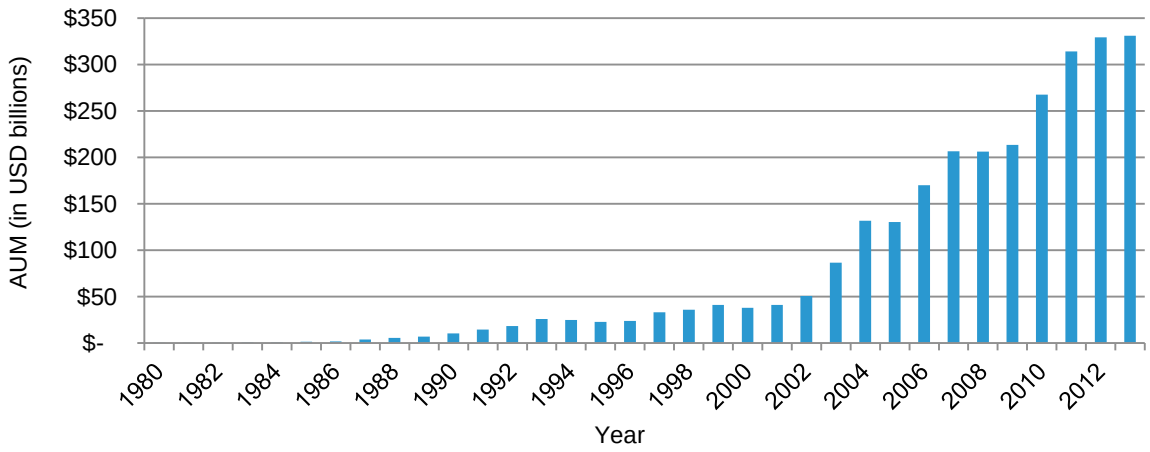
1. Introduction

Many managed futures funds, often referred to as Commodity Trading Advisors (CTAs), take a similar statistical approach to identify securities with favorable trending characteristics, illustrated by correlations as high as 0.9 between returns of two trend-following funds.[1] A similar approach leads to similar trades and similar positions.

CTAs have seen an explosive growth in assets under management (AUM) since 2002 (see Figure 1). After 2008 – a year in which CTAs were among the few hedge fund strategies that performed well – AUM growth accelerated further. As a result, the similar trading activity being undertaken by CTAs has grown substantially, which raises questions about the market footprint of these types of funds.[2] The deterioration of CTA performance since 2008 (Figure 2) supports the contention that the CTA footprint may have become significant.

Figure 1: CTA AUM



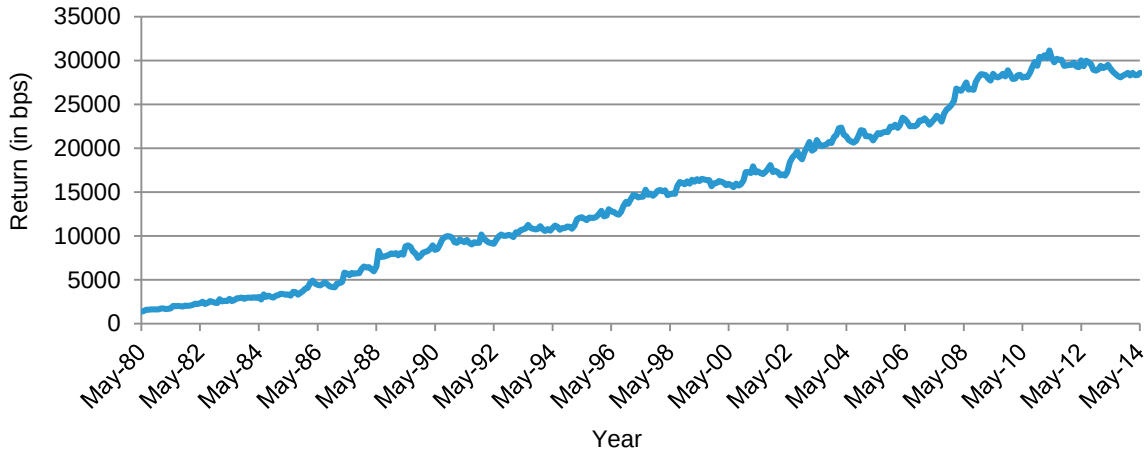
Note: This Figure plots the annual Assets under Management for CTAs. Data is from the BarclayHedge website.

In this paper we explore whether the trend-following trading style employed by many CTAs has become crowded. We focus on the turn of the month (TOM) period, during which trend-following (MOM) strategies have digested sizeable inflows, causing the managers to scale up the portfolio they were already holding at the time. We hypothesize that the buying pressure during the TOM period is large enough that it pushes prices temporarily in their favor. The main testable implication is an above-average return for MOM strategies on TOM days, which we refer to as the MOM-TOM effect.

Using the Newedge Trend Index as a proxy for the universe of trend followers, we indeed find a very strong MOM-TOM effect, with 90% of cumulative returns since 2000 being realized on the three TOM days. In addition, a replicating strategy we designed to closely track the Newedge Trend Index also displayed a strong MOM-TOM effect.

[1] A Newedge (2011) research note reports a 0.9 correlation of daily returns for several pairs of the 2011 Newedge CTA Index constituents.
[2] While most CTAs follow trends, it is not clear that most trend-followers are CTA funds. Among (non-CTA) macro funds and mutual funds trend-following strategies are also popular. Moreover, many CTAs offer managed accounts, for which the AUM may not be captured by the figure. It is thus plausible that the growth in trend-following strategies is highly understated by Figure 1.

Figure 2: Barclay CTA Index cumulative return



Note: This Figure plots the cumulative return of the Barclay CTA index, starting at 1000 in 1980. Data is from the BarclayHedge website.

A number of additional analyses are supportive of our hypothesis of trend-followers impacting prices. First, the MOM-TOM effect reverses partially over the subsequent non-TOM period, as one would expect from a temporary price pressure. Second, the MOM-TOM effect is much stronger for illiquid commodities, which one would expect to be particularly sensitive to price pressures, than it is for liquid commodities. Third, we show that the MOM-TOM effect is not simply explained by a TOM effect in passive long positions.

A number of papers have researched the price impact of institutional flows. Most papers have focused on mutual funds investing in stocks, for which (large) in- and outflows have been shown to impact both the fund return and the return of its holdings. For recent contributions, see e.g. Coval and Stafford (2007), Frazzini and Lamont (2008), Lou (2012), and Khan et al. (2012). Ahoniemi and Jylhä (2014) extend this literature to hedge funds. We augment this literature in three main ways. First, by using daily data and making use of the institutional feature that flows are concentrated around the month end, we are able to illustrate the large impact on daily returns. This pattern is obfuscated in monthly return data, typically employed by the prior literature. Second, in addition to using hedge fund index data, we also employ a replicating strategy that is highly correlated with the returns of the index, which allows us to do number of additional checks. For example we are able to analyze results for different asset classes, a longer sample period, and a modified replicating strategy with the typical long-bias of trend followers removed. Third, we focus our attention on trend-following strategies, which have shown a spectacular growth over the past decade and are thus of particular interest.

This paper proceeds as follows. In Section 2, we provide evidence for market impact by trend followers using the daily returns of the Newedge CTA and Newedge Trend Index. In Section 3, we introduce a replicating strategy, allowing us to gain a deeper understanding and derive additional results. Finally, in Section 4 we conclude.

2. Evidence from hedge fund returns

To test if (trend-following) CTAs have market impact, we examine whether returns for CTAs have been higher than normal around the moment inflows come in, which is typically at month end as most hedge funds offer monthly liquidity.[3,4] The idea is that on such days CTAs buy more of the same securities they already hold to deploy the additional capital they receive from new or existing clients. The resulting price pressure would increase CTA returns temporarily.

For an initial analysis, we use daily data from January 2000 (the start of the available data) to March 2014 for two Newedge indices, available from the Newedge website.[5]

The Newedge CTA Index (CTA Index) is an equal-weighted index of the largest CTAs that are open to new investments and which report returns on a daily basis. From 2007, the largest 20 CTAs are tracked; prior to that date a dynamic size threshold was employed.

The Newedge Trend Index (Trend Index) is an equal-weighted index of the largest trend-following CTAs that are open to new investments and report returns on a daily basis. Whether a CTA is considered a trend-follower is determined by the Newedge Index Committee, based on correlation analyses. From 2013, the 10 largest trend-following CTAs are tracked; prior to that year the trend-followers among the constituents of the CTA Index were used.

As we illustrate in Figure 3, the returns for the Trend Index are greatest on the two days straddling the close of the month (when inflows come in) and the day prior to that, which is consistent with some CTAs anticipating the upcoming price pressure and strategically trading early.[6] We will refer to these three days (the last two days of a month and the first day of the next month) as the turn-of-the-month (TOM) period. Trend-following is sometimes referred to as time-series momentum (MOM), which motivates us to dub the strong performance of MOM on TOM days as "the MOM-TOM effect".[7]

It is also noteworthy that over the two days following the TOM period (days two and three of the month) the average return is negative. This pattern further corroborates the above thesis of price pressure on days around inflows, followed by a subsequent reversal, and thus suggests that CTAs have market impact on days when they have to digest inflows.

[3] A Towers Watson (2012) document notes that "Hedge funds typically offer monthly, quarterly, or annual liquidity…". Given the liquid nature of the instruments traded by CTAs, we think it is common for CTAs to offer liquidity at the shorter end of this range, mostly monthly.

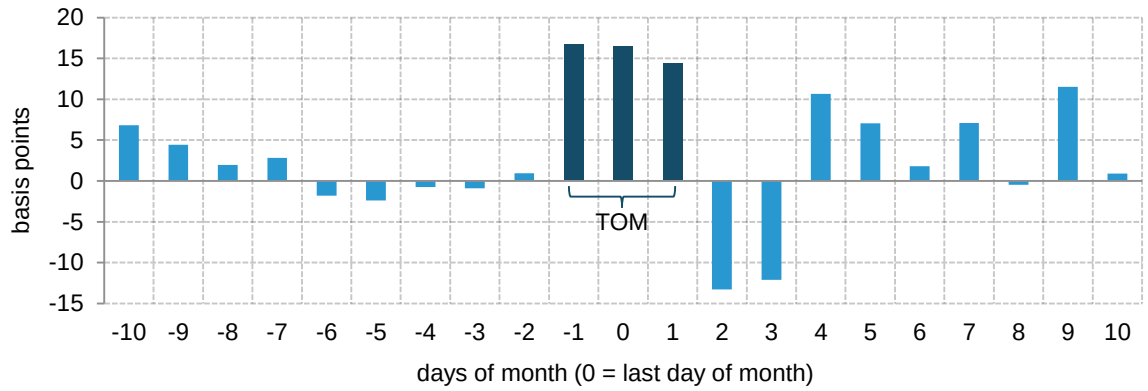
[4] In a related paper, Lou (2012) shows that flow-induced trading by mutual funds leads to a temporary price impact.

[5] See the Newedge website for more information and historical returns: http://www.newedge.com/content/newedgecom/en/brokerage-services/prime-brokerage/newedge-indices.html

[6] A similar shift forward in time is discussed in the financial media for the well-known January effect in small stocks, which was documented by Keim (1983) and Reinganum (1983). For example, a November 12th, 2011, Wall Street Journal article entitled "Playing the January effect" says "Even the time frame for the January Effect might be shifting forward a few weeks".

[7] Moskowitz et al (2012) illustrate the strong performance of a time series momentum signal applied to futures covering the major macro asset classes.

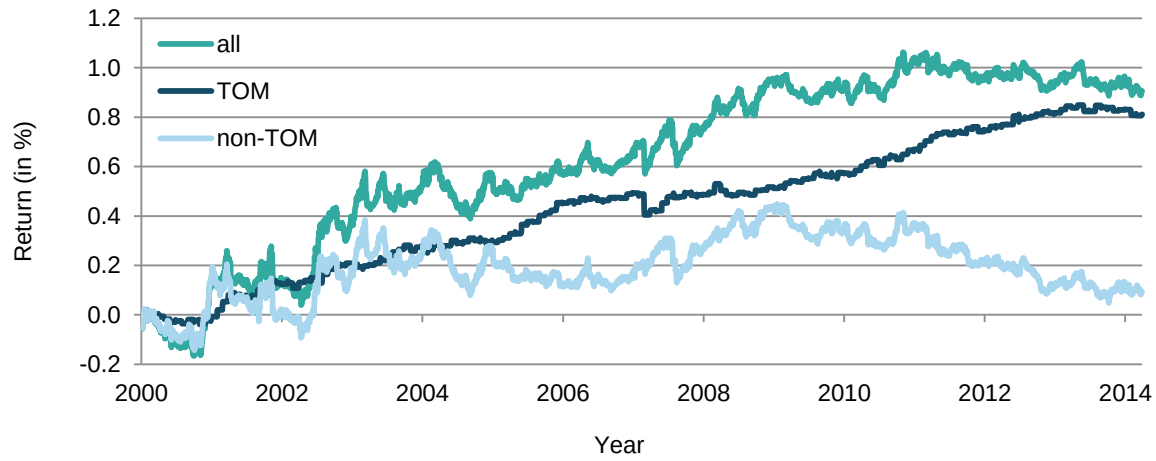
Figure 3: Average return for days of the month, Trend Index



Note: This Figure shows the average return for the Newedge Trend Index over January 2000 – March 2014 for different days of the month. Day 0 corresponds to the last day of the month. Day 1 corresponds to the first day of the month.

Figure 4 provides an even more striking picture by comparing the cumulative returns of the Trend Index using all days (green line), TOM days (dark blue line), and non-TOM days (light blue line). The two blue lines add up to the green line. A remarkable 90% of the total returns in the January 2000 – March 2014 period have been realized on the three TOM days of each month. In fact, since 2008 the non-TOM days have been a big drag on performance. Very recently, since mid-2013, the pattern seems to have reversed, and returns on TOM days have actually been negative; in line with evidence of recent outflows from CTA managers, which in turn may push prices against managers following MOM strategies during TOM days.[8]

Figure 4: Cumulative return, Trend Index



Note: This Figure plots the cumulative return of the Newedge Trend Index over January 2000 – March 2014, using (i) all days of the month, (ii) the TOM days, and (iii) the non-TOM days.

To assess the economic significance of TOM days having higher risk-adjusted returns than non-TOM days, we report in Table 1 the annualized Information Ratio (IR) on all days, TOM

[8] The CTA Intelligence Report (2014) for April 2014 reports positive net asset flows into CTAs for the first half of 2013 and negative net asset flows for the second half of 2013.

days, and non-TOM days.[9] We do this for both the Newedge indices. On TOM days the IR is 3.31 and 3.08, while on non-TOM days the IR is only 0.16 and 0.05 for the CTA Index and Trend Index respectively.

To determine the statistical significance, we regress index returns on a constant and a dummy taking the value of one on TOM days. We find a highly significant t-stat on the coefficient for the TOM dummy of 3.93 and 3.76 for the CTA Index and Trend Index respectively.[10]

Table 1: IR, Replication strategy (2000-Q1 2014)

	CTA Index	Trend Index
All	0.57	0.44
TOM	3.31	3.08
non-TOM	0.16	0.05

Note: This Table shows the annualized Information Ratio (IR) for the Newedge CTA Index and the Newedge Trend Index for (i) all days of the month, (ii) the TOM days, and (iii) the non-TOM days, using data from January 2000 – March 2014.

A salient feature of a temporary price pressure is that it (partially) reverses over time. It is a priori unclear over what time frame this reversal takes place. We thus test for a reversal over the full subsequent non-TOM period. (Extending the window further would be problematic because then a new TOM period starts.) We find that the correlation between TOM and subsequent non-TOM returns is -0.14 and -0.22 for the CTA Index and Trend Index respectively, consistent with a partial reversal.

Finally, it is well known that a long equities position performs well around the TOM.[11] We find that the CTA Index and Trend Index returns are slightly negatively correlated to the MSCI World Index on both TOM and non-TOM days (values ranging between -0.05 and -0.09) and thus conclude that the MOM-TOM effect cannot be explained by the TOM effect in long equities.

[9] The IR is computed as the ratio of the average daily return and the standard deviation of daily returns, multiplied by the square root of 250 to annualize.
[10] Using a Newey-West correction with 5 lags.
[11] Lakonishok and Smidt (1988) document the turn-of-the-month effect for the Dow Jones Industrial Average index over the 1897–1986 period.

3. Evidence from a replicating strategy

The CTA Index and Trend Index return data allow us to document a strong MOM-TOM effect, but because we don't know the underlying positions we are unable to explore further how strong the MOM-TOM effect is in different asset classes. To this end, we construct a replicating index utilizing 52 liquid futures (5 currencies, 20 commodities, 17 equity indices, 10 fixed income). At each time *t*, and for each security *i*, we construct a trend indicator view based on the moving average of returns, R, scaled by an estimate of the security's volatility to normalize.[12] For the past return we consider window length *k*, ranging from 20 to 320 days, using 20-day increments.

$$Risk\_View_t^i = \frac{\mu\left(R_s^i \middle| s = t, t-1, \dots, t-k\right)}{\sigma_t^i}$$

The above view represents the number of risk units one would invest in a single security. Next we divide (again) by the volatility estimate to turn this into a dollar view.

$$Dollar\_View_t^i = \frac{Risk\_View_t^i}{\sigma_t^i}$$

Finally, we normalize to make the portfolio have constant risk at each point in time, using the empirical covariance matrix for the security returns.[13] Without loss of generality, we set the target annualized volatility to 10% (the correlation and IR statistics are not impacted by the choice of volatility target).[14]

It turns out that the correlation of the above replicating strategy to the Trend Index peaks at 0.74 when using a moving average window of 100 days (k=100). Hence going forward we use this window length. Arguably, the 0.74 correlation is surprisingly high, considering the simplicity of the replicating strategy and the fact we are replicating (an index of) hedge funds, which charge investors substantial management and performance fees to reward managers for the proprietary and sophisticated models they have developed.

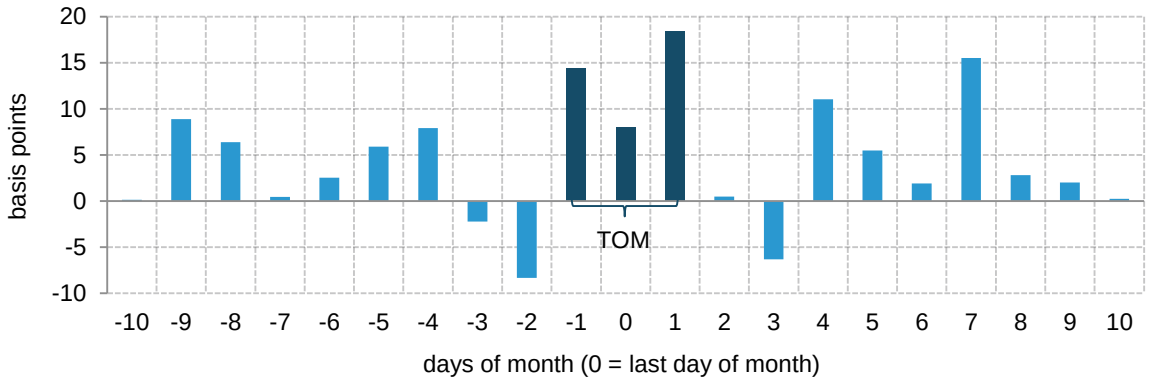
In Figures 5 and 6, we show that for this replicating strategy one can also observe a strong MOM-TOM effect. Similar to what we documented for the Trend Index, the three TOM days have high average returns and the subsequent two days have low average returns (see Figure 5). In terms of cumulative returns for the replicating strategy, about 50% is realized on the three TOM days (see Figure 6). While this is still a high percentage, it is lower than the 90% we documented for the Trend Index. It is intuitive that we find a lower percentage for the replicating strategy, as any position in the replicating portfolio but not held (or held in the opposite direction) by actual trend-followers at the time is likely to be subject to no (or negative) price pressures.

[12] We utilize a rolled return series, which is a continuous series based on an investment in the near contract up until the point the far contract becomes more liquid, at which point there is a roll-trade into the far contract. The volatility estimate is based on a mix of a short-term (about 2 months) and long-term (about 4 years) historical estimates using exponentially decaying weights.

[13] The covariance matrix is derived from the volatility estimates discussed in footnote 12 and medium-term (about 1 year) correlation estimates based on historical data using exponentially decaying weights.

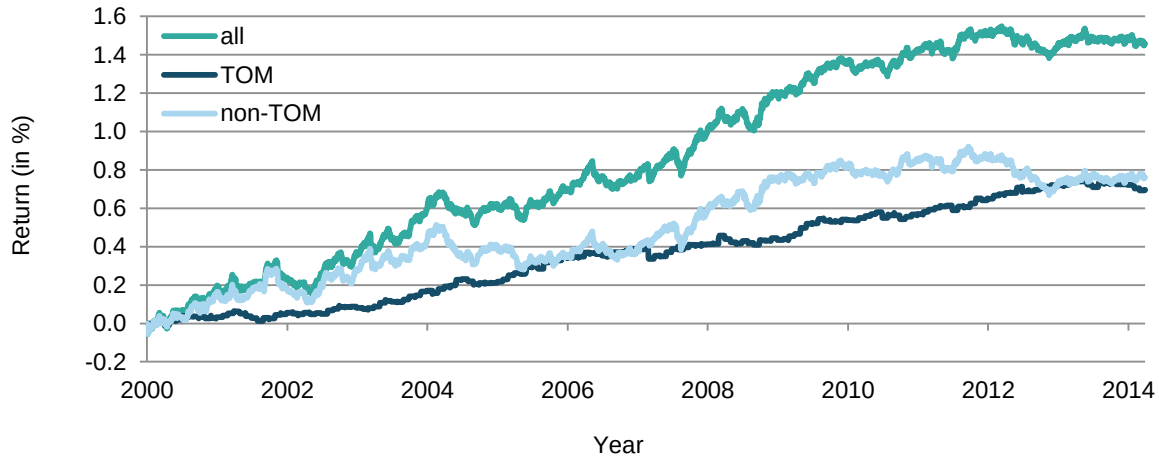
[14] For simplicity, we also abstract from fees, which we believe does not materially affect the comparison of risk-adjusted returns between TOM and non-TOM days.

Figure 5: Average return for days of the month, replication strategy (post 2000)



Note: This Figure shows the average return for the replication strategy over January 2000 – March 2014 for different days of the month. Day 0 corresponds to the last day of the month. Day 1 corresponds to the first day of the month.

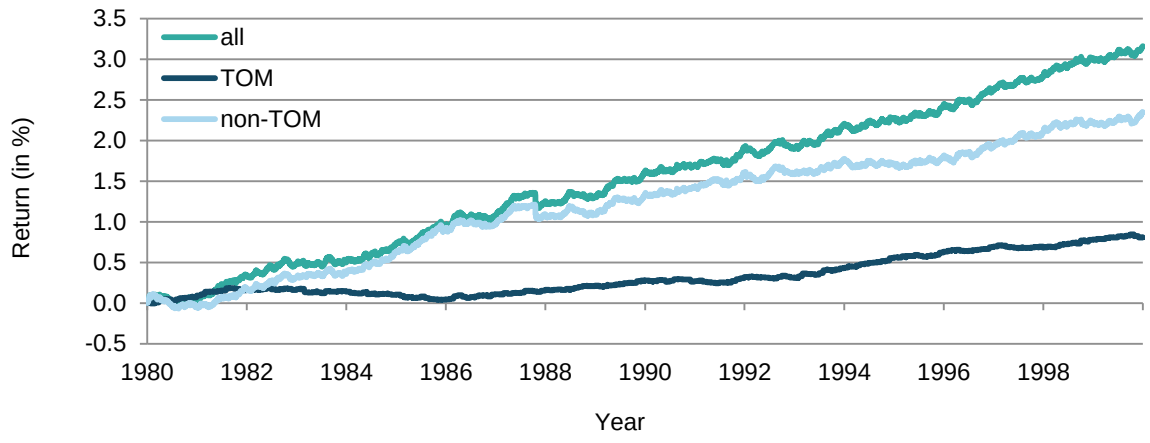
Figure 6: Replication strategy (post 2000)



Note: This Figure plots the cumulative return of the replication strategy over January 2000 – March 2014, using (i) all days of the month, (ii) the TOM days, and (iii) the non-TOM days.

The replicating strategy is not restricted to the post 2000 sample period, because we have security return data going back much further. In Figure 7 we plot the cumulative returns for all days, TOM days, and non-TOM days for the replicating strategy for the 1980 to 1999 period. Over this period TOM returns account for a much smaller portion of the total returns, in line with the theory that it is only recently (post 2000) that inflows into trend-following strategies have become meaningful enough to generate a strong MOM-TOM effect.

Figure 7: Replication strategy (1980 to 1999)



Note: This Figure plots the cumulative return of the replication strategy over January 1980 – December 1999, using (i) all days of the month, (ii) the TOM days, and (iii) the non-TOM days.

The results for the replicating strategy presented above were obtained when we apply the 100-day moving average indicator to securities of all asset classes. Additionally we can apply the indicator to specific asset classes, to see which asset classes display strong MOM-TOM effects. Table 2 presents the IR for all days, TOM days, and non-TOM days, for the different asset classes. A strong MOM-TOM effect is present for all asset classes, except for equity indices.

Table 2: IR, Replication Strategy (2000-Q1 2014)

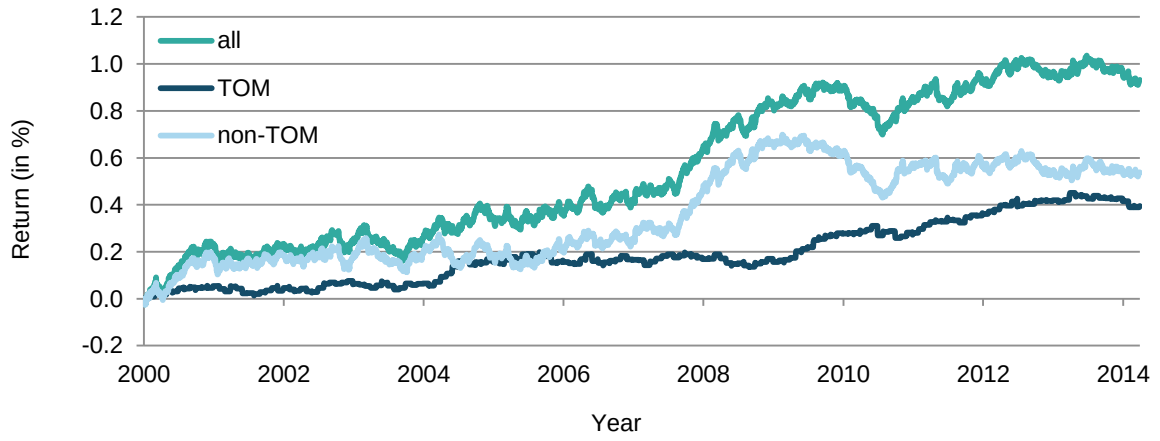
	All Securities	Commodities	Currencies	Equity Index	Fixed Income
All	0.93	0.58	0.67	0.33	0.62
TOM	3.23	2.41	2.75	0.83	2.85
non-TOM	0.56	0.29	0.36	0.26	0.28

Note: This Table shows the annualized Information Ratio (IR) for the replication strategy, applied to all securities and specific asset classes, for (i) all days of the month, (ii) the TOM days, and (iii) the non-TOM days, using data from January 2000 – March 2014.

The cross-section for commodities is large enough (20) to split it into a liquid and illiquid subset, using the classification of Baltas and Kosowski (2012), which is based on daily volume. We present the cumulative returns on all, TOM, and non-TOM days for liquid commodities (Figure 8) and illiquid commodities (Figure 9). For liquid commodities less than half of the cumulative returns have been realized on TOM days. In contrast, for illiquid commodities, almost all of the cumulative returns have been realized on TOM days. This result provides further evidence supportive of the price pressure hypothesis, as one would expect illiquid securities to be more sensitive to price pressures.

In the post 2000 period, the TOM returns have been positive for a passive long position in any of the asset classes considered (results not reported here). Since the 100-day moving average strategy is not de-meaned, it is long biased, as most securities have increased in price over the post 2000 period.

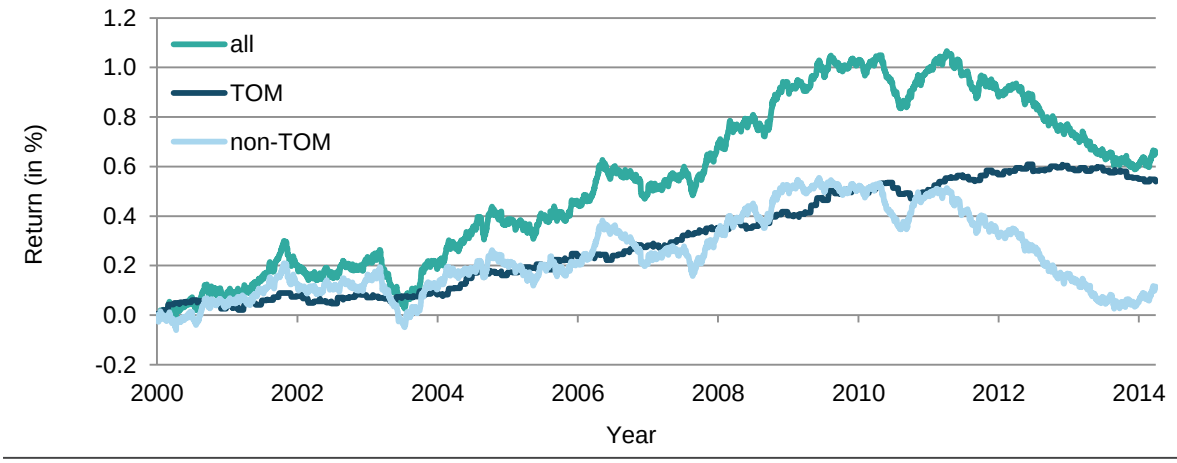
Figure 8: Replication strategy (liquid commodities)



Note: This Figure plots the cumulative return of the replication strategy applied to *liquid* commodities only over January 1980 – December 1999, using (i) all days of the month, (ii) the TOM days, and (iii) the non-TOM days.

To show that the MOM-TOM effect is not simply explained by the TOM effect in passive long positions, we consider a modified replicating strategy, where we de-mean and standardize the indicator view on a rolling basis. The correlation of this modified replicating strategy with the Trend Index is 0.65, versus a correlation of 0.74 for the replication strategy considered before, suggesting that in reality not all funds apply such a modification. The correlation of the modified replicating strategy to a passive long position is -0.01 when applied to all securities and close to zero when applied to the individual asset classes, suggesting the modification indeed took out the long bias of the replicating strategy.

Figure 9: Replication strategy (illiquid commodities)



Note: This Figure plots the cumulative return of the replication strategy applied to *illiquid* commodities only over January 1980 – December 1999, using (i) all days of the month, (ii) the TOM days, and (iii) the non-TOM days.

In Table 3 we report the IR of this modified replicating strategy for all days, TOM days, and non-TOM days for the different asset classes. While the IR on TOM days is slightly reduced versus what we reported in Table 2 for the replication strategy as previously constructed, we

still see a very big outperformance of TOM days relative to non-TOM days for all asset classes, except for equity indices.

Table 3: IR, Modified replication strategy (2000-Q1 2014)

	All Securities	Commodities	Currencies	Equity Index	Fixed Income
All	0.60	0.43	0.59	0.45	0.35
TOM	1.96	2.12	3.03	0.20	2.31
non-TOM	0.38	0.16	0.22	0.49	0.04

Note: This Table shows the annualized Information Ratio (IR) for the *modified* replication strategy, applied to all securities and specific asset classes, for (i) all days of the month, (ii) the TOM days, and (iii) the non-TOM days, using data from January 2000 – March 2014.

4. Concluding remarks

Motivated by the explosive growth in assets under management, in combination with the recent poor performance, we explored whether the trend-following trading style employed by many CTAs has become crowded. Explicitly, we tested the following hypothesis: around the turn of the month (TOM), trend-following (MOM) strategies have digested sizeable inflows, causing the managers to buy more of the portfolio they were already holding at the time, so pushing prices temporarily in their favor. The main testable implication is an above-average return for MOM strategies on TOM days, which we refer to as the MOM-TOM effect.

We did find a very strong MOM-TOM effect in the Newedge Trend Index returns, with 90% of cumulative returns since 2000 being realized on the three TOM days. In addition, a replicating strategy we designed to closely track the Newedge Trend Index also displayed a strong MOM-TOM effect.

We reported several additional findings which are supportive of our hypothesis. For example, the MOM-TOM effect reverses partially over the subsequent non-TOM period, as one would expect from a temporary price pressure. Also, the MOM-TOM effect is much stronger for illiquid commodities, which one would expect to be particularly sensitive to price pressures, than it is for liquid commodities. Finally, we showed that the MOM-TOM effect is not simply explained by a TOM effect in passive long positions.

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