# GAR_alpha_project

By Wensheng Li
GAR-alpha
June 11st

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# Pre EA return Extrapolation using industry early released EA jump

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# Motivation

- [Pre-Earnings Announcement Drift ]**had** shows that **Early-reporting firms** can predict performance of **later-reporting peers**.
- **Early-reporting firms** information is useful for **pre-announcement returns** and **EA jumps**, not necessarily **post-EA returns**.
- **Explanation - Information leakage**: The early-reporting companies may leak information about the companies that have not yet released their reports.
- **Explanation - Speculative trading:** Speculators often engage in trading before the EA is released. They base their speculation on the EA jump of the company on the performance of related companies in the same industry.

**Pre-Earnings Announcement Drift**

**Abstract**

We present evidence of a predictable drift in stock prices before the earnings announcements of firms that announce their earnings later than other firms in their industry. We form portfolios based on the returns of later announcers that are implied by the abnormal returns of earlier announcers and the historical pair-wise covariance of the abnormal earnings announcement date returns of earlier and later announcers. A long-short trading strategy based on these implied returns generates monthly returns of more than 100 basis points. The drift is neither due to the well-known momentum effect nor a manifestation of post-earnings announcement drift; it is evident both *between* the earlier announcers' earnings announcement dates and the later announcers' earnings announcement dates and *at* the later announcers' earnings announcement dates. The continued under-reaction after later announcers' earnings announcements is shown to be an under-reaction to the later announcers' own earnings announcements (i.e., post-earnings announcement drift) rather than a continued under-reaction to the earnings news of earlier announcers (i.e., pre-earnings announcement drift). We show that transaction costs explain the predictability of later announcers' returns.

# First test

- **Challenges to use Covariance used by paper directly:** Covariance calculation is complex, requires a long historical lookback period, is difficult to construct, and its interpretive meaning is unclear.
- **Testing Approach:** In specific tests, it is believed that companies in the **same industry, upstream and downstream industry chains**, **competitors, partners,** and those with **technological links** have stronger predictive correlation relationships.
- **Supporting Theory:** Many pieces of literature support the above view, including the famous **industry split over effect**, **lead-lag effect** between Economic link pairs, etc.

Within each of the thirty industries identified by Fama and French (1997), for a sample of firms making regular earnings announcements in the preceding five years, we estimate the pair-wise covariance of three-day earnings-announcement-period abnormal returns.[2] We use the returns of the earlier announcers in the industry and the historical covariance to calculate firm-level future

$$\hat{C}_{i,j} = \left(ER_{i,Q} - \bar{R}_i\right)\left(IR_{j,Q} - \bar{R}_j\right) \qquad (2)$$

where $\hat{C}_{i,j}$ is the sample covariance estimate from equation (1), $ER_{i,Q}$ is the daily abnormal return of firm $i$ on its earnings announcement day in quarter $Q$, $IR_{j,Q}$ is the implied abnormal return of firm $j$ on an unknown later earnings announcement date in quarter $Q$. Thus, the covariance implied return ($IR_{j,Q}$) for firm $j$ is defined as:[8]

$$IR_{j,Q} = \frac{\hat{C}_{i,j}}{ER_{i,Q} - \bar{R}_i} + \bar{R}_j \equiv \frac{1}{16}\sum_{q=Q-20}^{Q-5}\left(\frac{R_{iq} - \bar{R}_i}{ER_{i,Q} - \bar{R}_i}\right)\left(R_{jq} - \bar{R}_j\right) + \bar{R}_j \qquad (3)$$

## Industry Information Diffusion and the Lead-lag Effect in Stock Returns

**Kewei Hou**
Department of Finance, Fisher College of Business, The Ohio State University

I argue that the slow diffusion of industry information is a leading cause of the lead-lag effect in stock returns. I find that the lead-lag effect between big firms and small firms is predominantly an intra-industry phenomenon. Moreover, this effect is driven by sluggish adjustment to negative information, and is robust to alternative determinants of the lead-lag effect. Small, less competitive and neglected industries experience a more pronounced lead-lag effect. The lead-lag effect is related to the post-announcement drift of small firms following the earnings releases of big firms within the industry. (*JEL* G12, G14)

## Do industries lead stock markets?☆

Harrison Hong[a,*], Walter Torous[b], Rossen Valkanov[b]

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Received 16 June 2004; received in revised form 28 July 2005; accepted 9 September 2005
Available online 22 September 2006

**Abstract**

We investigate whether the returns of industry portfolios predict stock market movements. In the US, a significant number of industry returns, including retail, services, commercial real estate, metal, and petroleum, forecast the stock market by up to two months. Moreover, the propensity of an industry to predict the market is correlated with its propensity to forecast various indicators of economic activity. The eight largest non-US stock markets show remarkably similar patterns. These findings suggest that stock markets react with a delay to information contained in industry returns about their fundamentals and that information diffuses only gradually across markets.

# Benchmark test

- **Strategies:** I use the Earnings Announcement (EA) jump (also referred to as abnormal returns in literature) of companies **within the same industry that have already released their financial reports** as a signal to predict the pre-EA return of companies that release their reports later.
- **After backtesting**, I have demonstrated that:
  1. Correctly calculating indavg and trading pre-announcement > directly using the EA jump.
  2. Correctly calculating indavg and trading pre-announcement > directly calculating the indavg
  3. Correctly calculating indavg and trading pre-announcement > incorrect trading days and incorrect calculations
- **benchmark** for [https://www.trexsim.com/trexsim/dj/alpha/3924558_USA](https://www.trexsim.com/trexsim/dj/alpha/3924558_USA)

only use correct EA return

```
OS TEST RESULTS

Performance Test
ir since 2006:   0.078
ir since 2011:   0.099
ir since 2017:   0.097
numstk       :    2745
```

trexsim.com/trexsim/pysim/alpha/10951479/

better

Submitted one

```
OS TEST RESULTS

Performance Test
ir since 2006:   0.087
ir since 2011:   0.072
ir since 2017:   0.137
numstk       :    2861
```

trexsim.com/trexsim/pysim/alpha/10944695/

better

Betting on indavg but not trade on pre-EA days

```
OS TEST RESULTS

Performance Test
ir since 2006:   0.035
ir since 2011:   0.033
ir since 2017:   0.064
numstk       :    2861
```

trexsim.com/trexsim/pysim/alpha/10974697/

only betting on indavg without any conditionals

```
OS TEST RESULTS

Performance Test
ir since 2006:   0.055
ir since 2011:   0.058
ir since 2017:   0.051
numstk       :    2861
```

trexsim.com/trexsim/pysim/alpha/10970623/

# Benchmark test

- according to the data analysis of ***GAR-Earnings-Team-2 (Wensheng Li / Chenyu Wu) on Earnings Announcement Return Extrapolation***, neither *ret_0day_before_earn_ann_date* nor *ret_1day_after_earn_ann_date* provide accurate EA jump information.
- Therefore, when constructing factors, fs_next_ann_time is first used to distinguish companies that release financial reports at different times. This leads to the refinement of earning_jump_fill as follows:

```python
delay = 0
valid_mask = trading_days_til_next_ann==1
valid_effect_mask = np.zeros_like(valid_mask, dtype=np.float32)
for si, di in zip(*np.where((valid_mask == 1) & (close != np.nan))):

    # skip if we are unable to get the target
    if di + delay >= numdates:
        continue

    time = fs_next_ann_time[si, di]

    if time <= 1500:
        target_di = di
    elif time > 1500 and di + 1 < numdates:
        target_di = di+1
    if valid_effect_mask[si, target_di] != 1:
        valid_effect_mask[si, target_di] = 1

bet_days_mask = valid_effect_mask==1
bet_days_mask = op.at_nan2zero(bet_days_mask*1.0)
flatten_mask = (bet_days_mask==1.0)

earning_jump = np.where(flatten_mask[:,:-1] == 1, ret1[:,1:], np.nan)
earning_jump = np.concatenate((np.full((ret1.shape[0], 1), np.nan, dtype=np.float32), earning_jump), axis=-1)
earning_jump_fill = ts_fill(earning_jump)
```

After benchmark testing, I also found that using incorrect returns significantly increased the noise.

Incorrect EA returns

```
OS TEST RESULTS

Performance Test
ir since 2006:   0.041
ir since 2011:   0.028
ir since 2017:   0.014
numstk       :     900
```

trexsim.com/trexsim/pysim/alpha/10951513/

better →

Submitted one

```
OS TEST RESULTS

Performance Test
ir since 2006:   0.087
ir since 2011:   0.072
ir since 2017:   0.137
numstk       :    2861
```

trexsim.com/trexsim/pysim/alpha/10944695/

# Seasonality momentum is responsible for longer-horizon cross-firm predictability

By Wensheng Li

GAR-alpha

June 11st

# Extrapolation from above idea

- Apart from the above mentioned one

1. **Aaron Burt (2021)** also proposed that the information from industry peers **from many years ago** (such as EA return) still has **predictive power** for other related companies. This long-term predictive power cannot be explained by information diffusion, leading him to propose that the "**Seasonality commonality in momentum** is responsible for longer-horizon cross-firm predictability".
2. **My View**: I believe that the historical EA return information of industry peers can still predict the pre-EA return and EA jump of companies that have not yet released their financial reports. It's not just the latest EA jump.
3. **Latest vs Historical EA Jump**: The latest EA jump represents the slow diffusion of the latest information, but the historical EA jump represents the industry's seasonal predictive ability

Abstract

Cross-firm predictability among economically linked firms can arise when both firms exhibit their own momentum and their returns are contemporaneously correlated. We show that cross-firm predictability can last up to 10 years, which is hard to reconcile with an interpretation of slow information diffusion. However, it is consistent with the economically linked firms' commonality in momentum. The contribution of each source can be found by decomposing leaders' returns into the predictable (momentum) and news components. Sorting on each, we find that both sources contribute almost equally to 1-month predictability, whereas commonality in momentum is solely responsible for longer-horizon cross-firm predictability.

1-month horizon of 1.5% per month, some of which persist up to 1 year. The interpretation has been that markets are very inefficient.

We argue that such alphas may not always reflect delays in information diffusion. For intuition purposes, consider the persistent seasonalities documented by Heston and Sadka (2008), Bessembinder and Zhang (2014), and Keloharju, Linnainamaa, and Nyberg (2016). We show that sorting laggard firms into portfolios based on their linked leading firms' average returns in the predicted month over the last 10 years produces long–short portfolios with statistically significant 3-factor alphas as large as 76 basis points (bps) per month. As opposed to showing slow information diffusion, we argue that this 10-year cross-firm predictability is more likely due to common seasonal variation in the expected returns (rational or behavioral) among these economically linked firms.

# Benchmark test

- **Factor Calculation Steps:**

1. Use a 220-day Exponential Moving Weight (Emw) decay to weight the EA return of each company, resulting in ret_0day_before_mean.
2. Calculate the industry average and trade during pre-EA days.
3. Compute the operator for the Emw decay mean

```python
def rolling_unique_mean(data, window_size, alpha=0.002):
    unique_means = np.full(data.shape, np.nan, dtype= np.float32)
    weights = np.exp(alpha * np.arange(window_size+1,dtype=np.float32))
    weights /= np.sum(weights)
    weights = np.expand_dims(weights, axis=0)
    for i in ( range(window_size, data.shape[1])):
        unique_means[:, i] = np.nansum(data[:, i-window_size:i+1]*weights, axis=-1) / np.nansum(np.where(~np.isnan(data[:, i-window_size:i+1]),weights,np.nan), axis=-1)
    return unique_means
ret_0day_masked = np.where(op.ts_delay(flatten_mask*1.0, 1)==1.0, earning_jump_fill, np.nan)
ret_0day_before_mean = at_nan2zero(rolling_unique_mean(ret_0day_masked, 220))
```

- **Benchmark Testing**: After benchmark testing, it was found that not using the operator and directly using ts_mean would introduce noise.

ts_mean(ret_0day_before_earn_ann_date)

```
OS TEST RESULTS

Performance Test
ir since 2006:   0.047
ir since 2011:   0.042
ir since 2017:  -0.029
numstk       :    2861
```

better

submitted 3927458_USA

```
OS TEST RESULTS

Performance Test
ir since 2006:   0.101
ir since 2011:   0.109
ir since 2017:   0.101
numstk       :    2861
```

trexsim.com/trexsim/pysim/alpha/10974916/

trexsim.com/trexsim/pysim/alpha/10960784/

# Benchmark test

- For alpha without subindustry avg and alpha without emw decay mean of the historical EA jump, their results are both worse than calculating the subindavg of the historical moving emw average EA jump, which shows historical average EA jump and subindustry average both add value here.
- Alpha link: https://www.trexsim.com/trexsim/dj/alpha/3927458_USA

only use indavg without betting on pre-annoucement days

```
OS TEST RESULTS

Performance Test
ir since 2006:   0.092
ir since 2011:   0.106
ir since 2017:   0.136
numstk       :    2862
```

https://trexsim.com/trexsim/pysim/alpha/10970750/

Only by historical emw mean EAjump

```
OS TEST RESULTS

Performance Test
ir since 2006:  0.097
ir since 2011:  0.120
ir since 2017:  0.140
numstk       :   2862
```

https://trexsim.com/trexsim/pysim/alpha/10969527/

better

submitted3927458_USA

```
OS TEST RESULTS

Performance Test
ir since 2006:   0.101
ir since 2011:   0.109
ir since 2017:   0.101
numstk       :    2861
```

trexsim.com/trexsim/pysim/alpha/10960784/

- Alpha2 link: https://www.trexsim.com/trexsim/dj/alpha/3927332_USA
- This is industry version (just replace subindustry to industry).
- But these 2 alpha have a very low corr only 0.19.

# Economic link prediction

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# Motivation

- Companies in the same industry have an extrapolation effect which is mentioned above
- Also, Companies within the **supply chain** and those related within the industry, such as **partners or [competitors](#)**, should also have **an extrapolation effect.**

## Economic Links and Predictable Returns

LAUREN COHEN and ANDREA FRAZZINI*

ABSTRACT

This paper finds evidence of return predictability across economically linked firms. We test the hypothesis that in the presence of investors subject to attention constraints, stock prices do not promptly incorporate news about economically related firms, generating return predictability across assets. Using a data set of firms' principal customers to identify a set of economically related firms, we show that stock prices do not incorporate news involving related firms, generating predictable subsequent price moves. A long–short equity strategy based on this effect yields monthly alphas of over 150 basis points.

## Competition Links and Stock Returns

Assaf Eisdorfer, Kenneth Froot, Gideon Ozik, Ronnie Sadka*

October 2019

ABSTRACT

We consider a firm's competitiveness based on the manner by which other firms mention it on their 10-K filings. Using all public firm filings simultaneously, we implement a PageRank-type algorithm to produce a dynamic measure of firm competitiveness, denoted C-Rank. A high-minus-low C-Rank portfolio yields 16% alpha annually, where return predictability mainly stems from cross-sector competitiveness. The findings are largely consistent with investor underreaction to firm business opportunities identified by other strong firms. Nevertheless, stock return covariation with the C-Rank portfolio spread suggests that part of the return predictability can be interpreted as compensation for systematic cross-sector disruption risk.

## Technological Links and Predictable Returns

Charles M. C. Lee, Stephen Teng Sun, Rongfei Wang, and Ran Zhang**

First Draft: September 10, 2017
Current Draft: March 7, 2018

*Journal of Financial Economics* (Forthcoming)

Abstract

Employing a classic measure of technological closeness between firms, we show that the returns of technology-linked firms have strong predictive power for focal firm returns. A long-short strategy based on this effect yields monthly alpha of 117 basis points. This effect is distinct from industry momentum and is not easily attributable to risk-based explanations. It is more pronounced for focal firms that: (a) have a more intense and specific technology focus, (b) receive lower investor attention, and (c) are more difficult to arbitrage. Our results are broadly consistent with sluggish price adjustment to more nuanced technological news.

# Motivation

- Considering that companies with economic links may experience stock price changes not only around **EA days, but also on other days**, possibly due to factors like **news sentiment**, these could potentially have a **lagged impact** on the stock prices of other related companies, as demonstrated in the literature '[Economic Links and Predictable Returns]'.
- Therefore, in this analysis, **we have discarded the restriction of trading only around EA days.** We simply hope that the *ret5_excess* of companies with economic links can be used to extrapolate their own future return performance."

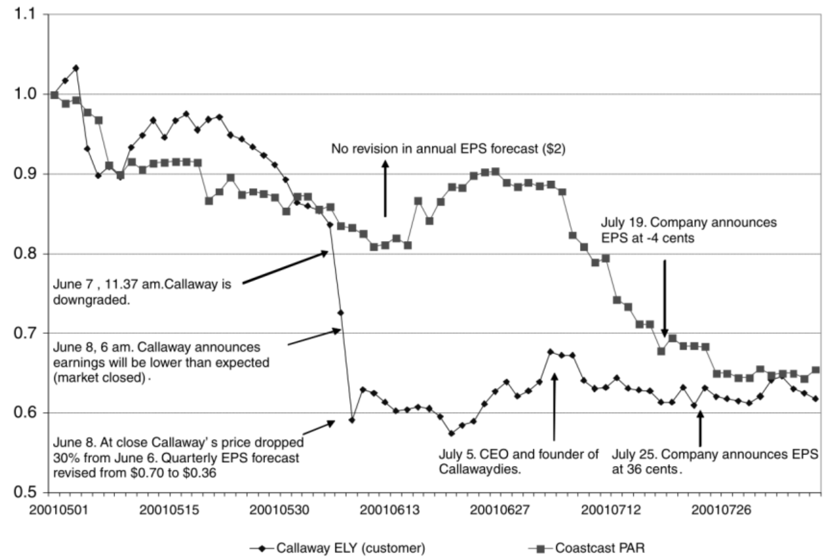


**Figure 1. Coastcast Corporation and Callaway Golf Corporation.** This figure plots the stock prices of Coastcast Corporation (ticker = PAR) and Callaway Golf Corporation (ticker = ELY) between May and August 2001. Prices are normalized (05/01/2001 = 1).

# Benchmark test

- Alpha link: https://www.trexsim.com/trexsim/dj/alpha/3926684_USA
- **Economic Links is useful:** Using ret5_excess of economically linked companies outperforms using the company's own. See first benchmark below.
- **Selection of different Economic Links:** I selected those with higher coverage, such as revere_all_partner and revere_competitor. Also because **partner and competitors** usually have **higher historical average ret correlation** compared to others, which the research paper below tells us that high **historical corr will predict better.**
- Secondly, because of companies may not always disclose their partner or competitor **completely** in their financial statements, so considering using them both will be a robust idea. By doing benchmark test, I confirmed that using both partner and competitors' information will beat the result of using one alone.
- **Benchmarks test**
- https://www.trexsim.com/trexsim/pysim/alpha/10960828/ only re5_excess beaten
https://www.trexsim.com/trexsim/pysim/alpha/10960836/ only bet on revere_all_parterner beaten
https://www.trexsim.com/trexsim/pysim/alpha/10960834/ only bet on revere_competitor beaten
https://www.trexsim.com/trexsim/pysim/alpha/10960831/ without factorneutral beaten

Competition Links and Stock Returns

Assaf Eisdorfer, Kenneth Froot, Gideon Ozik, Ronnie Sadka*

October 2019

ABSTRACT

We consider a firm's competitiveness based on the manner by which other firms mention it on their 10-K filings. Using all public firm filings simultaneously, we implement a PageRank-type algorithm to produce a dynamic measure of firm competitiveness, denoted C-Rank. A high-minus-low C-Rank portfolio yields 16% alpha annually, where return predictability mainly stems from cross-sector competitiveness. The findings are largely consistent with investor underreaction to firm business opportunities identified by other strong firms. Nevertheless, stock

Does prior stock return correlation predict future stock return correlation?

Jonathan Ross[1]

Received: 10 June 2022 / Accepted: 8 August 2023 / Published online: 24 August 2023


Abstract

Using the sample time period 1950–2020, the historical average stock return correlation of a portfolio of firms is a strong positive predictor of that same portfolio's future average stock return correlation. The prediction improves when more prior monthly returns are used. The prediction holds after controlling for macroeconomic factors. The prediction also is much better for portfolios comprised of small firms

# Change in Skewness with future stock return

By Wensheng Li

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June 11st

# Motivation

- Skewness has been empirically proven in numerous studies to exhibit a significant correlation with future stock returns.
- However, the **change in skewness** often contains valuable information as well.
- "[Time-Varying Skewness in Stock Returns]" points out that changes in skewness can be explained by behavioral prospect theory, where skewness change measures the **uncertainty level among traders regarding the possibility of good or bad news in the future**.
- The impact of skewness change tends to be more pronounced, [especially around earnings announcement dates] (later factors will involve).

small and large stocks. Aggarwal and Aggarwal (1993) show that skewness properties differ across the organized stock markets, and Alles and Kling (1994) document a significant presence of negative skewness in return distributions and changes of the degree of skewness with the stages of the business and stock market cycles.

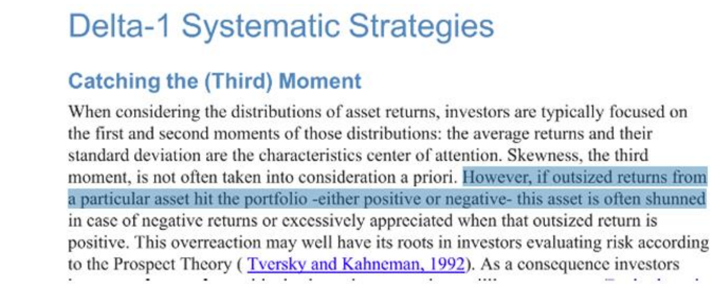
the negative skewness phenomenon. Damodaran (1985) shows that a negative skewness can be introduced into stock return distributions when firms have a greater propensity to release good news versus bad news, and McNichols (1988) finds less positive skewness during earnings announcement periods versus non-announcement periods. Damodaran's skewness bias is predicted to be evident mostly over short time intervals. McNichol's negative skewness effect is a comparative bias

Second, this paper investigates whether alternative behavioral theory-based explanations can provide answers for the systematic variation of skewness as economic environments change, documented in Alles and Kling (1994). We demonstrate that as economic conditions change, the changes that investors make in categorizing news as good or bad relative to a subjective reference point, and the changes they make to the levels of uncertainty attached to good and bad news can give rise to variation in skewness.

We extend the studies of Amaya et al. (2015) and Bollerslev et al. (2020) by showing that realized measures around important corporate announcements have stronger predictive power than those in non-announcement periods. Amaya et al. (2015) and Bollerslev et al. (2020) explore the unconditional relation between realized measures and future stock returns. They show that realized volatility cannot consistently predict subsequent stock returns. In contrast, we find that pre-announcement realized variance positively and significantly predicts post-event stock returns. Our findings are consistent with the results of Choi and Lee (2017) that examine realized moments around analyst forecasts and recommendations. More interestingly, we observe a negative estimated coefficient on realized skewness in the univariate regression. However, the coefficient changes from "negative" to "positive" after controlling for realized jump, while realized jump remains negatively and statistically significant in both univariate and multivariate models. This finding is in line with that of Bollerslev et al. (2020). Bollerslev et al. (2020) provide an econometric rationale and argue that there may

# Benchmark test

- JP morgan's article Catching the third moment also mentions that Before performance announcements, uninformed traders show risk aversion towards assets with high absolute skewness or change of skewness, **regardless of its direction.**



Delta-1 Systematic Strategies

**Catching the (Third) Moment**

When considering the distributions of asset returns, investors are typically focused on the first and second moments of those distributions: the average returns and their standard deviation are the characteristics center of attention. Skewness, the third moment, is not often taken into consideration a priori. However, if outsized returns from a particular asset hit the portfolio -either positive or negative- this asset is often shunned in case of negative returns or excessively appreciated when that outsized return is positive. This overreaction may well have its roots in investors evaluating risk according to the Prospect Theory ( Tversky and Kahneman, 1992). As a consequence investors

- **Therefore, I use the short-term changes between days in intraday skewness to construct an alpha**

- Alpha link: https://www.trexsim.com/trexsim/dj/alpha/3927456_USA
- **Benchmarks test**
- https://www.trexsim.com/trexsim/pysim/alpha/10960839/ only var it self
- https://www.trexsim.com/trexsim/pysim/alpha/10960848/ ts_zscore(var) tvr too high
- https://www.trexsim.com/trexsim/pysim/alpha/10968807/ ts_mean(ts_zscore(var))
- https://www.trexsim.com/trexsim/pysim/alpha/10960853/ cs_factorneutral lower the corr2vol
- https://trexsim.com/trexsim/pysim/alpha/10849221/ cs_rank lose information
- It's clear that bet on spread add value here, because bet on spread can increase the ir_tvr of using ts_zscore() alone by keeping tvr at a reasonable level
- What's more, using ts_zscore() have a very high tvr>1.
- Compared to ts_mean(ts_zscore(var)) , betting on spread increase **ir** a lot.
- What's more betting on spread have a very low corr with using ts_zscore(var) alone about 0.33, which means that they are different.

# Thanks

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Jack(Wensheng) Li