10-K Similarity (Lazy Prices)

Researchers: Porter Olson & Josh Oldroyd

February 25, 2026

1 Introduction

As one of the seven deadly sins slothfulness — or in other words, laziness — is one of the downfalls of humanity (according to Ponticus). Laziness is found in financial markets as well, as investors are unable or unwilling to incorporate information into financial markets; thus, creating market inefficiency.

This phenomenon is primary driver for the *Lazy Prices* trading strategy. Cohen, Malloy, and Nguyen (CMN) argue that because of the size of 10-K (and 10-Q) documents, investors are unable/unwilling to incorporate all of the relevant information into the stock; thus, creating a mispricing. CMN propose a strategy in their paper where one goes long in stocks that are non-changers and shorts changers in order to collect risk-neutral return.

They argue that firms that do not change their 10-K/10-Q filings as much will be comparatively less mispriced than non-changers (also the mispricing CMN find typically is a lack of incorporating bad information).

2 Data

2.1 CMN's Data

"We download all complete 10-K, 10-K405, 10-KSB and 10-Q filings from the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) website from 1995 to 2014. All complete 10-K and 10-Q filings are in HTML text format and contain an aggregation of all information that are submitted with each firm's file, such as exhibits, graphics, XBRL files, PDF files, and Excel files. Similar to Loughran and McDonald (2011), we concentrate our analysis on the textual content of the document. We only extract the main 10-K and 10-Q texts in each document and remove all tables (if their numeric character content is greater than 15 XLS, and other binary files (CMN 2019)."

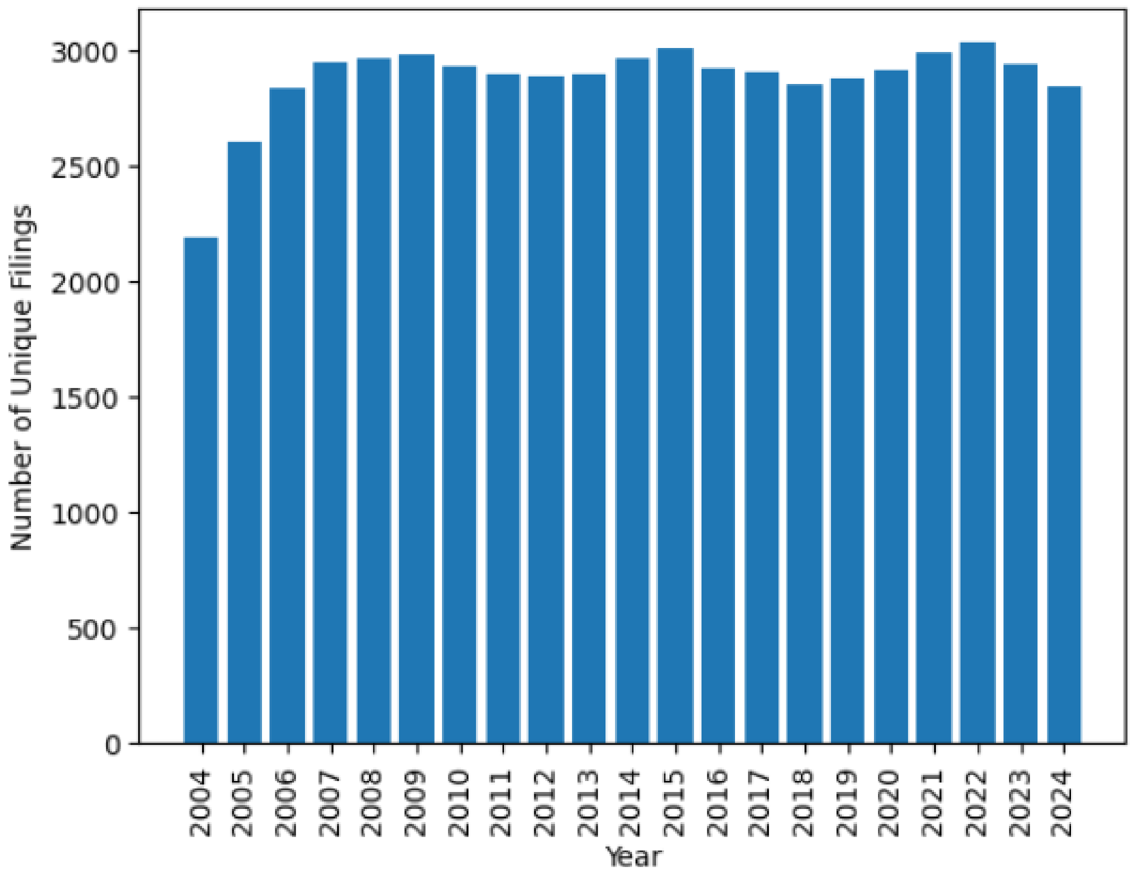


Figure 1: Russell-3000 10-K Coverage

2.2 Our Data

Similar to CMN's approach we use data from SEC EDGAR. To limit the amount of cleaning we had to do, we utilize the free API wrapper *edgartools* where all semi-recent ($year \geq 2004$) filings are cleaned in nice html/xrbl format.

Through this API, we use CIK [1] to query for each of the 10-K filings for stocks in our benchmark; doing so yields the coverage seen in Figure 1. In order to conduct our replication and extension we use the following data:

1. 10-K data (edgartools)

2. Pricing data (Barra/CRSP)

[1]CIK can be obtained through COMPUSTAT on WRDS; Compustat Capital IQ → Compustat North America → Fundamentals Annual

3 CMN's Results

CMN find that firms that make larger textual changes ("changers") significantly underperform firms that make few changes ("non-changers"), with a long–short portfolio earning roughly 34–58 basis points per month even after controlling for standard risk factors. Importantly, they find there is no essentially no announcement-day return; instead, returns accrue gradually over the following 6–12 months, consistent with investor inattention rather than risk compensation. Changes are especially predictive when concentrated in risk factors (Item 1A), litigation language (Item 3), and executive turnover references (Item 7), and they also forecast future negative earnings surprises, profitability declines, news events, and bankruptcies.[2]

4 Our Replication

Since, for our replication, we only had 10-K data (whereas CMN have 10-K and 10-Q data), we should expect our initial results to differ slightly (but perhaps remain directionally similar). Further, the data we were able to get from EDGAR was from 2004 to 2024. Thus, we have nearly 10 years in sample and 10 years out of sample — which may help us know if this signal/paper was simply data-mined.

4.1 Data Cleaning

While the data we got from *edgartools* was already quite clean, we did some initial cleaning[3] to make sure that we have the right year comparison for each CIK.

4.2 Similarity Calculation

CMN utilize four different similarity metrics to calculate similarity between 10-K filings and previous year - same quarter 10-Q filings. The four methods they use are: Cosine Similarity, Jaccard Similarity, MinEdit, Simple Similarity.[4]

$$CosineSim(A, B) = \frac{A \cdot B}{\|A\| \|B\|} \tag{1}$$

Cosine similarity is calculated by vectorizing the 10-K/10-Q text. This vectorization is done in such a way where each word is assigned a count value (how many times it appears

[2] This is my edited version of ChatGPT's summary; figured I would give it credit.
[3] Code for cleaning is available at the GitHub link provided in the references.
[4] A much more detailed explanation of their similarity metrics is found in the data section of their paper.

in the text). After repeating this process for the both documents, the Cosine similarity of the two vectors is calculated as shown in (1).

In our replication, we only use Cosine similarity as it is inherently simple to understand and because in *Lazy Prices* it seems to be the best at picking up on differences in item text.

With that being said, in the future we plan to research other methods of calculating similarity — whether that be methods used in *Lazy Prices* or more novel methods (such as ML or DL approaches).

4.3 Portfolio Construction

In CMN's construction, they form quintile portfolios based on similarity — as such, we do the same in order to match their methodology. Furthermore, because CMN have 10-K and 10-Q data they define their holding period as 3 months — or in other words until their next data point. Since we do not have 10-Q data, we experiment with different holding periods but eventually decide on holding for 12 months[5] as it is most intuitive.

Additionally, CMN only reported five different items from 10-K/10-Q filings[6] While some analysis was done (on our part) to explore the similarity signal in other items present in 10-K filings, we spent very little time and energy researching this; thus, a logical extension for future research would be to explore other items more fully.

CMN (and us as well), find that `Item 1A - Risk Factors` is most predictive of future returns. Also it is important to note that we only did equal-weighting, whereas CMN did both equal and value weighting.[7]

Below we report our Fama-French 5-factor regression for the quintile sort of Item 1A; note that all other results for all items are reported in the appendix.

From the five factor regression below in Table 1., we see that the spread portfolio has a significant intercept of 65 bps (per month). Further, the spread portfolio does not load on any of the other risk factors, indicative of a truly risk neutral strategy.

While other items present in 10-K reports did not signal as well in our replication, Item 1A seems to be robust to lack of data (only having a yearly signal). One plausible explanation may be: firms often simply reuse the text of Item 1A in their 10-Q reports and then only annually update their risk factors in their corresponding 10-K.

With that being said, it seems that the alpha generated by most other 10-K/10-Q items

[5]CMN find some decay in the similarity signal over time. They estimate that this signal lasts approximately 6 months. Thus, one area of future research will be regarding the optimal holding period with 10-K data.

[6]The five items that CMN report are as follows: Item 1A - Risk Factors, Item 3 - Legal Proceedings, Item 7 - Management's Discussion, Item 7A - Market Risk Factors, Item 9B - Other Information.

[7]While CMN do both weighting schemes, it is important to note that most of the alpha reported was in the equal weight construction; perhaps indicative of the signal being more predictive in small-cap stocks.

are not robust to only having annual data. Thus, it may be useful to consider getting 10-Q data to fully take advantage of this signal in the future.

Table 1: Fama-French 5-Factor Regressions by Bin (Item 1A; 12-mo holding)

	Bin 0	Bin 1	Bin 2	Bin 3	Bin 4	Bin Spread
Intercept	-0.0026	0.0046	0.0066	0.0027	0.0039	0.0065
	(-1.12)	(1.97)	(2.69)	(1.44)	(2.31)	(2.37)
MKT	1.0654	1.0918	1.0838	1.1110	0.9985	-0.0670
	(19.43)	(19.87)	(18.75)	(25.33)	(24.94)	(-1.03)
SMB	0.6887	0.8226	0.6952	0.7678	0.8417	0.1530
	(7.06)	(8.42)	(6.77)	(9.84)	(11.83)	(1.33)
HML	0.1775	0.2252	0.2043	0.0701	-0.0282	-0.2057
	(1.83)	(2.32)	(2.00)	(0.91)	(-0.40)	(-1.80)
RMW	-0.0794	-0.0315	-0.2174	-0.1140	-0.2435	-0.1641
	(-0.65)	(-0.26)	(-1.68)	(-1.16)	(-2.71)	(-1.13)
CMA	0.0263	0.0500	-0.0667	0.0096	-0.0670	-0.0933
	(0.17)	(0.32)	(-0.40)	(0.08)	(-0.58)	(-0.50)

5 MVE Backtest

Motivated by the signifcant alpha in our five-factor regression for Item 1A, we attempt to do a MVE backtest in which we compute the Mean-Variance-Efficient portfolio for each trading day.

We use Grinold and Kahn's alpha formula (Equation 2). Where we ex-ante use an IC of 0.05.

$$alpha = IC * spec\_risk * z\_score \tag{2}$$

In order to translate our yearly signal into a 12-month holding, we forward fill our computed alpha 250 trading days (after lagging one day to avoid lookahead-bias). We fill the remaining null alpha values with zero.

After constructing the alphas as above, we run a MVE backtest using the Zero Beta and Zero Investment constraints. Using these constraints yields the active portfolio with with weights summing to zero. We also gamma-tune and use a gamma value of 4200 to get to $\approx 5\%$ active risk.

A plot of the MVE backtest along with its statistics are shown below; turnover, drawdown, leverage are shown in the appendix.

Figure 2: Item 1A MVE Backtest (12-mo holding)

	Count	Mean Return (%)	Volatility (%)	Total Return (%)	Sharpe
Portfolio	5285	4.79	5.13	165.64	0.93

Table 2: Item 1A MVE Backtest Summary Statistics

6 Extensions

6.1 Tonal Analysis

6.1.1 Methodology

[8] To establish a good baseline for tonal analysis and also generate labels for distillation, I used FinBERT-tone, a BERT-based model fine-tuned for financial sentiment analysis. Using this model, I obtained labels and sentiment scores (logits) for every item in every 10-K in 2014.

Distillation is a technique where a student model is trained to mimic the predictions of a teacher model. Utilizing FinBERT-tone as the teacher, I fine-tuned Llama-3.1-8B-Instruct using LoRA to classify sentiment of 10-K text. The final result was a trained Llama model that could mimic the final layer output (logits) of FinBERT (I refer to this as the soft label).

[8]This was my CS-474 project.

This model was trained as a sequence classification model using KL divergence to match the teacher's distribution. This setup trained LoRA adapters on the attention projection layers (q_proj, k_proj, v_proj, o_proj) with rank of 32, lora_alpha=32, and dropout. This resulted in 27.3 million trainable parameters (0.36% of the base model). Training loss decreased from 14.92 at the first step to 3.42 at the final step.

This model was fine-tuned for 3 epochs with a learning rate of 1e-4 using the AdamW optimizer. The model was trained on 90% of the data and validated on the other 10%; fine-tuning was done on a NVIDIA A100 GPU hosted on Google Colab.

6.2 Tonal Analysis Results

As one who is not the most adept with regards to finetuning, my goal was simply to test the model I developed for my CS-474 project and nothing more. In the case my model performed poorly, I was not willing to spend more time refining my model to attempt to get it to work.

Thus, to test my model I simply ran the deployed the model on the 10-K data available and then observed the results for items[9]: 1A, 7, and 7A. The results were subpar at best and thus I did not continue to research this avenue (results in Appendix).

7 Next Steps

As alluded to earlier in the paper, there are many research avenues that could be worth exploring. Below, we list some areas that we are considering:

1. Look at different items.
2. Explore composite signals across items (e.g. non-changers in both Item 3 & 7)
3. Test different holding periods (6mo, 12mo). See if there is signal decay.
4. Test different measures for similarity (e.g. Jaccard, ML, DL, etc.).
5. Get 10Q data and reconstruct the paper more accurately.
6. Add 10K data to grpquant?
7. Try a price filter (like 5 dollars).
8. Since the intuition is very similiar to momentum, it might be useful to see how correlated this strategy is to momentum.

[9] Item 1A, 7, and 7A are the most discretionary; thus, a tonal analysis on these items is likely more viable than other items.

References

[1] Cohen, Lauren and Malloy, Christopher J. and Nguyen, Quoc, Lazy Prices (September 2018). NBER Working Paper No. w25084, Available at SSRN: https://ssrn.com/abstract=3254078

[2] https://github.com/porterolson/lazyprices

APPENDIX

Supplementary Quantile-based Tables/Charts

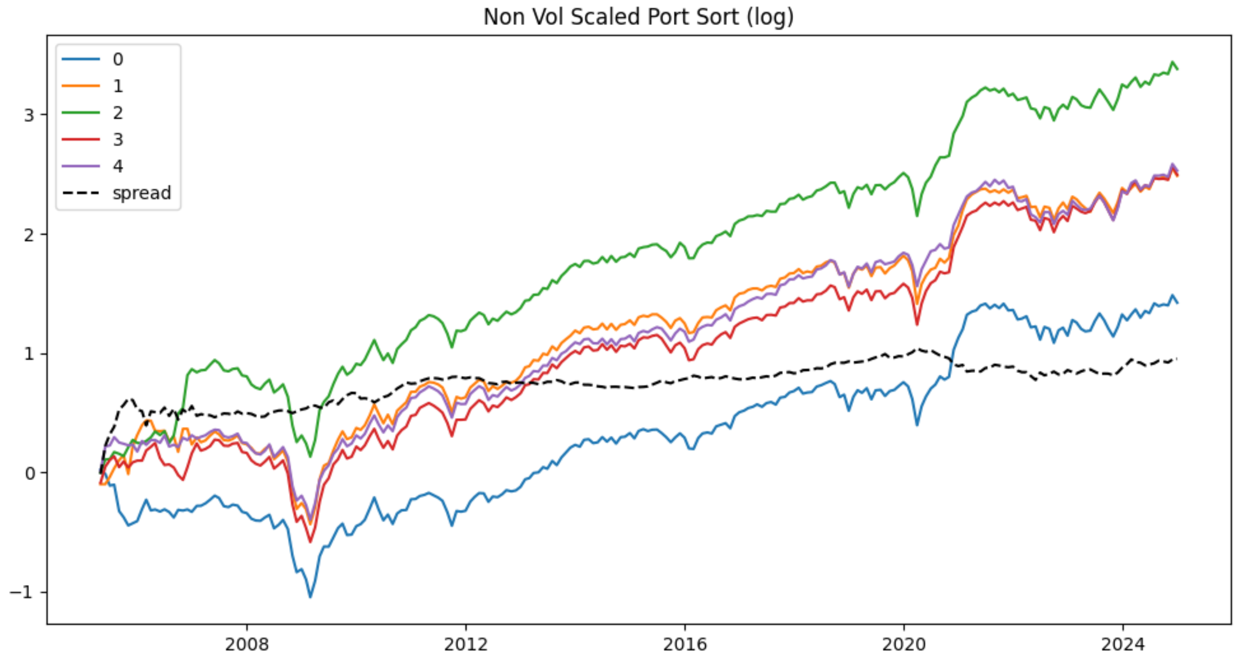


Figure 3: Raw Returns Item 1A Quintile Sort

Table 3: Fama-French 5-Factor Regressions by Bin (Item 1A; 12-mo holding)

	Bin 0	Bin 1	Bin 2	Bin 3	Bin 4	Bin Spread
Intercept	-0.0026	0.0046	0.0066	0.0027	0.0039	0.0065
	(-1.12)	(1.97)	(2.69)	(1.44)	(2.31)	(2.37)
MKT	1.0654	1.0918	1.0838	1.1110	0.9985	-0.0670
	(19.43)	(19.87)	(18.75)	(25.33)	(24.94)	(-1.03)
SMB	0.6887	0.8226	0.6952	0.7678	0.8417	0.1530
	(7.06)	(8.42)	(6.77)	(9.84)	(11.83)	(1.33)
HML	0.1775	0.2252	0.2043	0.0701	-0.0282	-0.2057
	(1.83)	(2.32)	(2.00)	(0.91)	(-0.40)	(-1.80)
RMW	-0.0794	-0.0315	-0.2174	-0.1140	-0.2435	-0.1641
	(-0.65)	(-0.26)	(-1.68)	(-1.16)	(-2.71)	(-1.13)
CMA	0.0263	0.0500	-0.0667	0.0096	-0.0670	-0.0933
	(0.17)	(0.32)	(-0.40)	(0.08)	(-0.58)	(-0.50)

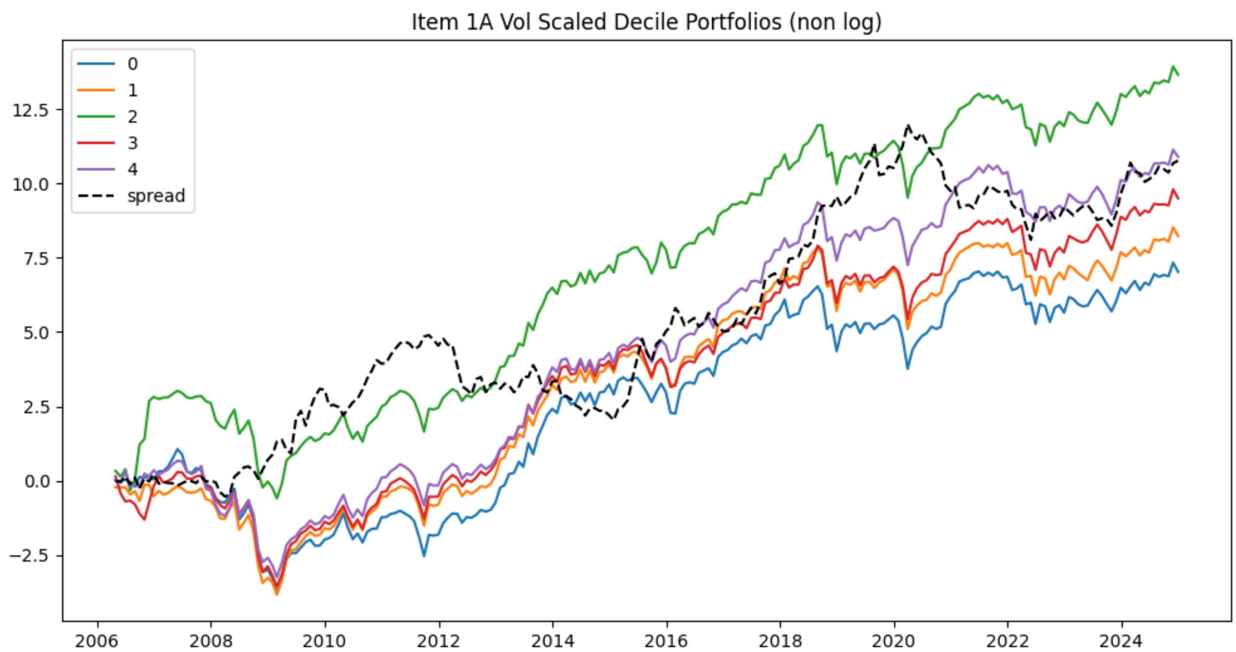


Figure 4: Volatility Scaled Returns: Item 1A

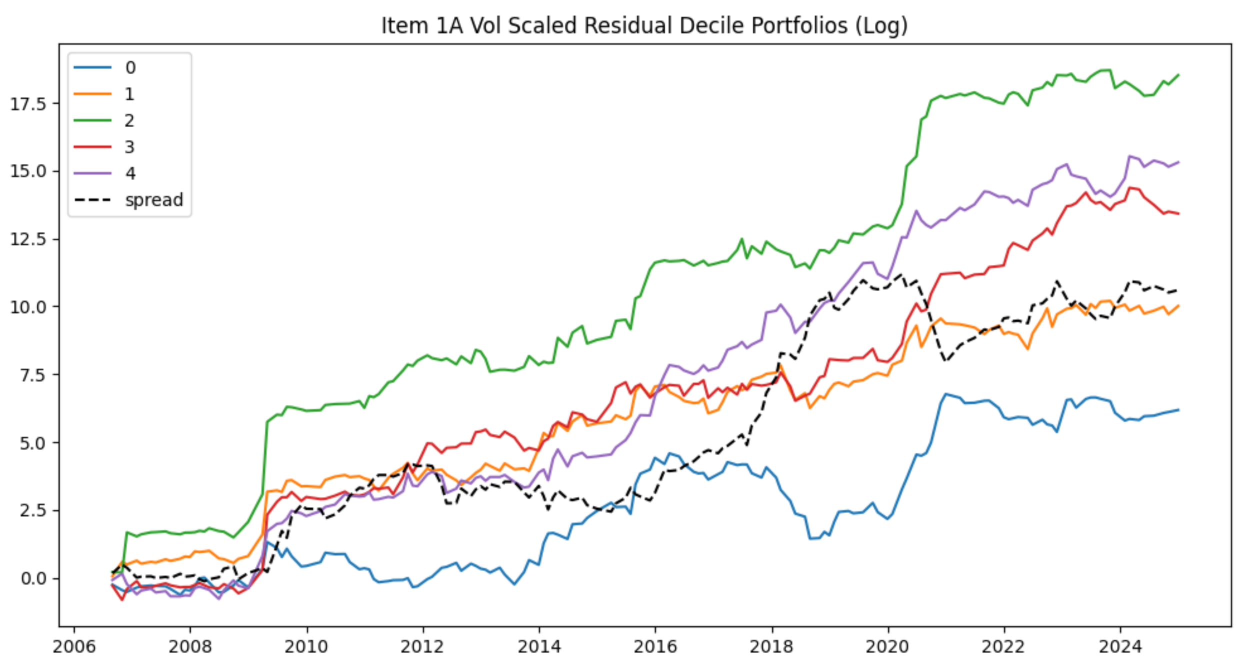


Figure 5: Residualized (to FF5) Returns for Item 1A (12-mo holding)

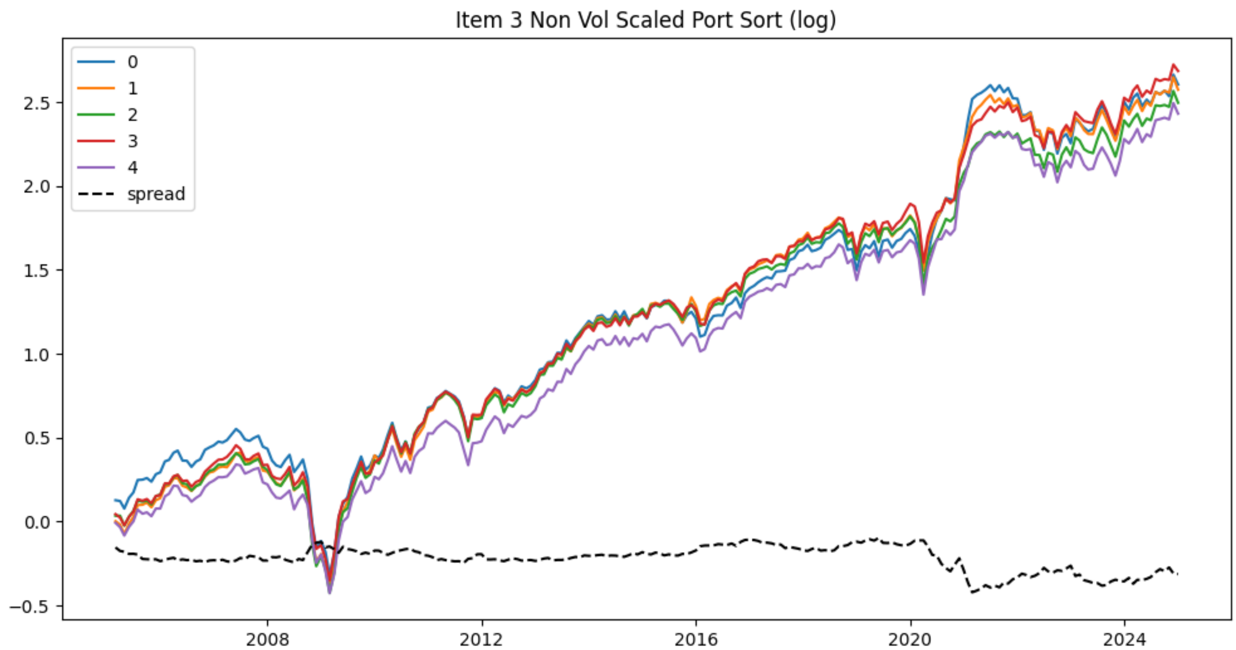


Figure 6: Raw Returns Item 3 Quintiles (12-mo holding)

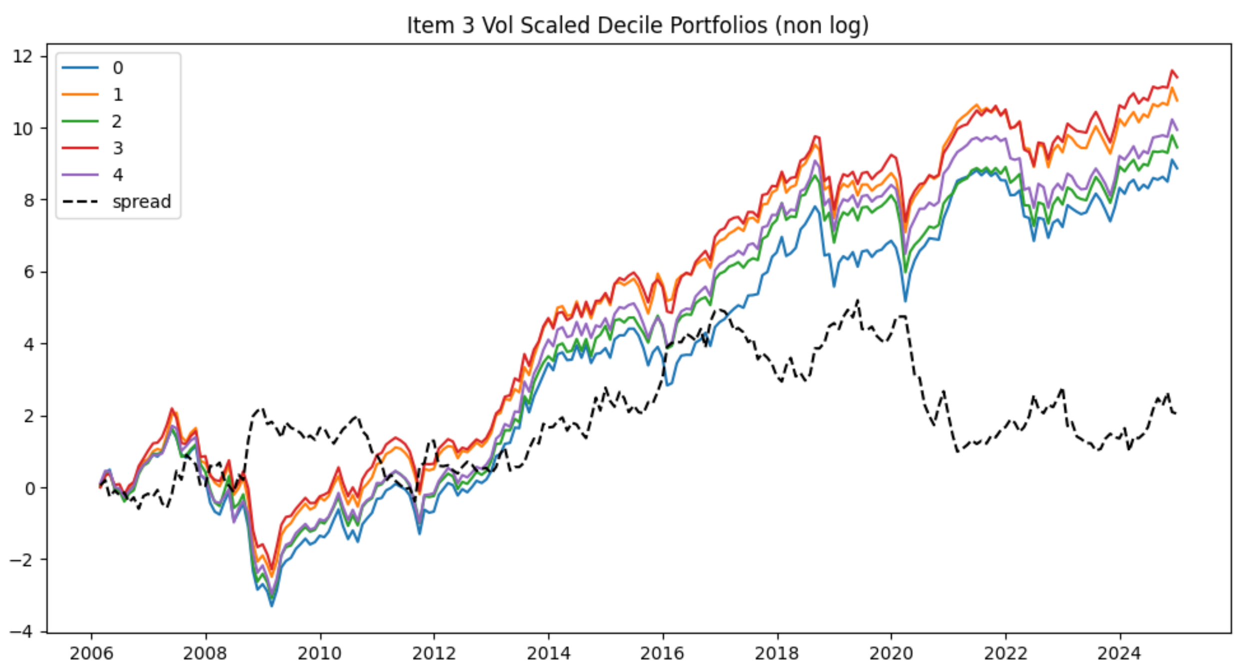


Figure 7: Vol Scaled Returns Item 3 Quintiles (12-mo holding)

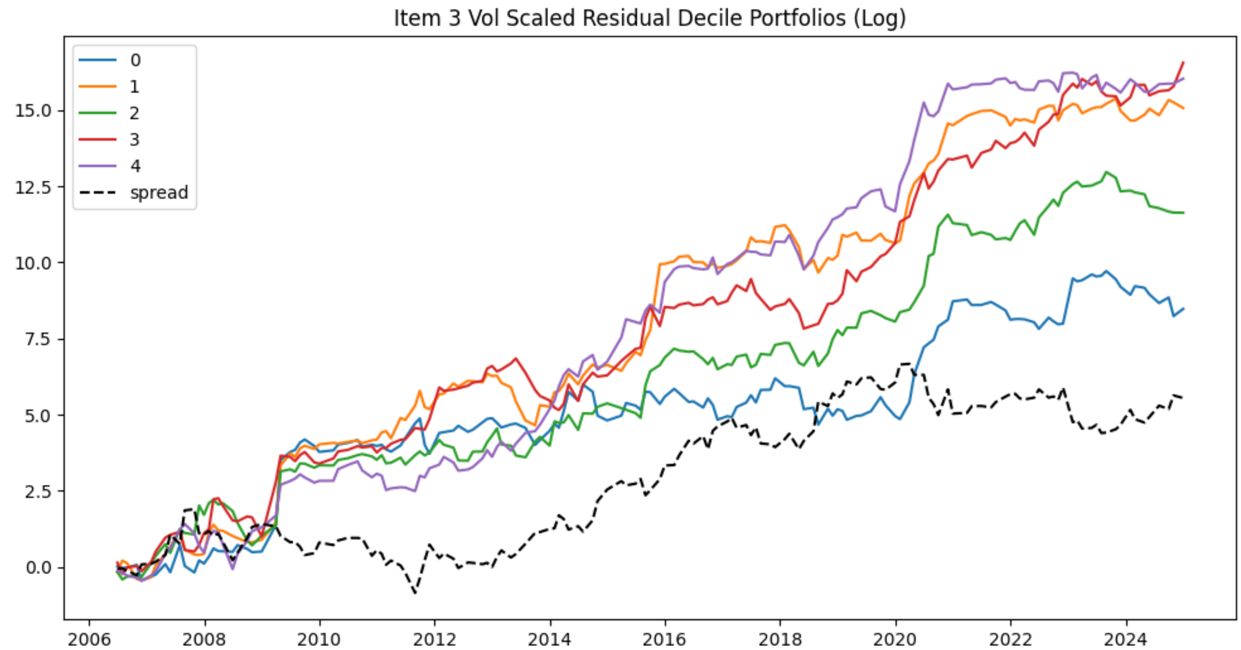


Figure 8: Residualized (to FF5) Returns for Item 3 (12-mo holding)

Table 4: Fama-French 5-Factor Regressions by Bin (Item 3)

	Bin 0	Bin 1	Bin 2	Bin 3	Bin 4	Bin Spread
Intercept	0.0031	0.0038	0.0029	0.0040	0.0031	0.0001
	(2.27)	(3.46)	(2.68)	(3.89)	(3.11)	(0.06)
MKT	1.1329	1.0815	1.0784	1.0311	0.9725	-0.1604
	(35.29)	(41.80)	(42.14)	(41.82)	(40.36)	(-4.63)
SMB	0.7511	0.8183	0.7567	0.7021	0.8336	0.0825
	(13.16)	(17.79)	(16.64)	(16.02)	(19.46)	(1.34)
HML	0.0742	0.0747	0.2584	0.1986	0.1776	0.1033
	(1.31)	(1.64)	(5.73)	(4.57)	(4.18)	(1.69)
RMW	-0.1932	-0.1349	-0.0713	-0.1792	-0.0958	0.0974
	(-2.68)	(-2.32)	(-1.24)	(-3.24)	(-1.77)	(1.25)
CMA	-0.0355	0.1005	-0.0673	-0.1338	-0.0299	0.0056
	(-0.38)	(1.35)	(-0.91)	(-1.88)	(-0.43)	(0.06)

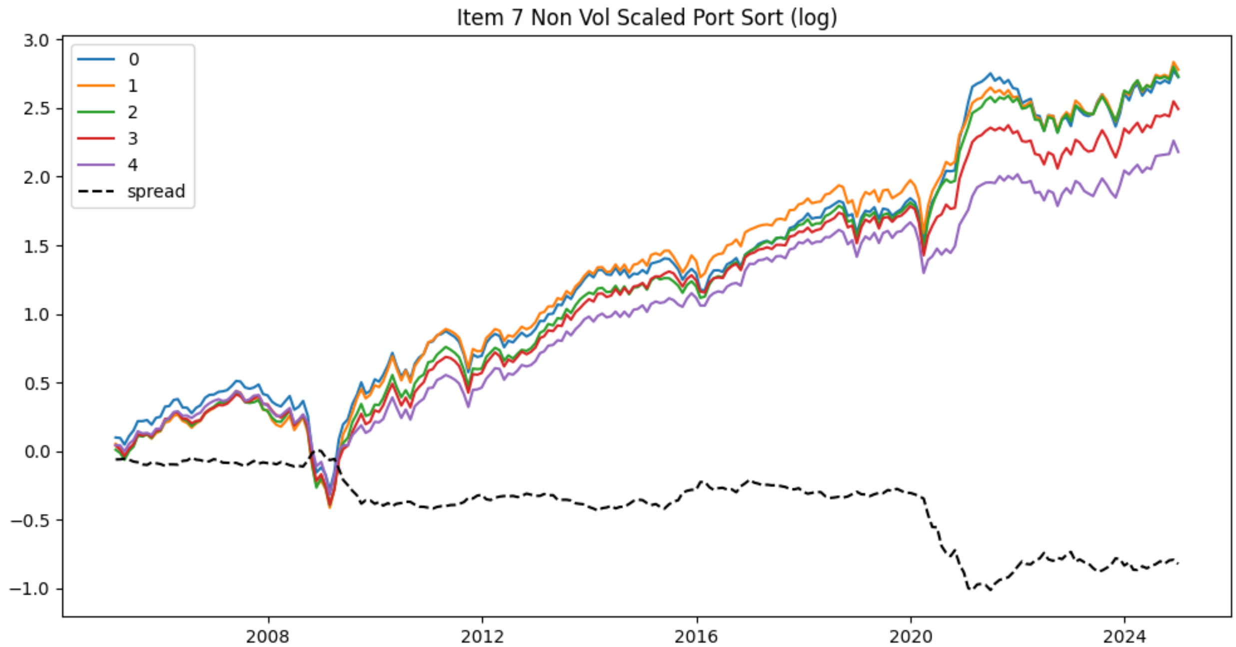


Figure 9: Raw Returns Item 7 Quintiles (12-mo holding)

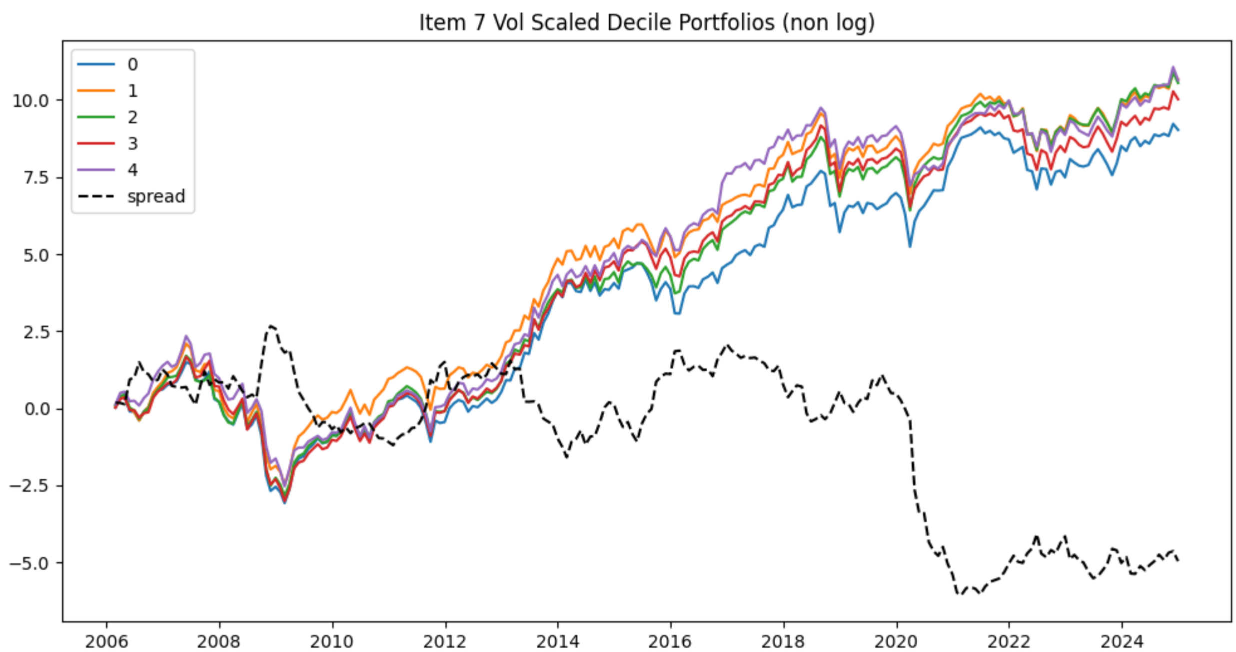


Figure 10: Vol-Scaled Returns Item 7 Quintiles (12-mo holding)

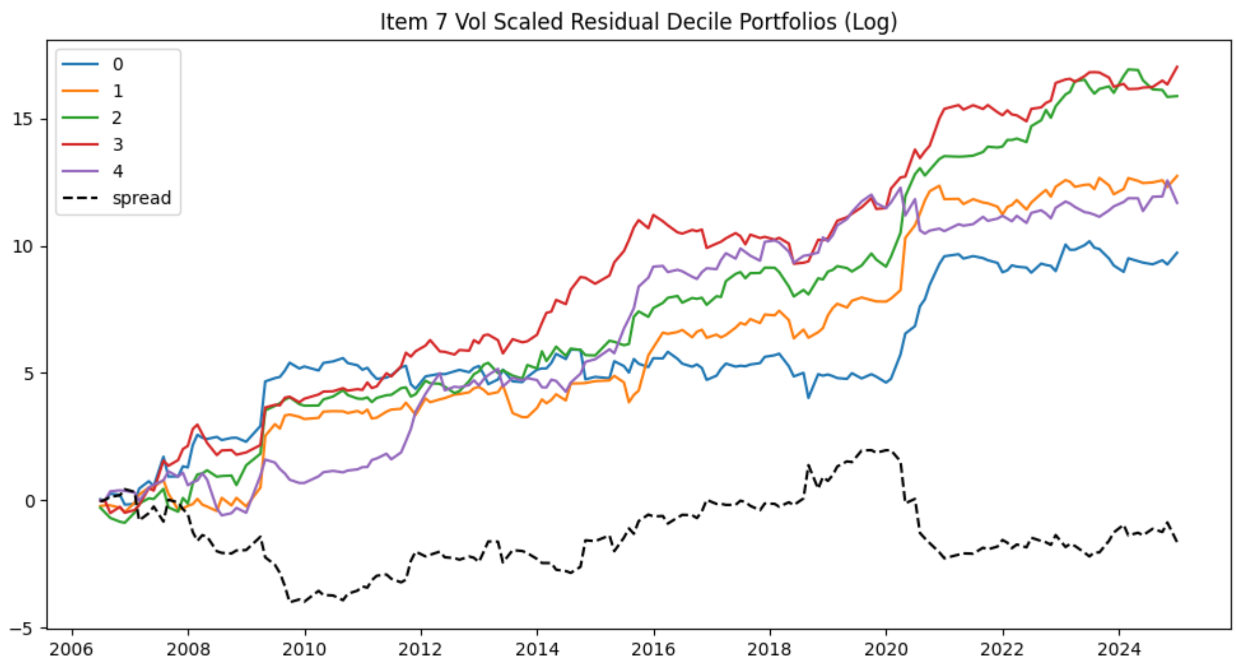


Figure 11: Residualized (to FF5) Returns for Item 7 (12-mo holding)

Table 5: Fama-French 5-Factor Regressions by Bin (Item 7)

	Bin 0	Bin 1	Bin 2	Bin 3	Bin 4	Bin Spread
Intercept	0.0037	0.0036	0.0043	0.0033	0.0026	-0.0011
	(2.65)	(2.90)	(3.84)	(3.87)	(2.50)	(-0.66)
MKT	1.1631	1.1173	1.0947	1.0418	0.8837	-0.2794
	(35.05)	(38.26)	(40.89)	(51.38)	(36.14)	(-6.92)
SMB	0.8166	0.8455	0.7965	0.7689	0.6406	-0.1760
	(13.84)	(16.29)	(16.74)	(21.33)	(14.74)	(-2.45)
HML	0.0457	0.1117	0.0794	0.1799	0.3570	0.3113
	(0.78)	(2.17)	(1.68)	(5.03)	(8.29)	(4.38)
RMW	-0.2217	-0.1460	-0.1797	-0.1219	-0.0193	0.2025
	(-2.98)	(-2.23)	(-2.99)	(-2.68)	(-0.35)	(2.24)
CMA	-0.0285	0.0210	0.0805	-0.0874	-0.1689	-0.1403
	(-0.30)	(0.25)	(1.04)	(-1.49)	(-2.39)	(-1.20)

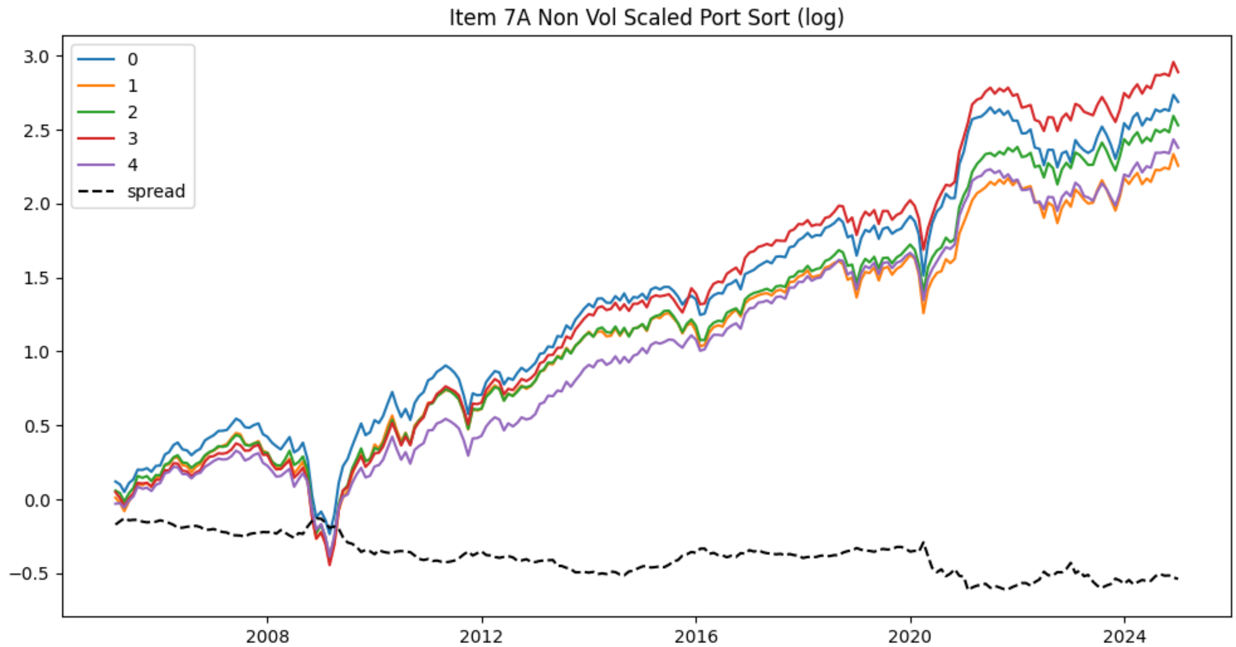


Figure 12: Raw Returns Item 7A Quintiles (12-mo holding)

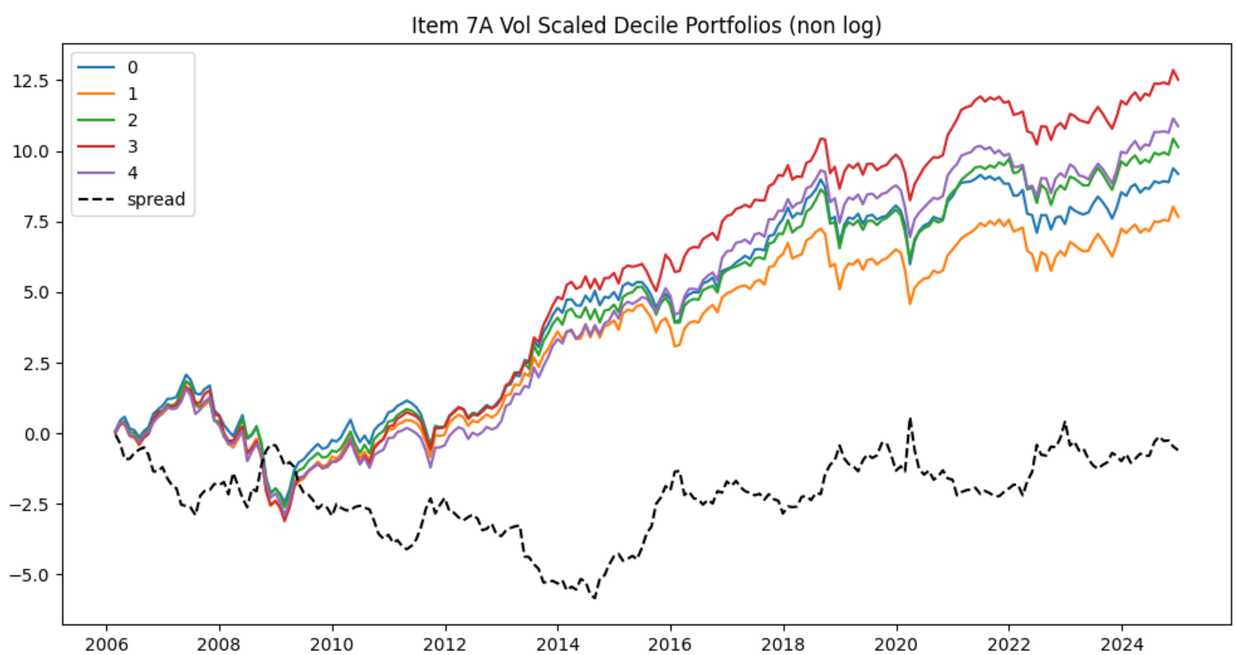


Figure 13: Vol-Scaled Returns Item 7A Quintiles (12-mo holding)

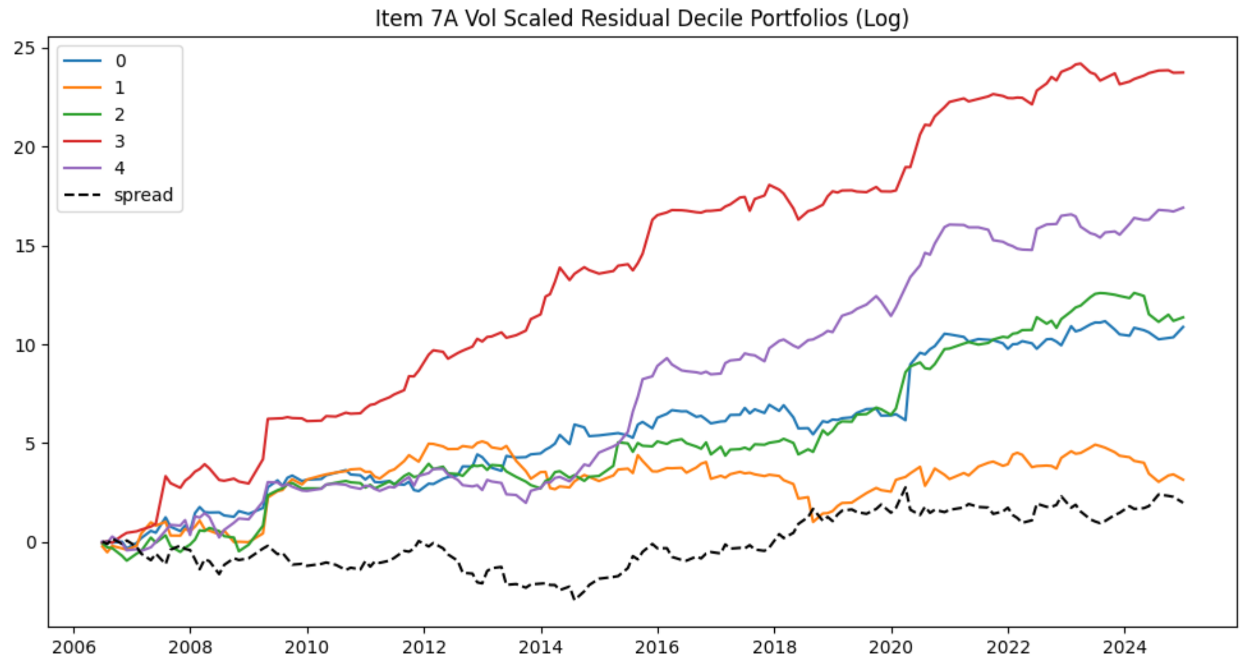


Figure 14: Residualized (to FF5) Returns for Item 7A (12-mo holding)

Table 6: Fama-French 5-Factor Regressions by Bin (Item 7A)

	Bin 0	Bin 1	Bin 2	Bin 3	Bin 4	Bin Spread
Intercept	0.0035	0.0018	0.0031	0.0049	0.0031	-0.0004
	(2.53)	(1.79)	(3.10)	(4.38)	(2.90)	(-0.26)
MKT	1.1645	1.0965	1.0861	1.0372	0.9206	-0.2439
	(35.37)	(46.33)	(45.98)	(38.83)	(36.22)	(-6.58)
SMB	0.7872	0.8206	0.7542	0.7788	0.7010	-0.0863
	(13.45)	(19.51)	(17.96)	(16.40)	(15.52)	(-1.31)
HML	0.1153	0.1618	0.1476	0.1521	0.2084	0.0931
	(1.99)	(3.88)	(3.55)	(3.23)	(4.65)	(1.43)
RMW	-0.1832	-0.0636	-0.0227	-0.2094	-0.1786	0.0046
	(-2.48)	(-1.20)	(-0.43)	(-3.50)	(-3.13)	(0.05)
CMA	-0.0981	0.0061	0.0506	-0.0916	-0.0230	0.0751
	(-1.03)	(0.09)	(0.74)	(-1.19)	(-0.31)	(0.70)

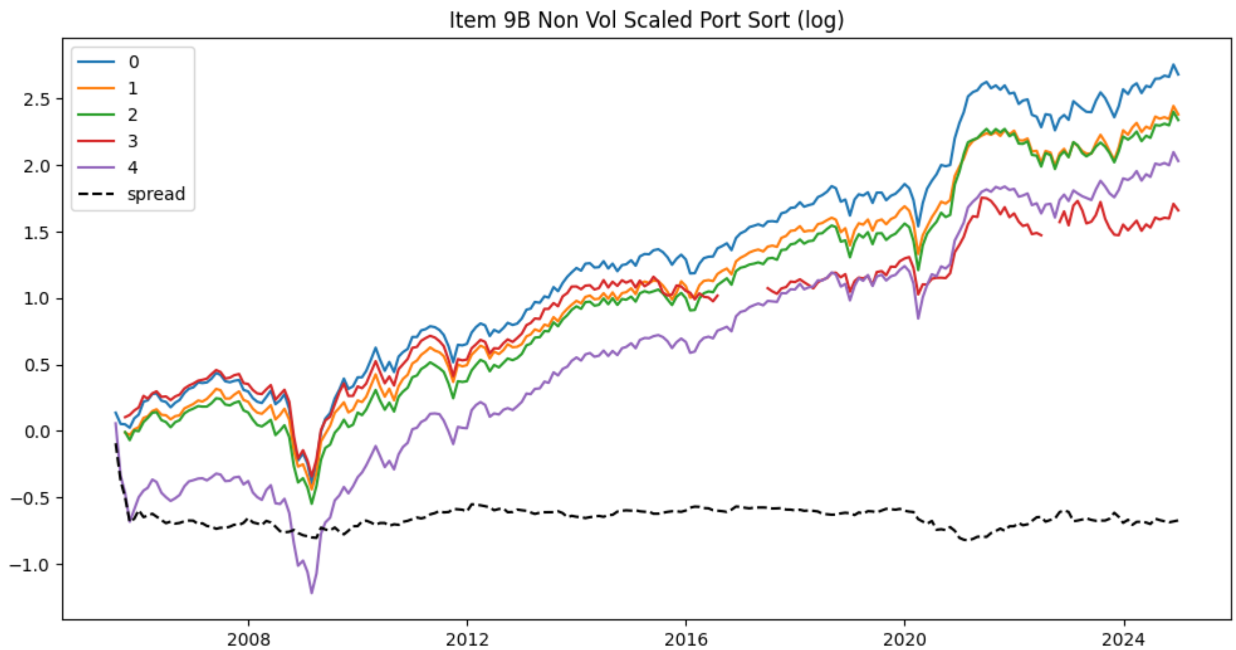


Figure 15: Raw Returns Item 9B Quintiles (12-mo holding)

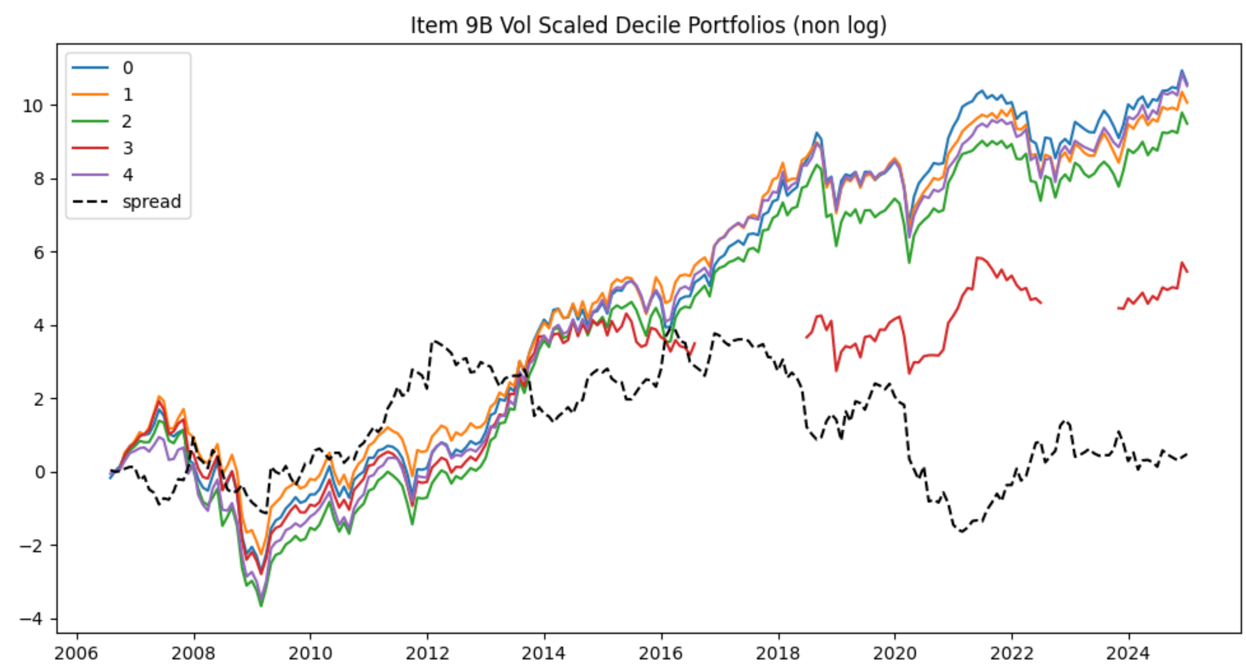


Figure 16: Vol-Scaled Returns Item 9B Quintiles (12-mo holding)

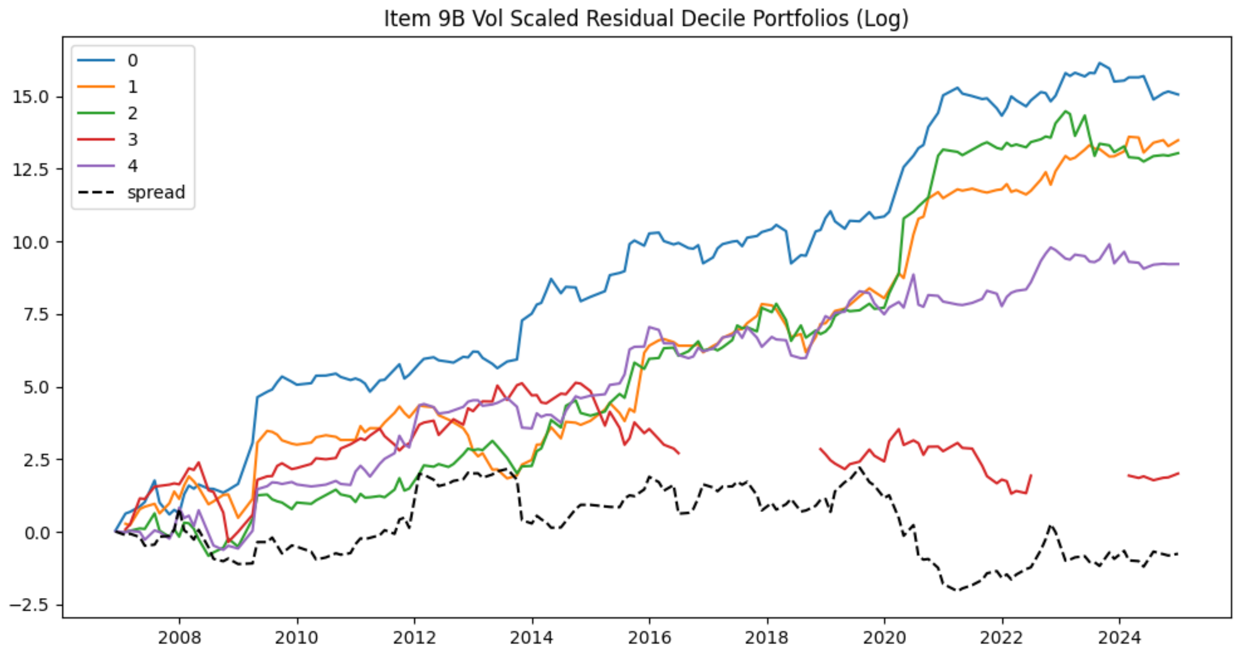


Figure 17: Residualized (to FF5) Returns for Item 9B (12-mo holding)

Table 7: Fama-French 5-Factor Regressions by Bin (Item 9B)

	Bin 0	Bin 1	Bin 2	Bin 3	Bin 4	Bin Spread
Intercept	0.0038	0.0029	0.0024	0.0024	-0.0002	-0.0039
	(3.06)	(2.68)	(2.23)	(1.01)	(-0.06)	(-1.57)
MKT	1.0974	1.0322	1.0461	0.8566	1.1263	0.0290
	(37.69)	(40.39)	(41.30)	(15.34)	(16.07)	(0.49)
SMB	0.8286	0.7689	0.8138	0.7673	0.8409	0.0123
	(15.94)	(16.84)	(17.98)	(7.67)	(6.72)	(0.12)
HML	0.0582	0.1627	0.0738	0.3496	0.1323	0.0740
	(1.13)	(3.59)	(1.64)	(3.53)	(1.07)	(0.71)
RMW	-0.1623	-0.0907	-0.1341	-0.1982	0.2147	0.3770
	(-2.49)	(-1.57)	(-2.35)	(-1.56)	(1.37)	(2.84)
CMA	-0.0114	0.0027	0.0294	-0.1601	0.0290	0.0404
	(-0.14)	(0.04)	(0.40)	(-1.00)	(0.14)	(0.24)

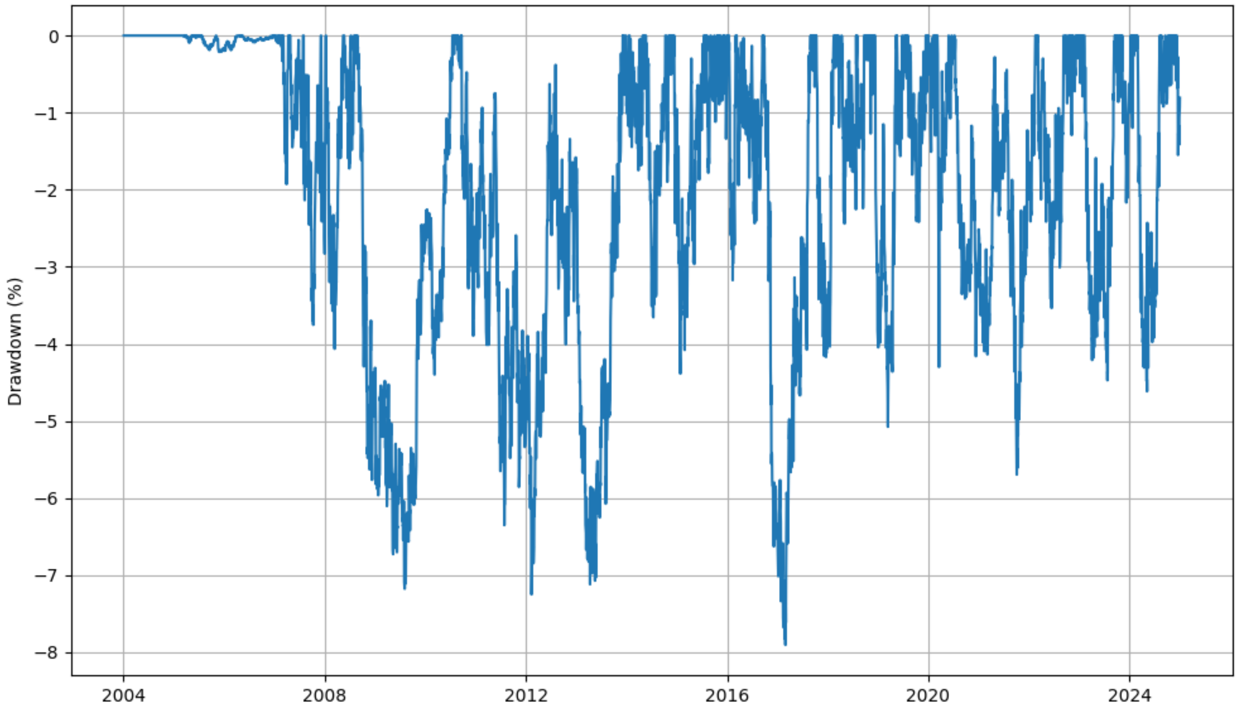
Supplementary MVE-Based Tables/Charts

Figure 18: Item 1A MVE Backtest Leverage (12-mo holding)

	Count	Mean Leverage	Min Leverage	Max Leverage	Std. Leverage
Portfolio	5285	4.83	0.00	7.67	2.38

Table 8: Leverage Summary Statistics

Figure 19: Item 1A MVE Backtest Drawdown (12-mo holding)



	Count	Mean (%)	Max (%)	Current (%)	Longest (days)
Porfolio	5285	-1.96	-7.90	-0.81	809

Table 9: Drawdown Statistics

Figure 20: Item 1A MVE Backtest Turnover (12-mo holding)

	Mean Turnover	Min Turnover	Max Turnover
Portfolio	0.1411	0.000	0.2502

Table 10: Turnover Statistics

Table 11: MVE Active Portfolio Fama-French 5 Factor Regression

	Active Portfolio
Intercept	0.0003
	(6.94)
MKT	-0.0013
	(-0.32)
SMB	-0.0079
	(-0.99)
HML	0.0066
	(0.92)
RMW	-0.0035
	(-0.32)
CMA	-0.0102
	(-0.70)

Figure 21: Tonal Quintile Sort (Vol-Scaled; 12-Month Holding)

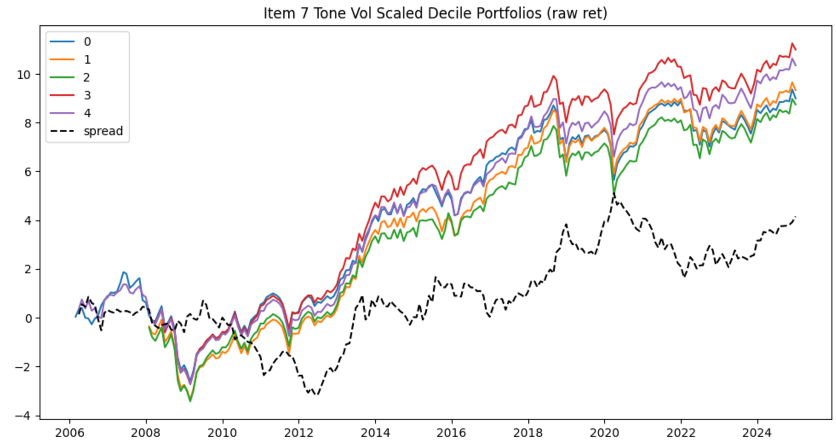


Figure 22: Item 1A Vol Scaled Tonal Quintile

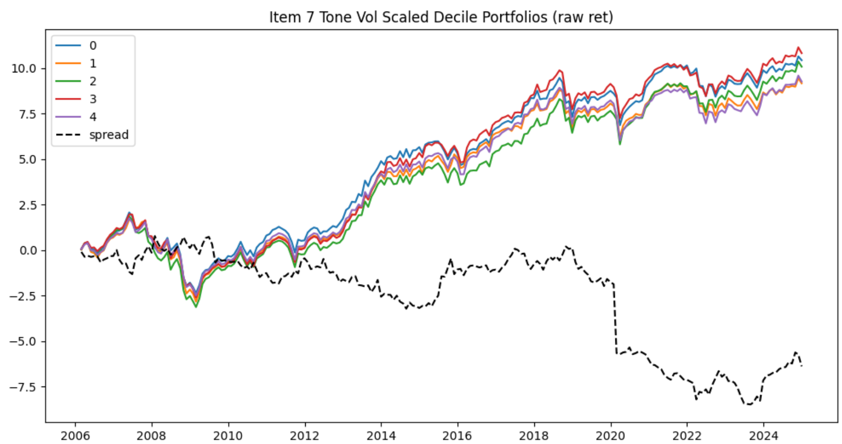


Figure 23: Item 7 Vol Scaled Tonal Quintile

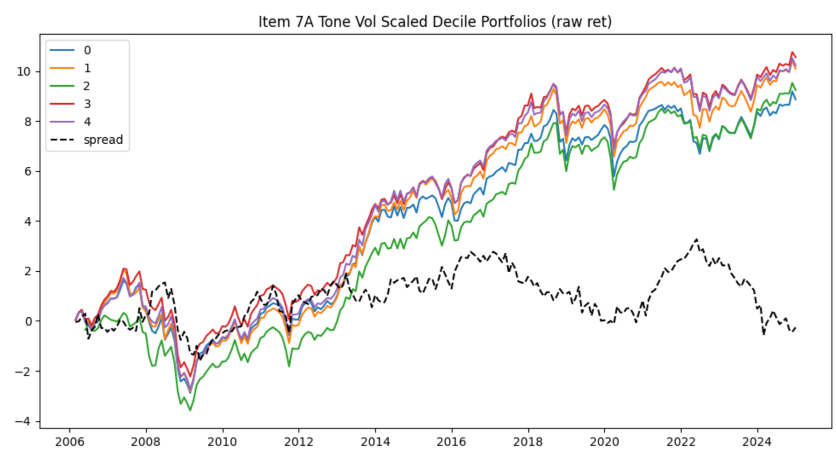


Figure 24: Item 7A Vol Scaled Tonal Quintile

Table 12: Fama-French 5-Factor Regressions by Bin

Item 1A Tonal Signal

	Bin 0	Bin 1	Bin 2	Bin 3	Bin 4	Spread
Intercept	0.0027	0.0031	0.0037	0.0040	0.0042	0.0015
	(2.89)	(3.46)	(2.92)	(3.94)	(2.84)	(1.05)
MKT	1.0864	1.0329	1.0933	1.0065	1.0180	-0.0683
	(48.80)	(51.13)	(38.12)	(43.45)	(29.10)	(-2.05)
SMB	0.7587	0.7742	0.7797	0.8047	0.7596	0.0008
	(19.17)	(20.92)	(14.84)	(18.97)	(12.22)	(0.01)
HML	0.2624	0.1676	0.2235	0.1795	0.1807	-0.0817
	(6.69)	(4.59)	(4.31)	(4.28)	(2.93)	(-1.39)
RMW	-0.0133	-0.1019	-0.0769	-0.1720	-0.3057	-0.2924
	(-0.27)	(-2.23)	(-1.19)	(-3.29)	(-3.90)	(-3.91)
CMA	-0.0743	-0.0322	-0.1132	-0.1261	-0.1036	-0.0292
	(-1.16)	(-0.54)	(-1.33)	(-1.84)	(-1.03)	(-0.30)

Item 7 Tonal Signal

	Bin 0	Bin 1	Bin 2	Bin 3	Bin 4	Spread
Intercept	0.0037	0.0033	0.0031	0.0032	0.0027	-0.0010
	(4.21)	(3.38)	(2.79)	(3.34)	(2.81)	(-1.17)
MKT	1.0926	1.0377	1.0765	1.0053	1.0316	-0.0610
	(52.06)	(44.08)	(40.28)	(44.10)	(44.90)	(-2.99)
SMB	0.7308	0.8033	0.8142	0.7268	0.7517	0.0208
	(19.59)	(19.20)	(17.14)	(17.94)	(18.41)	(0.57)
HML	0.2148	0.2012	0.1806	0.2004	0.2266	0.0118
	(5.81)	(4.85)	(3.84)	(4.99)	(5.60)	(0.33)
RMW	-0.1466	-0.1022	-0.1036	-0.1899	-0.0970	0.0496
	(-3.12)	(-1.94)	(-1.73)	(-3.72)	(-1.88)	(1.08)
CMA	-0.0655	-0.1152	-0.0556	-0.1126	-0.0846	-0.0191
	(-1.08)	(-1.70)	(-0.72)	(-1.71)	(-1.28)	(-0.32)

Item 7A Tonal Signal

	Bin 0	Bin 1	Bin 2	Bin 3	Bin 4	Spread
Intercept	0.0032	0.0034	0.0035	0.0029	0.0028	-0.0004
	(3.44)	(3.50)	(2.64)	(3.52)	(2.79)	(-0.41)
MKT	1.0156	0.9963	1.0487	1.0732	1.1204	0.1048
	(46.50)	(42.88)	(33.33)	(53.82)	(47.13)	(4.77)
SMB	0.7955	0.7785	0.7902	0.7355	0.7774	-0.0181
	(20.49)	(18.85)	(14.13)	(20.75)	(18.40)	(-0.46)
HML	0.1681	0.2573	0.2468	0.1747	0.1600	-0.0081
	(4.37)	(6.29)	(4.44)	(4.97)	(3.82)	(-0.21)
RMW	-0.1686	-0.1550	-0.1560	-0.0698	-0.0482	0.1205
	(-3.44)	(-2.98)	(-2.21)	(-1.56)	(-0.90)	(2.45)
CMA	-0.1090	-0.1020	-0.2346	-0.0426	0.0197	0.1287
	(-1.73)	(-1.52)	(-2.58)	(-0.74)	(0.29)	(2.03)