Does Peer-Reviewed Research Help Predict Stock Returns?

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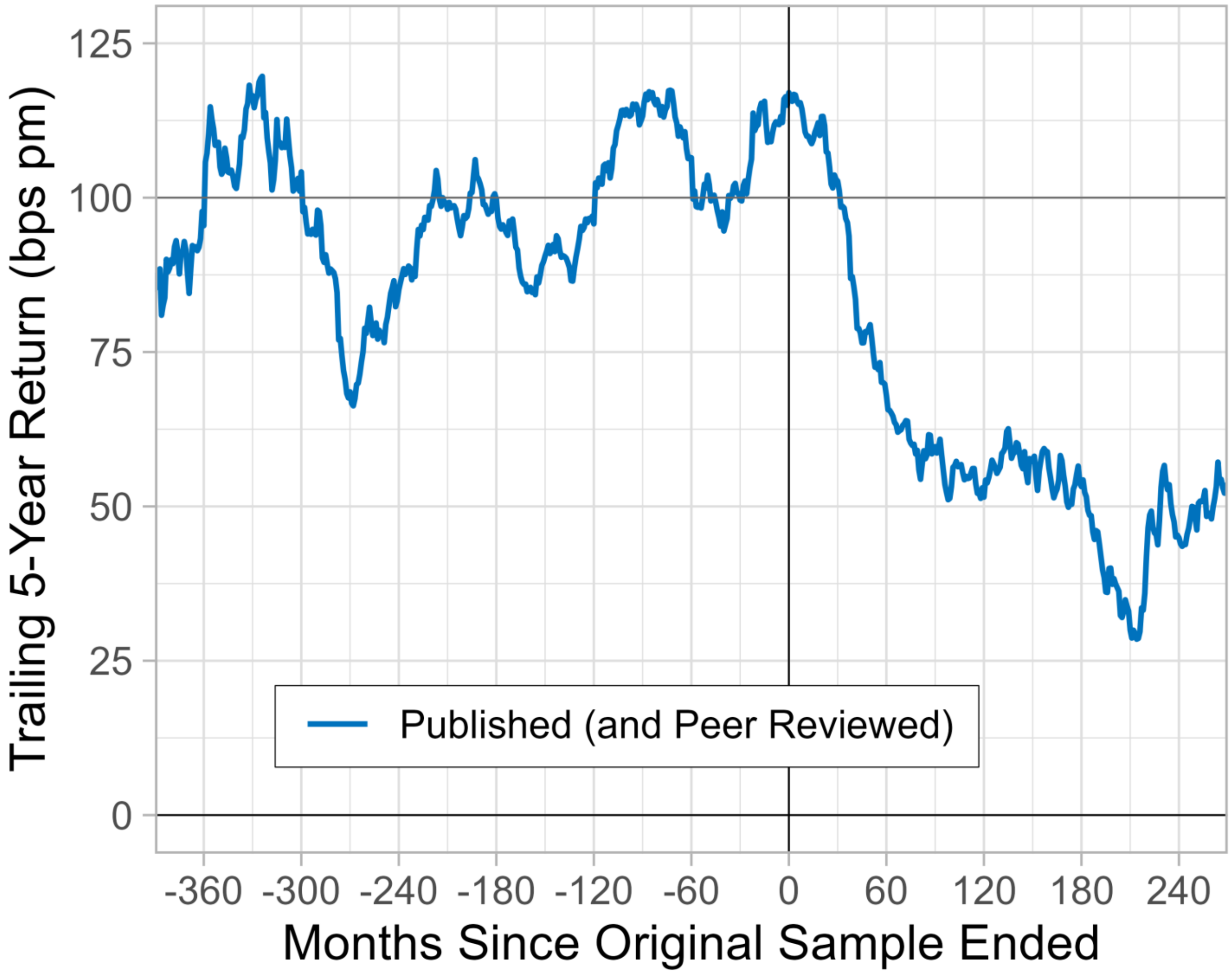
- **How should your expected out-of-sample return depend on his answer?**

Our answer:



Trailing 5-Year Return (bps pm)
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75
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-360 -300 -240 -180 -120 -60 0 60 120 180 240
Months Since Original Sample Ended
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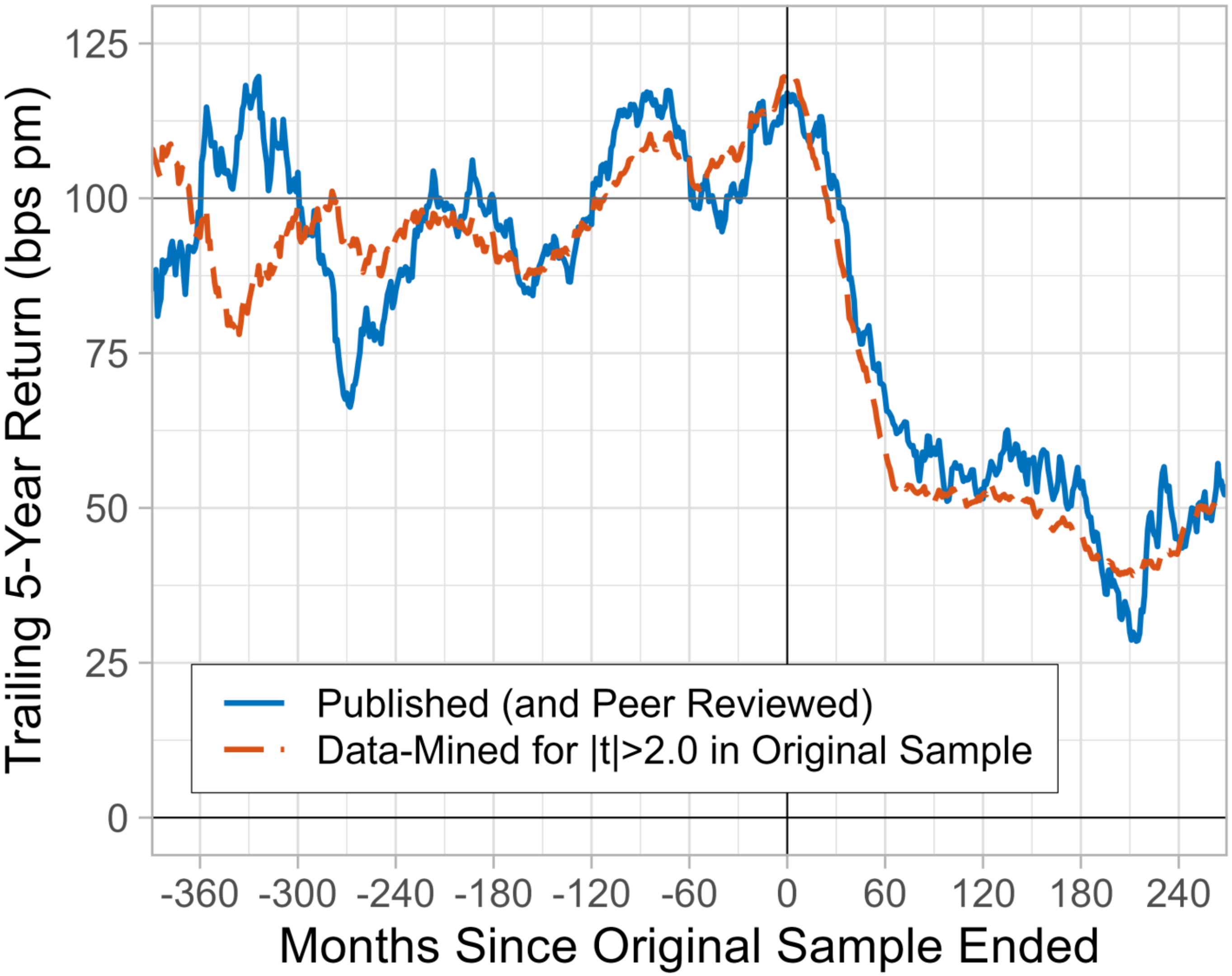

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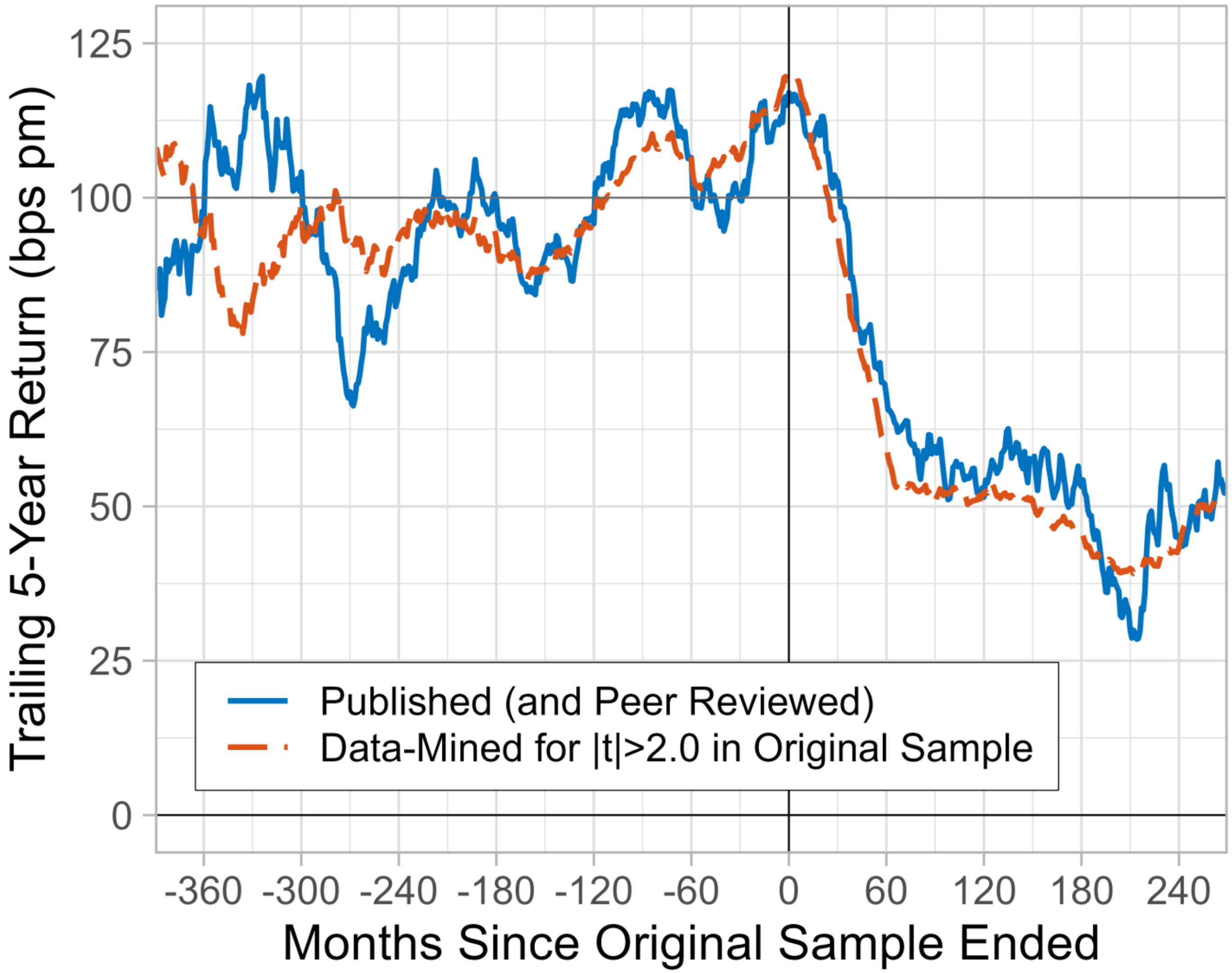
Our answer:

- **Publishable ideas outperform data mining by perhaps 2 bps per month**



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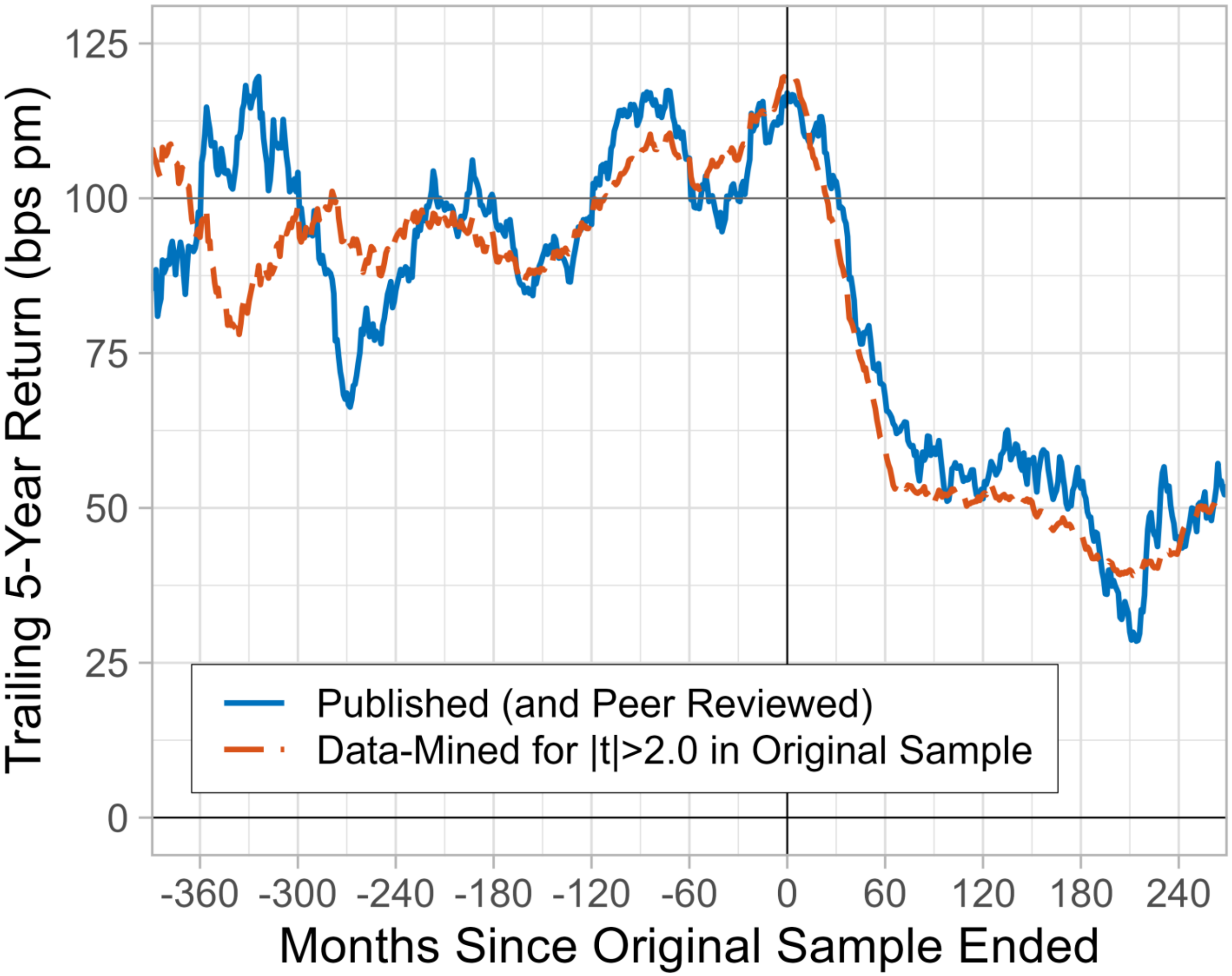

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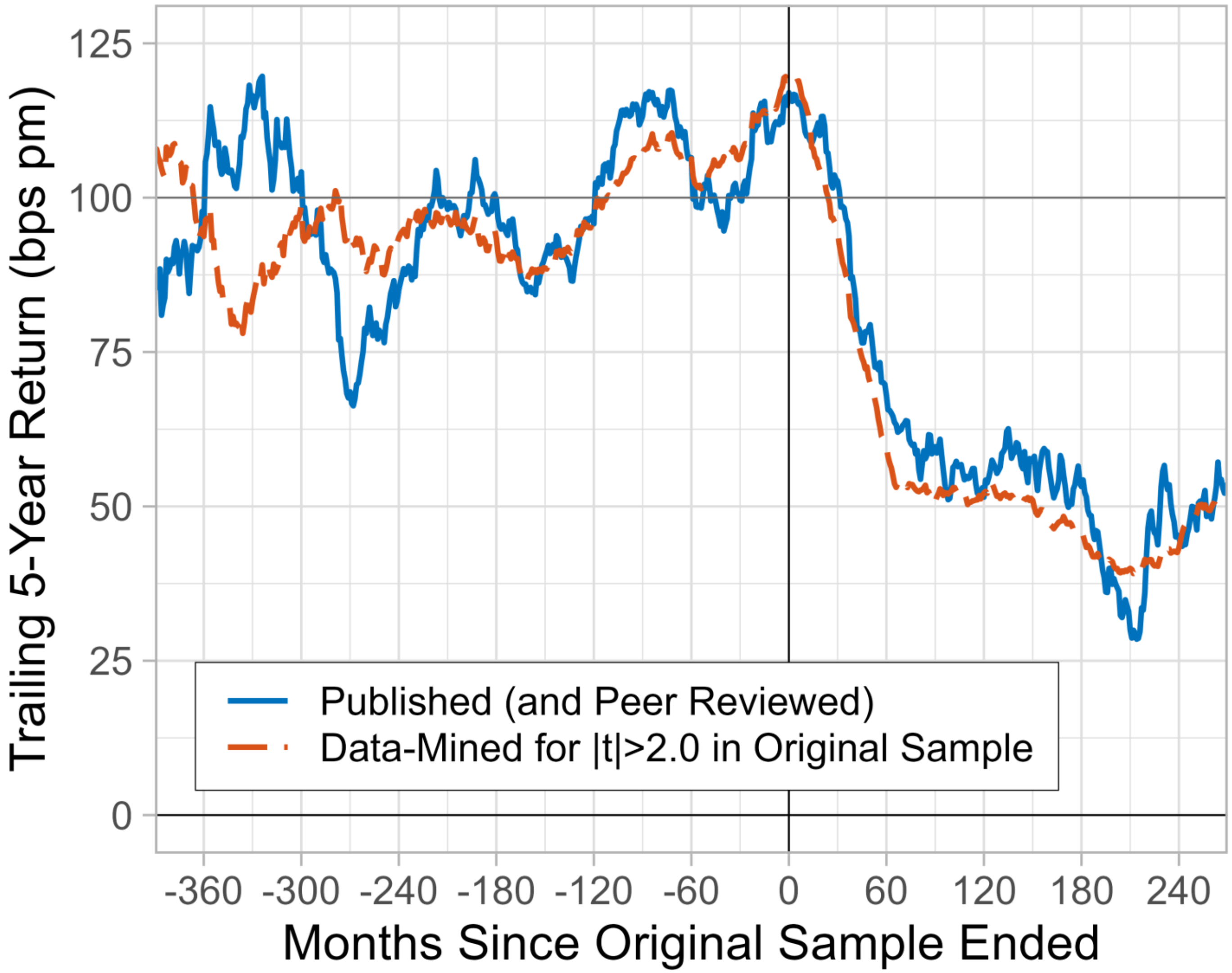

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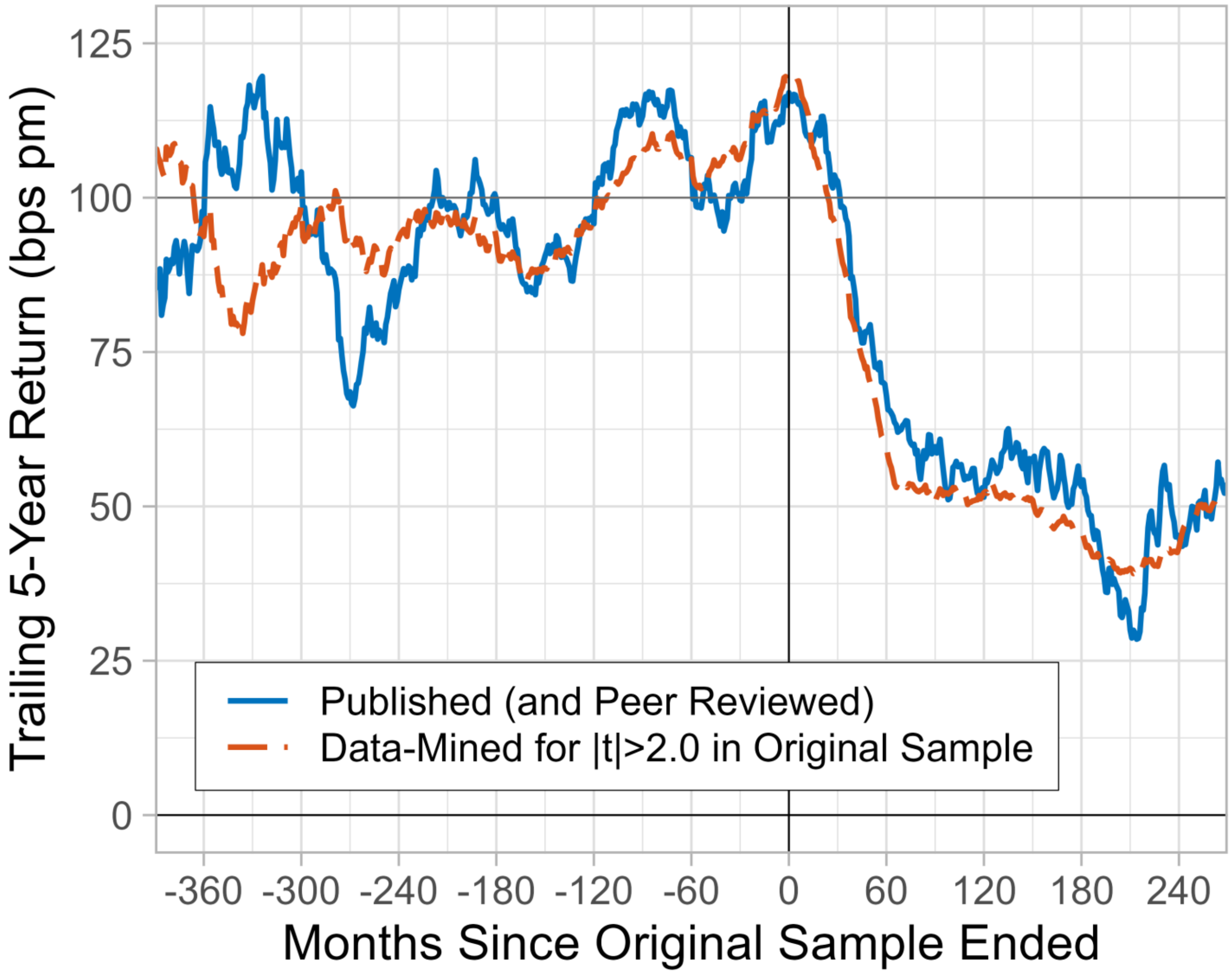
  - Reminiscent of data mining successes in language modeling (e.g. ChatGPT)



Data Mined Returns

Data-mined long-short strategies

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- Using each ratio, form long-short decile strategies
- **Arguably no economics, no look-ahead bias**

Data mining generates large "out-of-sample" returns

In-Sample Bin	Equal-Weighted Long-Short Deciles				Value-Weighted Long-Short Deciles			
	Past 30 Years (IS)		Next Year (OOS)		Past 30 Years (IS)		Next Year (OOS)	
	Return (bps pm)	t-stat	Return (bps pm)	Decay (%)	Return (bps pm)	t-stat	Return (bps pm)	Decay (%)
1	-59.3	-4.24	-49.4	16.7	-37.6	-2.06	-16.3	56.6
2	-29.1	-2.46	-18.9	35.1	-15.7	-1.02	-5.6	64.0
3	-13.3	-1.20	-3.2	75.9	-4.9	-0.33	-1.8	62.7
4	-0.3	-0.04	5.6		5.4	0.35	-0.0	
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  - *Consistent w/ Chen 2024: Harvey-Liu 2020 misinterprets FDR methods*

Data-mined strategies with |t|>2 are diverse

Covariance structure of long-short returns

Panel (a): Pairwise correlations

Quantiles	Q1	Q5	Q10	Q25	Q50	Q75	Q90	Q95	Q99
Equal-Weighted	-0.42	-0.23	-0.15	-0.04	0.05	0.16	0.29	0.38	0.56
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Panel (b): PCA Explained Variance (%)

Number of PCs	1	5	10	20	30	40	50	60	70	80	90	100
Equal-Weighted	24	47	55	63	68	72	75	78	80	82	84	85
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- **Data mining doesn't just pick up size, B/M, profitability**

Themes from mining the 1963-1980 sample

20 numerators and stock weights that produce largest t-stats

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Numerator (Stock Weight)	Pct Short	t-stat
ΔAssets (ew)	100	4.0
ΔIntangible assets (ew)	100	4.0
ΔPPE net (ew)	98	4.0
ΔPPE gross (ew)	98	3.8
ΔInvested capital (ew)	100	3.5
ΔCapital expenditure (ew)	100	3.2
ΔCommon stock (ew)	100	5.1
ΔLiabilities (ew)	100	4.7
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ΔIntangible assets (ew)	100	4.0
ΔPPE net (ew)	98	4.0
ΔPPE gross (ew)	98	3.8
ΔInvested capital (ew)	100	3.5
ΔCapital expenditure (ew)	100	3.2
Ext Financing (Spiess/Affleck-Graves 1999)		
ΔCommon stock (ew)	100	5.1
ΔLiabilities (ew)	100	4.7
ΔCapital surplus (ew)	100	4.1
ΔLong-term debt (ew)	100	3.6
ΔCapital surplus (vw)	98	3.0

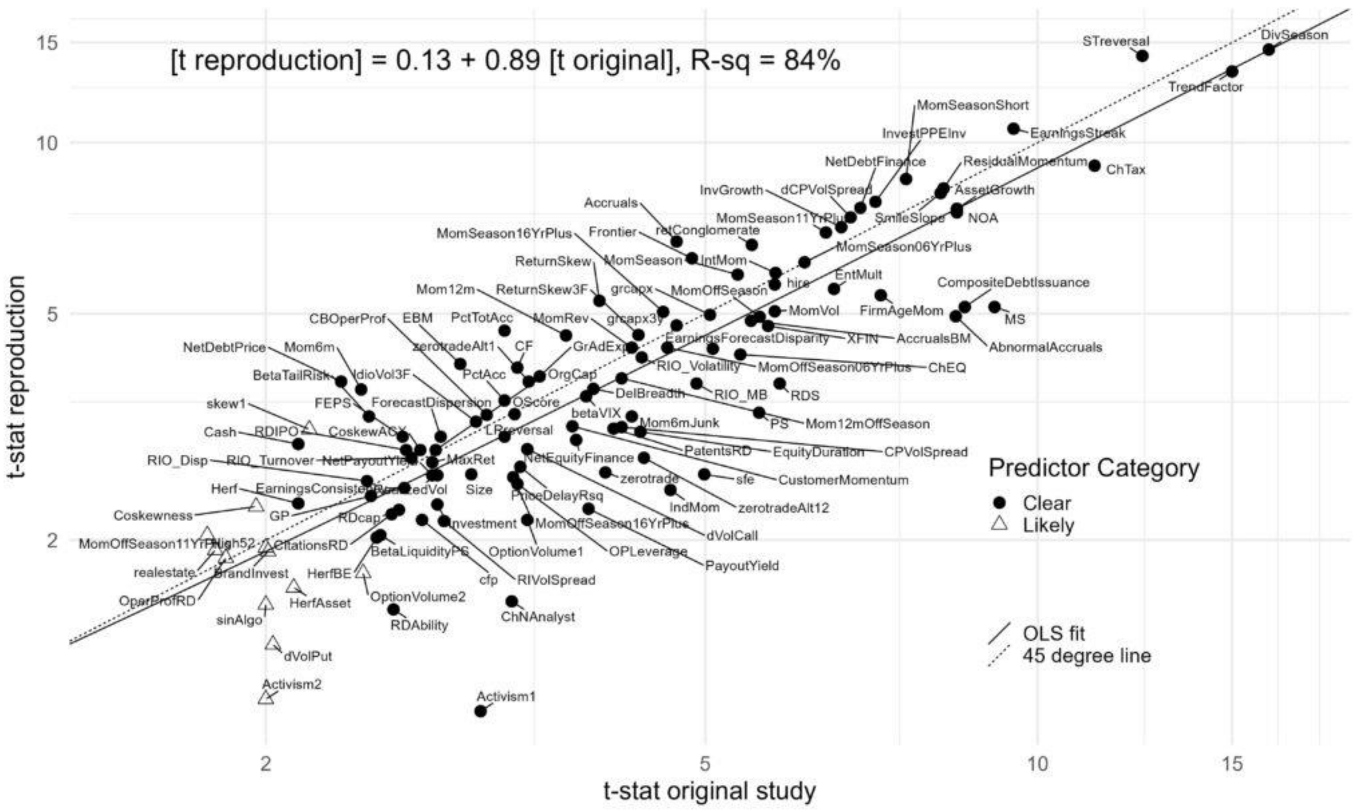
Numerator (Stock Weight)	Pct Short	t-stat
Accruals (Sloan 1996; Thomas-Zhang 2002)		
ΔInventories (ew)	100	4.2
ΔNotes payable st (ew)	100	3.8
ΔReceivables (ew)	100	3.7
ΔDebt in current liab (ew)	100	3.7
ΔCurrent liabilities (ew)	100	3.7
Earnings Surprise (Foster et. al 1984)		
ΔCost of goods sold (ew)	100	3.7
ΔOperating expenses (ew)	98	3.5
ΔSG&A (ew)	100	3.3
ΔInterest expense (ew)	98	3.3

- **All top 20 numerators fit into themes from academic publications**
- **But data mining can find the themes long before they are published**

Peer Review vs Data Mining

Peer-reviewed long-short strategies

- Chen-Zimmermann (2022) dataset
  - Dataset w/ most accurate reproductions of original tables
- Filter to have post-sample period $\geq$ 9 years
- Baseline data: 199 predictors



Data-mined return benchmarks

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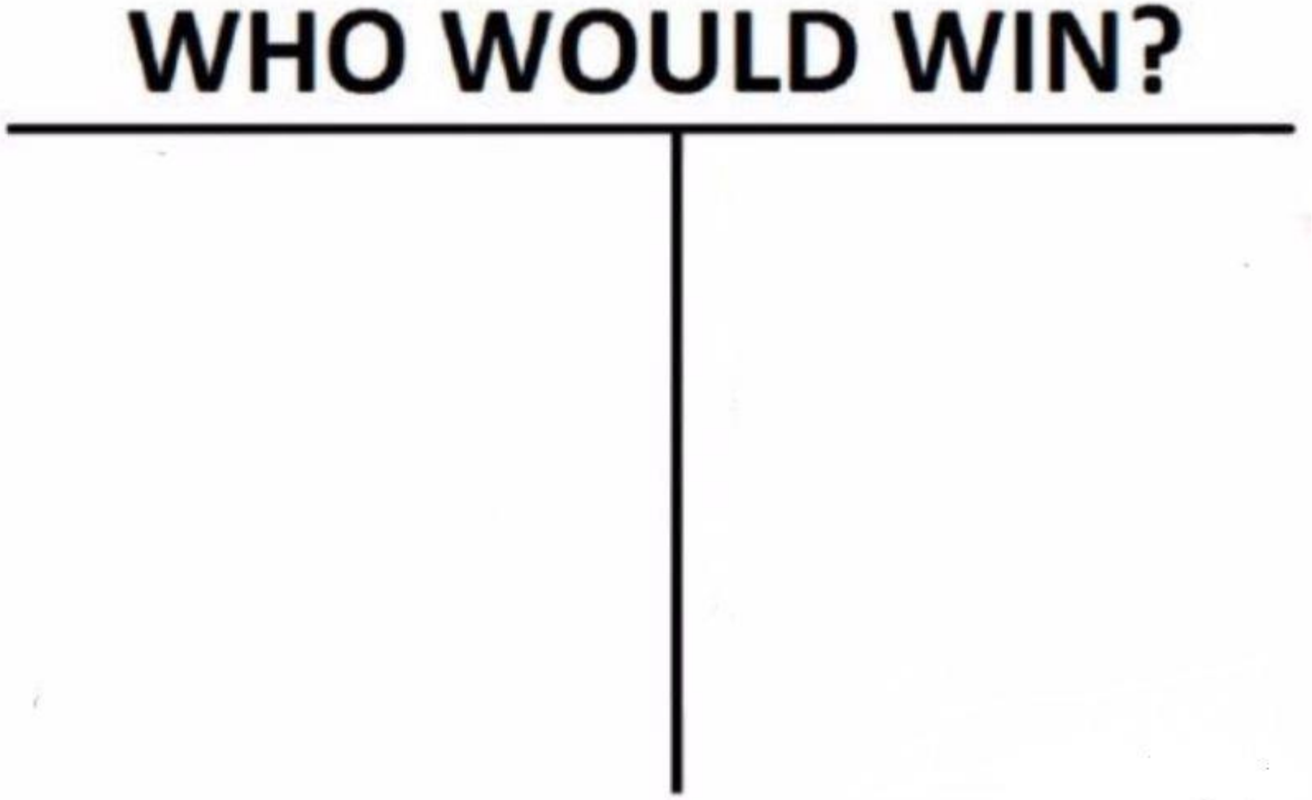

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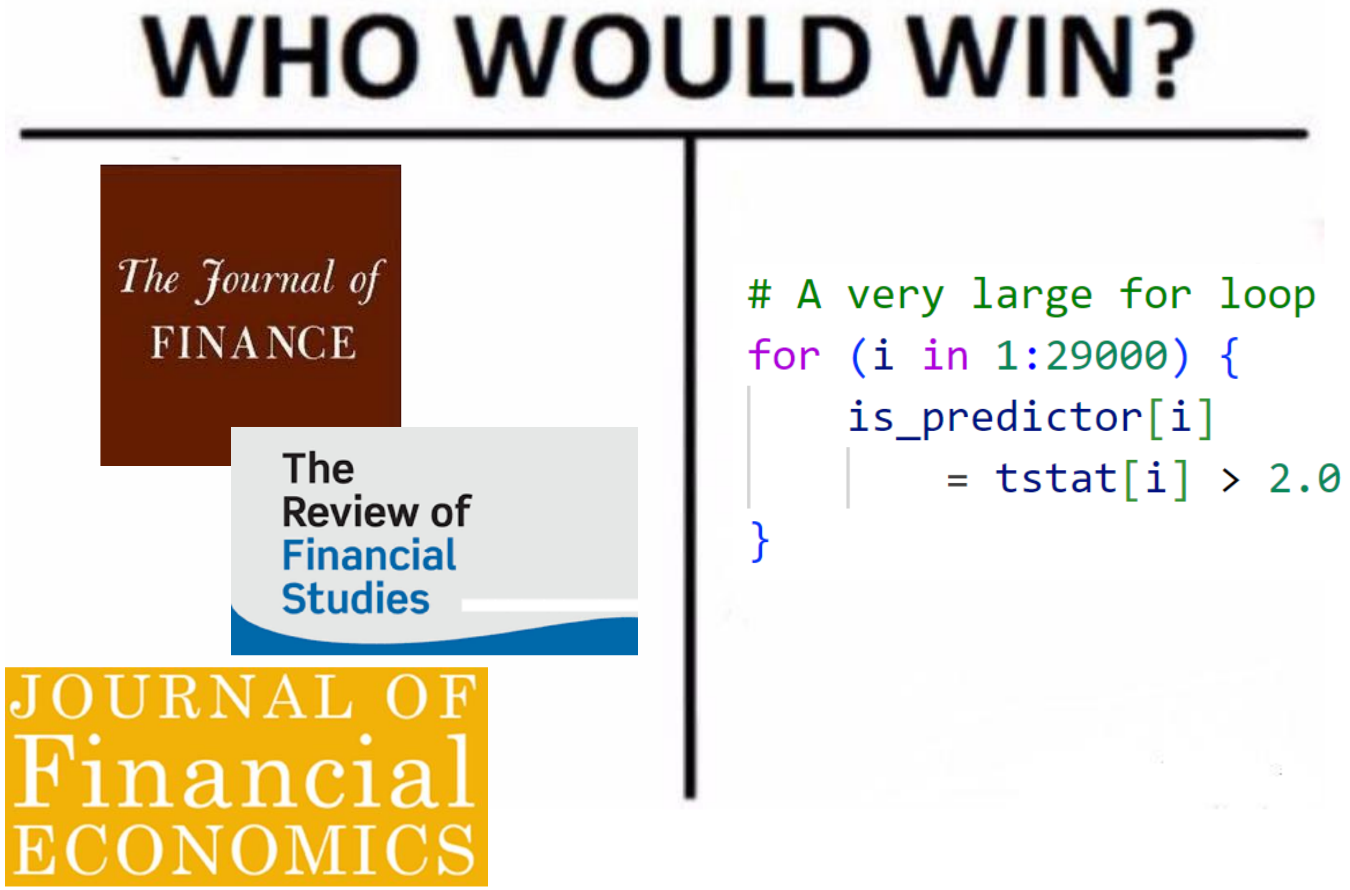
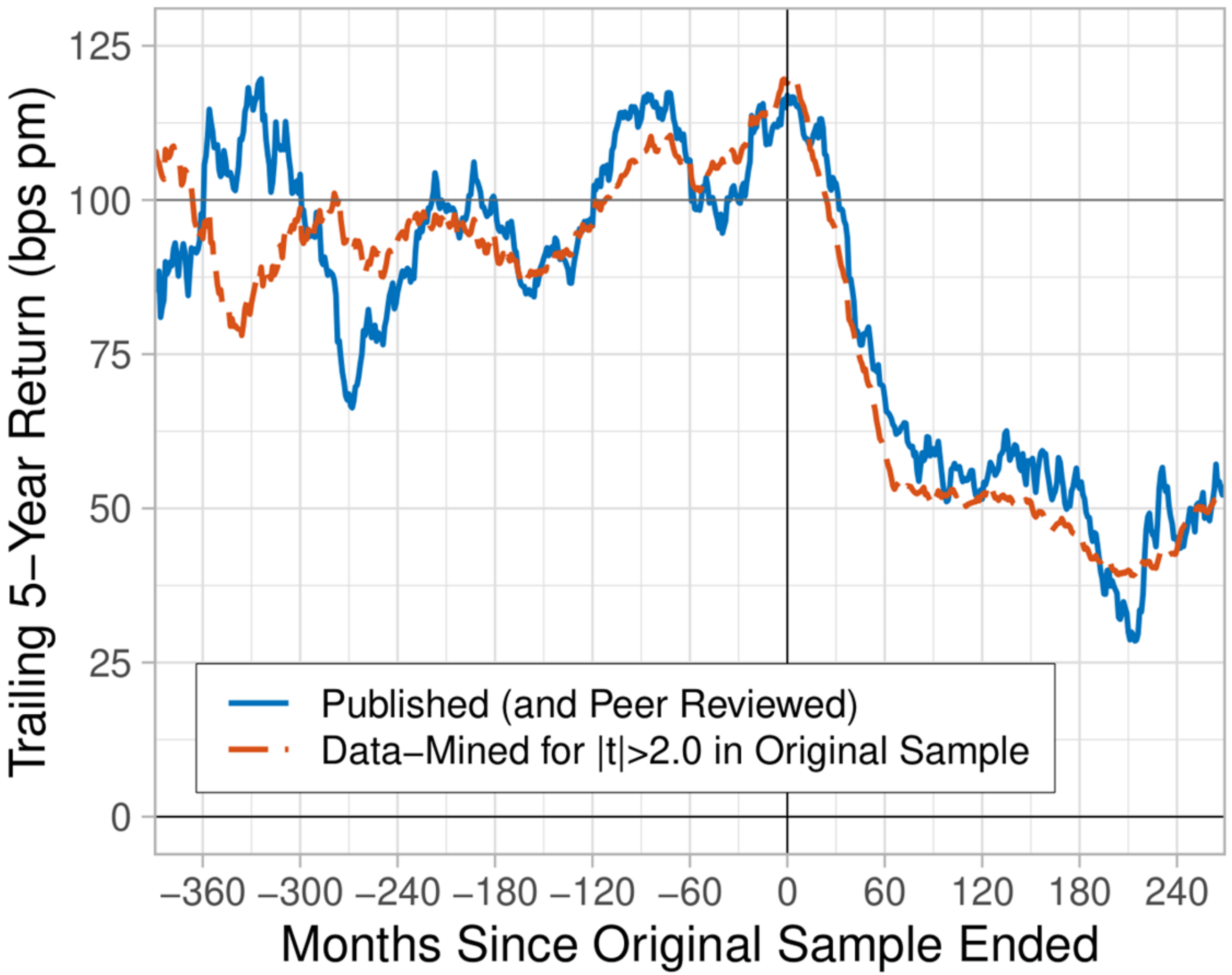


Does peer-reviewed research help predict the cross-section post-sample?



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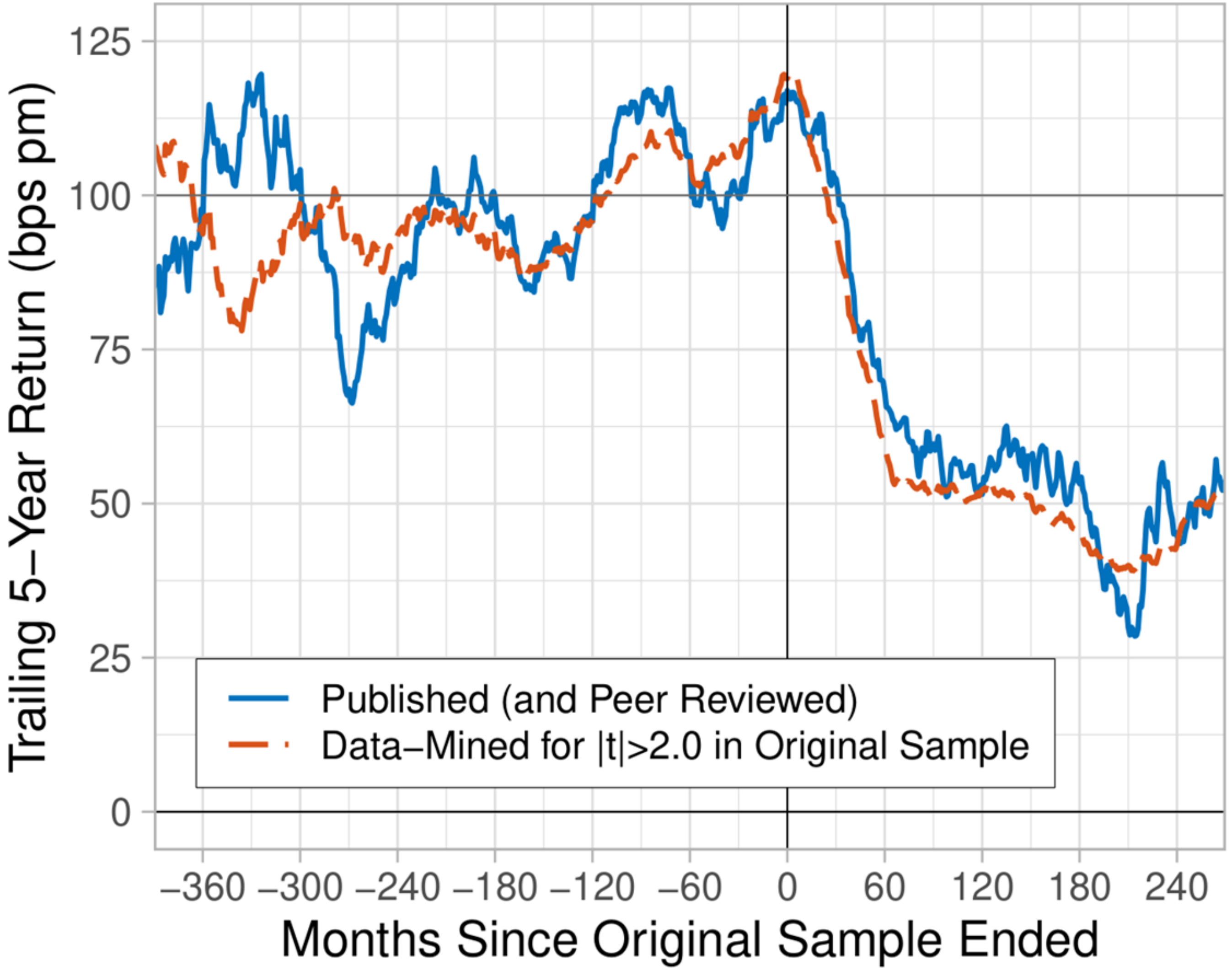

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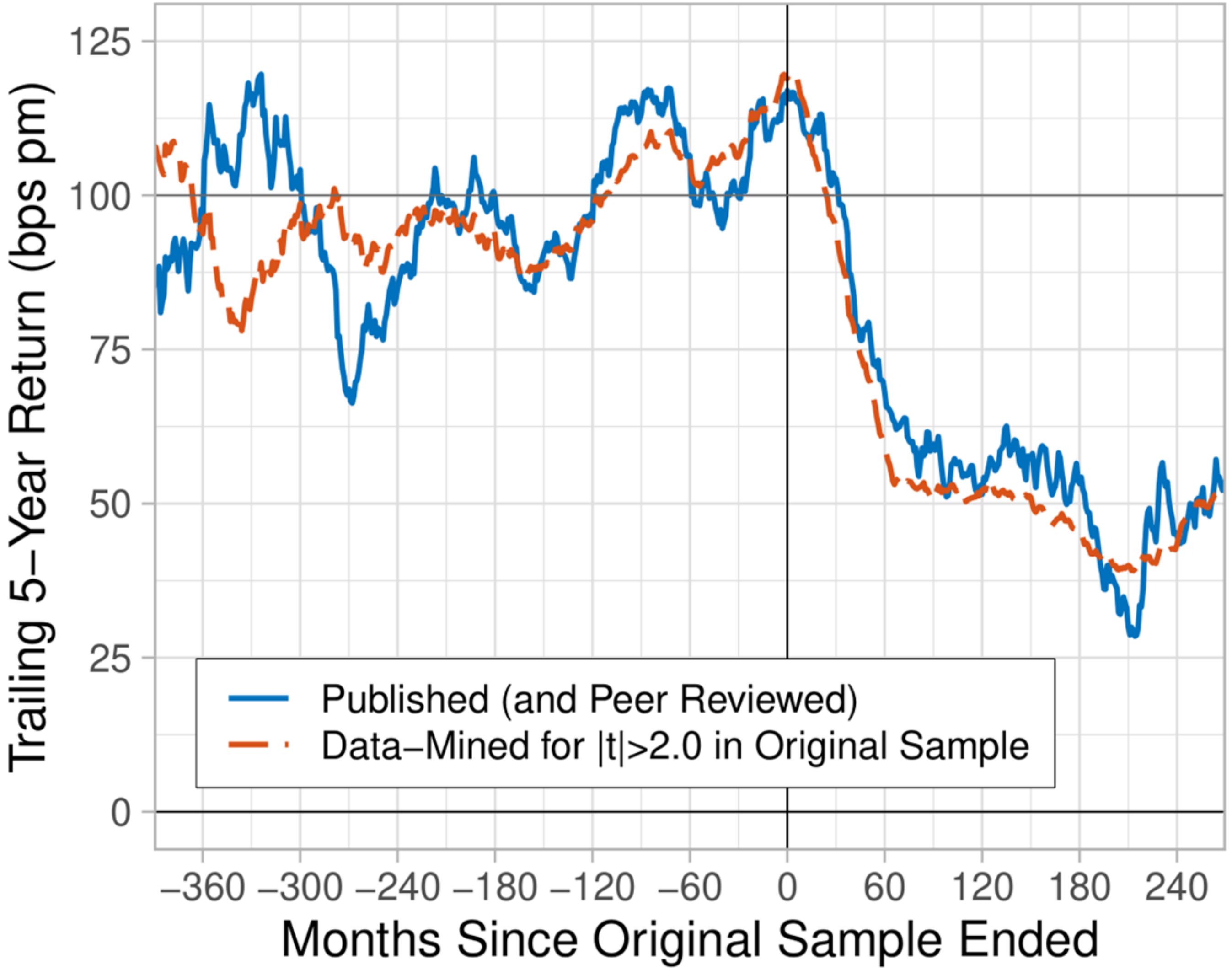

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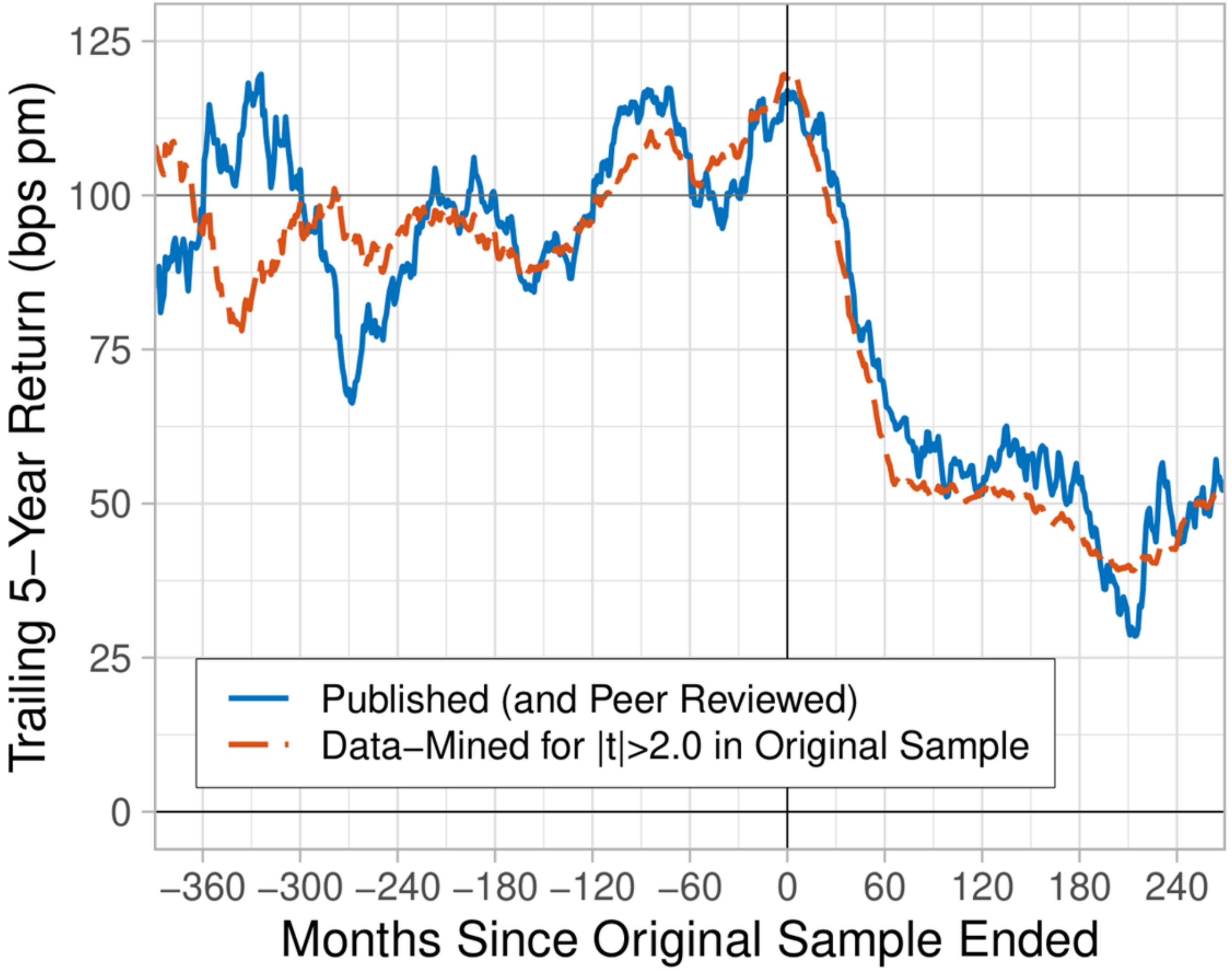
- **51% remains for data-mined benchmarks**
  - **(This paper)**



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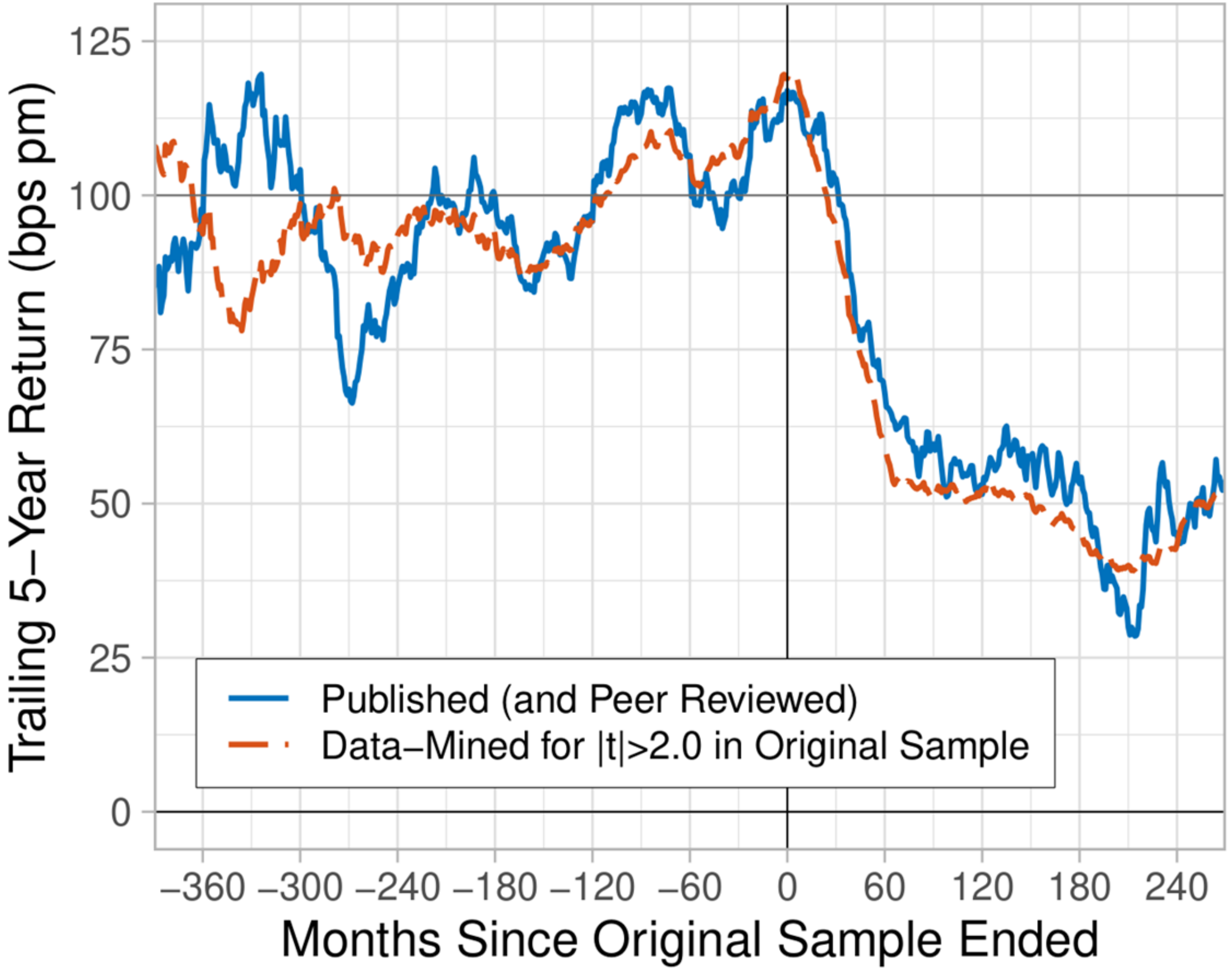

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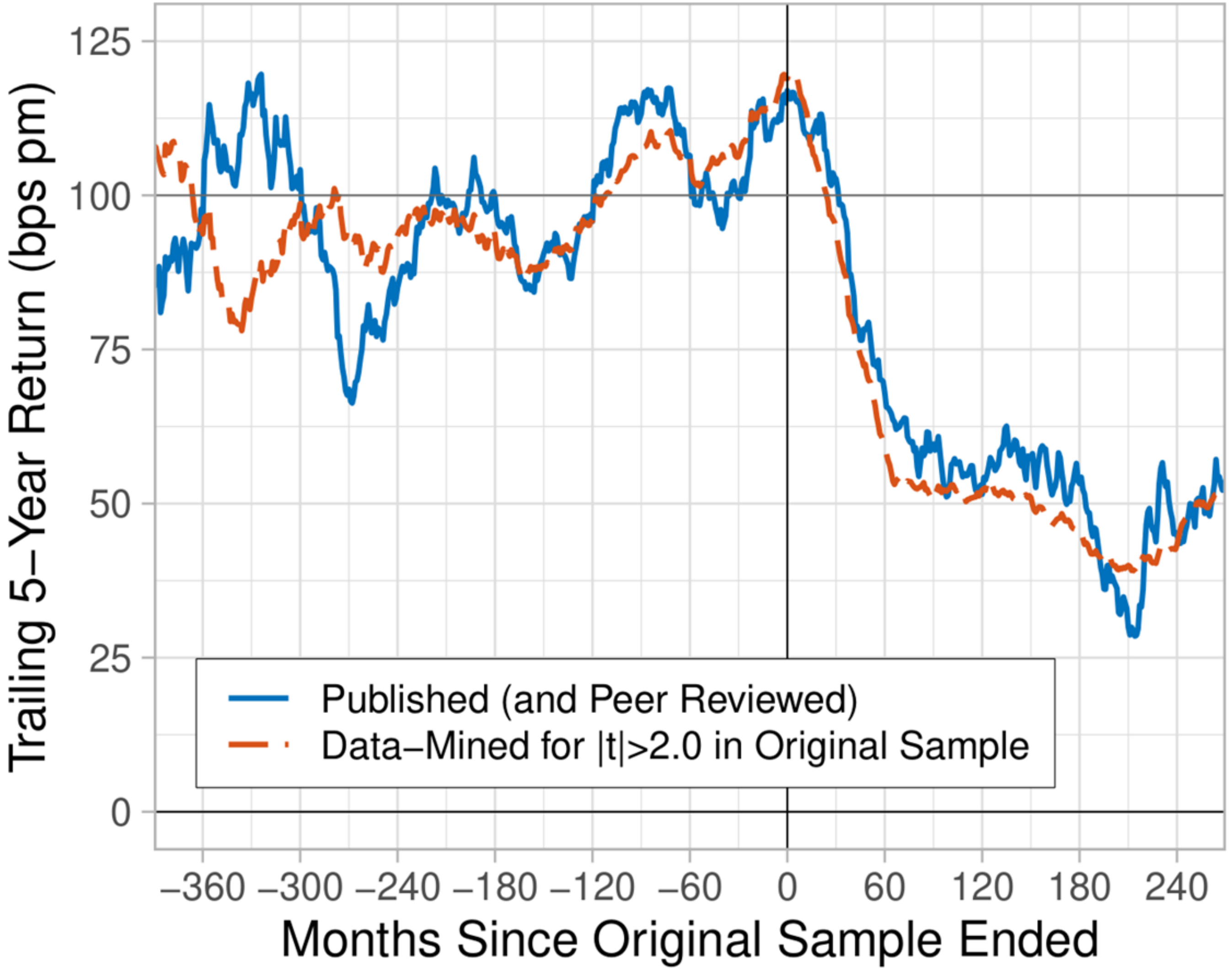

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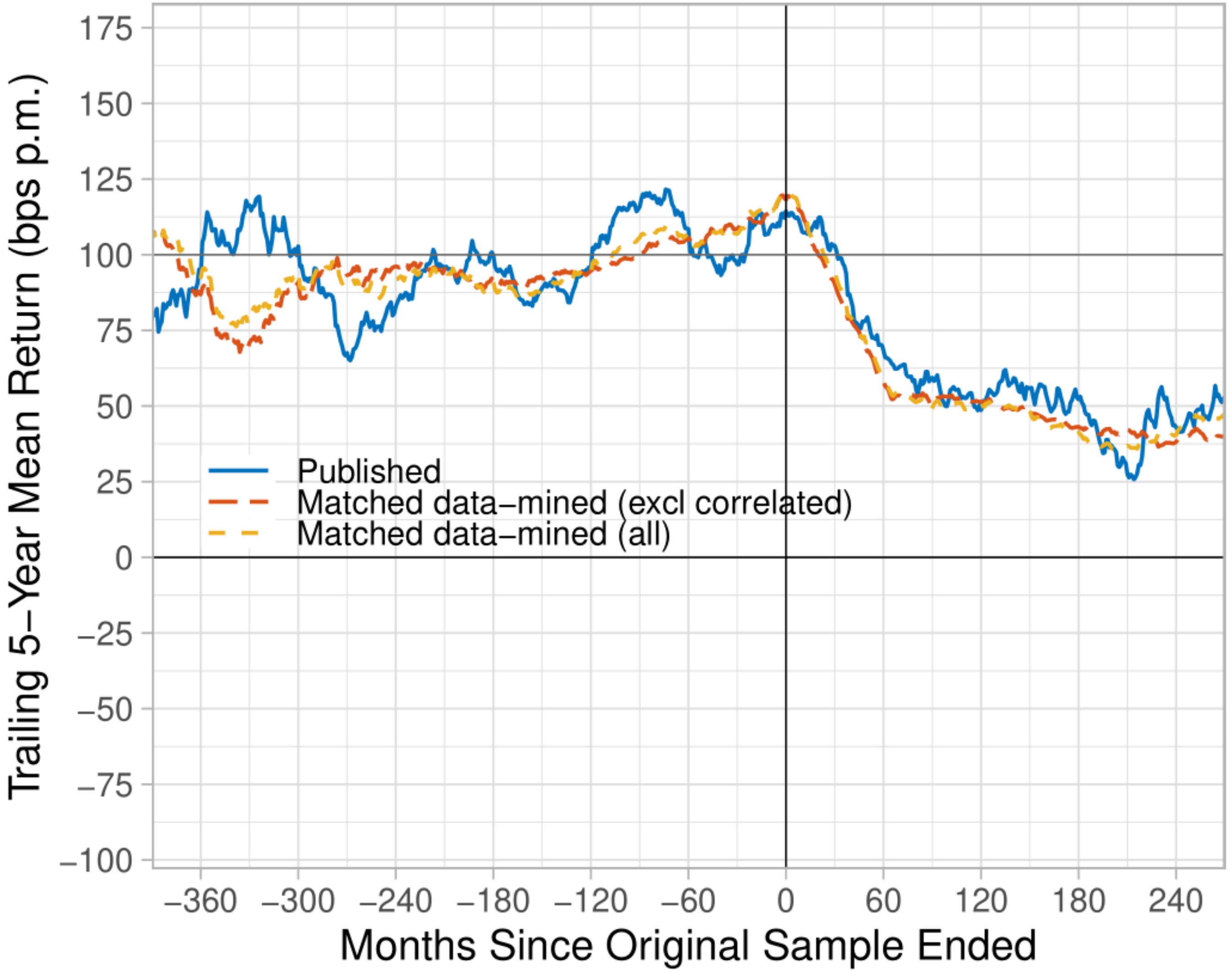
  - Matching on in-sample returns and t-stats
  - Excluding correlated benchmarks



Do Risk-Based Explanations Help?

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- **Do papers that follow Cochrane’s advice outperform data mining?**
- **Method: Manually categorize explanations in original papers**
  1. Find summary passage
  2. Categorize passage as “risk,” “mispricing,” or “agnostic”
  3. Post passages and categories on GitHub, ask public for objections

Risk or Mispricing? According to Peer Review

Category	Num Predictors: Any Journal	Num Predictors: JF, JFE, RFS	Example Predictor	Example Passage
Risk	36	33	Real estate holdings (Tuzel 2010)	Firms with high real estate holdings are more vulnerable to bad productivity shocks and hence are riskier and have higher expected returns.
Mispricing	117	65	Share repurchases (Ikenberry, Lakonishok, Vermaelen 1995)	The market errs in its initial response and appears to ignore much of the information conveyed through repurchase announcements
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Total	199	123		

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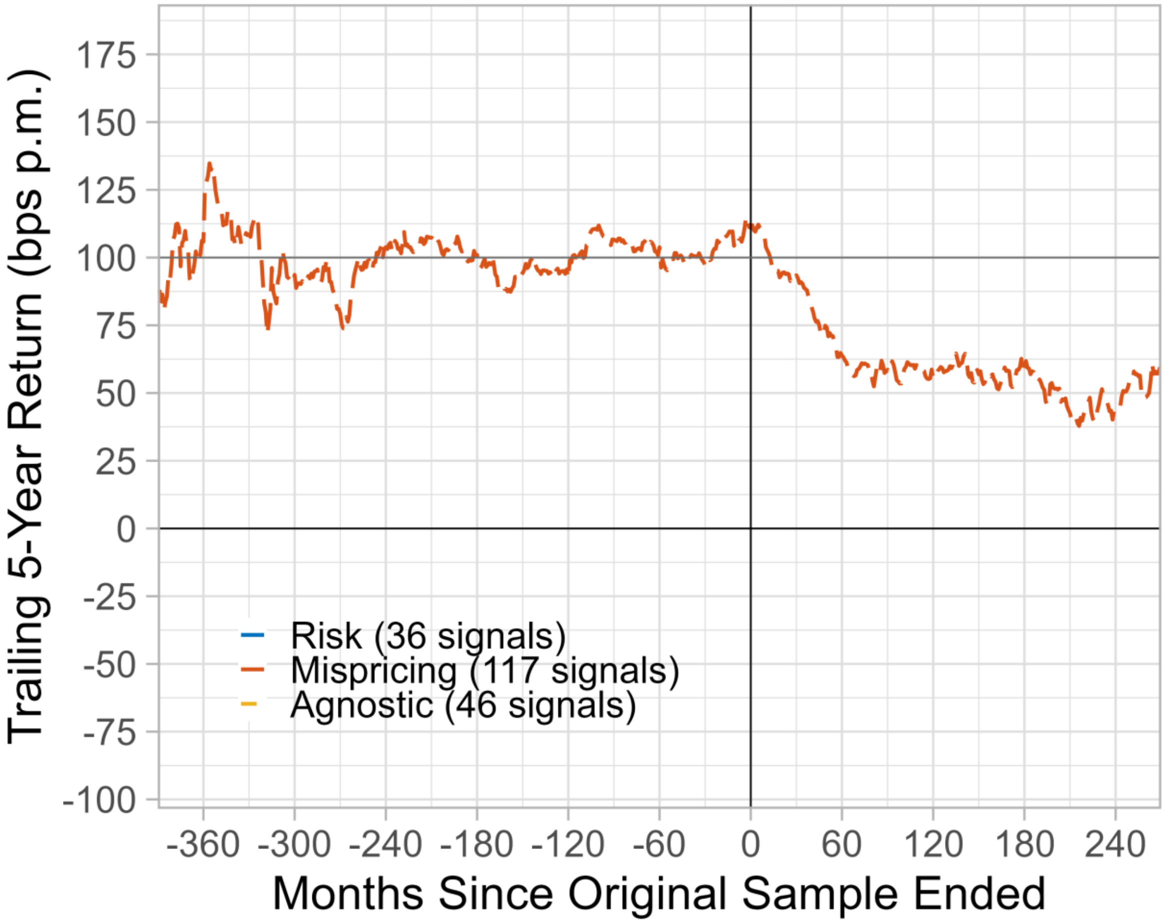
- **Only small minority 36/199= 18% are attributed to risk**
  - **Top 3 Finance journals: 27% are risk**

Post-sample decay: risk vs mispricing



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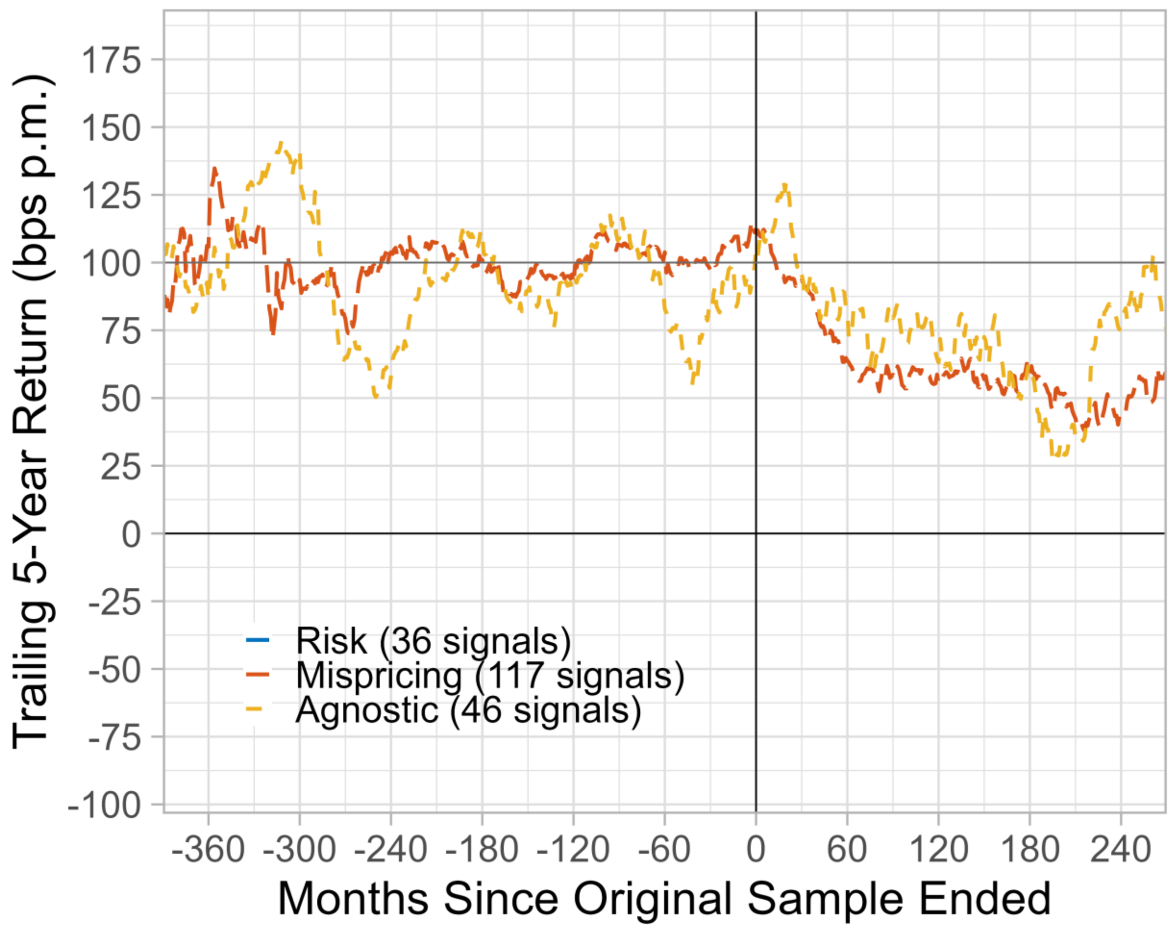

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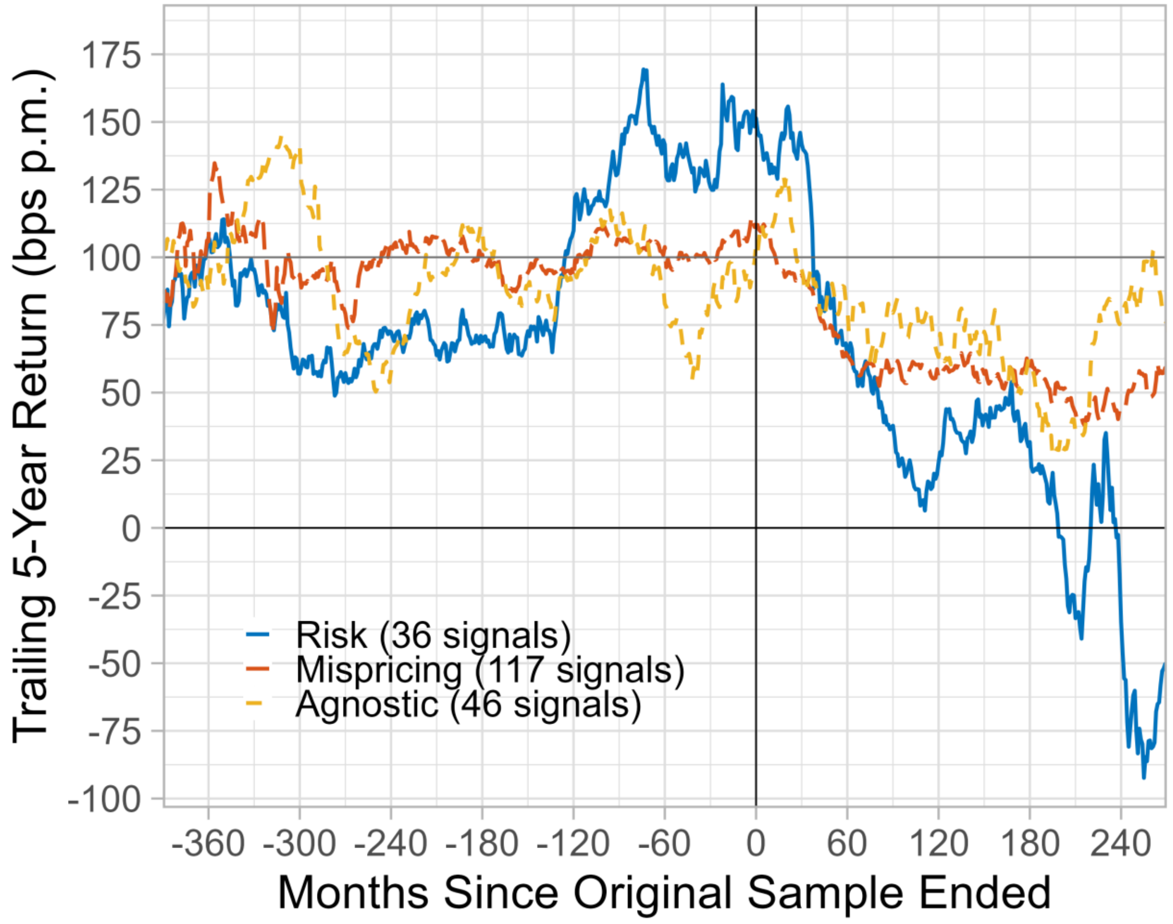
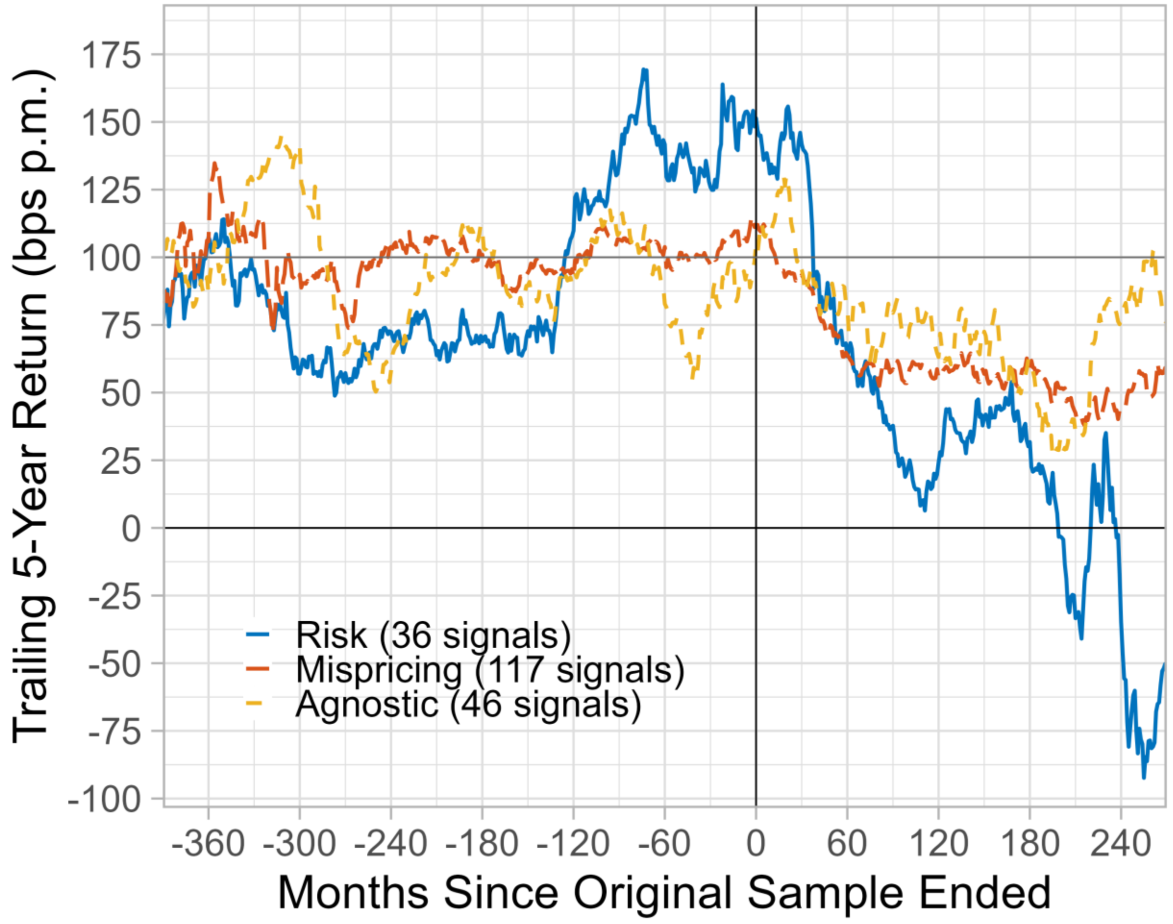
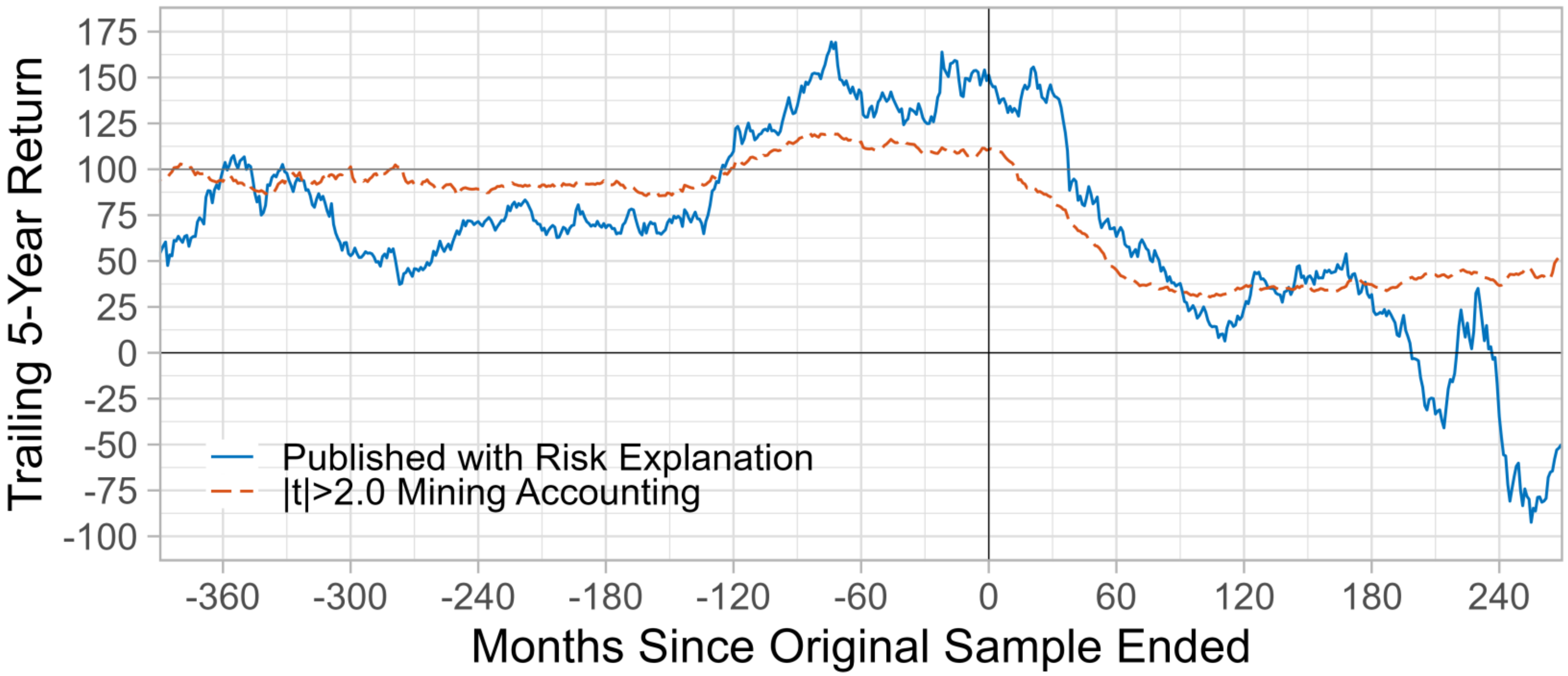


Post-sample decay: risk vs mispricing

- **No, publishable risk-based explanations do not help**
  - If anything, they lead to underperformance



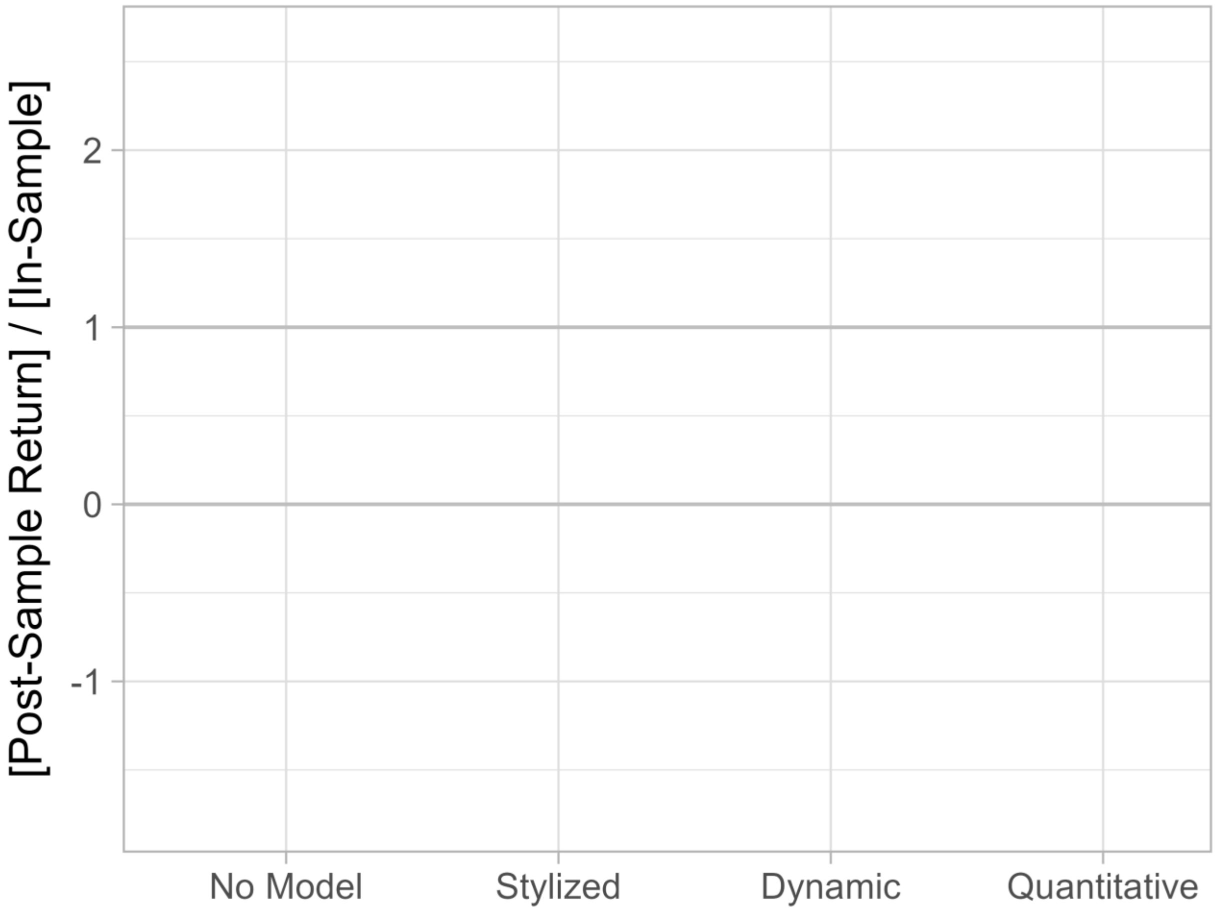
Risk vs data mining



- **Risk-based predictors fail to outperform data-mined benchmarks**
  - Data-mined benchmarks are exposed to the same market conditions

Robustness: Modeling Rigor

- Theory should help by disciplining the statistics (e.g. Fama French 2018)



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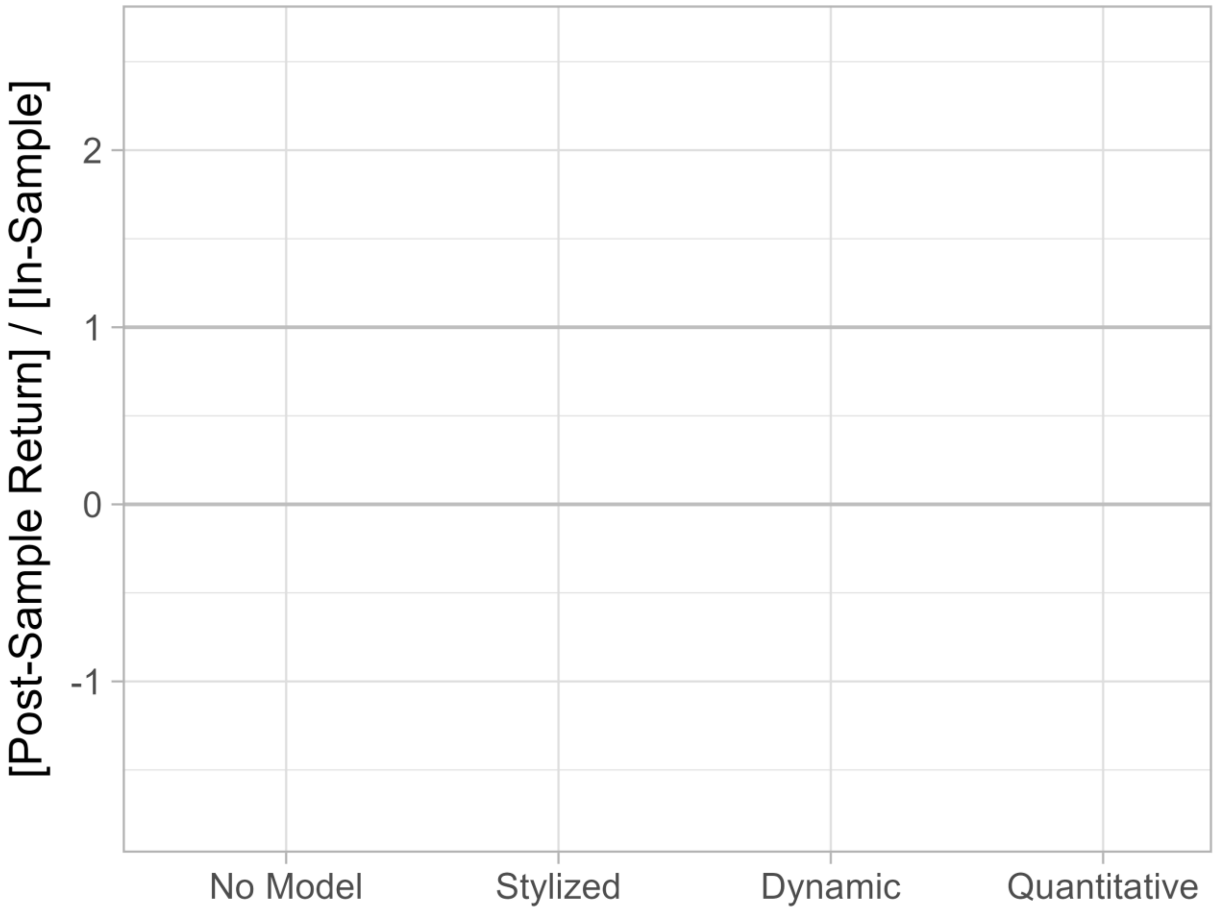

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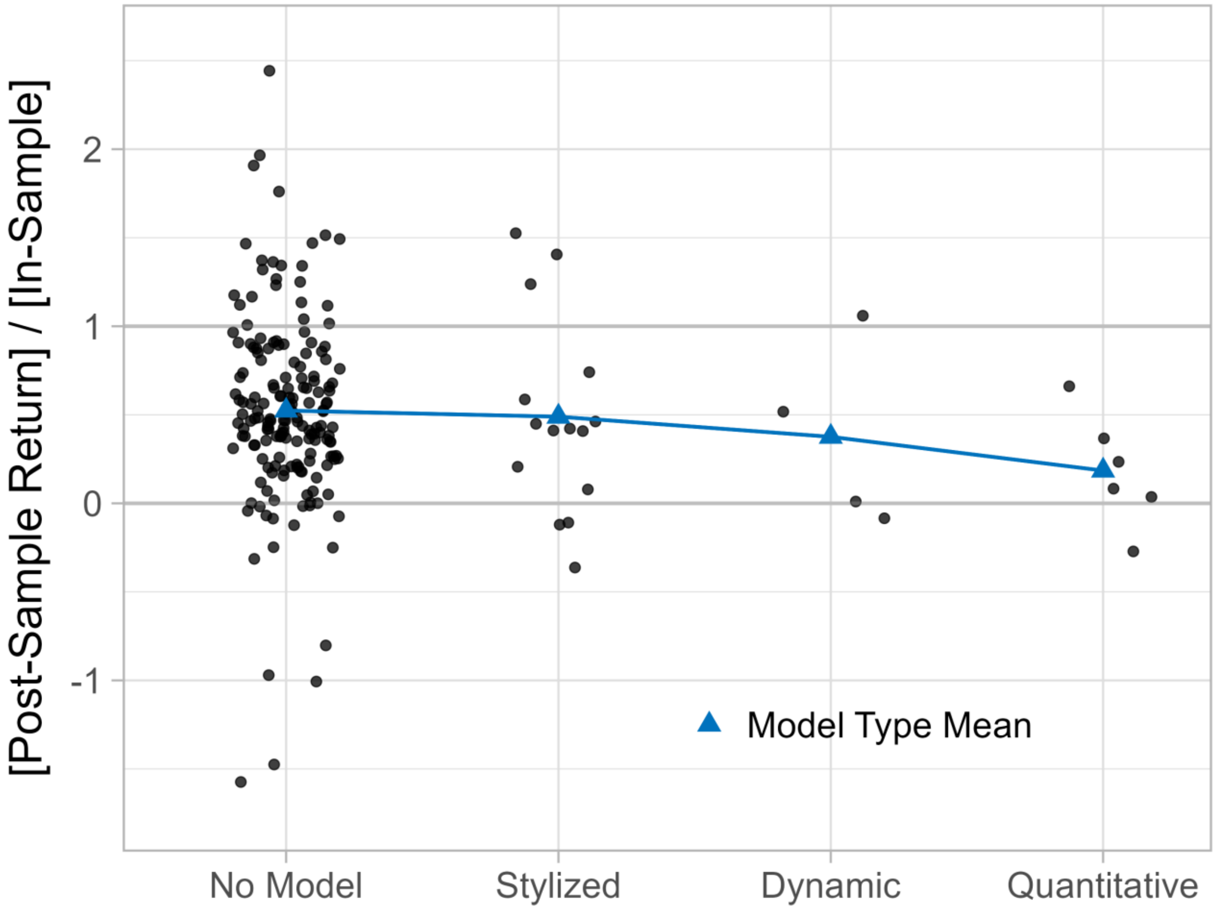

Robustness: Modeling Rigor

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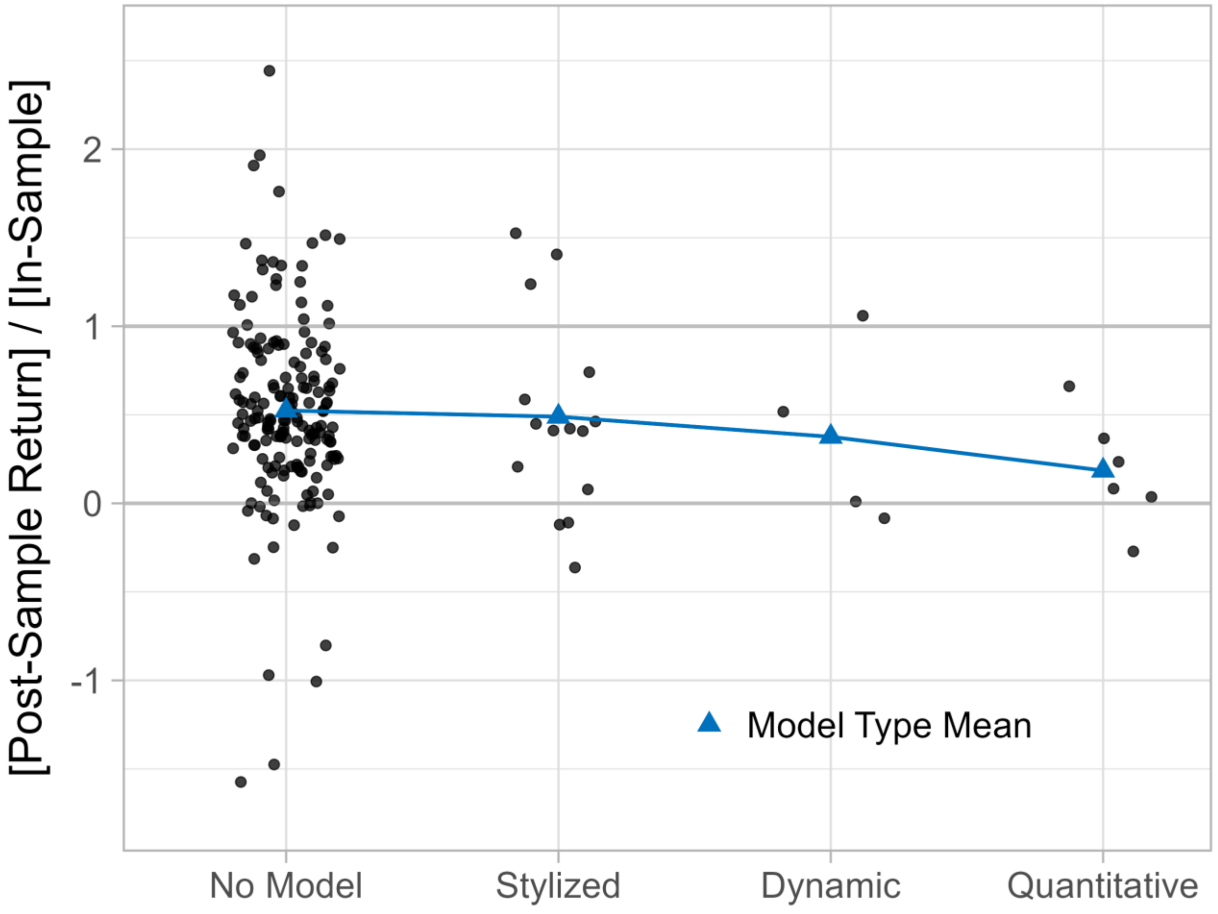
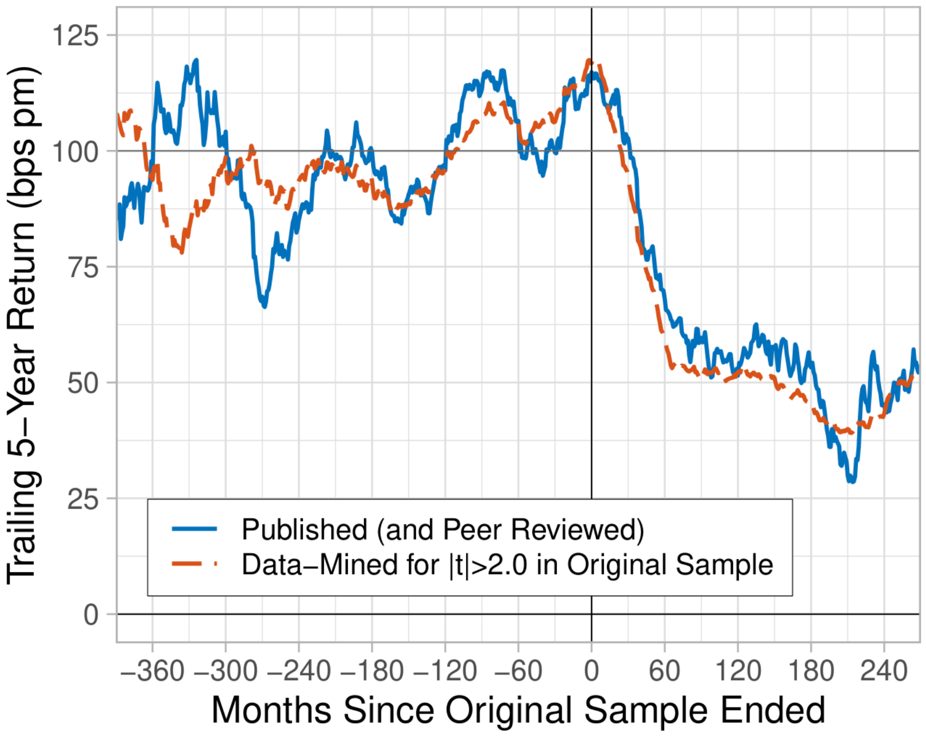
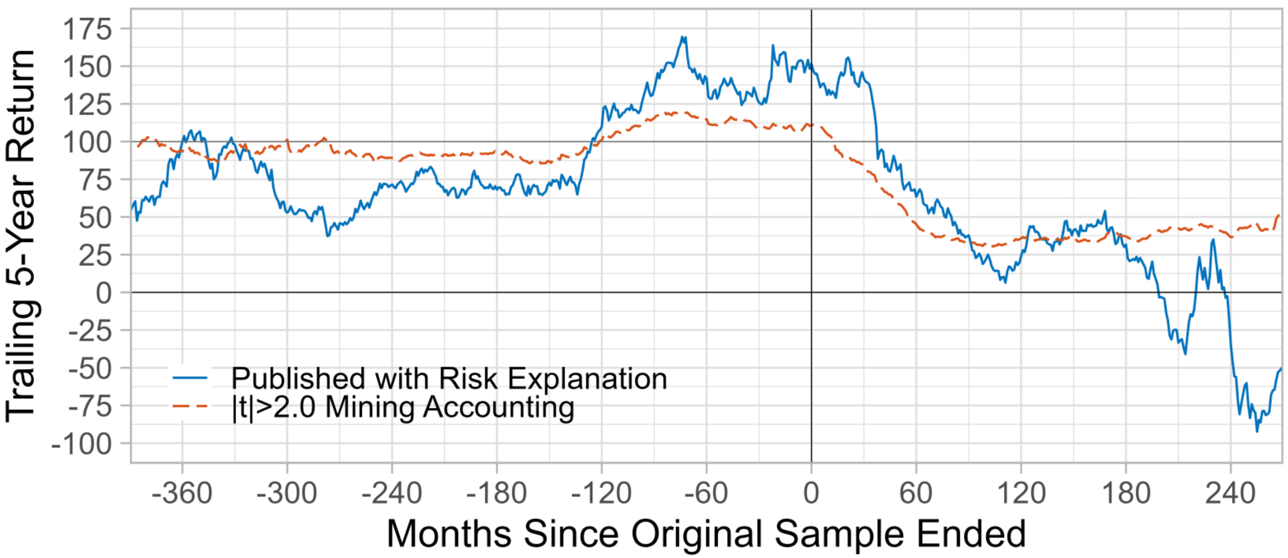
- **Empirically: more discipline ⇒ less post-sample robustness**



What do we make of this?

Peer reviewed predictability is similar to data mining---risk-based predictability is worse





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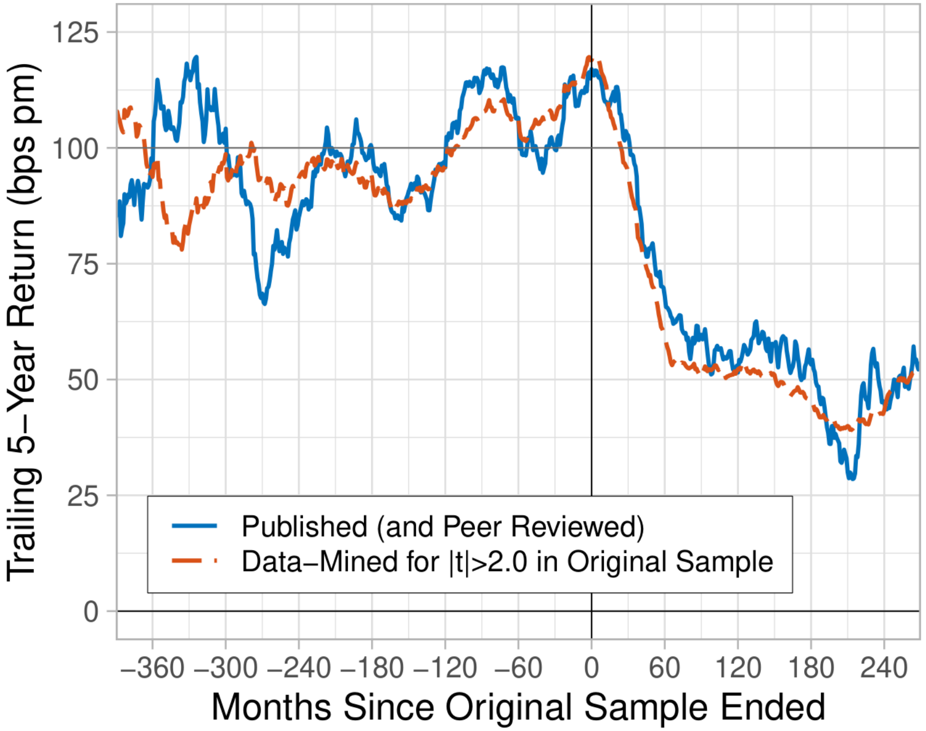
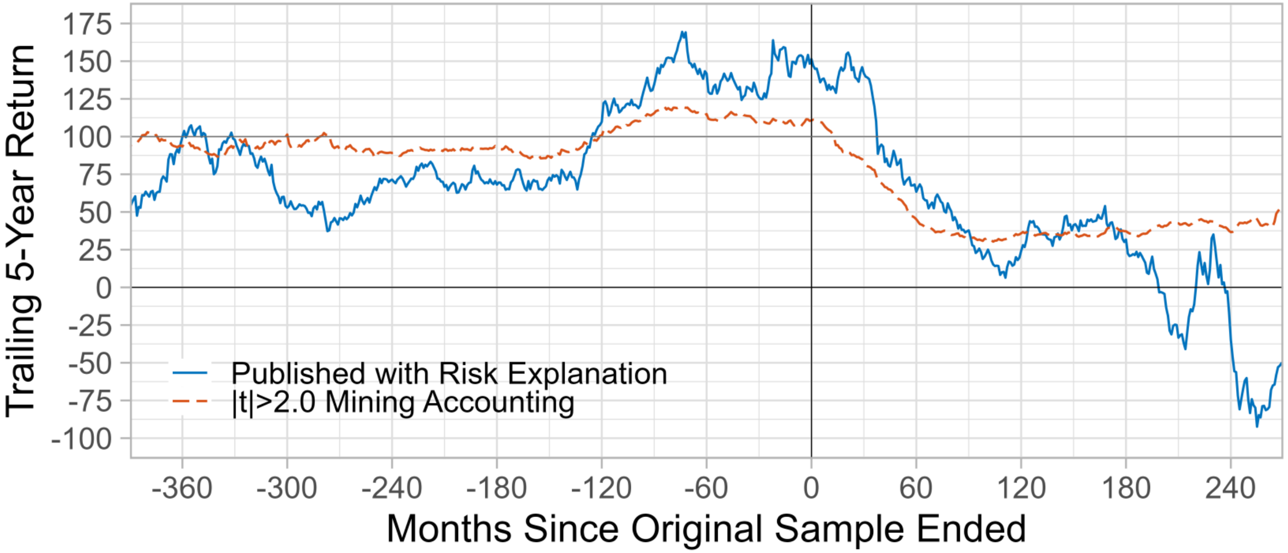
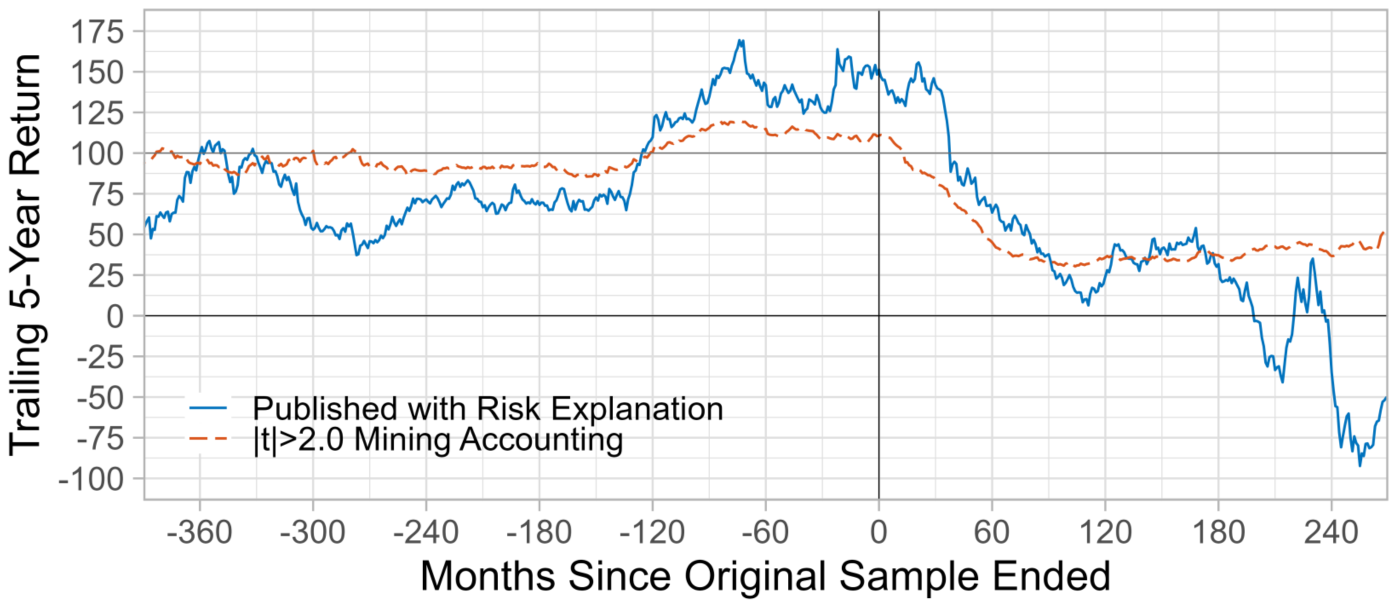




Two choices…

Choice 1: Cross-sectional stock predictability is not risk



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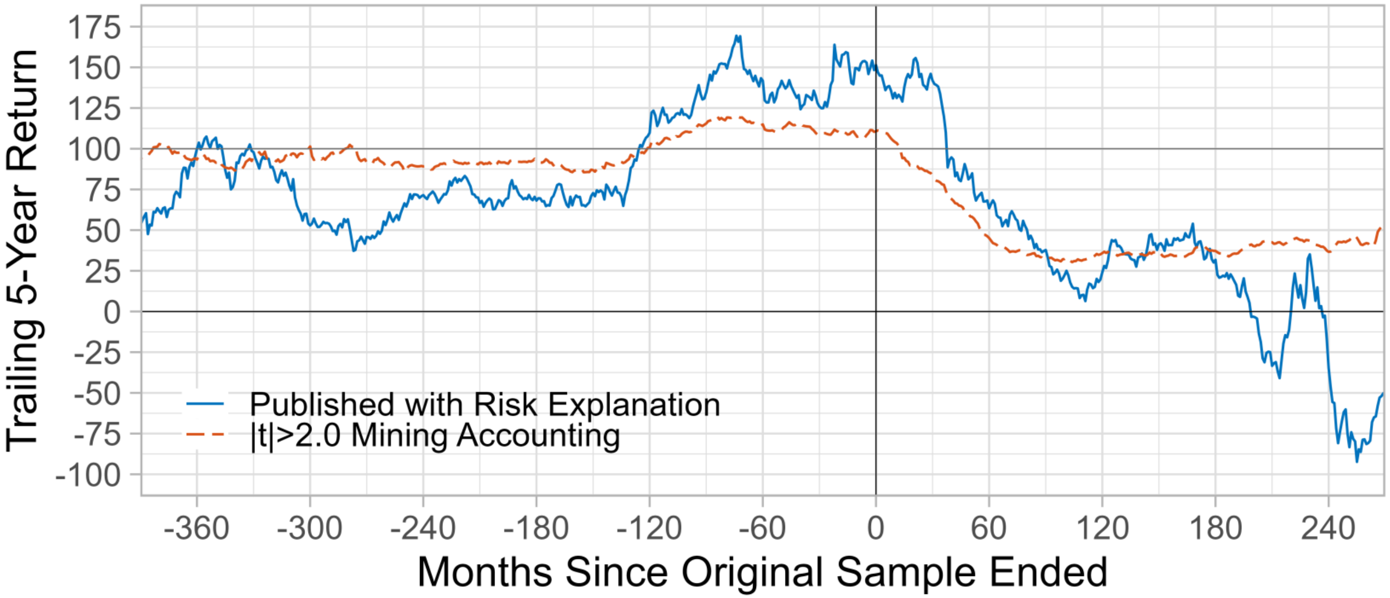

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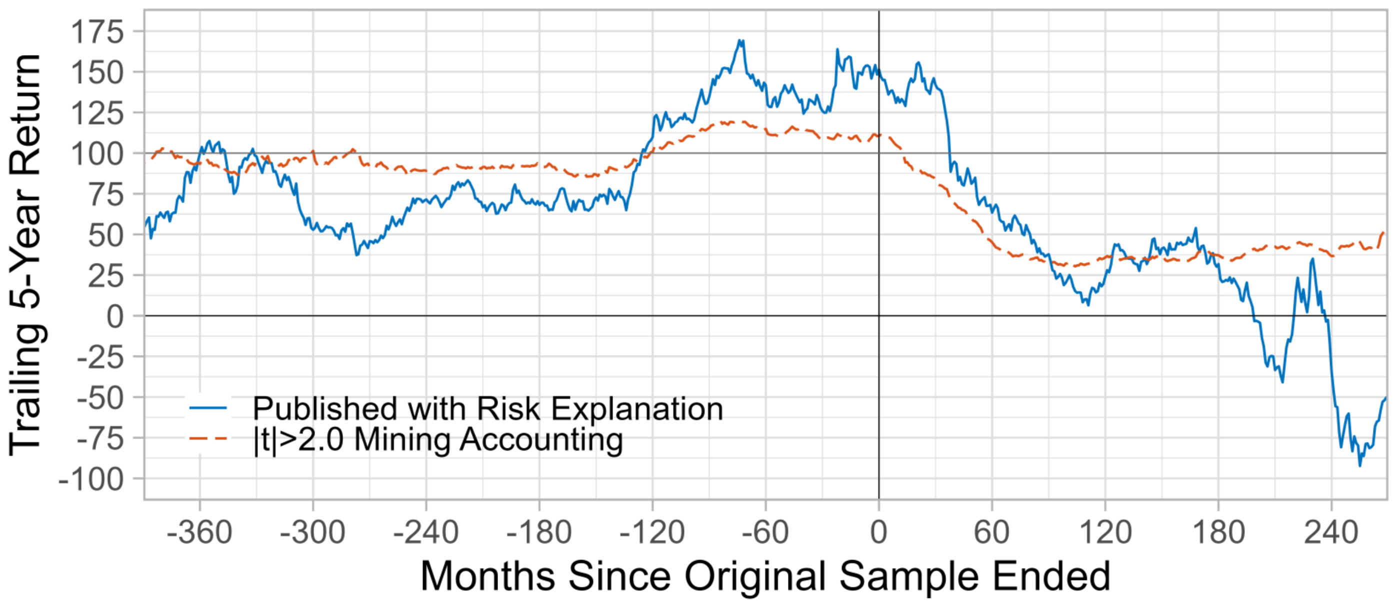

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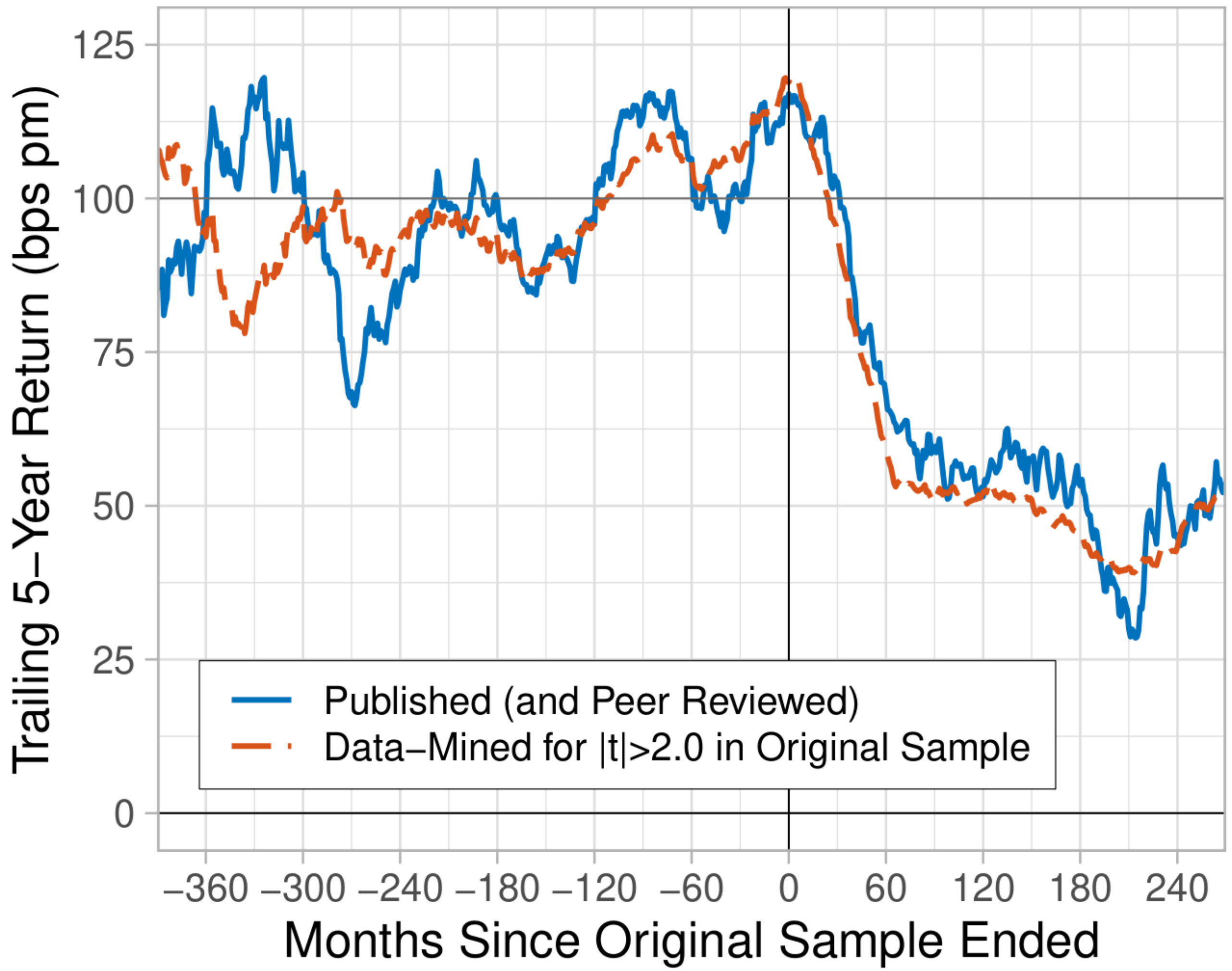
- But peer-review is a massive computer, designed to explore the full class
- **Over the past 40 years, this massive computer**
  - **Finds little risk**
  - **The "risk" it finds, decays out-of-sample, like data-mined predictability**

Or Choice 2: Peer review is not working properly



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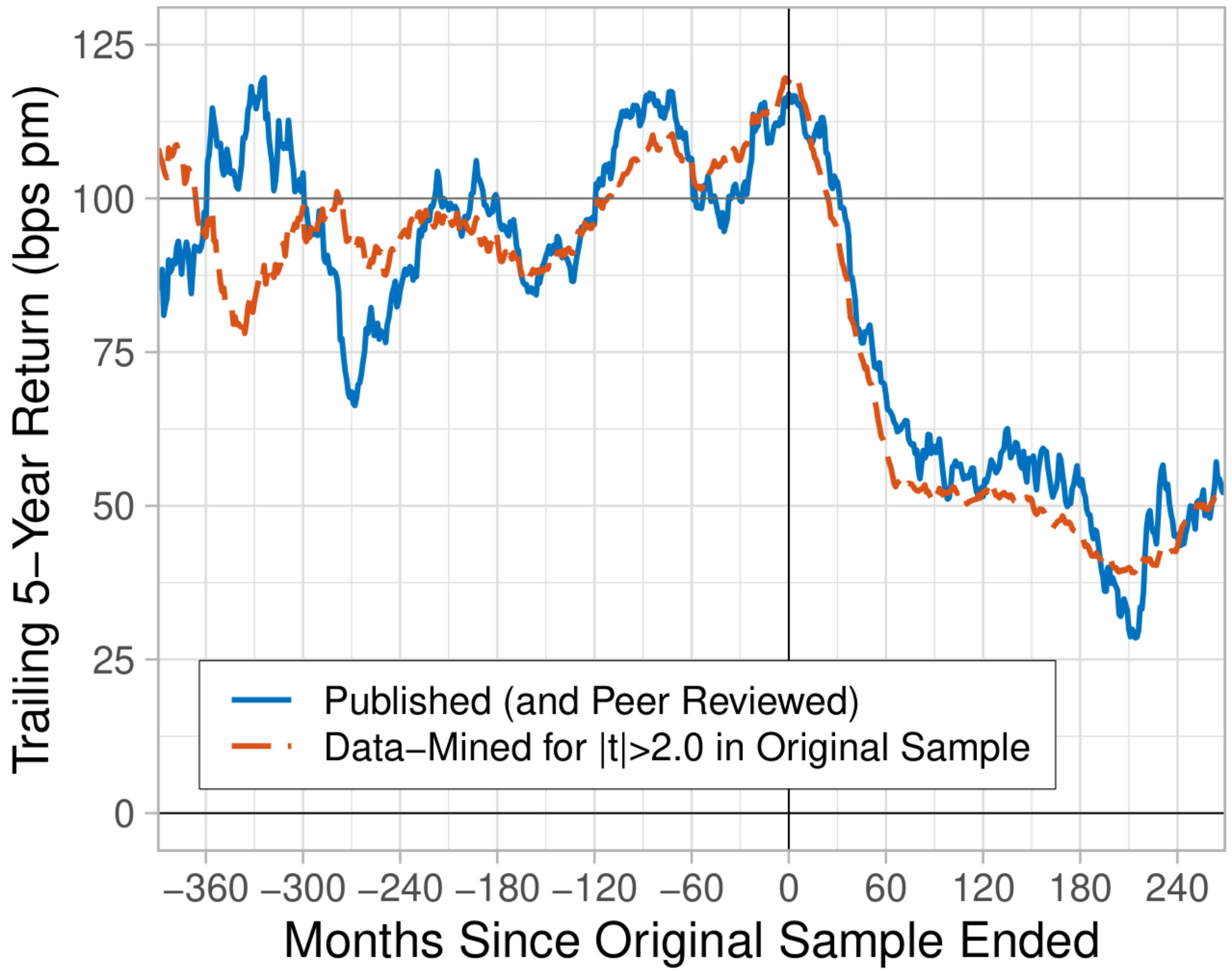

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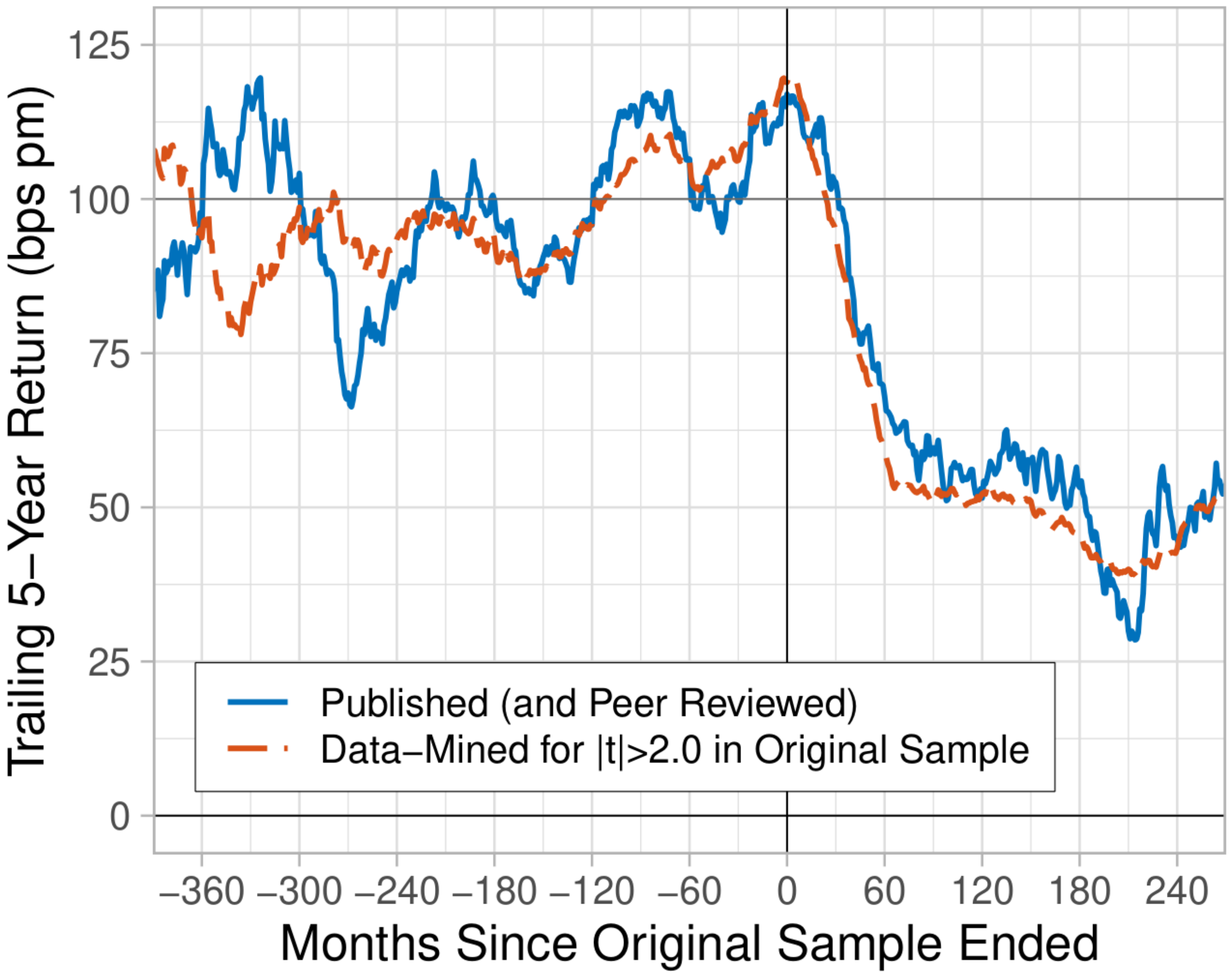

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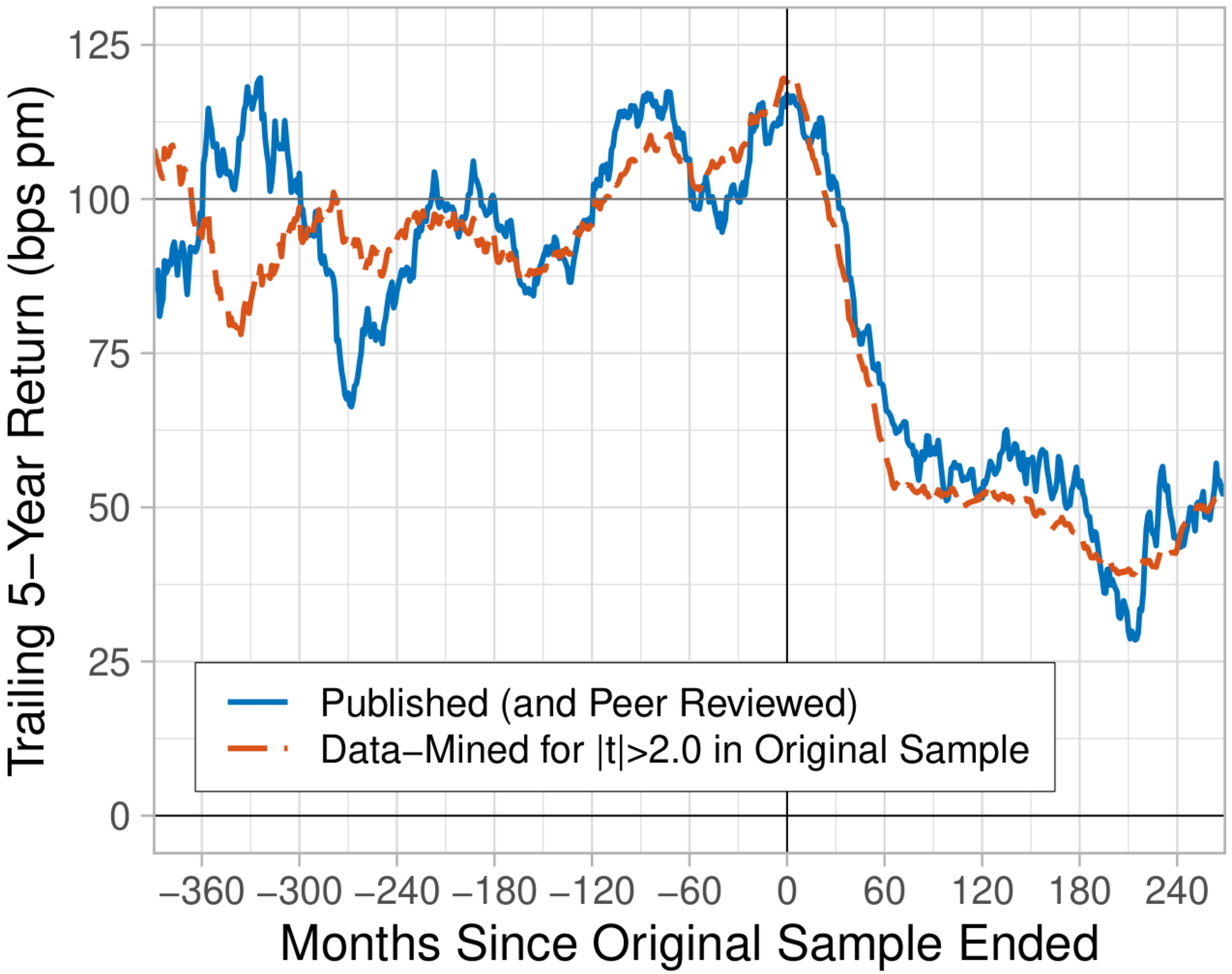

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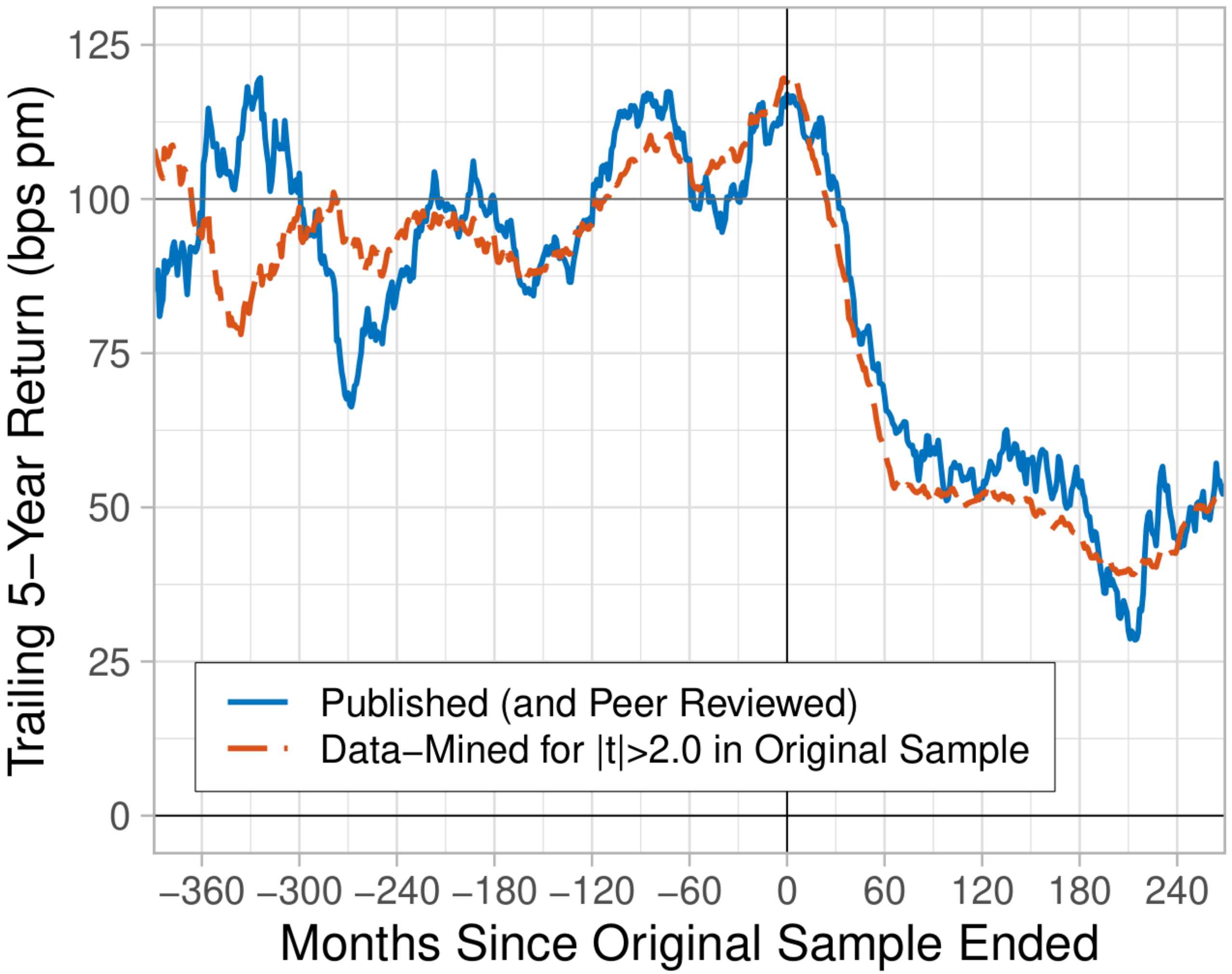
- **We cannot reject this model**



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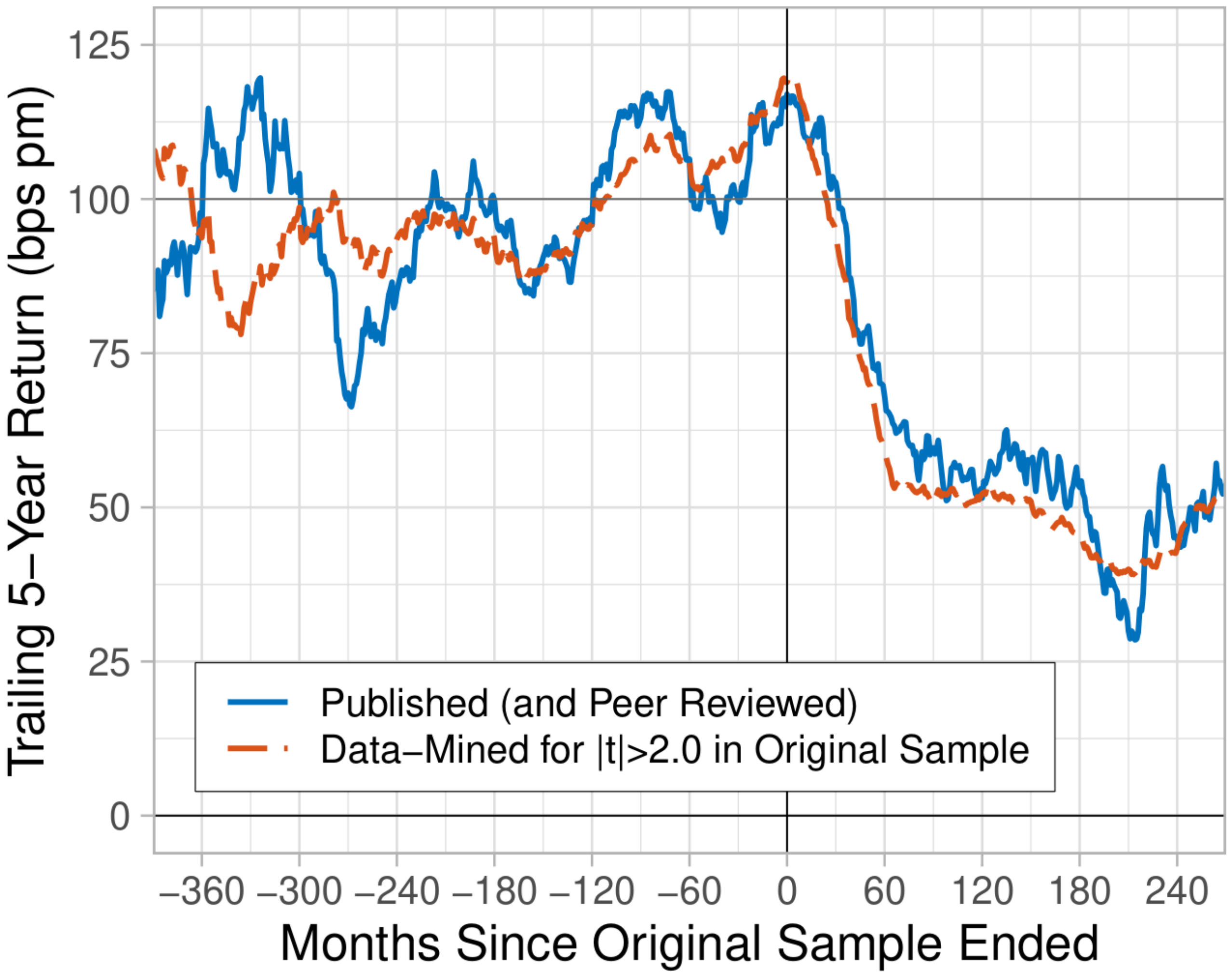

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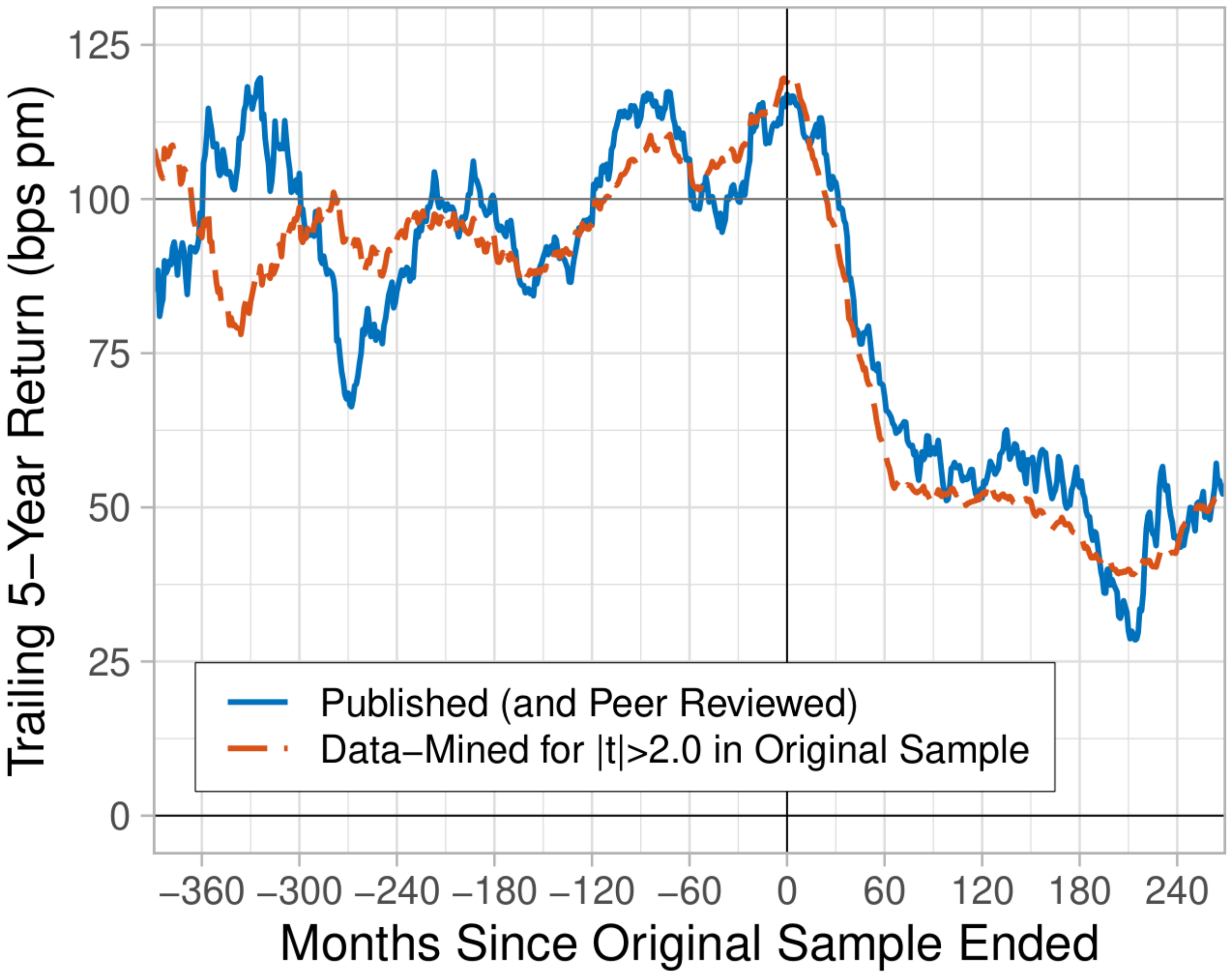

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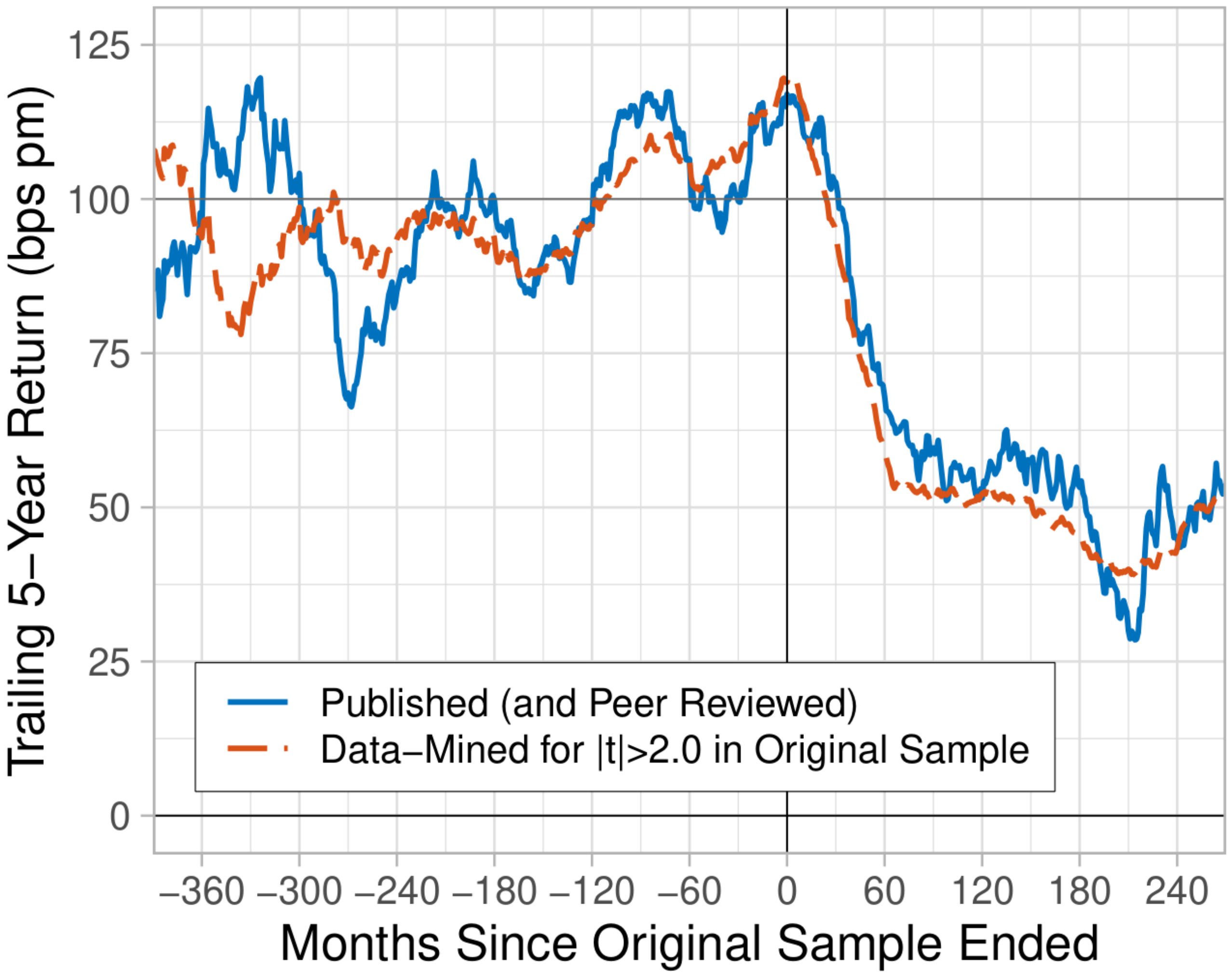

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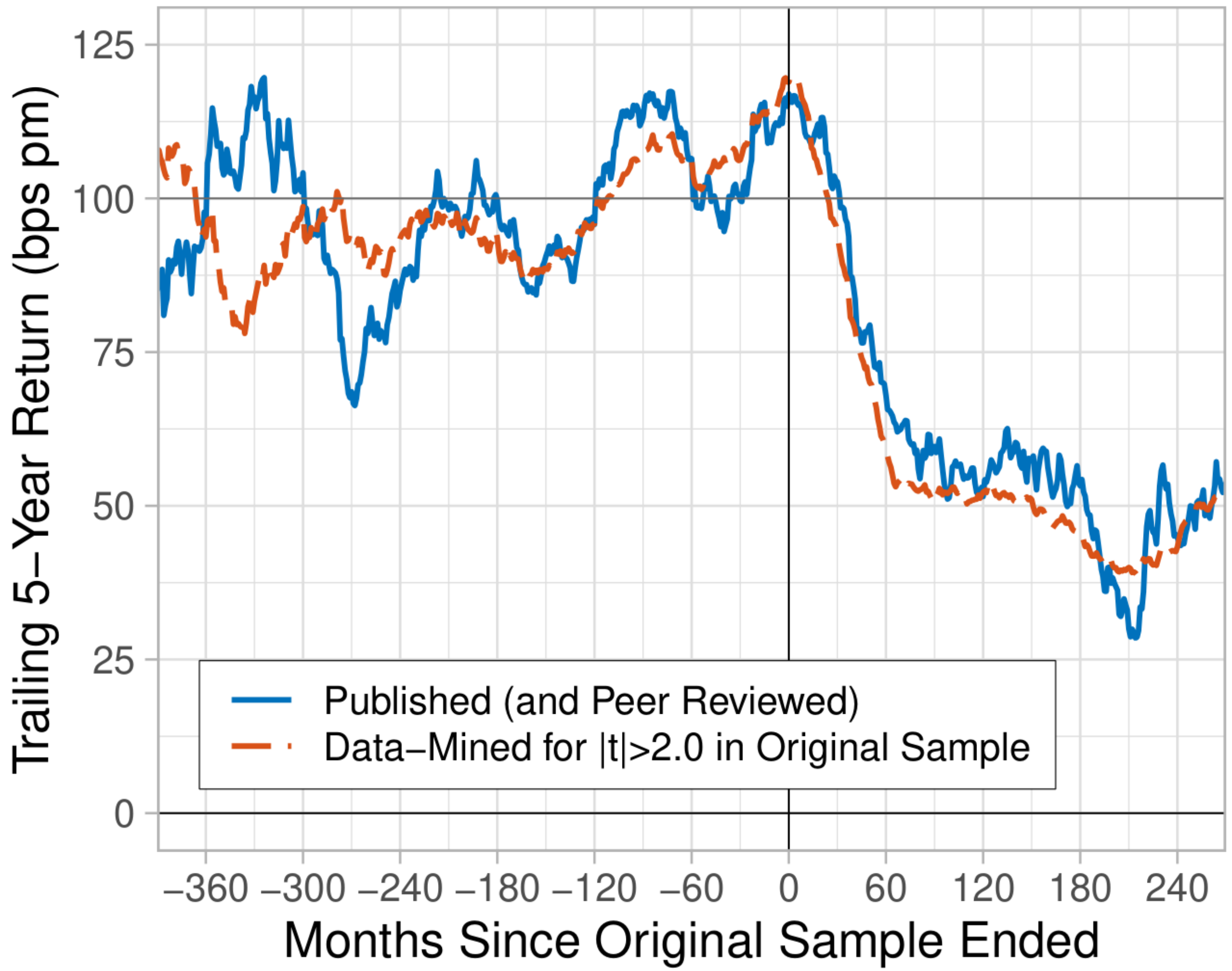

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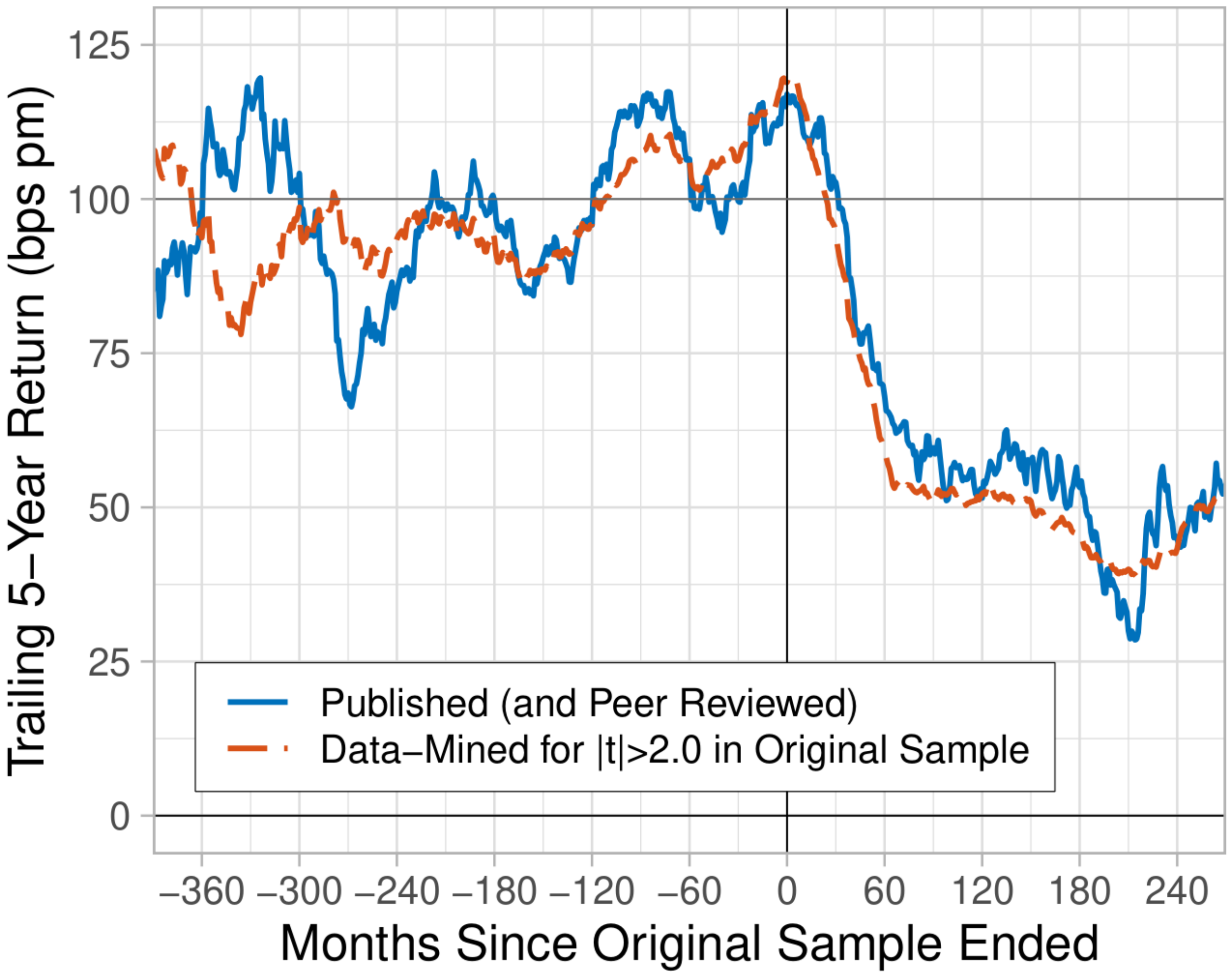

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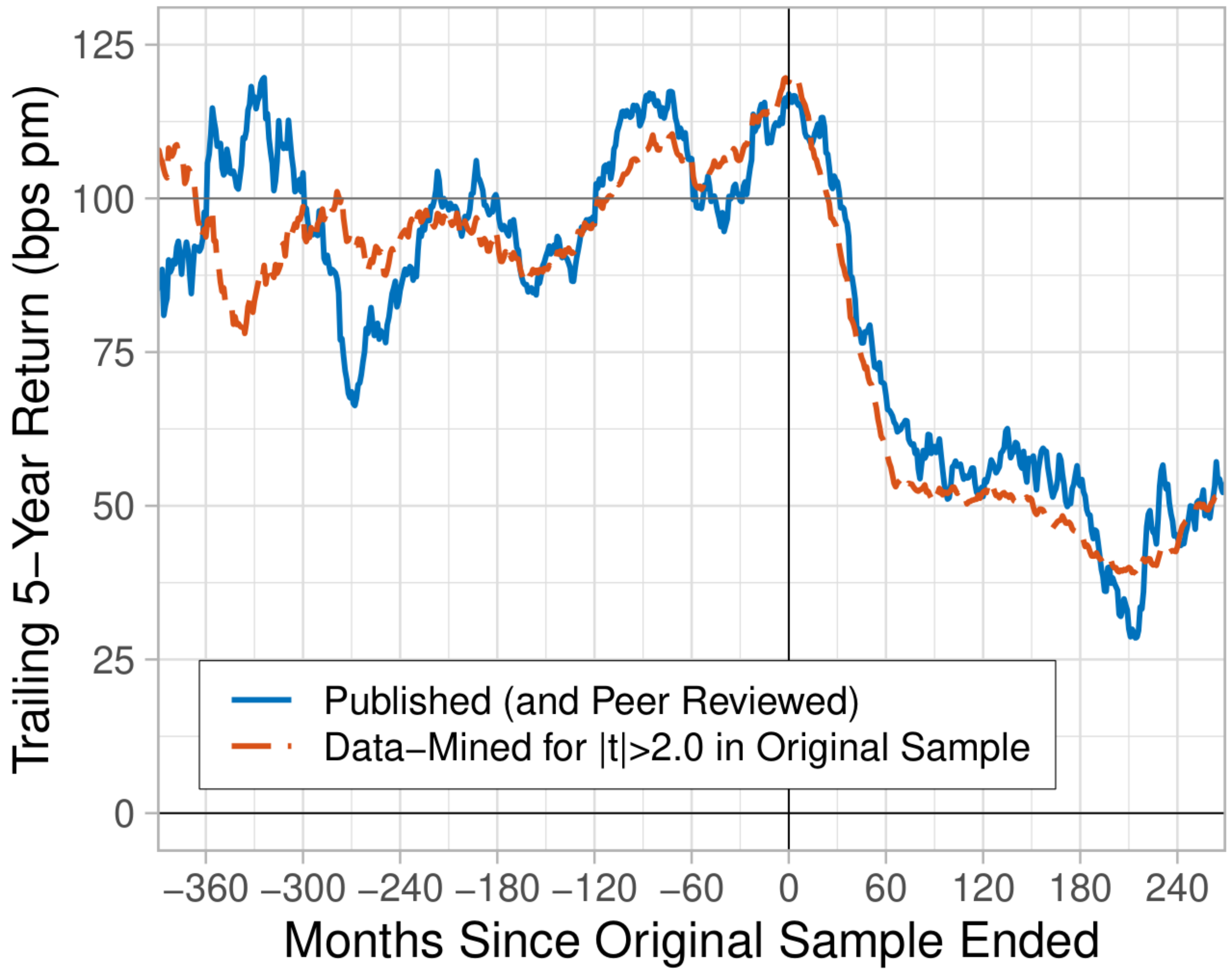

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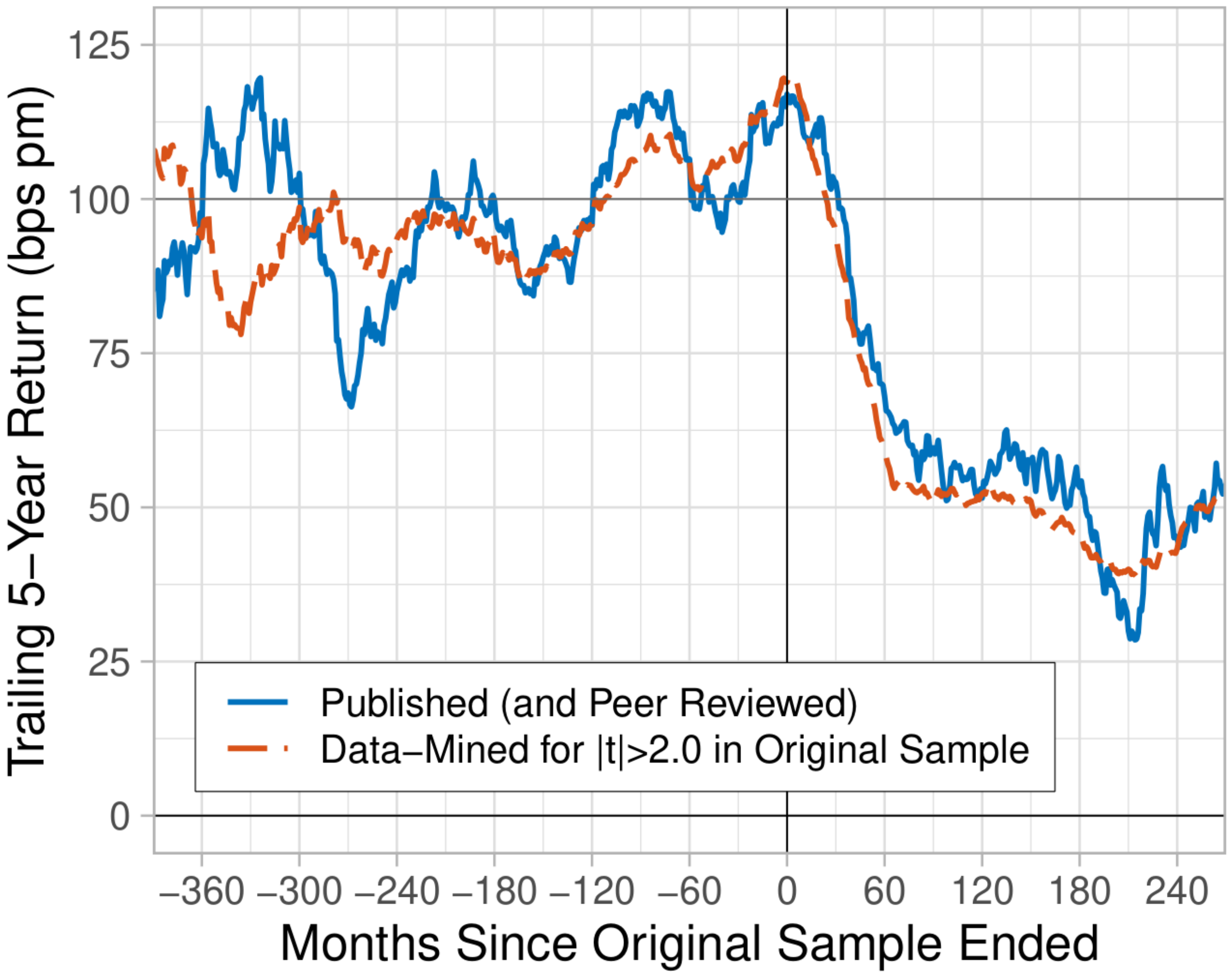

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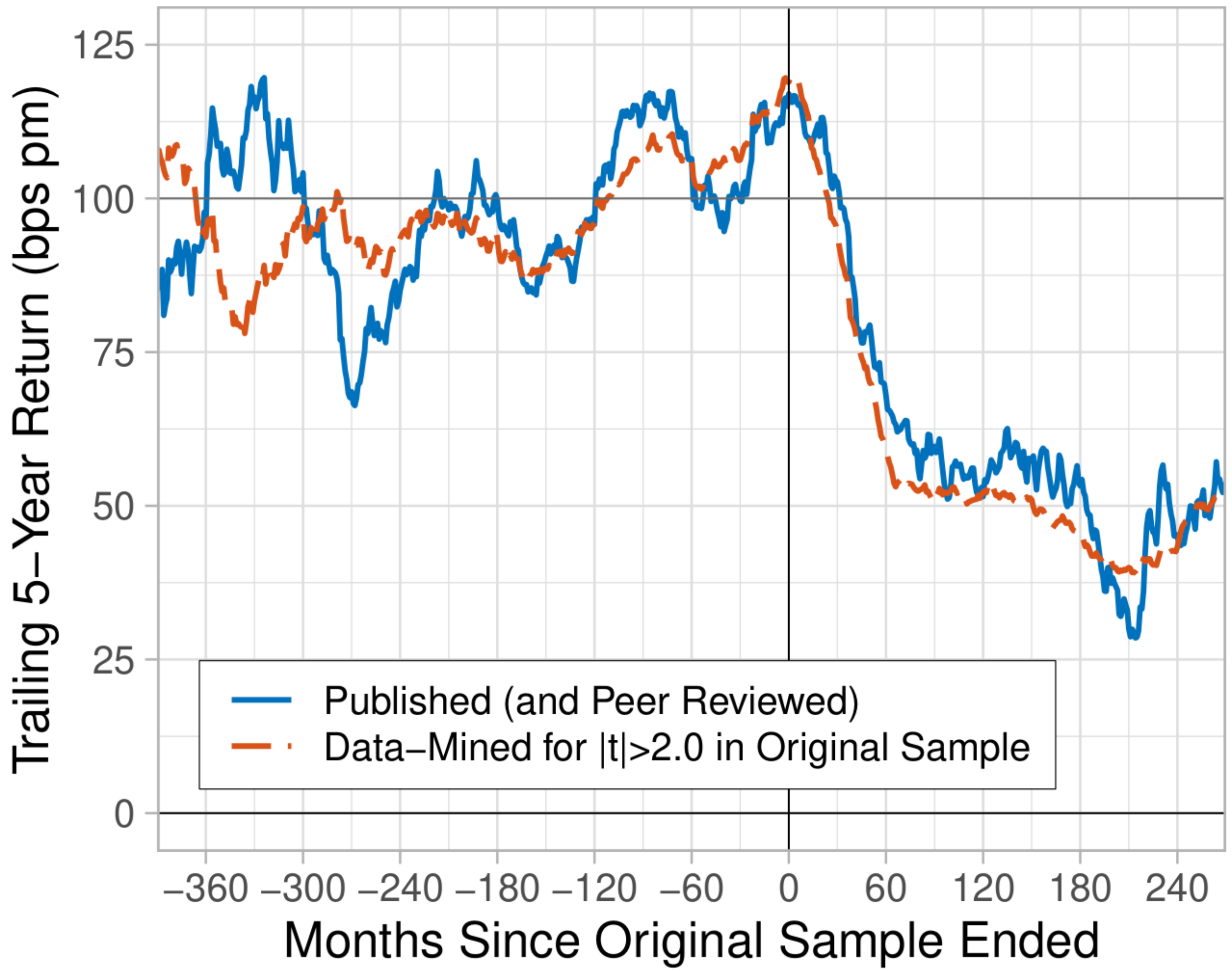

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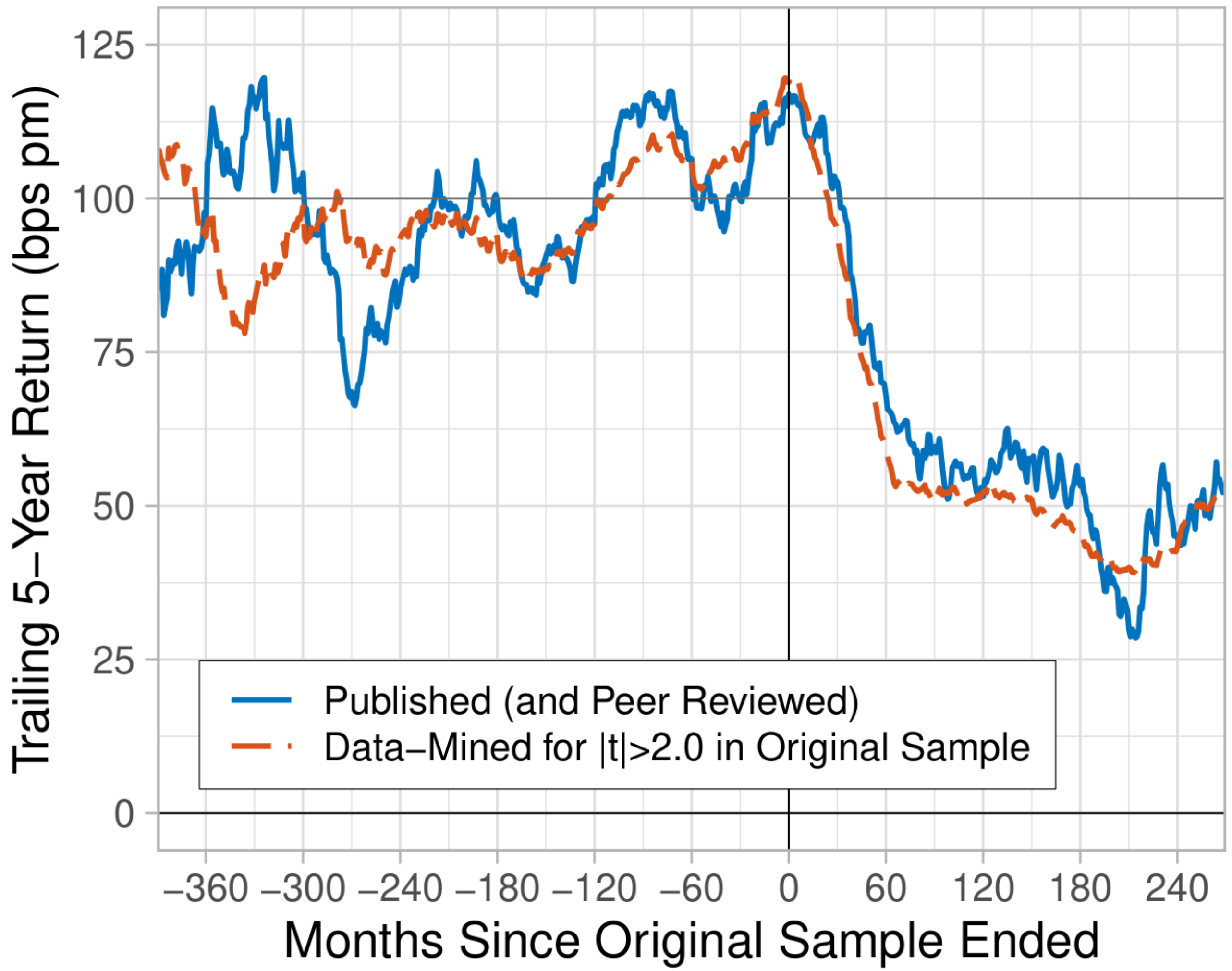
- Other fields have turned to data-centric methods (e.g. ChatGPT)



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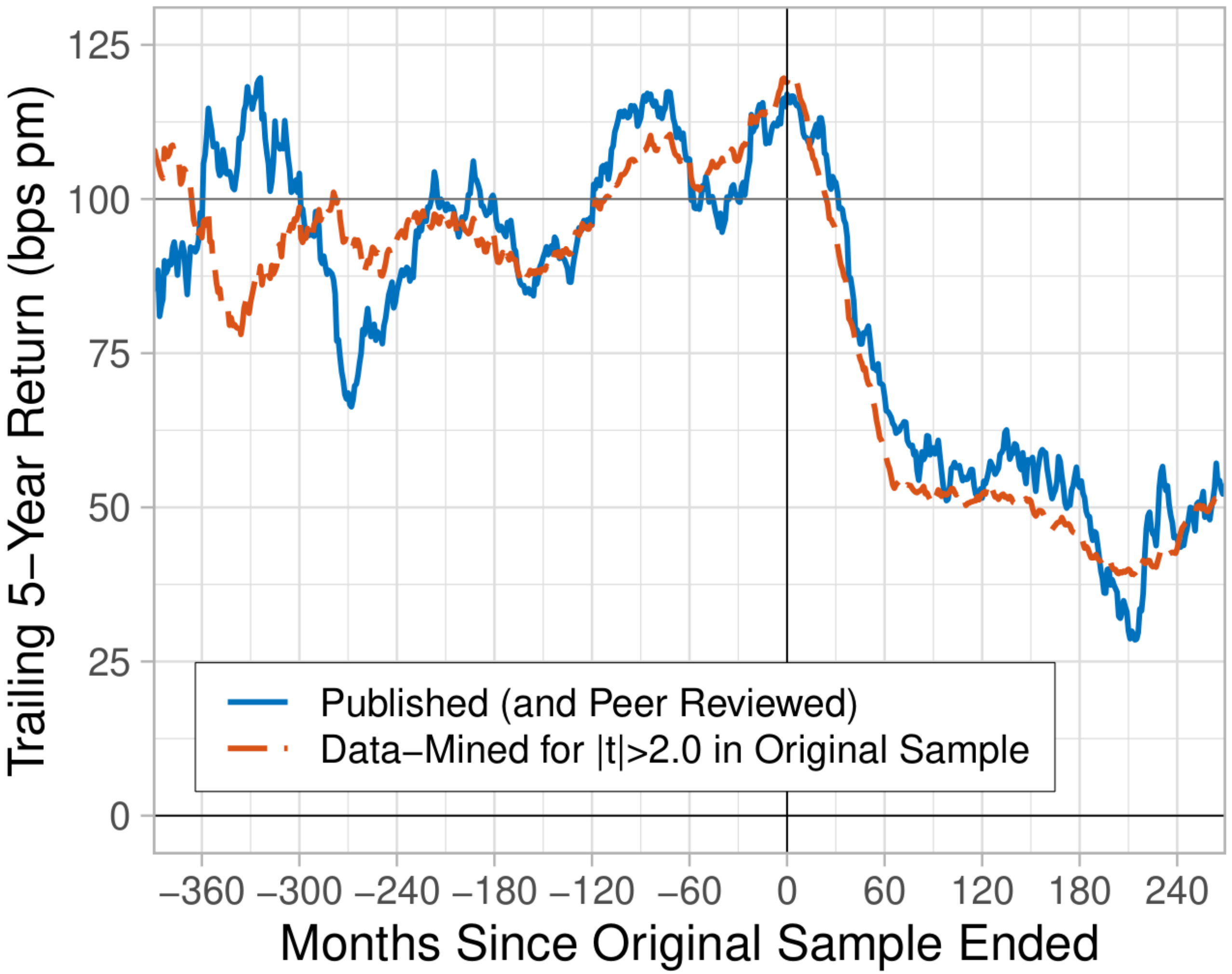

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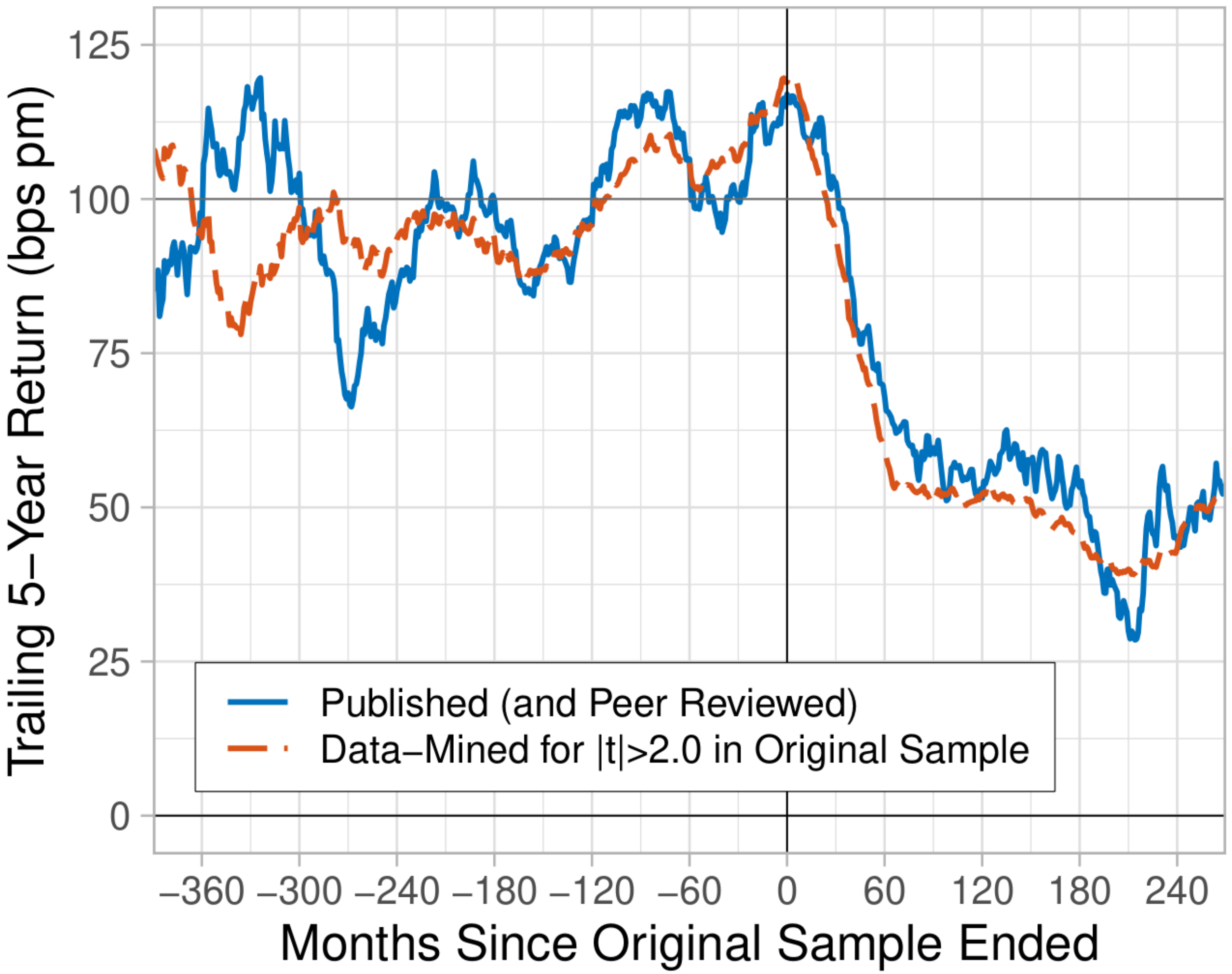
  - Beloved, hand-crafted solutions end up "irrelevant, or worse"



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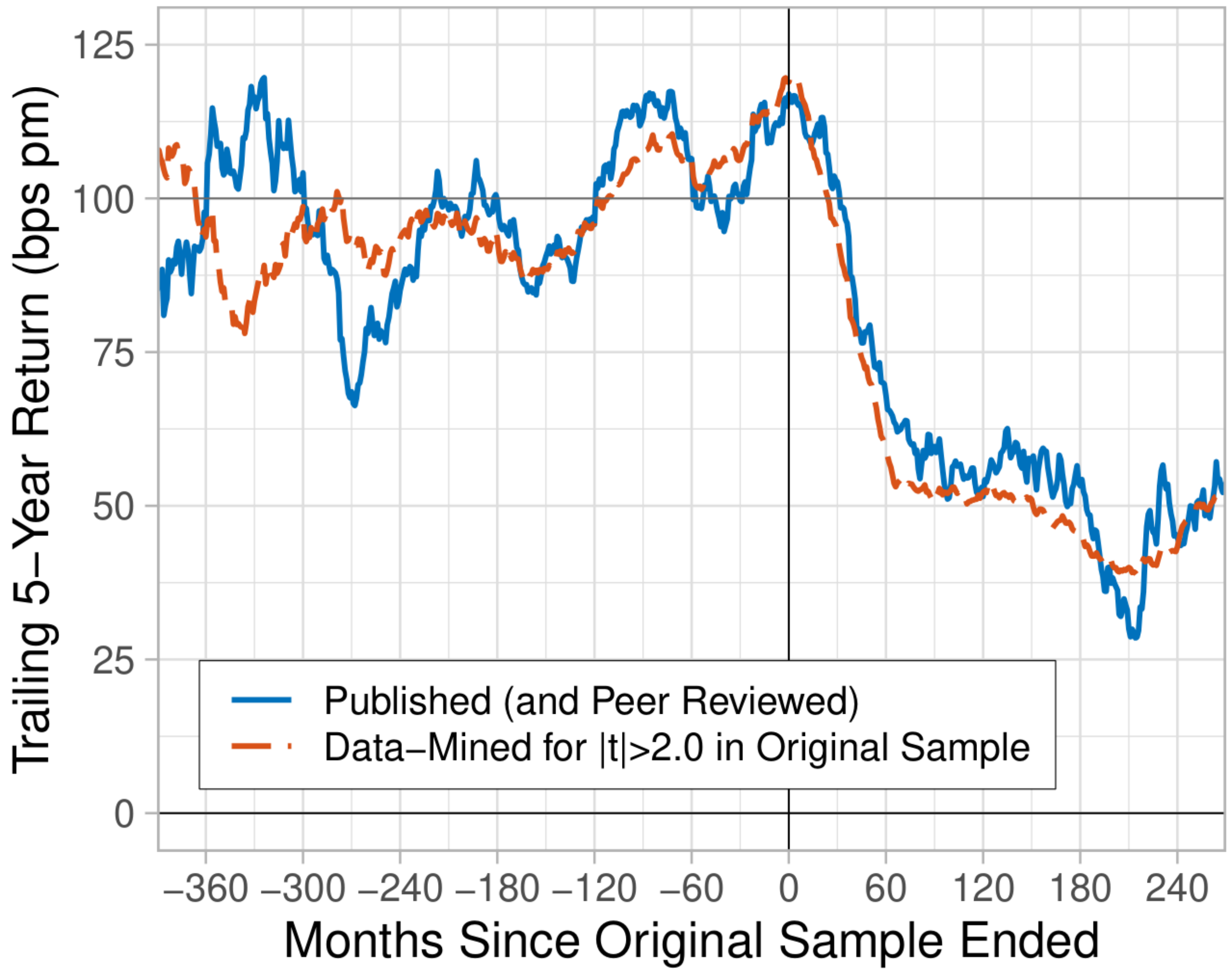

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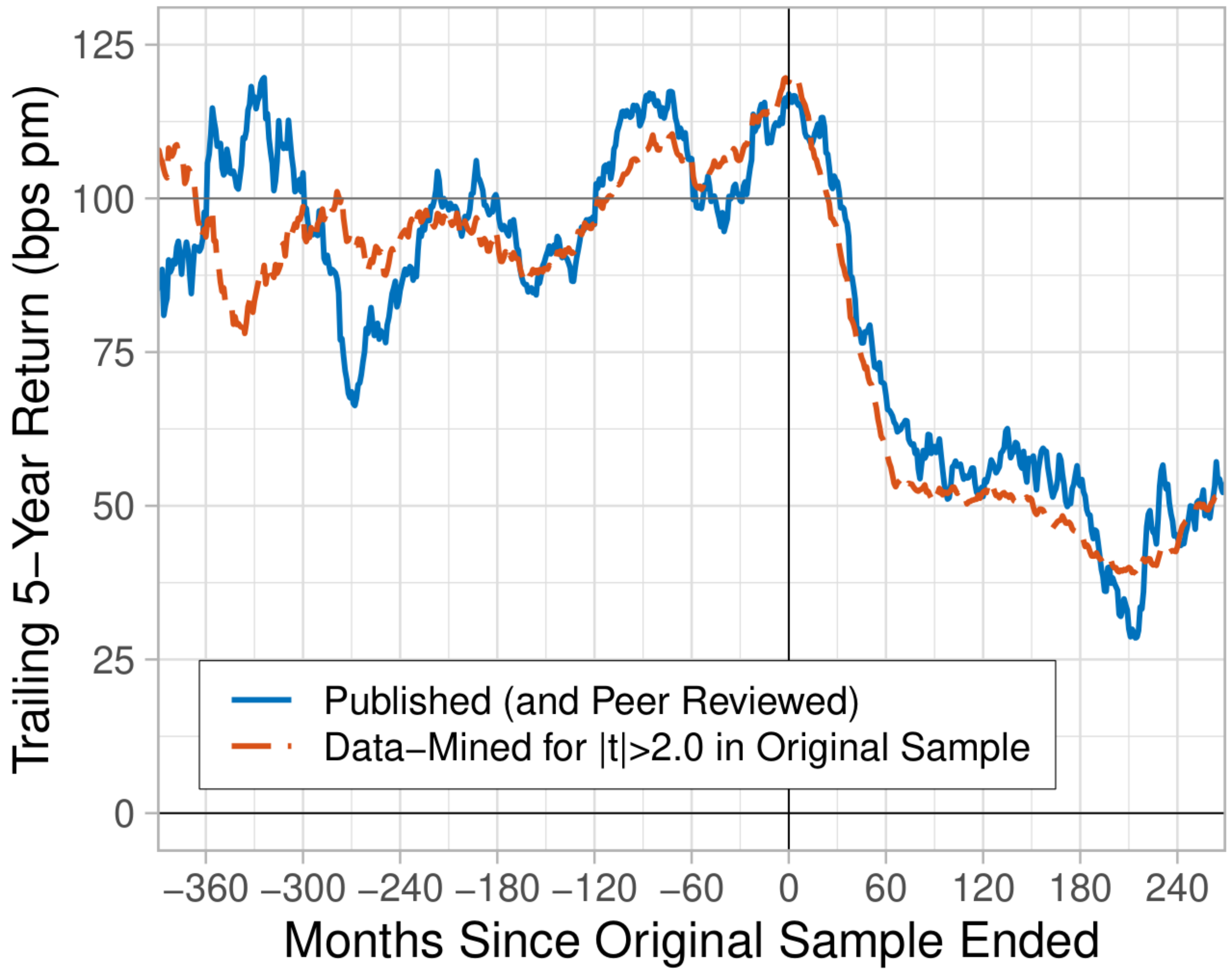
- **The real world is "tremendously, irredeemably complex"**



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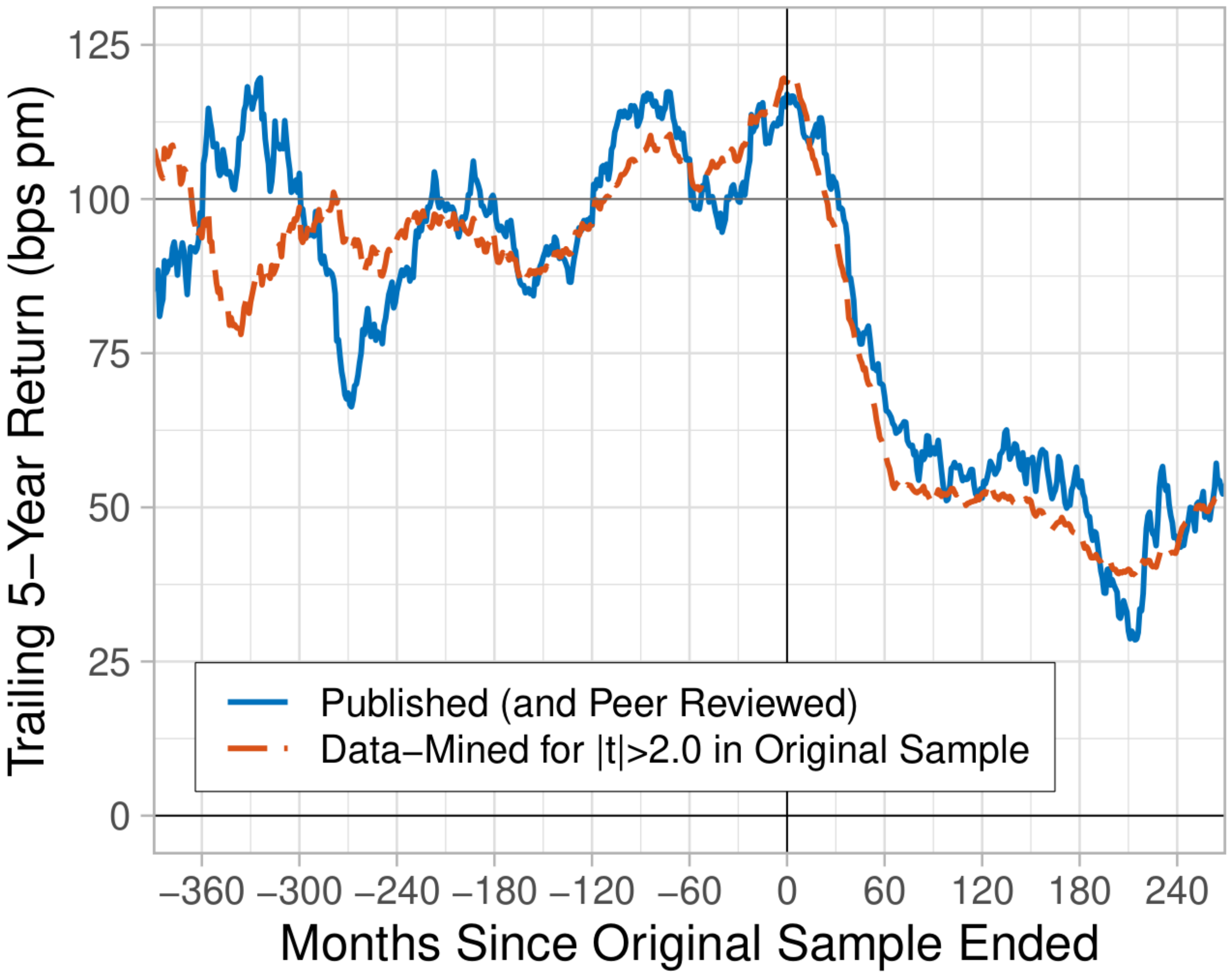

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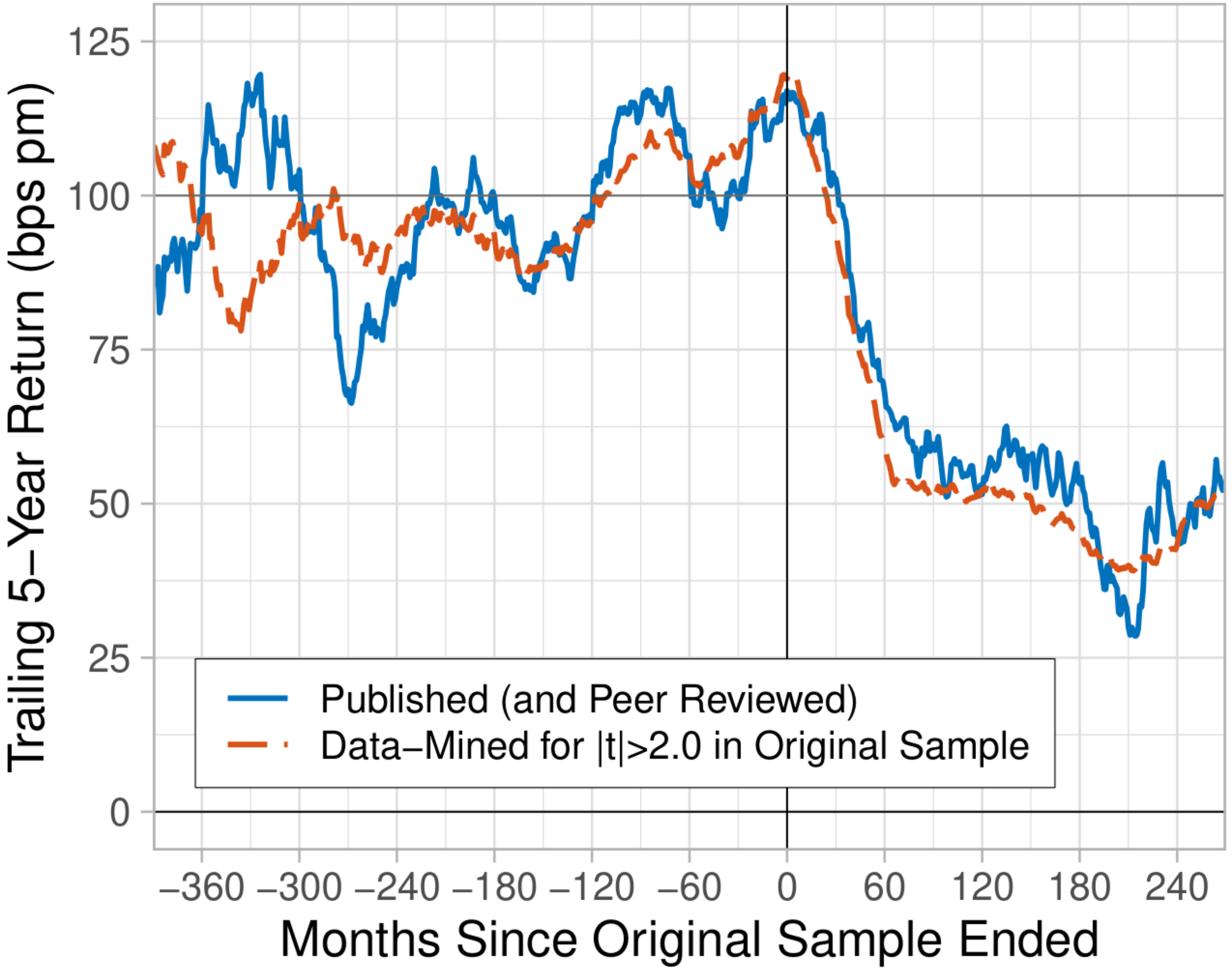
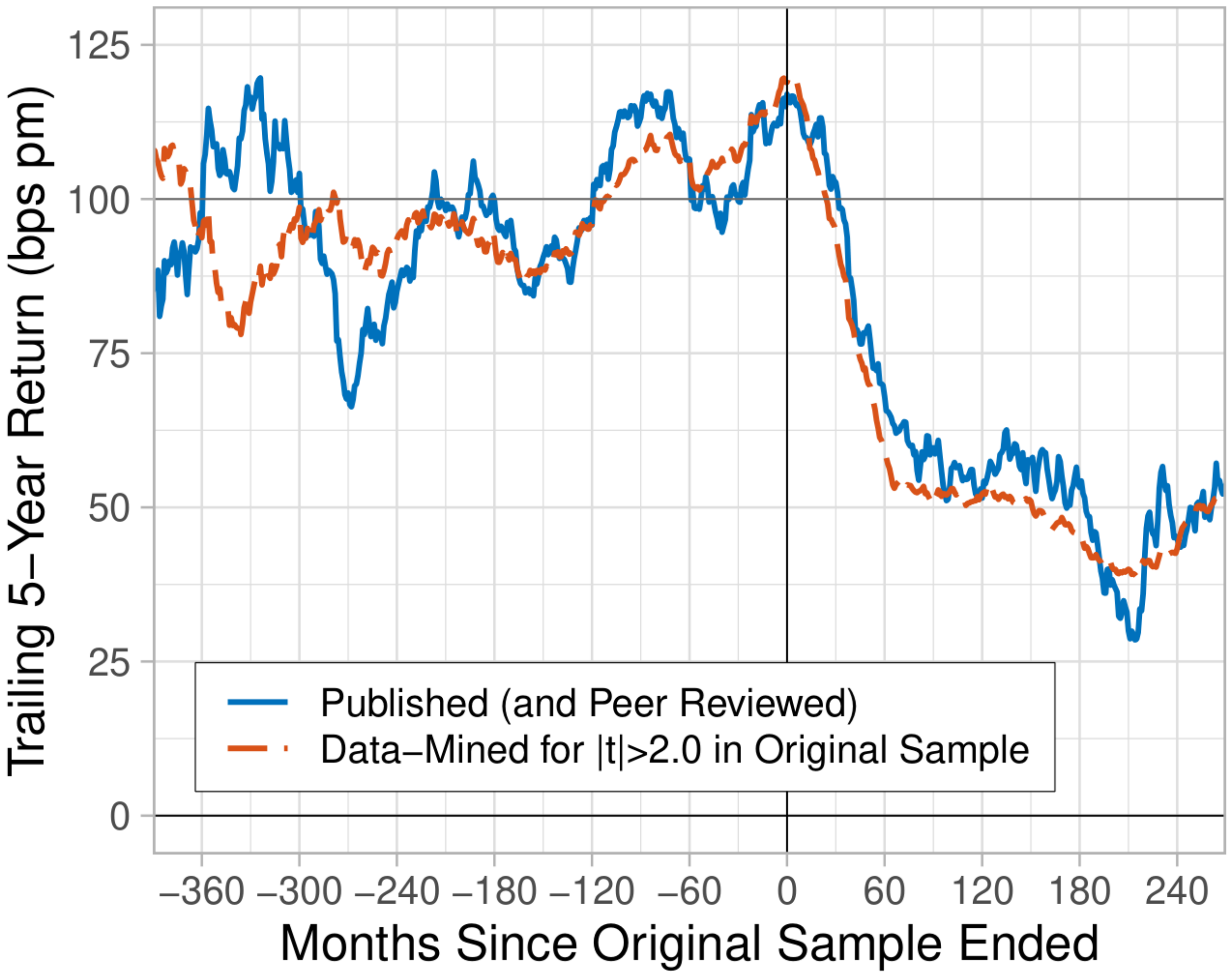
- **But perhaps if we fully explore the data...**
  - (embrace data mining)



Regardless, data mining is clearly undervalued

- Economics is about beloved, hand-crafted parables
- **But perhaps if we fully explore the data…**
  - (embrace data mining)
- **….we can produce parables that are closer to the tremendously, irredeemably complex real world**



Extra Slides

Regression of monthly returns on indicators

- Post-sample, returns decay 42% (McLean-Pontiff 2016)

	LHS: Long-Short Strategy Return (bps pm, scaled)				
RHS Variables	(1)	(2)	(3)	(4)	(5)
Intercept	100	100	100	100	102.3
	(6.4)	(6.4)	(6.4)	(6.4)	(6.8)
Post-Sample	-42.2	-25.1	-36.5	-24.4	0.7
	(8.7)	(11.7)	(10.3)	(15.3)	(14.6)
Post-Pub		-21.3		-14.9	
		(12.1)		(17.5)	
Post-Sample x Risk	-28.8	-18.8	-34.4	-19.5	-23.4
	(15.5)	(20.2)	(17.1)	(22.8)	(15.2)
Post-Pub x Risk		-14		-20.3	
		(27.2)		(30.2)	
Post-Sample x Mispricing			-8	-1	
			(7.8)	(15.5)	
Post-Pub x Mispricing				-9	
				(17.5)	
Post-2004					-59.6
					(16.7)
Null: Risk No Decay	< 0.1%	< 0.1%	< 0.1%	< 0.1%	< 0.1%

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Regression of monthly returns on indicators

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- Predictors with risk explanations decay *more*
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- **Does risk-based theory prevent out-of-sample decay?**
  - No, strongly reject

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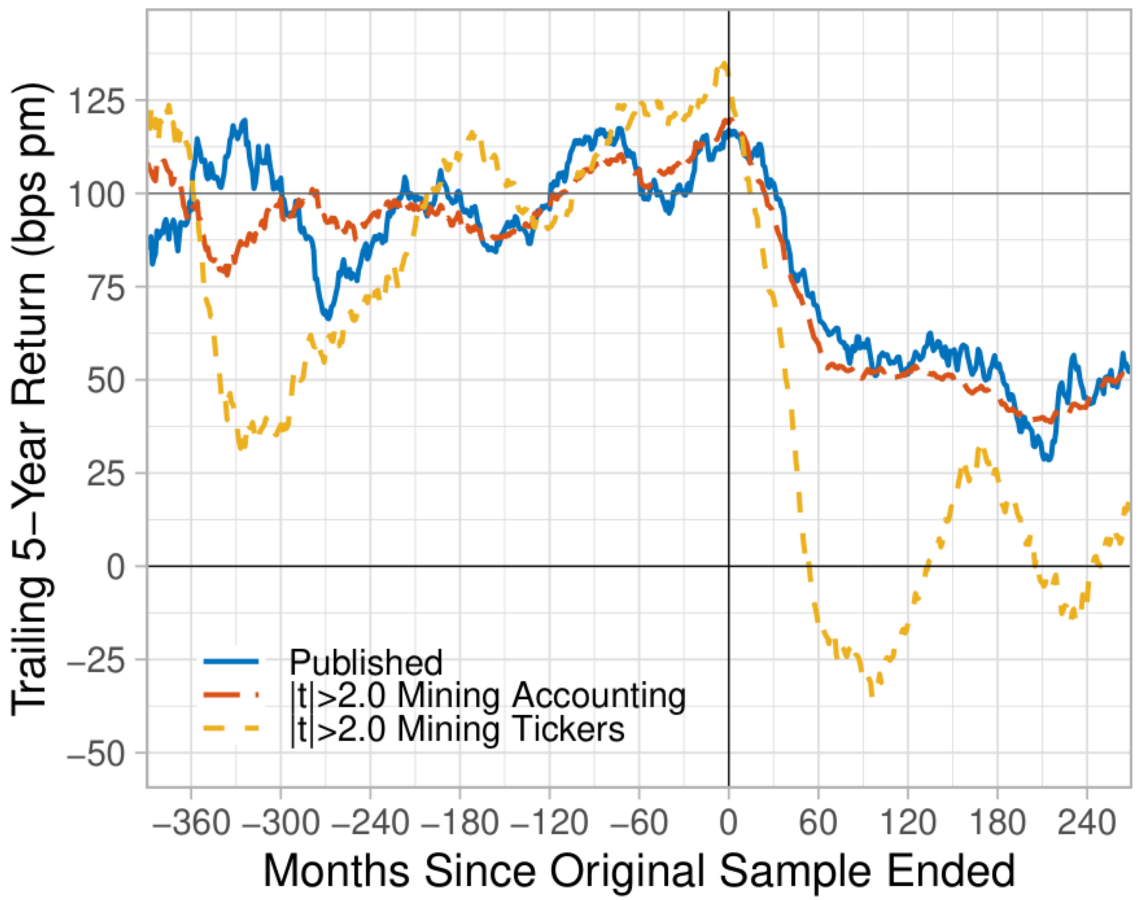
Robustness: Data mining procedure

- Construct 3,000 long-short portfolios based on letters of stock tickers
  - Suggested in Harvey (2017)
  - Far fewer than the 29,000 data-mined portfolios



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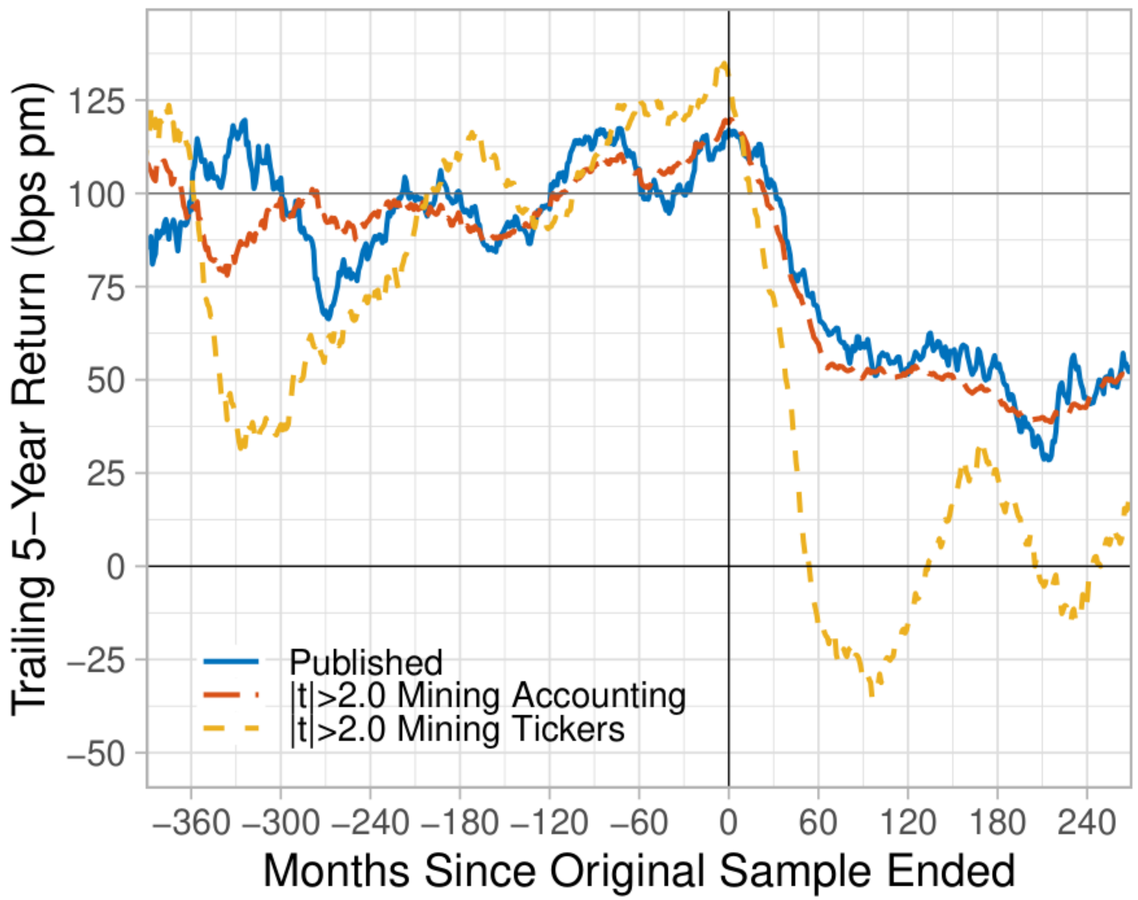

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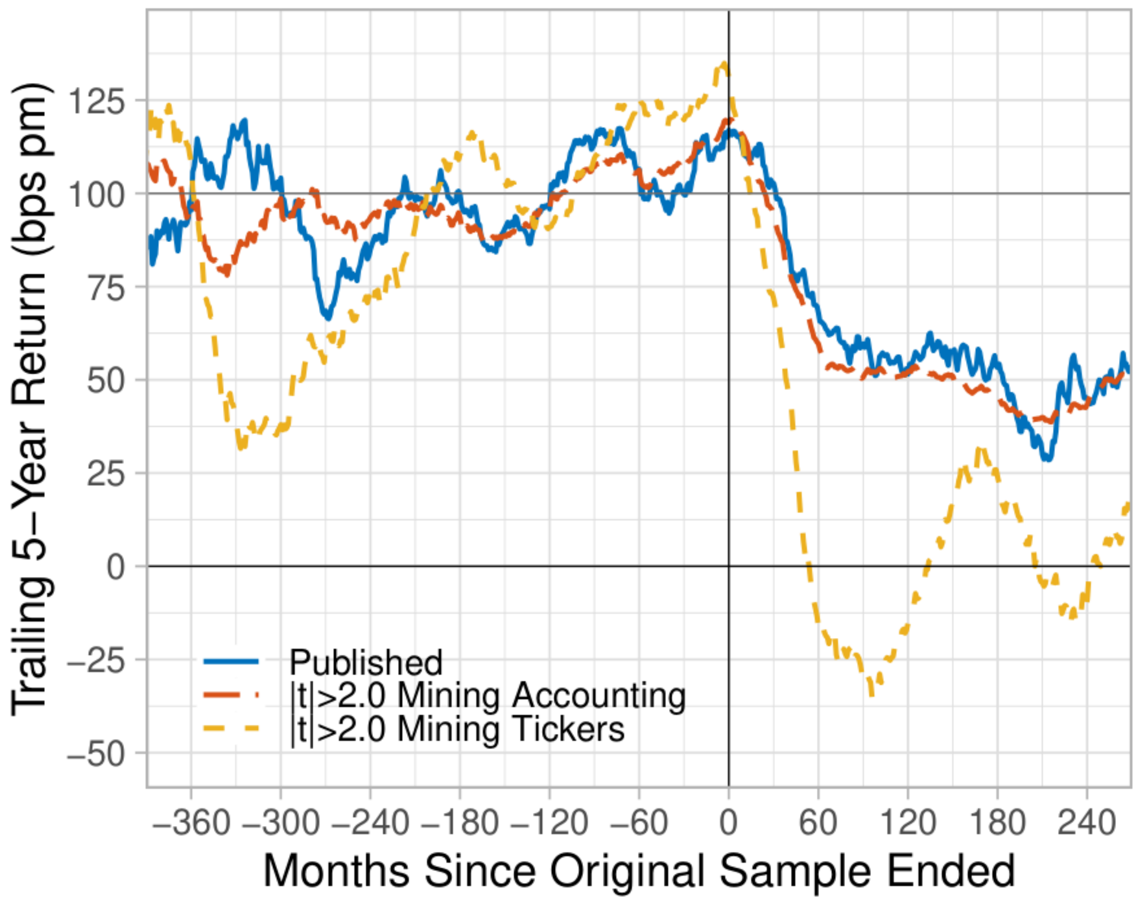

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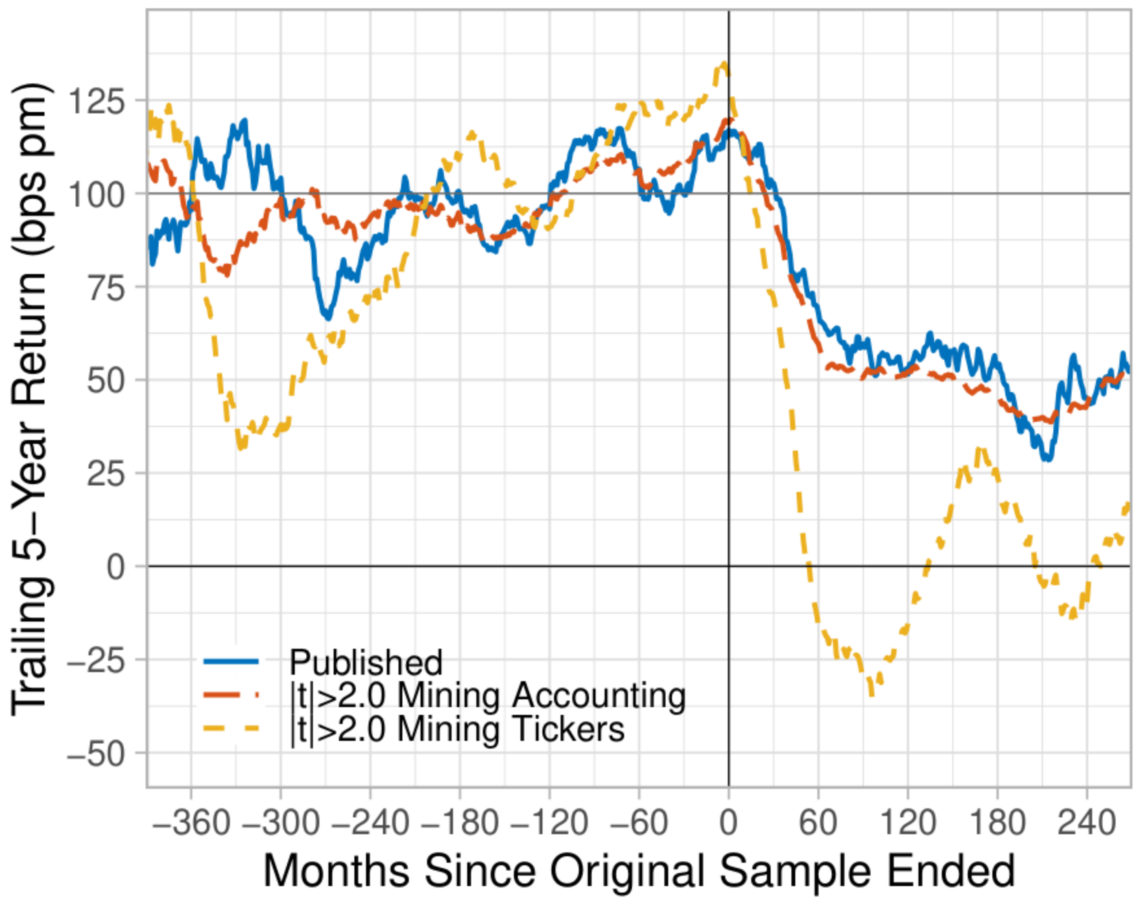
  1. **The type of data being mined is important**
  2. **The amount of data mining is not**



Post-2004 pubs only