Technomics Better Decisions Faster

"Well, That Escalated Quickly" – A Novel Approach to Forecasting Escalation

ICEAA Professional Development Workshop 2024

Agenda

Check out our Long-Form Research Paper!

Vector Decisions Faster

Well, That Escalated Quickly – A Novel Approach to Forecasting Escalation

> Sean Wells - Swells@technomics.net Kaitlyn Hagy - Khagy@technomics.net

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Intro & Background

Data Sources

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Analysis and Results

Cost Example

Recommendations & Next Steps

The Team



Sean Wells

Lead Analyst

Sean has been with Technomics since July 2023 and currently provides cost support to Navy Integrated Warfare Systems 6.0 and the Canadian National Shipbuilding Service. Sean has an MS in Contracts Acquisition and Management from the Florida Institute of Technology and has 3+ years of professional experience working Ford Class Carrier and Virginia Class Submarine estimates. He is an ICEAA Certified Cost Estimator/Analyst (CCEA).



Kaitlyn Hagy

Associate

Kaitlyn has been with Technomics since August 2023 and currently provides System Security and Cyber Security support to Navy Integrated Warfare Systems 4.0. Kaitlyn graduated with a B.S. in Security and Risk Analysis from Pennsylvania State University.



Show of Hands

- Who has used an escalation or inflation table in an estimate/model?
- Who has developed an escalation/inflation table?

Average Annual Consumer Price Index (CPI) (1982 – 1984 = 100)									
Year	Year CPI Year CPI Year CPI								
1976	56.9	1989	124.0	2001	177.1				
1977	60.6	1990	130.7	2002	179.9				
1978	65.2	1991	136.2	2003	184.0				
1979	72.6	1992	140.3	2004	188.9				
1980	82.4	1993	144.5	2005	195.3				
1981	90.9	1994	148.2	2006	201.6				
1982	96.5	1995	152.4	2007	207.3				
1983	99.6	1996	156.9	2008	215.3				
1984	103.9	1997	160.5	2009	214.5				
1985	107.6	1998	163.0	2010	218.1				
1986	109.6	1999	166.6	2011	224.9				
1987	113.6	2000	172.2	2012	229.6				
1988	118.3								



Overview

Thesis - Cost analysts can and should improve the credibility of their estimates via discrete treatment of escalation uncertainty based on historical forecast accuracy

Escalating the Problem:



Guiding Questions

- 1. How statistically accurate (or inaccurate) are escalation forecasts?
- 2. Where will the commercial model outperform the moving average model and vice versa? Will the difference be visible based on index volatility, prediction years, or commodity type?
- 3. "Did accuracy increase as moving average years increased?" and "Did accuracy decrease as prediction years increased, as would be expected?"



Background and Data Sources



Derive Initial Results and Recommendations



Leverage Error Statistics to answer Guiding Questions



Analyze Global Insights / Moving Average Forecasts against Bureau of Labor Statistics Data



Construct Dynamic Moving Average Model



Collect Historical Escalation Data / Forecasts



Background

Escalation Inputs:

(1) Factors that historically occurred / are projected forward

(2) Factors that may have historical analogies but rely on scheduled future events

(3) "Unknown Unknowns"



CP = Constant Price (no escalation or inflation

CY = Constant Year (real price change)

TY = Then Year (Real Price Change + Inflation = Escalation)

Escalation Forecasts rely on a combination of Inputs to model Real Price Change



Escalation Data Sources

Category	Title	Short Title
Energy	Gas Fuels	Gas
AHE	Manufacturing	Manufacturing
Steel	Iron and Steel	Steel
Fabricated Metals	Aluminum Cans	Aluminum
Chemicals	Industrial Chemicals	Chemicals
Building Materials	Lumber and Wood Products	Wood
Electrical Components	Semiconductor & Other Electronic Components	Semiconductors
Transportation Eqpt	Other Aircraft Parts & Auxiliary Equipment	Aircraft Parts
Paper	Corrugated and Solid Fiber Boxes	Paper Boxes
Defense & Aerospace	Search, Detection & Navigation Instruments	Defense Instruments



BLS data via BLS website:

- Date range 2004-2022
- Monthly indices; used average to calculate annual values

Global Insights data in MS Excel format:

- Date range 2006-2023 (partial)
- Monthly and Annual indices

Model Development



Derive Initial Results and Recommendations



Leverage Error Statistics to answer Guiding Questions



Analyze Global Insights / Moving Average Forecasts against Bureau of Labor Statistics Data



Construct Dynamic Moving Average Model



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Method

Moving Average Model has three primary selection criteria that align with desired inputs:

- 1. Index Select from the 10 sample indices curated
- 2. Moving Average Years Select the number of years of historical data to inform model predictions.
 - Annual/Quarterly: One, Two-, or Three-year moving average
- 3. Prediction Years Select the number of years the model should forecast.
 - Annual: One-, Two-, Five-, or Ten-year prediction
 - Quarterly: One- or Two-year prediction



Note: from here on, MA = Moving Average, MoM = Month over Month, YoY = Year over Year



Analysis Framework and Statistics Overview



Derive Initial Results and Recommendations



Leverage Error Statistics to answer Guiding Questions



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Analysis Framework

- Analytical Framework:
 - 1. Develop MA Percentage
 - 2. Use MA Percentage to project index value
 - 3. Calculate error percentage between MA MoM, MA YoY, and Global Insights models against actual BLS values
 - 4. Calculate error statistics
- Number of MA Trials:
 - Quarterly = 60 Trials (1, 2, or 3 MA years x 1 or 2 Prediction years)
 - Annual = 120 Trials (1, 2, or 3 MA years x 1, 2, 5, or 10 Prediction years
 - Thus, 180 Trials of MA Models per sample index



Error Statistics

Statistic	Calculation	Explanation
Mean	$\dot{x} = \frac{\Sigma x i}{n}$	Measures arithmetic mean of data (outliers contribute).
Median	$x = \left\{\frac{(n+1)}{2}\right\}^{th}$	Measures the 50 th percentile of date (outliers do not contribute).
Standard Deviation	$\sqrt{\frac{\sum (x-\bar{x})^2}{n-1}}$	Measures spread of data.
Range	Maximum - Minimum	Measures the accuracy window for all outcomes in sample.
RMSE	$\sqrt{\frac{1}{n} \sum_{t=1}^{n} (y_i - \hat{y}_i)^2}$	Measures dispersion of forecast errors, sensitive to large errors (i.e., outliers); optimal values should be close to zero, large RMSE indicates high model error.
MAPE	$\frac{1}{n} \sum_{i=1}^{n} \frac{\left y_i - \hat{y}_i \right }{y_i}$	Measures dispersion of forecast errors, less sensitive to outliers, sensitive to near-zero input values; optimal values should be close to zero, large MAPE indicates high model error.

RMSE = Root Mean Square Error

MAPE = Mean Absolute Percentage Error (considered most important statistic)



Data Framework

• Sample Data (Defense Instruments, 2 Year MA, 2 Year Forecast)

Year	Quarter	BLS	Global Insights	МоМ	YoY
2011	Q1	131.8	127.5	132.6	133.7
2012	Q1	135.1	134.0	135.9	137.1
2013	Q1	138.2	135.8	139.2	141.8
2014	Q1	140.1	139.1	141.6	143.2
2015	Q1	142.9	142.3	143.4	144.6
2016	Q1	144.9	142.8	146.9	148.0
2017	Q1	148.4	144.1	149.0	150.3
2018	Q1	152.9	147.7	153.9	157.4
2019	Q1	163.6	153.5	164.8	169.6
2020	Q1	172.4	155.8	175.6	182.8
2021	Q1	172.4	166.3	181.3	184.3

1. BLS Actual and Model Predicted Index Values

3. Error Statistics

	Measure	Global Insights	МоМ	YoY
	Min	-9.64%	0.37%	1.19%
	Max	-0.42%	1.88%	6.05%
	Range	9.22%	1.52%	4.86%
	Std Dev	2.88%	0.48%	1.48%
	Average	-3.05%	0.83%	2.51%
	Median	-2.30%	0.66%	2.20%
	RMSE	6.74	1.48	4.60
ſ	MAPE	3.27	1.23	2.91

2. Model Value Percent Error from BLS Index

	Year	Quarter	Global Insights	МоМ	ΥοΥ
	2011	Q1	-3.24%	0.60%	1.47%
	2012	Q1	-0.81%	0.59%	1.49%
	2013	Q1	-1.71%	0.73%	2.64%
•	2014	Q1	-0.74%	1.09%	2.25%
/	2015	Q1	-0.42%	0.37%	1.19%
	2016	Q1	-1.45%	1.36%	2.15%
	2017	Q1	-2.89%	0.40%	1.30%
	2018	Q1	-3.40%	0.60%	2.91%
	2019	Q1	-6.16%	0.72%	3.66%
	2020	Q1	-9.64%	1.88%	6.05%
	2021	Q1	-3.55%	5.19%	6.90%



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Data Analysis



Data Analysis (1)

How statistically accurate (or inaccurate) are escalation forecasts?





Data Analysis (2)

Where did the commercial model outperform the moving average model and vice versa? Was the difference visible based on index volatility, prediction years, or commodity type?

MA Model **outperforms** Global Insights in **80%** of quarterly and **87%** of annual 1- and 2-year trials

MA Model **underperforms** Global Insights in **90%** of annual 5- and 10year trials

MA Yrs -			MA Yrs -			MA Yrs -		
Predict Yrs	Model	MAPE	Predict Yrs	Model	MAPE	Predict Yrs	Model	MAPE
1 MA 1 Pred	Global Insights	7.65	2 MA 1 Pred	Global Insights	6.33	3 MA 1 Pred	Global Insights	5.37
1 MA 1 Pred	MoM	5.23	2 MA 1 Pred	MoM	3.25	3 MA 1 Pred	MoM	3.75
1 MA 1 Pred	YoY	11.03	2 MA 1 Pred	YoY	4.84	3 MA 1 Pred	YoY	4.77
1 MA 2 Pred	Global Insights	10.49	2 MA 2 Pred	Global Insights	8.37	3 MA 2 Pred	Global Insights	7.40
1 MA 2 Pred	MoM	10.39	2 MA 2 Pred	MoM	4.57	3 MA 2 Pred	MoM	5.64
1 MA 2 Pred	YoY	18.77	2 MA 2 Pred	YoY	6.00	3 MA 2 Pred	YoY	4.19
1 MA 5 Pred	Global Insights	14.79	2 MA 5 Pred	Global Insights	12.68	3 MA 5 Pred	Global Insights	11.09
1 MA 5 Pred	MoM	53.98	2 MA 5 Pred	MoM	18.52	3 MA 5 Pred	MoM	17.59
1 MA 5 Pred	YoY	53.54	2 MA 5 Pred	YoY	21.72	3 MA 5 Pred	YoY	11.30
1 MA 10 Pred	Global Insights	16.38	2 MA 10 Pred	Global Insights	15.79	3 MA 10 Pred	Global Insights	16.25
1 MA 10 Pred	MoM	423.02	2 MA 10 Pred	MoM	36.64	3 MA 10 Pred	MoM	32.54
1 MA 10 Pred	YoY	116.39	2 MA 10 Pred	YoY	61.90	3 MA 10 Pred	YoY	32.74

Annual Trial Data – 10-Index Summary

MAPE										
	1 MA 1 MA 2 MA 2 MA 3 MA 3 MA									
Index	1 Pred	2 Pred	1 Pred	2 Pred	1 Pred	2 Pred				
CEU 300 000008	YoY	IHS	YoY	IHS	YoY	YoY				
PCU3222113222110	MoM	MoM	MoM	MoM	MoM	YoY				
PCU33441-33441-	YoY	YoY	YoY	MoM	YoY	YoY				
PCU334511334511	YoY	MoM	YoY	MoM	YoY	YoY				
PCU336413336413	IHS	IHS	YoY	IHS	YoY	YoY				
WPU053	IHS	IHS	IHS	MoM	IHS	IHS				
WPU061	MoM	MoM	MoM	MoM	MoM	MoM				
WPU08	MoM	IHS	MoM	MoM	MoM	YoY				
WPU101	MoM	IHS	MoM	MoM	MoM	YoY				
WPU103103	MoM	MoM	MoM	MoM	MoM	MoM				



Data Analysis (3)

"Did accuracy increase as moving average years increased?" and "Did accuracy decrease as prediction years increased, as would be expected?"

MA Yrs - Predict Yrs	Model	Average	Median	RMSE	MAPE
2 MA 1 Pred	Global Insights	0.016	0.016	19.72	6.33
2 MA 1 Pred	MoM	0.007	0.005	8.76	3.25
2 MA 1 Pred	YoY	0.008	0.005	13.41	4.84
2 MA 2 Pred	Global Insights	0.035	0.026	23.26	8.37
2 MA 2 Pred	MoM	0.029	0.021	12.46	4.57
2 MA 2 Pred	YoY	0.013	0.010	13.67	6.00
2 MA 5 Pred	Global Insights	0.107	0.113	34.29	12.68
2 MA 5 Pred	MoM	0.224	0.041	113.53	18.52
2 MA 5 Pred	YoY	0.102	0.001	61.48	21.72
2 MA 10 Pred	Global Insights	0 189	0.212	45 70	15 79
2 MA 10 Pred	MoM	5.874	0.465	2207.09	36.64
2 MA 10 Pred	YoY	1.338	0.539	511.33	61.90

Accuracy as MA

Annual Trial Data – 10-Index Summary, 2 MA

Annual Trial Data – 10-Index Summary, 3 MA

MA Yrs -					
Predict Yrs	Model	Average	Median	RMSE	MAPE
3 MA 1 Pred	Global Insights	0.028	0.022	15.28	5.37
3 MA 1 Pred	MoM	0.018	0.010	8.91	3.75
3 MA 1 Pred	YoY	0.028	0.006	14.35	4.77
3 MA 2 Pred	Global Insights	0.050	0.031	19.95	7.40
3 MA 2 Pred	MoM	0.038	0.016	13.98	5.64
3 MA 2 Pred	YoY	0.015	0.003	10.36	4.19
3 MA 5 Pred	Global Insights	0.125	0.115	26.70	11.09
3 MA 5 Pred	MoM	0.137	0.047	52.36	17.59
3 MA 5 Pred	YoY	0.070	0.025	32.94	11.30
3 MA 10 Pred	Global Insights	0.252	0.236	45.89	16.25
3 MA 10 Pred	MoM	0.818	0.384	185.30	32.54
3 MA 10 Pred	YoY	0.688	0.289	151.77	32.74

Accuracy J as Prediction Yrs

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Results and Recommendations



Derive Initial Results and Recommendations

Leverage Error Statistics to answer Guiding Questions



Analyze Global Insights / Moving Average Forecasts against Bureau of Labor Statistics Data



Construct Dynamic Moving Average Model



Collect Historical Escalation Data / Forecasts



Cost Example

Example: Compare various escalation methods for a piece of navigational equipment costing \$1M in Then Year 2011

- 2% Annual Inflation: ~\$110K underestimation at 10 years

- Global Insights: ~\$200K underestimation at 10 years

- MA models overestimated after 5 years

Years	2% Annual	BLS Actual	Global Insights	МоМ	ΥοΥ
Base	\$1,000,000	\$1,000,000	\$1,000,000	\$1,000,000	\$1,000,000
1	\$1,020,000	\$1,024,224	\$1,016,503	\$1,015,897	\$1,020,439
2	\$1,040,400	\$1,049,962	\$1,030,129	\$1,062,074	\$1,074,943
5	\$1,104,081	\$1,099,924	\$1,071,083	\$1,186,223	\$1,183,195
10	\$1,218,994	\$1,331,567	\$1,133,005	\$1,990,916	\$1,820,590



Recommendations for Use

- 1. Calculate Volatility (simple metric as % change from year to year)
- 2. Use error metrics to calculate historical accuracy of indices
- 3. Leverage volatility and error metrics to form risk range
- 4. Incorporate risk range around Composite Annual Growth Rate (CAGR)



Next Steps

- Expand Sample Dataset (more indices, wider date range, additional commercial models
- 2. Add complexity to moving average model (EWMA, ARIMA, optimization techniques)
- 3. Establish clear guidelines for assessing forecast accuracy / assigning risk factors





Questions?

swells@technomics.net khagy@technomics.net