When do U.S. Small Caps outperform U.S. Larger Caps?

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Abstract

The U.S. investment industry encompasses a very wide range of financial instruments suitable for every kind of investor. Investing typically correlates with risk tolerance. Based on our aversion to risk, you or others on your behalf may pivot from one asset class to another. Furthermore, within each asset class and financial market, various types of securities are available. To simplify matters, we will divide investing into two categories: money markets and capital markets. Money markets are where short-term, highly liquid debt securities are traded. On the other hand, capital markets typically involve riskier asset classes due to the longer holding periods associated with debt securities and the uncertainty that market dynamics bring to the equation for equity securities. In this empirical paper, I will delve deep into equity securities, focusing specifically on the U.S. stock market. Common stock signifies ownership in a corporation, a fundamental concept known to every investor. However, it is intriguing to note that the average person is only familiar with twenty to twenty-five companies in the S&P 500 index. Yet, this index, serving as the main benchmark for stocks, encompasses the largest five hundred corporations. Being a market-cap-weighted index, size indeed matters; however, the inclusion of five hundred, rather than just twenty-five companies, is deliberate. Moreover, the Russell 2000 index comprises corporations ranking from 1000 to 3000 based on market capitalization, employing a methodology akin to that of the S&P 500, and known as “Small Caps”. Through my investigation, I seek to highlight the indispensable role of 'smaller' companies in the U.S. stock market's long-term vitality, and how they outperform larger caps in various scenarios. I will substantiate this idea with historical return data from the primary U.S. stock indexes and the performance of key U.S. macroeconomic variables since October 1987, when the Rusell 2000 appeared in scene.

When do U.S. Small Caps outperform U.S. Larger Caps?

In my view, it is understandable to seek the highest quality when it comes to investing overall, but particularly in the equity markets. When engaging in discussions about quality in the U.S. equity markets, it is common to focus on the S&P 500. That is wise, and there is empirical evidence to support it. Since the beginning of 1926, the most famous stock index in the world has returned more than 10% per year on average. Adjusting for inflation, we find an average return of close to 7% per year. We are talking about a hundred years now... realistically, nothing surpasses this figure. However, the average 10% annual return previously mentioned comes with ups and downs. In the last forty to fifty years, how many ups and downs can we find? Plenty. In fact, when it comes to the S&P 500, there is a common saying on Wall Street that describes how the index fluctuates between green and red based on just a handful of days throughout the year. My argument here, and the discussion I want to bring to the table, is that there are opportunity windows when those downs happen in the S&P 500 for other financial instruments in the U.S. equity markets. An investor must keep an eye and allocate some capital to the S&P 500 over the course of their life; however, they must also consider diversifying into other instruments. Among these, I believe that the Russell 2000 deserves attention.

The question now is how I am linking the idea of assuming that smaller caps can outperform larger caps in certain periods of time. Equities are complex, requiring hundreds of hours of fundamental and technical analyses, employing multiple different approaches to determine how a company is performing compared to the industry and the market overall. The results of these analyses typically provide insight into whether a stock is undervalued or overvalued, along with the reasons behind it and forecasts for the stock's performance in the near future. Despite the complexity, it ultimately boils down to numbers. Wall Street scrutinizes the financial statements of any company, whether small or large, to provide definitive answers. However, why do seemingly healthy companies underperform for many years over a span of, let's say, fifty years? Or why does it make sense to invest in a smaller market capitalization company, even when the forecast is typically expected to be worse than their larger peers? This is where the macro side of the equation comes into play.

In a different research paper, I would argue that the microeconomic components, namely the fundamentals of the company and the industry, are more important. This means, in simple terms, that you can make money regardless of the business cycle the U.S. is experiencing. However, this applies to stock picking. In our discussion today, we are focusing on whole indexes comprising the 3000 biggest companies in the United States moving as one, or as two if we break them down into large and small caps (with mid-caps in the middle). For indexes, macroeconomics is the key. The various business cycle phases exert significant influence on the movement of these indexes.

In a business cycle, we encounter expansion, peak, contraction, and trough stages. Ultimately, it's a concept similar to what I mentioned earlier regarding stock analysis. In macroeconomics, there are also numerous economic analyses that must be conducted, but ultimately, everything boils down to the numbers once more. In this instance, it involves various sectors within the U.S. economy, and we could make the same assertion about any other country in the world. We encounter GDP growth, inflation gauges, employment, consumer sentiment, industrial production, manufacturing, services, housing market, retail sales, wholesale trade, domestic private investment, public government investment, international trade, treasuries, and commodities. All these factors contribute to a country's expansion or contraction at times. They do not move at the same rhythm because they are, in some cases, completely different areas within an economy, but they provide economists and analysts with key information to understand the present and, most importantly, forecast the near future of the economy of a country. Once we understand this step, we move to the stock indexes themselves such as the S&P 500 and the Russell 2000 in the U.S. Again, all these macro variables are not definitive for the stock market, especially in some instances. However, again, the economic variables reflect the business cycle, and the stock indexes usually do so too. Now, it is time to enter the discussion about differentiating the indexes comprising larger and smaller caps. In this case, they do differ in their performances compared to the business cycle the U.S. is in; therefore, they differ in how they react to all the independent variables mentioned.

My research will examine nineteen macroeconomic variables in the U.S., which I consider to be the main determinants of the U.S. economy. The objective is to gain a comprehensive understanding of how these macro variables individually impact the performance of the S&P 500 and the Russell 2000 since 1987. Based on this period, I aim to forecast opportune moments for investing in smaller caps over larger caps based on key U.S. economic indicators.

Before diving into the topic, I would like to mention insights from a couple of literature papers or articles that I gathered information from before starting my research.

“Whereas Switzer & Fan (2007) came to the result that the high returns of small caps could be country-specific (Switzer, 2010). Based on the results of Fama & French (1993), that smaller and therefore riskier firms achieve higher returns than larger companies, Pandev & Sehgal (2016) identified several factors which caused the higher risk. With their investigation Pandev & Sehgal (2016) support the existence of anomaly caused by company size. A recent study

by Norland (2020) resumes for the US an outperformance of large versus small caps during economic expansion, whereas small caps outperformed large caps during economic downtrend."
"Smaller caps have offered a better risk/return performance in the post-GFC era (2008-2020) in EU and Germany." - Fahling, E., Ghiani, M., Simmert, D. (2020). *Scientific Research*

"Small-cap firms outperform large caps over the year subsequent to an economic trough. In the year prior to the business cycle peak, however, small caps tend to lag." – US and Canada. Switzer, L. (2010). *ScienceDirect*

"Based on the results, the following assumptions can be made. First, one could assume that small cap indices are normally young companies and therefore more growth potential is seen with small caps. At the same time these companies also represent a higher risk of default. However, this assumption only applies to the US-market, as the Sharpe ratio demonstrates. With regard to Europe, the small cap indices clearly have beaten the large cap indices. The SDAX also clearly outperformed the DAX with regard to the German indices. By contrast, the American large cap index outperformed the small cap index in terms of volatility. In contrast, in terms of return the two indices are quite close to each other, which illustrates once again with the comparison of return and risk." - Fahling, E., Ghiani, M., Simmert, D. (2020). *Scientific Research*

I will revisit some of these assertions and thoughts towards the end of my research paper, aiming to link my analyses with some already existing great ideas on the matter.

Methodology, Econometric Models

Firstly, I'd like to describe the variables utilized in my research. As mentioned earlier, these comprise the key macroeconomic indicators for the United States on the independent side, while the dependent side includes the S&P 500 and the Russell 2000 indexes. It's important to note that these macro variables may also be employed for various purposes or in examining their relationships with other financial instruments.

When discussing macroeconomics in the U.S., we typically observe five key areas, which I refer to as the overall position, employment, goods and services, housing, and international endeavors. I will now list these five areas, mentioning the selected variables for each:

- Overall position: Goldman Sachs Commodity Index, treasuries spread (10-year Note – T-Bill), consumer sentiment index, real GDP growth, YoY Core CPI, YoY PCE, and YoY all commodities PPI
- Employment: unemployment rate
- Goods and services: net Government investment (excluding defense), industrial production, net private domestic investment, ISM manufacturing index, ISM non-manufacturing index, advance retail sales, and total wholesale trade
- Housing: existing house sales
- International endeavors: international trade balance

Before delving into the actual models and the answers they provide, I'd like to clarify that the sample periods will be specific to each of the econometric techniques employed. The overarching framework for each individual variable and/or equation is as follows:

In-Sample Period: 1987M10 – 2024 M01

Now, the sample period for VAR, Vector-Error, and related econometric techniques will be as follows:

In-Sample Period: 1998M07 – 2022 M12

It is a smaller group of years given some variables started to appear on scene later in time, and we do not have recent data that fits for the research for others. However, this only applies for advance retail sales, international trade, ISM non-manufacturing, and net Government investment (excluding defense), respectively.

I want to introduce here the second goal of this research, more in line with what I have learned in my Econometrics classes this last year. Besides studying the relationship between smaller and larger caps in the U.S. stock market and the business cycle, I will forecast the Russell 2000 in 2023 and compare the results to the actual data we have in our hands:

In-Sample Period: 1987M10 – 2023 M01

Out-of-Sample Period: 2023 M01 – 2024M01

The first step for my mean research will be to delve deep into every single variable, both dependent and independent. The steps will follow as:

- Show the no cointegration between two stock indexes such as the S&P 500 and the Russell 2000
- Recognize the stationarity or fix the trend in case they are non-stationary using ADF analysis, of each of the variables
- Assess seasonality in each of the variables

- Apply VAR, Vector-Error, Granger Causality, and Cholesky processes providing answers to my main research questions

On the other hand, exclusively for the Russell 2000 forecast in 2023, the steps will follow as:

- Recognize the stationarity in the Russell 2000 data
- Apply ADF processes to correct the trend, and to see if the random walk contains a time trend, a drift, or none
- Selecting and applying time trend fixes (quadratic, exponential, etc.) as deemed suitable
- Analyze the short-run dynamics via ACF/PACF correlograms and Q-stats in the residuals to ensure the stabilization and sufficiency of variables and the overall model
- Based on the previous point, establish the right ARMA model
- Forecast the Russell 2000 in 2023, and compare the results with the actual data

Empirical Analysis

Frequency: Monthly

Variable names:

1. gsci: Goldman Sachs Commodity Index
2. gspc: S&P500 Stock Index
3. rut: Russell 2000 Stock Index
4. treasurspread: 10-year T-Note – T-Bill
5. unemrate: US Unemployment Rate, seasonally adjusted
6. us_10_yr_note: US 10-year Treasury Note
7. us_conssentindex: US Consumer Sentiment Index (1966Q1=100)
8. us_gvntinvnetnondef: US Net Gvnt. Investment, excluding defense, not seasonally adjusted, in $Millions
9. us_hexistingsales: US Existing House Sales, seasonally adjusted, in $Millions
10. us_indusproduction: US Industrial Production index (2017=100), seasonally adjusted
11. us_inttradebalance: US International Trade Balance, seasonally adjusted, in $Millions
12. us_invdomestic: US Net Private Domestic Investment, seasonally adjusted, in $Millions
13. us_ismm: US ISM Manufacturing Index, above 50 means expansion
14. us_isms: US ISM Non-Manufacturing Index, since 1997, above 50 means expansion
15. us_realgdp: US Real GDP (adjusted for inflation), seasonally adjusted
16. us_rsalesadvance: US Retail Sales Advance, seasonally adjusted, in $Millions
17. us_t_bill: US Treasury Bill (1 year)
18. us_whtradetotal: US Total Wholesale Trade, seasonally adjusted, in $Millions
19. yoy_corecpi: US YoY Core CPI (inflation gauge), seasonally adjusted
20. yoy_pce: US YoY PCE (inflation gauge), seasonally adjusted
21. yoy_ppi: US YoY All commodities PPI (inflation gauge), not seasonally adjusted

Cointegration does not occur between two stock indexes because indexes are comprised of individual stocks, each of which follows a random walk with its corresponding stochastic trend. This theory was posited by Engle and Granger in 1987. However, I wanted to double-check it:

Date: 04/08/24 Time: 20:59
Series: RUT GSPC
Sample: 1987M10 2024M01
Included observations: 436
Null hypothesis: Series are not cointegrated
Cointegrating equation deterministics: C
Automatic lags specification based on Schwarz criterion (maxlag=17)

Dependent	tau-statistic	Prob.*	z-statistic	Prob.*
RUT	-1.132882	0.8747	-5.533187	0.6882
GSPC	-0.507953	0.9619	-2.416931	0.9110

*MacKinnon (1996) p-values.

Intermediate Results:

	RUT	GSPC
Rho – 1	-0.012720	-0.005556
Rho S.E.	0.011228	0.010938
Residual variance	891.8845	3307.237
Long-run residual variance	891.8845	3307.237
Number of lags	0	0
Number of observations	435	435
Number of stochastic trends**	2	2

**Number of stochastic trends in asymptotic distribution

We observe the null hypothesis "series are not cointegrated" must be accepted as both P-values for RUT and GSPC are insignificant.

Now, I will start by forecasting the Russell 2000. The data is non-stationary, so I will follow different ADF processes to correct it before reaching the necessary ARMA model:

Dependent Variable: D(RUT)
Method: Least Squares
Date: 04/10/24 Time: 11:48
Sample (adjusted): 1987M12 2024M01
Included observations: 434 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.

C	-4.944591	5.800562	-0.852433	0.3944
RUT(-1)	-0.031997	0.012460	-2.568057	0.0106
TIME	0.148672	0.055302	2.688370	0.0075
D(RUT(-1))	-0.021537	0.048419	-0.444810	0.6567

R-squared	0.017940	Mean dependent var	4.229585
Adjusted R-squared	0.011089	S.D. dependent var	54.36137
S.E. of regression	54.05914	Akaike info criterion	10.82721
Sum squared resid	1256628.	Schwarz criterion	10.86475
Log likelihood	-2345.504	Hannan-Quinn criter.	10.84203
F-statistic	2.618401	Durbin-Watson stat	1.996710
Prob(F-statistic)	0.050481		

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	3.634087	(2, 430)	0.0272
Chi-square	7.268174	2	0.0264

Null Hypothesis: C(2)=0, C(3)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(2)	-0.031997	0.012460
C(3)	0.148672	0.055302

Restrictions are linear in coefficients.

The Wald Test provides us with the answer to whether RUT contains a time trend besides a U.R. We observe the F-stat value of 3.63 is smaller than the $\phi 3$ value of 5.36 in the respective statistical table at the 10% significance level and taking in mind the number of observations tested. This leads us to the scenario where the empirical value is smaller than the critical value, meaning that we accept the null hypothesis, and the fact that RUT contains a U.R., but not a time trend.

However, we can go further, and see if RUT contains a drift. We follow the same process, excluding the TIME (trend) variable:

Dependent Variable: D(RUT)
Method: Least Squares
Date: 04/09/24 Time: 12:26
Sample (adjusted): 1987M12 2024M01
Included observations: 434 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.115919	4.463855	1.146076	0.2524
RUT(-1)	-0.000944	0.004705	-0.200652	0.8411
D(RUT(-1))	-0.035814	0.048473	-0.738849	0.4604

R-squared	0.001434	Mean dependent var	4.229585
Adjusted R-squared	-0.003200	S.D. dependent var	54.36137
S.E. of regression	54.44827	Akaike info criterion	10.83927
Sum squared resid	1277749.	Schwarz criterion	10.86742
Log likelihood	-2349.121	Hannan-Quinn criter.	10.85038
F-statistic	0.309464	Durbin-Watson stat	1.997955
Prob(F-statistic)	0.734003		

Wald Test:
Equation: RUTADF2

Test Statistic	Value	df	Probability
F-statistic	1.422220	(2, 431)	0.2423
Chi-square	2.844441	2	0.2412

Null Hypothesis: C(1)=0, C(2)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(1)	5.115919	4.463855
C(2)	-0.000944	0.004705

Restrictions are linear in coefficients.

The Wald Test provides us with the answer to whether RUT contains a drift besides a U.R. We observe the F-stat value of 1.42 is smaller than the ϕ1 value of 3.79 in the respective statistical table at the 10% significance level and taking in mind the number of observations tested. This leads us to the scenario where the empirical value is smaller than the critical value, meaning that we accept the null hypothesis, and the fact that RUT contains a U.R., but not a drift. We could agree that it is something not common to see in a stock index, but the volatility small caps bring to the table is the answer to our why’s.

I now proceed to check the correlogram for d(rut) c rut(-1) d(rut(-1)). I am trying to analyze the short-run dynamics via ACF/PACF correlograms and Q-stats in the residuals to understand the best possible ARMA model to forecast the Russell 2000 in 2023:

Date: 04/17/24 Time: 10:21
Sample: 1987M10 2023M01
Included observations: 422
Q-statistic probabilities adjusted for 2 dynamic regressors

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.002	0.002	0.0022	0.963
		2	0.038	0.038	0.6101	0.737
		3	0.047	0.047	1.5587	0.669
		4	-0.028	-0.030	1.8998	0.754
		5	0.041	0.038	2.6171	0.759
		6	-0.020	-0.020	2.7836	0.835
		7	0.071	0.071	4.9301	0.668
		8	0.015	0.011	5.0272	0.755
		9	-0.122	-0.124	11.435	0.247
		10	-0.004	-0.014	11.443	0.324
		11	-0.089	-0.077	14.919	0.186
		12	-0.114	-0.109	20.545	0.057
		13	-0.071	-0.073	22.772	0.045
		14	-0.094	-0.080	26.611	0.022
		15	0.024	0.027	26.866	0.030
		16	0.025	0.055	27.132	0.040
		17	0.011	0.025	[illegible]	0.055

We observe an ARMA model focusing on lags 7, 9, 11, 12, 13, or 14 could be appropriate. After different analyses, I arrived at the conclusion of using AR(7), AR(9), AR(11) and AR(12). However, I still had some autocorrelation issues, so I added MA(1). My model, therefore, is:

Dependent Variable: D(RUT)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 04/10/24 Time: 21:36
Sample: 1987M11 2023M01
Included observations: 423

Convergence achieved after 44 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.375146	2.030700	2.154502	0.0318
AR(7)	0.098543	0.040987	2.404244	0.0166
AR(9)	-0.144253	0.031411	-4.592440	0.0000
AR(11)	-0.085136	0.032166	-2.646726	0.0084
AR(12)	-0.135406	0.042454	-3.189468	0.0015
MA(1)	-0.073618	0.028698	-2.565284	0.0107
SIGMASQ	2511.296	97.53274	25.74824	0.0000

R-squared	0.052520	Mean dependent var	4.287659
Adjusted R-squared	0.038855	S.D. dependent var	51.54398
S.E. of regression	50.53270	Akaike info criterion	10.70091
Sum squared resid	1062278.	Schwarz criterion	10.76789
Log likelihood	-2256.243	Hannan-Quinn criter.	10.72738
F-statistic	3.843262	Durbin-Watson stat	1.991861
Prob(F-statistic)	0.000962		

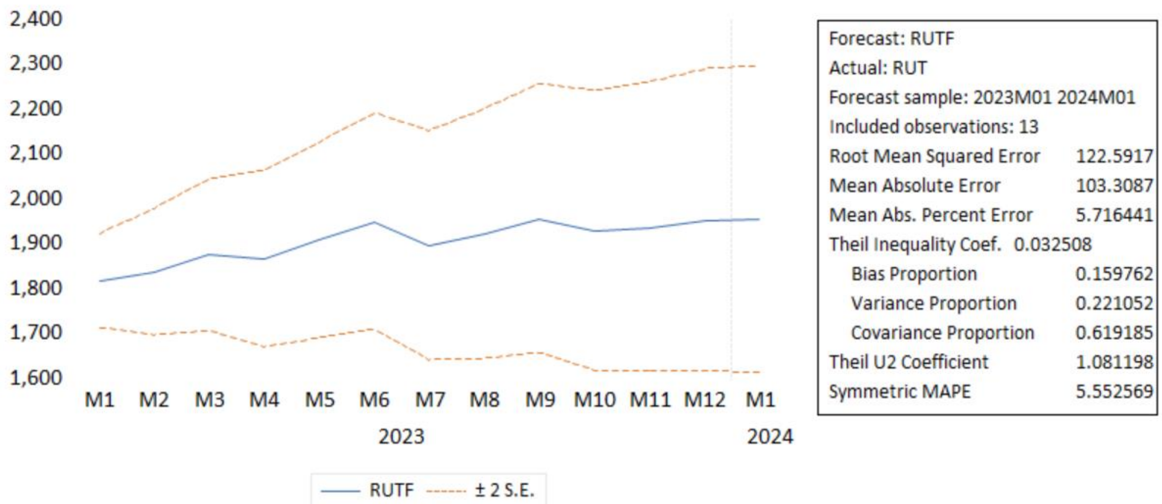
Inverted AR Roots	.86-.24i	.86+.24i	.57+.66i	.57-.66i
	.20+.77i	.20-.77i	-.23-.86i	-.23+.86i
	-.66+.55i	-.66-.55i	-.75-.15i	-.75+.15i
Inverted MA Roots	.07			

We observe every variable has significant P-values, and no autocorrelation given the insignificant Q-stats values in the correlogram:

Date: 04/17/24 Time: 10:31
Sample: 1987M10 2023M01
Included observations: 423
Q-statistic probabilities adjusted for 5 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.002	-0.002	0.0017	
		2	0.024	0.024	0.2427	
		3	0.020	0.020	0.4199	
		4	-0.009	-0.010	0.4557	
		5	0.037	0.036	1.0390	
		6	-0.032	-0.032	1.4810	0.224
		7	0.002	0.001	1.4830	0.476
		8	0.003	0.003	1.4861	0.685
		9	-0.027	-0.025	1.7914	0.774
		10	0.000	-0.002	1.7915	0.877
		11	-0.005	-0.002	1.8024	0.937
		12	-0.001	-0.001	1.8027	0.970
		13	-0.072	-0.073	4.0794	0.850
		14	-0.101	-0.100	8.5818	0.477
		15	0.033	0.034	9.0497	0.527
		16	0.024	0.033	9.3112	0.593
		17	0.006	0.005	9.3285	0.675

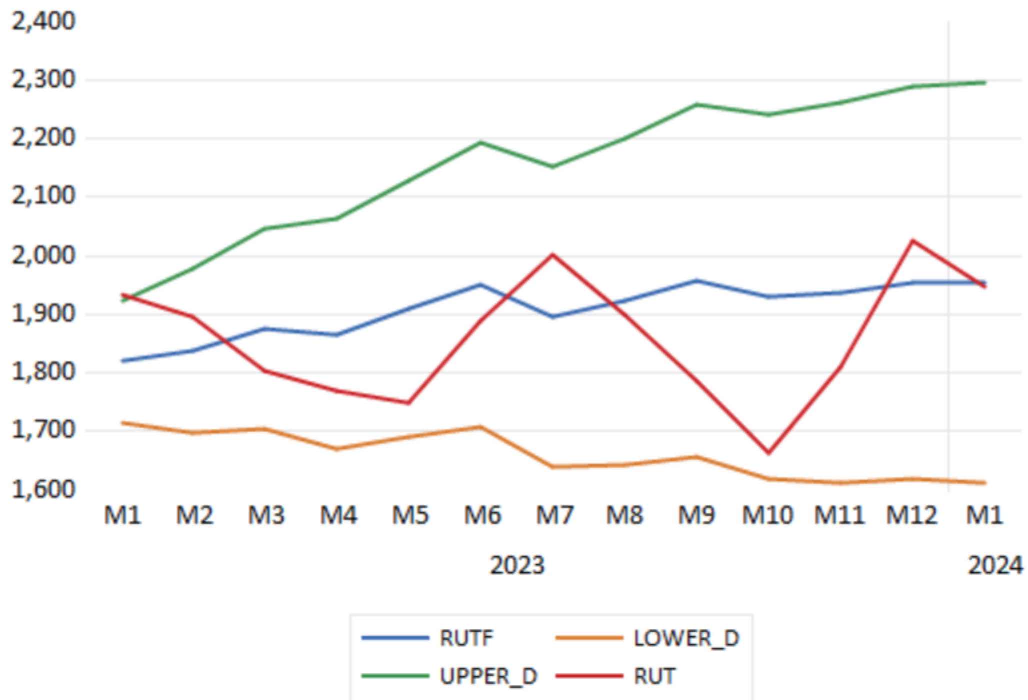
Now, we are in a good position to start the forecasting processes. It is important to make sure we establish the Out-of-Sample Period to 2023M01 – 2024M01. I chose dynamic because it is more realistic than static:



I created the lower and upper bonds to make sure I include the 95% confidence intervals that are important for the final resolution of the forecast:

	RUTF	LOWER_D	UPPER_D	RUT
2023M01	1818.808	1714.247	1923.369	1931.940
2023M02	1837.287	1697.101	1977.473	1896.990
2023M03	1875.843	1705.965	2045.720	1802.480
2023M04	1866.039	1669.741	2062.338	1768.990
2023M05	1908.752	1690.218	2127.286	1749.650
2023M06	1950.126	1708.776	2191.476	1888.730
2023M07	1896.542	1640.278	2152.805	2003.180
2023M08	1922.864	1644.313	2201.414	1899.680
2023M09	1957.089	1656.921	2257.258	1785.100
2023M10	1930.081	1619.604	2240.558	1662.280
2023M11	1937.281	1613.145	2261.418	1809.020
2023M12	1953.539	1617.748	2289.329	2027.070
2024M01	1955.203	1613.085	2297.322	1947.340

The final resolution for the Russell 2000 in 2023 comparing it to the actual data stands as follows:



As everyone knows, we are currently experiencing a highly uncertain period in the U.S. economy and the investment industry. While we won't delve deeply into this topic in this paper, it's essential to note a few things to understand the graph above. The U.S. is undergoing its most significant inflationary period in decades, along with the most substantial tightening of Fed interest rates since 2022. Many anticipated a recession to hit the country last year in 2023. However, that never materialized. Nonetheless, almost every financial market experienced ups and downs throughout the year due to the prevailing uncertainty.

In the graph (red line), we observe the rough start to the year, followed by a recovery during the summer fueled by hopes of cooling inflation, which would imply the Fed halting interest rate hikes. This, as we will later see, plays a significant role for small caps during the business cycle.

However, the Russell 2000 corrected itself before October 27th, when essentially everything hit bottom in the financial markets. From then until the end of 2023, economic data and expectations supported the theory of a possible soft-landing scenario in the U.S., with the Fed potentially cutting rates sooner than expected. All of this contributed to a rally in the last eight weeks of the year.

The interesting point here is that you can see the actual data and the forecast (blue line) ending up in very similar spots. This tells us that while technology can't predict market dynamics, by regressing and utilizing historical lags in the analysis, we can conclude about how the year ends. Throughout the year, numerous events occur on both the macroeconomic and microeconomic sides of things, making market dynamics and systemic risk impossible to predict. However, when discussing years or longer periods of time, it becomes easier to predict potential outcomes and understand the reasons behind them.

Now, I move forward to the main aspect of my research, which, remember, is to observe the relationship between the S&P 500 and the Russell 2000 with the U.S. business cycle or the main macroeconomic variables. The first step was to double-check the stationarity of the variables via ADF processes. As expected, most of them (including the stock indexes) were non-stationary, except for the consumer sentiment index, ISM manufacturing, ISM non-manufacturing, YoY PCE, and YoY PPI. To address this issue, I converted all of them to Month-over-Month percentage changes.

Regarding seasonality, as indicated in the empirical analysis description, all of them were already adjusted except for PPI all commodities and Government spending (excluding defense). Therefore, it is acceptable to proceed with the research and utilize them in their current form.

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I believe VAR would help me understand the relationship between stock indexes and macroeconomic variables in the U.S. Not only that, but through Granger Causality and Cholesky simulations, I will be able to see closer the response these economic variables induce in our RUT and GSPC independent variables:

Vector Autoregression Estimates
Date: 04/08/24 Time: 21:22
Sample (adjusted): 1997M09 2022M12
Included observations: 304 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Determinant resid covariance (dof adj.)	7.05E-37
Determinant resid covariance	5.19E-38
Log likelihood	4853.641
Akaike information criterion	-27.05685
Schwarz criterion	-17.99659
Number of coefficients	741

Before proceeding, I need to adjust the lag selection criteria for VAR, especially looking at AIC this time given the smaller number compared to SC we see above. I observe the lag selection should be 12:

VAR Lag Order Selection Criteria
Endogenous variables: MOM_RUT MOM_GSPC MOM_GSCI MOM_TREASURSPREAD MOM_USGVNTINVNETNONDEF MOM_USHEXISTINGSALES MOM_USINDUSPRODUCTION MOM_USINTTRADEBALANCE MOM_USINVNETPRIVDOMESTIC MOM_USREALGDP MOM_USRSALESADVANCE MOM_USWHTRADETOTAL MOM_YOYCORECPI UNEMRATE YOY_PCE YOY_PPI US_ISMM US_ISMS US_CONSSENTINDEX
Exogenous variables: C
Date: 04/08/24 Time: 21:26
Sample: 1987M10 2024M01
Included observations: 294

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1859.177	NA	1.40e-29	-12.51821	-12.28015	-12.42287
1	4255.805	4467.186	1.36e-35	-26.36602	-21.60493*	-24.45935*
2	4678.989	734.0936	9.15e-36	-26.78904	-17.50491	-23.07103
3	5097.625	672.0957	6.63e-36	-27.18112	-13.37396	-21.65177
4	5574.159	703.4552	3.47e-36*	-27.96707	-9.636872	-20.62638
5	5892.900	429.3249	5.84e-36	-27.67959	-4.826362	-18.52756
6	6295.550	490.3018	6.34e-36	-27.96293	-0.586661	-16.99956
7	6677.036	415.2228	9.45e-36	-28.10229	3.797013	-15.32758
8	7152.377	455.9393	9.39e-36	-28.88012	7.542219	-14.29407
9	7696.679	451.7336	7.99e-36	-30.12707	10.81830	-13.72968
10	8294.928	419.1813*	7.27e-36	-31.74101	13.72740	-13.53228

11	8981.415	392.2782	6.81e-36	-33.95520	16.03624	-13.93514
12	9812.809	367.6235	6.29e-36	-37.15517*	17.35931	-15.32376

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Up to this point, we have gathered all the information we need. Moving forward, we are going to begin examining the answers to all the questions I have for my main research.

Let's start by using Granger Causality to truly understand the relationship between all these macro variables and both stock indexes. First, the Russell 2000:

Dependent variable: MOM_RUT

Excluded	Chi-sq	df	Prob.
MOM_GSPC	18.03158	12	0.1147
MOM_GSCI	24.83362	12	0.0156
MOM_TREASURSPRE...	26.41065	12	0.0094
MOM_USGVNTINVNET...	35.17809	12	0.0004
MOM_USHEXISTINGS...	13.81372	12	0.3128
MOM_USINDUSPROD...	24.83357	12	0.0156
MOM_USINTTRADEBA...	30.30215	12	0.0025
MOM_USINVNETPRIV...	22.87748	12	0.0288
MOM_USREALGDP	31.22750	12	0.0018
MOM_USRSALESADV...	20.01525	12	0.0668
MOM_USWHTRADET...	21.38233	12	0.0451
MOM_YOYCORECPI	22.92045	12	0.0284
UNEMRATE	19.64495	12	0.0741
YOY_PCE	11.83505	12	0.4590
YOY_PPI	6.337255	12	0.8981
US_ISMM	24.12273	12	0.0196
US_ISMS	14.82204	12	0.2513
US_CONSSENTINDEX	15.65256	12	0.2077
All	312.5841	216	0.0000

I can see RUT not being affected at the 10% significance level by the following U.S. macro variables: US EXISTING HOME SALES, YOY PCE, YOY PPI, US ISM NON-MANUFACTURING, and US CONSUMER SENTIMENT INDEX. Besides, I observe as well that RUT does not to seem bothered by GSPC (S&P 500).

In the S&P 500 case:

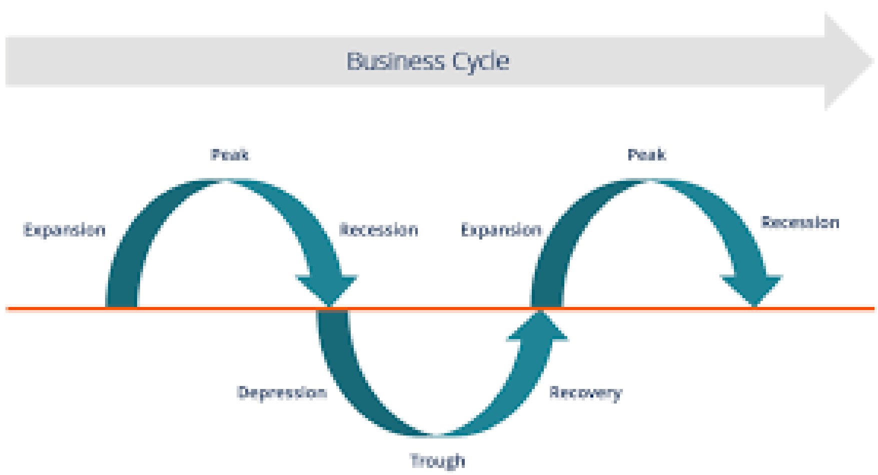
Dependent variable: MOM_GSPC

Excluded	Chi-sq	df	Prob.
MOM_RUT	18.27598	12	0.1076
MOM_GSCI	22.73442	12	0.0301
MOM_TREASURSPRE...	21.40928	12	0.0447
MOM_USGVNTINVNET...	28.78310	12	0.0042
MOM_USHEXISTINGS...	19.43433	12	0.0786
MOM_USINDUSPROD...	26.82445	12	0.0082
MOM_USINTTRADEBA...	18.07808	12	0.1133
MOM_USINVNETPRIV...	11.78993	12	0.4627
MOM_USREALGDP	22.67798	12	0.0306
MOM_USRSALESADV...	18.65899	12	0.0971
MOM_USWHTRADET...	24.47697	12	0.0175
MOM_YOYCORECPI	14.74001	12	0.2560
UNEMRATE	11.72323	12	0.4682
YOY_PCE	19.85267	12	0.0699
YOY_PPI	8.631011	12	0.7341
US_ISMM	18.96849	12	0.0893
US_ISMS	19.18751	12	0.0841
US_CONSSENTINDEX	22.28728	12	0.0344
All	305.8878	216	0.0001

I can see GSPC not being affected at the 10% significance level by the following U.S. macro variables: US INTERNATIONAL TRADE BALANCE, US NET PRIVATE INVESTMENT, YOY CORE CPI, UNEMPLOYMENT RATE, AND YOY PPI. Besides, I observe as well that GSPC does not to seem bothered by RUT (Russell 2000).

We are now able to disregard all those U.S. macro variables that do not affect both the Russell 2000 and the S&P 500, respectively, in my research. It's important to note that using a different sample for my observations or specific scenarios where both independent and dependent variables intervene might alter this outcome, meaning that those insignificant variables might become important, and the opposite for others.

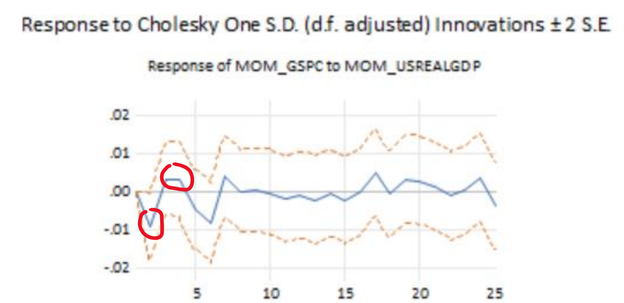
The next step is to delve fully into the U.S. business cycle and observe how smaller caps (RUT) and larger caps (GSPC) historically react depending on the phase. As we all know, economies around the world typically reach a peak where people spend money, and companies invest in the future. This phase is beneficial, but unfortunately, it cannot last forever due to rising inflation and other economic factors. When we reach this point, central banks, such as the Fed in our case, start hiking rates intentionally to cool down the economy. This new phase is called contraction, and we eventually reach the trough, which can manifest as either a recession or a soft landing, where the economy needs to be reactivated. This is a point where inflation has been brought under control, but now we face high unemployment, reduced consumer spending, and decreased corporate investment. This stage is where the Fed would start cutting rates, just to initiate the expansionary phase again. Eventually, the economy will hit the peak spot again, and the U.S. business cycle restarts.

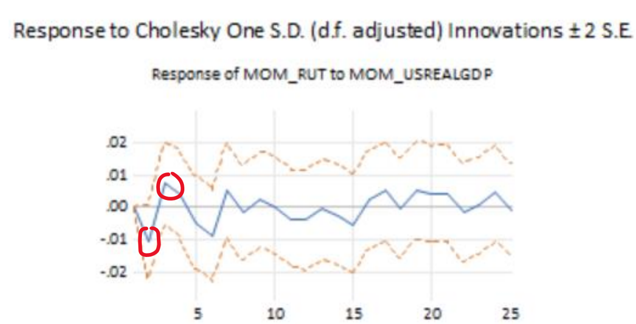


For this stage of the research, I focus on identifying which variables, among the remaining ones, are important for both RUT and GSPC and match in both cases. These variables include treasury spread, government net investing (excluding defense), industrial production, real GDP growth, advance retail sales, wholesale trade, and ISM manufacturing. While these variables allow for various analyses, I will simplify by exclusively focusing on real GDP growth, as it ultimately provides the answers regarding the current business cycle. Additionally, I will also analyze the unemployment rate, despite it not being shared by both RUT and GSPC. This is because it has a significant impact on smaller caps and serves as a major business cycle indicator.

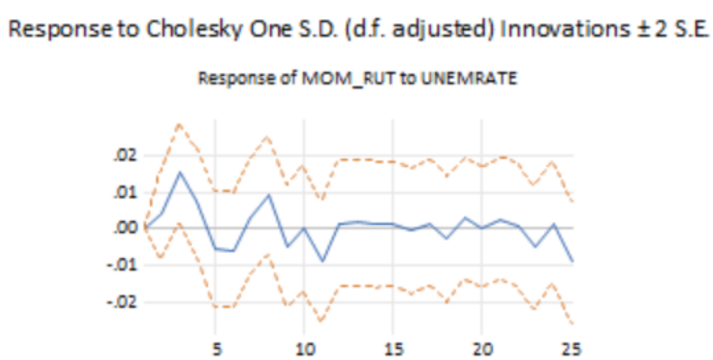
Cholesky simulations help us understand the response of any variable when subjected to standard deviation shocks induced by another related variable. This means observing how a variable responds when there is an increased present risk in the variable being compared to.

I believe this analysis addresses the primary question in my research. What I am attempting to achieve now is to observe firsthand the response of both the Russell 2000 (RUT) and the S&P 500 (GSPC) to shocks occurring in the standard deviation of U.S. real GDP in the last twenty-five periods, assuming real GDP growth offers insights into the business cycle:





We could spend a lot of time observing these two graphs, but I want to go straight to the point. We observe the response of RUT to shocks occurring in the standard deviation of U.S. real GDP in the lower graph, and the response of GPSC to shocks occurring in the standard deviation of U.S. real GDP in the upper graph. As a reminder, my main question along this research paper has been when do U.S. smaller caps outperform U.S. larger caps focusing on the business cycle. Observing the red circles as a clear example, we see bigger shocks for the good and for the bad in the case of the Russell 2000. Not only in those cases, but in almost any response, as well as noting the 95% confidence intervals are higher and lower in RUT's case, meaning a more important response in terms of the magnitude induced into the U.S. small caps stock index regarding U.S. real GDP growth, or in other words, the U.S. business cycle.



When explicitly discussing the Russell 2000 and the unemployment rate in the U.S., we observe a similar response. A higher or lower unemployment rate indicates different phases of the business cycle. Once again, we observe the significant response (blue line) to shocks occurring in the standard deviation of U.S. unemployment.

Conclusion

In my opinion, everything makes sense, and historically, it aligns as well. Smaller caps tend to perform better in an environment of lower interest rates due to their higher debt levels and comparatively lower quality fundamentals compared to larger caps. This trend fits within an environment where smaller caps excel during the expansionary and peak phases of the business cycle. However, it's crucial to remember that the stock market, along with other asset classes, always prices in the future. When the economy hits bottom, even though conditions may not be favorable, anticipation of rate cuts becomes evident. This is where an opportunity window opens for smaller caps in the U.S., especially in the period following the trough through the recovery phase. As we begin to expand, the stock market eventually starts pricing in future rate hikes, typically around the peak. At this juncture, larger caps demonstrate their strength, as seen in Cholesky simulations where shocks are less volatile in the downside. Moreover, during contractionary phases, both indexes usually face downward pressure.

In the literature reviews, we have observed how the theory operates in other parts of the world as well, often over longer periods, such as in the case of the European Union or Germany since the Global Financial Crisis. This suggests that smaller caps not only present opportunity windows throughout the business cycle but also entire trends for extended periods outside our country. In my view, this scenario is unlikely to occur in the U.S. because smaller caps will never match the technological prowess of companies like Apple, Microsoft, Nvidia, and others. U.S. mega tech is unparalleled. However, there are indeed opportunity windows to invest in smaller-cap companies within the United States.

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