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Technology Momentum: Peer Networks from Patents

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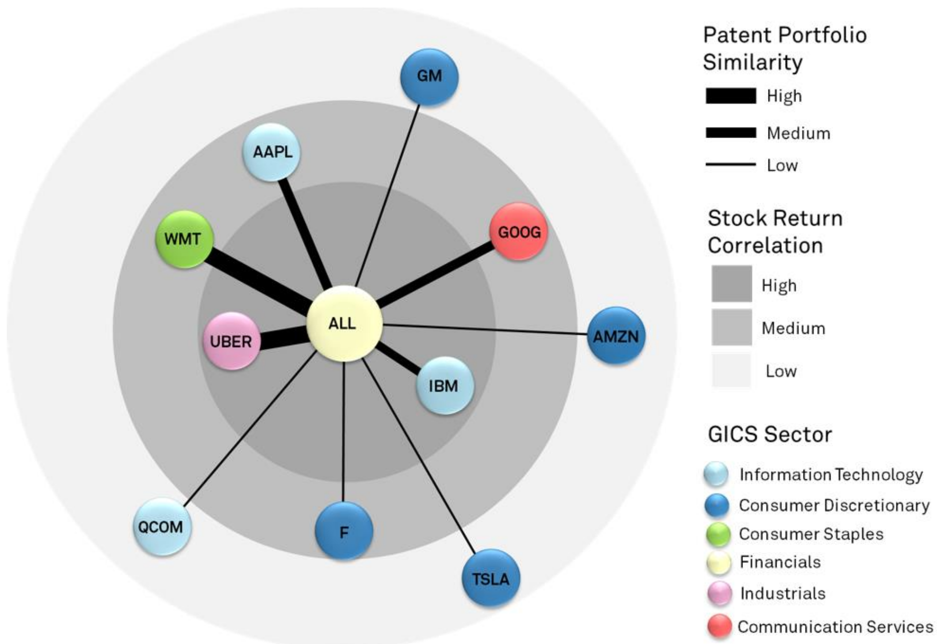
Companies strategically innovate and acquire intellectual property. That innovation is increasingly taking place outside of a firm's traditional business focus and varies widely between companies in the same sector. Investors can group firms by their shared technology attributes using patent data**.** Because of the importance of intellectual property in a firm's value, stock prices of companies with similar patent portfolios exhibit peer group momentum. For example, Allstate and Uber each hold more than 50 patents in autonomous driving technology and have highly correlated stock returns, despite the two having different sector assignments (Figure 1).

Figure 1: Patent Portfolio Similarity and Stock Return Correlation, 2015 –2021
Allstate and Top 10 U.S Autonomous Driving Patent Holders



Source: IPQwery and S&P Global Market Intelligence Quantamental Research. Data as of 06/20/2021.

Findings in this report include:

- **Companies with similar patent portfolios exhibit peer group momentum.** A strategy that buys (sells) stocks of focal companies in the Russell 3000 with outperforming (underperforming) technology peers produces an annualized risk-adjusted return of **5.23%** in a historical backtest.
- **The strategy returns are more pronounced for smaller companies.** In the Russell 2000, the strategy demonstrates more efficacy with annualized long-short return of **7.32%.**
- **The strategy is distinct from sector momentum strategies**. After controlling for sector momentum, **3.60%** excess return in the Russell 3000 can be attributed to technology peer group momentum.

1. Introduction

By analyzing and comparing patents, investors can uncover overlaps in technology between companies from different sectors. For example, Allstate and Uber are not sector peers but their patent portfolio overlaps in several technologies. Both companies have patents related to autonomous vehicles, driver monitoring, route navigation and food delivery (Table 1). Because of their shared technology, Uber and Allstate are technology peers.

Table 1: Patent Titles Owned by Uber and Allstate in Overlapping Technologies

Uber Technologies	Allstate Corporation
System and methods to enable control of an autonomous vehicle	Testing autonomous cars
Detecting vehicle collisions based on moble computing device data	Event-based connected vehicle control and response systems
Network computer system to evaluate operator of a freight vehicle	Vehicle telematics based driving assessment
Safe routing for navigation systems	Route risk mitigation
Autonomous vehicle positioning for trip optimization	Altering autonomous vehicle operation based on route traversal
On-demand coordinated comestible item delivery system	Food delivery service and insurance systems

Source: IPQwery and S&P Global Market Intelligence Quantamental Research. Data as of 06/20/2021.

Stock returns of companies with similar attributes may exhibit co-movement. Literature has documented co-movement between stock returns of companies in the same industry, supply chain and analyst networks[1]. Recent studies have shown that stock returns of companies that have similar patents are also correlated[2]. This suggests that companies sharing technology have peer group momentum.

Technology overlaps between patents can be identified by the International Patent Classification (IPC) codes which maps each patent to relevant technology classes. Using a similar approach to Lee et al (2007), patent peers are identified by correlating the patent technology classification distribution between each company's patent portfolios. A trading signal, Technology Momentum ($TECHMom$), is formed by ranking stocks by the performance of their patent peers.

[1] See Cohen and Frazzini (2007), Grinblatt and Moskowitz (1999), Parsons et al (2016) , Wu and Jain (2020), Oyeniyi et al (2021)
[2] Bekkerman et al (2020) and Lee et al (2018)

2. Methodology

Companies with more than 50 patents and membership in the specified index[3] are included in the investable universe. For each company, a vector representation of the patent portfolio is generated from patents published within a 5-year trailing window and grouped by IPC (International Patent Classification) technology subclass code[4]. Using Equation 1, where for company i, $T_{it} = (T_{it1}, T_{it2} \ldots T_{itn})$ is the vector of patent counts across n subclasses at time t, a patent similarity score between each company in the Index is computed to obtain an n by n matrix, $TECH_{ijt}$[5]. See Appendix A for a worked example.

$$TECH_{ijt} = \frac{(T_{it} * T'_{jt})}{(T_{it} * T'_{it})^{1/2} * (T_{Jt} * T'_{jt})^{1/2}} \qquad Equation\ 1$$

The intermediate price momentum, MOM, is calculated as the total stock price return over the past 12 months, excluding the most recent month. Similarly, the standard deviation of returns, $Stdev\_Return$, is calculated using monthly returns over the past 12 months, excluding the most recent month.

By using the patent similarity score from $TECH_{ijt}$ (Equation 1) as a weighing scheme, for each focal company i, a weighted intermediate momentum sum and a weighted standard deviation sum of returns of its index peers are calculated. The test signal, $TECHMom_{it}$ is obtained by deflating the weighted peer intermediate momentum by the weighted peer standard deviation of returns (Equation 2). Peers that have a higher similarity score to the focal company contribute more to the signal.

$$TECHMom_{it} = \frac{\sum_j TECH_{ijt} * MOM_{jt}}{\sum_j TECH_{ijt} * Stdev\_Return_{jt}} \qquad Equation\ 2$$

At the end of each month, $TECHMom_{it}$ is ranked GICS sector neutral.

[3] Analyses were performed in the Russell 1000 (Large-Cap), Russell 2000 (Small-Cap), and Russell 3000 (All-Cap)
[4] A patent can be tagged to multiple technology subclasses. IPC contains 646 subclasses
[5] The diagonal of the matrix is set to 0 to remove a focal stock's own momentum.

3. Technology Momentum

Companies that share similar patents have technology peer group momentum. By buying (selling) stocks of outperforming (underperforming) technology peers, $TECHMom$ yields a long and long-short return of **2.74%** and **5.23%** respectively in the broad-cap Russell 3000 after adjusting for risks (Table 2). The signal is more effective in the smaller cap Russell 2000 but is not statistically significant in the larger cap Russell 1000.

Table 2: Technology Momentum Risk Adjusted Returns[6]
December, 2010 – February, 2021

Test Universe	Average Quintile Count	1-month Information Coefficient	Anualized Long-Only Active Return	Information Ratio (Long Only Active Return)	(Long-Only Active Return)	Annualized Long-Short Return	Annualized Information Ratio (Long-Short Return)	Hit Rate (Long-Short Return)
Russell 3000	123	0.02***	2.74%**	0.92***	56%***	5.23%***	0.97***	58%***
Russell 1000	63	0.02**	0.83%	0.33	53%*	2.30%*	0.51*	53%*
Russell 2000	55	0.02***	4.11%***	0.77***	58%***	7.32%***	0.83***	59%***

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.

Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 06/20/2021.

Although the strategy is more pronounced for smaller cap companies, it is effective in a broad market cap range. The signal is statistically significant in both the smaller half of the Russell 1000 and the larger half of Russell 2000 (Table 3). Because market cap and investor attention are strongly correlated, the signal may not be effective in the larger half of the Russell 1000 because these companies receive more investor attention and new information is impounded quickly into their stock prices.

Table 3: Signal Performance[7] within Russell 1000, 2000
December, 2010 – February, 2021

Test Universe	Market Cap Half	Average Tertile Count	1-month Information Coefficient	Anualized Long-Only Active Return	Annualized Information Ratio (Long Only Active Return)	Hit Rate (Long-Only Active Return)	Annualized Long-Short Return	Annualized Information Ratio (Long-Short Return)	Hit Rate (Long-Short Return)
Russell 1000	Top	55	0.01	1.10%	0.11	52%	1.57%	0.11	52%
	Bottom	40	0.02***	2.32%**	0.66**	56%**	4.69%***	0.77**	56%**
Russell 2000	Top	49	0.02**	3.11%**	0.59**	55%**	4.67%***	0.80**	57%**
	Bottom	40	0.03***	5.14%***	0.77**	60%***	8.73%***	0.92***	62%***

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.

Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 06/20/2021.

[6] All returns included in this paper are Fama French 4 adjusted which includes an adjustment for intermediate price momentum

[7] Tertiled portfolios are used instead of quantiles because of the resulting small number of stocks after bifurcating the test universe by market cap.

3.1 Sector Momentum and Technology Momentum

Sector momentum strategies buy (sell) stocks of winning (losing) sectors. To disentangle technology momentum from sector momentum, Equation 3 regresses out excess returns attributed to sector momentum[8] from $TECHMom$ long-short monthly quantile returns. The backtest excess performance of 44 basis points per month in the Russell 3000 can be attributed to around 14 basis points from sector momentum and 30 basis points from information contained in the patent data (Table 4).

$$TECHmom_t = \alpha + \beta_t SectorMomentum + \varepsilon \qquad Equation\ 3$$

Table 4: Technology Momentum Excess Monthly Return Regression Coefficients
Russell 3000; December, 2010 – February, 2021

Variable	*Coefficients*
Intercept	**0.30****
Sector Momemtum	**0.14****

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.

Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 06/20/2021.

4. Data

The Point-in-Time patent data used in this report is provided by IPqwery through Xpressfeed. IPqwery provides Point-in-Time intellectual property (IP) data for trademarks and patents for US companies with observation dates from 2009 onwards. Time aware patent ownership for more than 6 million unique patents is established covering 600,000 private and public companies and linked to publicly traded tickers. Meta data for each patent, including textual abstract and International Patent Classification (IPC) codes, is provided allowing investors to gain insights on trends in intellectual property filings by companies. The data was linked using Exchange and Ticker information provided by IPqwery.

5. Conclusion

Patent data reveals connectedness between companies not captured by sector classification schemes. This offers investors an alternate approach to group peer companies by shared technology attributes. Companies from different sectors can share similar technologies and have technology peer group momentum. When stocks of technology peers do well, the focal company stock tends to perform well. Because the technology momentum signal is distinct from sector momentum, investors can gain additive benefits by incorporating technology momentum to existing momentum strategies.

[8] Sector momentum is calculated using GICS 11 sector ranked each month by their 11-month price return skipping the most recent month (PM12M1M). Long-short returns are calculated using quintiles.

APPENDIX A

This section illustrates a trivial implementation of (Equation 1) by assuming 3 fictitious companies, **X,Y,Z** that own patents across 8 patent classes and compute the patent similarity score between company X and its peers, Y and Z.

		Company		
		X	**Y**	**Z**
Patent Class	**A**	1	0	0
	B	0	1	0
	C	4	1	7
	D	2	10	1
	E	1	2	0

$$TECH_{ijt} = \frac{(T_{it}.*T'_{jt})}{\left(T_{it} * T'_{it}\right)^{1/2} * \left(T_{Jt} * T'_{jt}\right)^{1/2}} \qquad Equation\ 1$$

Per Equation 1, where for company i, $T_{it} = (T_{it1}, T_{it2} \ldots T_{itn})$ is the vector of patent counts across n subclasses at time t, the vector of patent distributions for company **X**,**Y** and **Z** are as follows:

$$T_{Xt} = (1{,}0{,}4{,}2{,}1)$$
$$T_{Yt} = (0{,}1{,}1{,}10{,}2)$$
$$T_{Zt} = (0{,}1{,}1{,}10{,}2)$$

To compute the similarity between company X and Y:

$$(T_{xt}.*T'_{yt}) = \sum[(1*0),(0*1),(4*1),(2*10),(1*2)] = 26$$
$$(T_{xt}.*T'_{xt}) = \sum[(1*1),(0*0),(4*4),(2*2),(1*1)] = 22$$
$$(T_{yt}.*T'_{yt}) = \sum[(0*0),(1*1),(1*1),(10*10),(2*2)] = 106$$

$$TECH_{xyt} = \frac{26}{\sqrt{22}*\sqrt{106}} = 0.538$$

Applying equation to each company pair and setting the diagonal elements to 0,

$$TECH_{ijt} = \begin{array}{c|ccc|} & X & Y & Z \\ X & 0 & 0.538 & 0.905 \\ Y & 0.538 & 0 & 0.234 \\ Z & 0.905 & 0.234 & 0 \end{array}$$

APPENDIX B

The test period is divided into two equal time horizons. Technology momentum is consistent across both sub-periods and the signal is statistically significant in the Russell 3000 and Russell 2000 at the 5% level (Table 5, Table 6). In both sub-periods, the signal is more effective in the smaller-cap Russell 2000. The signal is more profitable in the recent sub period with stronger performance in all the test universes, including in the Russell 1000 where the signal becomes statistically significant.

Table 5: Technology Momentum Risk Adjusted Returns
December, 2010 – December, 2015

Test Universe	Average Quintile Count	1-month Information Coefficient	Anualized Long-Only Active Return	Annualized Information Ratio (Long Only Active Return)	Hit Rate (Long-Only Active Return)	Annualized Long-Short Return	Annualized Information Ratio (Long-Short Return)	Hit Rate (Long-Short Return)
Russell 3000	95	0.020**	2.23%**	0.84***	55%**	3.97%***	0.90***	57%**
Russell 1000	56	0.009	-0.48%	-0.21	49%	-0.72%	-0.13	50%
Russell 2000	41	0.018*	2.31%**	0.54*	58%**	5.75%***	0.67**	59%***

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.

Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 06/20/2021.

A possible explanation for stronger signal performance in the recent sub-period is because of improved coverage in the IPqwery patent dataset, resulting in more stocks per quantile and more patent peers in the focal stock's network. The former reduces idiosyncratic noise and the latter improves the signal efficacy.

Table 6: Technology Momentum Risk Adjusted Returns
January, 2016 – February, 2021

Test Universe	Average Quintile Count	1-month Information Coefficient	Anualized Long-Only Active Return	Annualized Information Ratio (Long Only Active Return)	Hit Rate (Long-Only Active Return)	Annualized Long-Short Return	Annualized Information Ratio (Long-Short Return)	Hit Rate (Long-Short Return)
Russell 3000	149	0.024***	3.53%**	1.08***	57%**	6.12%***	1.22***	57%**
Russell 1000	79	0.025***	2.29%**	0.89**	55%**	5.16%**	0.92**	55%**
Russell 2000	71	0.020*	6.32%***	1.10***	58%**	9.77%***	1.12***	60%***

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.

Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 06/20/2021.

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Our Recent Research

July 2021: Branching Out: Graph Theory Fundamentals

Investment analysis has evolved beyond financial data to non-financial, or alternative data. Typically, the focus has been on using alternative datasets that are purely time-series and tabular. Graph networks meanwhile offer investors the ability to gain deeper insights into the connections between economies, industries, and individual corporations.

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Company annual filings are a vital but often under-analyzed source of information for investors. Market moving content is buried within an ever-growing body of text that on average is equivalent to a 240-page novel. The filings contain subtle revisions making a computational linguistic approach imperative. Faced with this voluminous amount of text and the minute number of changes, investors have historically overlooked the newly embedded information and the implications of those additions.

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