RavenPack
QUANTITATIVE RESEARCH

Alpha Generation through Job Analytics

A Novel Approach to Measuring Tech Adoption

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Executive Summary

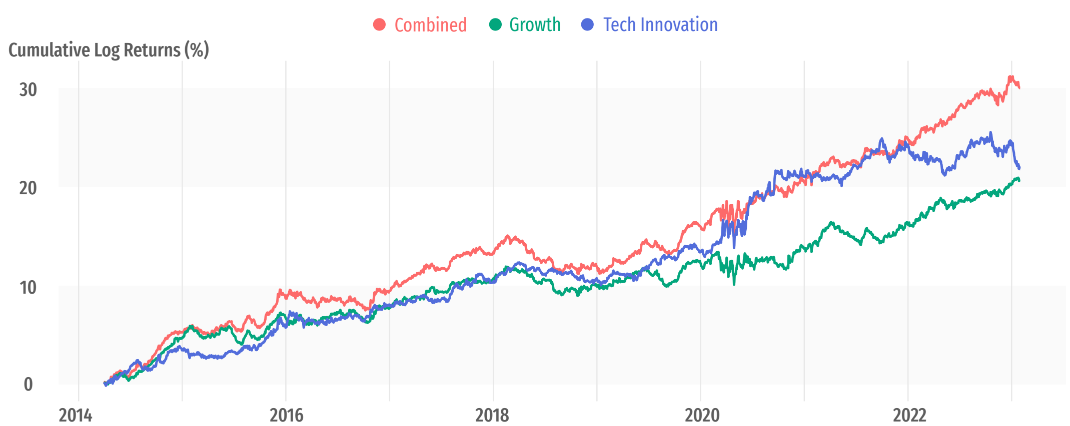
In this study, we quantify technological adoption in hiring posts using RavenPack Job Analytics to determine whether companies that consistently hire individuals with novel technology skills outperform their peers from an investment perspective. We find that:

(i) **A long-only portfolio using the number of novel technology skills detected as a signal** delivers an Information Ratio of 1.1 and Annualized Excess Returns of 2.8% relative to sector, with a near one-month effective holding period (5% Daily Turnover).

(ii) **The alpha of the technology adoption signal remains robust** after controlling for traditional factors.

(iii) **The correlation between technology adoption and monthly hiring growth is low**, resulting in enhanced portfolio performance with an Information Ratio of 1.4 and an annualized excess return of 3.4% when both signals are combined.

This application of the RavenPack Job Taxonomy paves the way for further exploration of the hiring landscape and trends and its impact on the markets.



Cumulative log returns for the technology adoption, monthly hiring growth, and combined portfolio for U.S. mid/large-cap companies.

1. Introduction

The rapid pace of technological advancements has greatly impacted the way companies operate and compete in recent years. Ultimately, the acquisition and implementation of new technologies has become a critical factor for success. As a result, there is a strong focus today on identifying and hiring individuals with the necessary technical skills to drive innovation and growth.

In this paper, we aim to demonstrate that companies that prioritize the acquisition of new technology skills in their hiring processes outperform their peers from an investment perspective. By analyzing the relationship between the volume of new technology skills sought in job postings and a company's subsequent investment performance, we explore how new technology skills in hiring posts can be a source of alpha for investors.

The paper outlines the use of RavenPack Job Analytics to identify and measure technological adoption in hiring posts, and is structured as follows.

In **SECTION 2**, we provide an overview of RavenPack Job Analytics, focusing on the characteristics of the Job Taxonomy hierarchy.

In **SECTION 3**, we outline the process for quantifying technological adoption in hiring posts, and create a signal.

In **SECTION 4**, we evaluate the performance of the signal and the ability of technology innovation to generate alpha.

SECTION 5 examines the combination of the technology adoption signal with a monthly hiring growth strategy. Finally, we discuss our findings in **SECTION 6**.

2. Data description

RavenPack Job Analytics data is collected by our partner LinkUp directly from corporate websites, and includes more than 200 million job listings from over 60,000 companies, with data dating back to 2007. The dataset is updated daily and is focused on U.S. companies, with coverage of 80% of our mid/large-cap[1] universe.

The Job Analytics provides a comprehensive, organized view of the job market through machine-generated titles that contains employer, position classification[2], and location information.

A unique feature of these analytics is the Job Taxonomy, which offers a structured framework for analyzing hiring trends, and benchmarks the job market.

The Taxonomy classifies job postings based on established dimensions, such as benefits, work values, and skills, enabling a broad comparison of jobs across different categories.

As a result, it offers a sophisticated and insightful perspective on job data for both investors and corporations. **FIGURE 1** showcases a subset of the Job Taxonomy hierarchy. The RavenPack Job Taxonomy has two powerful attributes that make it a valuable tool for analyzing the job market.

Firstly, through the point-in-time sensitivity of our analytics, it allows users to gain insights into the state of the hiring market at specific moments in time. Secondly, it is editorially maintained, which enables it

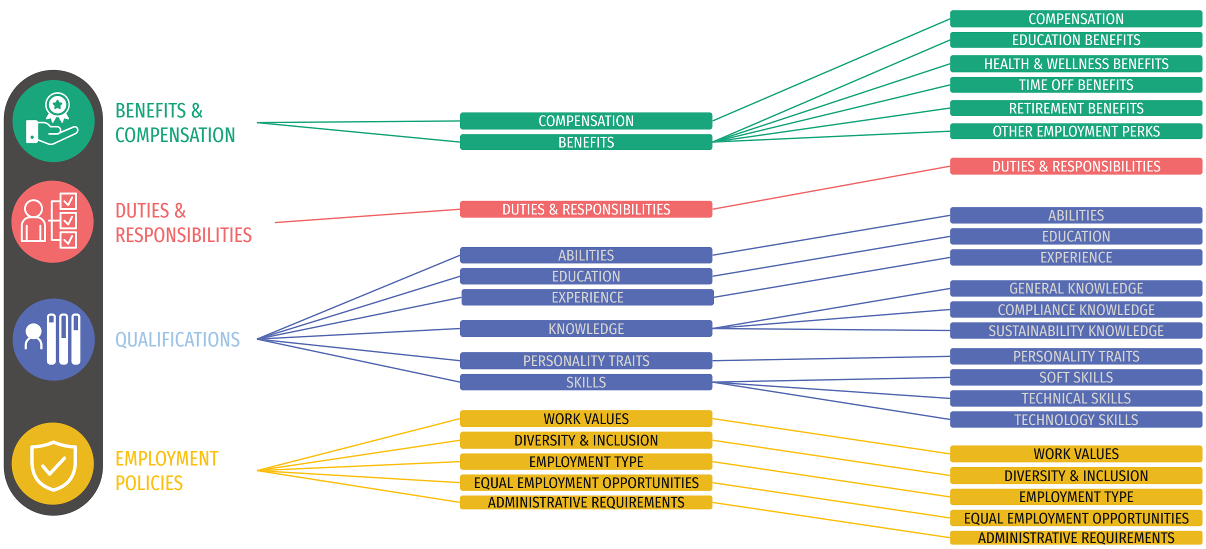


FIGURE 1. The Job Taxonomy hierarchy from less granular to more granular themes (left to right). In this paper, we will focus on Technology skills. *Source: RavenPack, January 2023*

1 The large-, mid-, and small-cap categorizations for the U.S. are achieved by assigning top 1,000 ranked companies by market cap to large/mid- and 1,001-3,000 companies to small-cap groups, annually.

2 More details can be found here: **O*NET-SOC Taxonomy at O*NET Resource Center (onetcenter.org)**

to keep pace with the jobs market as it evolves. This is illustrated in **Figure 2**, which displays monthly growth of 10% in the number of distinct job-related entities.

This real-time curation is crucial for ensuring the viability of the proposed strategy, as it allows for the collection of new skills as they emerge across the hiring landscape[3].

This study will focus specifically on the Technology subset of skills in the Job Taxonomy. As of January 2023, the Technology skill subset encompasses approximately 2,100 unique entities[4], with around 50% of these skills related to software products, as shown in **Figure 3**.

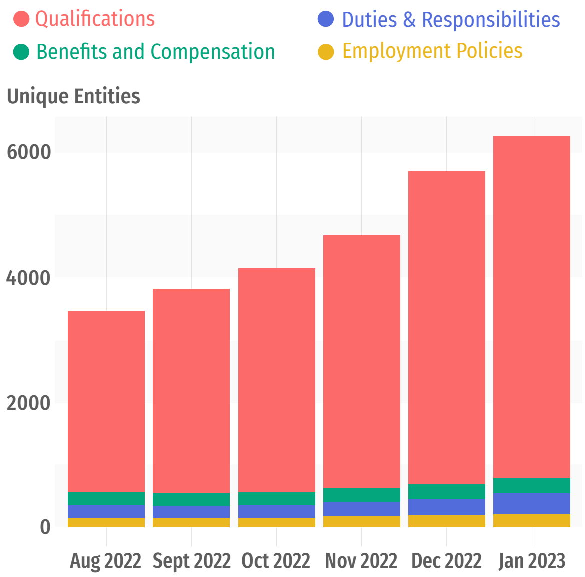


FIGURE 2. Evolution of the number of unique entities and the topic distribution in the Job Taxonomy watchlist.
Source: RavenPack, January 2023

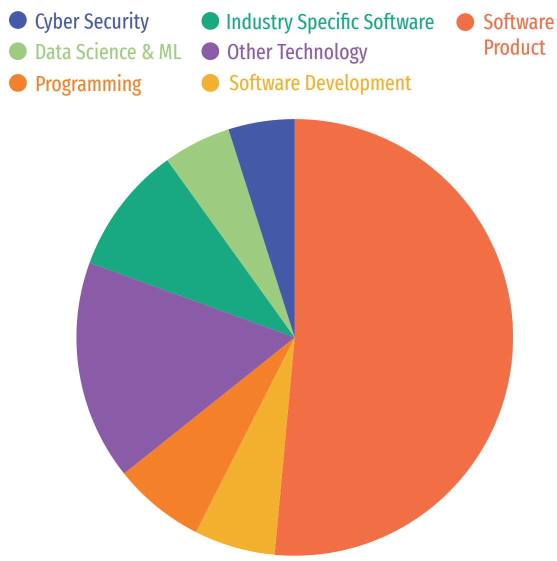


FIGURE 3. Distribution of Technology skills in the RavenPack Job Taxonomy. *Source: RavenPack, January 2023*

3 Furthermore, users can also use keyword search in order to incorporate any additional themes or concepts if they are not included in our database.

4 We manually exclude widely used technologies like browsers, email, and social media platforms

3. Constructing a novel technology skills indicator

By utilizing RavenPack Job Analytics, we are able to track the in-demand skills that employers are looking for, including cutting-edge technology that can identify innovative trends or companies filling skill gaps when compared to its peers.

For any given day t and for each company i in our universe, we define the set $S_i(t)$ as the unique *technological skills* appearing in hiring posts over the expanding window $[t_0, t]$, where t_0 marks the start of the archive[1]. Mathematically:

$$S_i(t) = \{\text{skills} \mid \text{skills} \in \text{hiring posts over the window } [t_0, t]\}$$

The novel technology skills for a company over the period $\Delta, \mathrm{U}_i(t,\Delta)$, are then calculated using the set difference operator as:

$$\mathrm{U}_i(t,\Delta) = S_i(t) - S_i(t-\Delta-1)$$

This measures the new unique skills compared to the previous time period, Δ days ago, which is typically a month or quarter. The final step is to determine the "technology adoption score" for the company by counting the total number of detections of the skills in $\mathrm{U}_i(t,\Delta)$ within the jobs posted over the orresponding preceding time period, Δ.

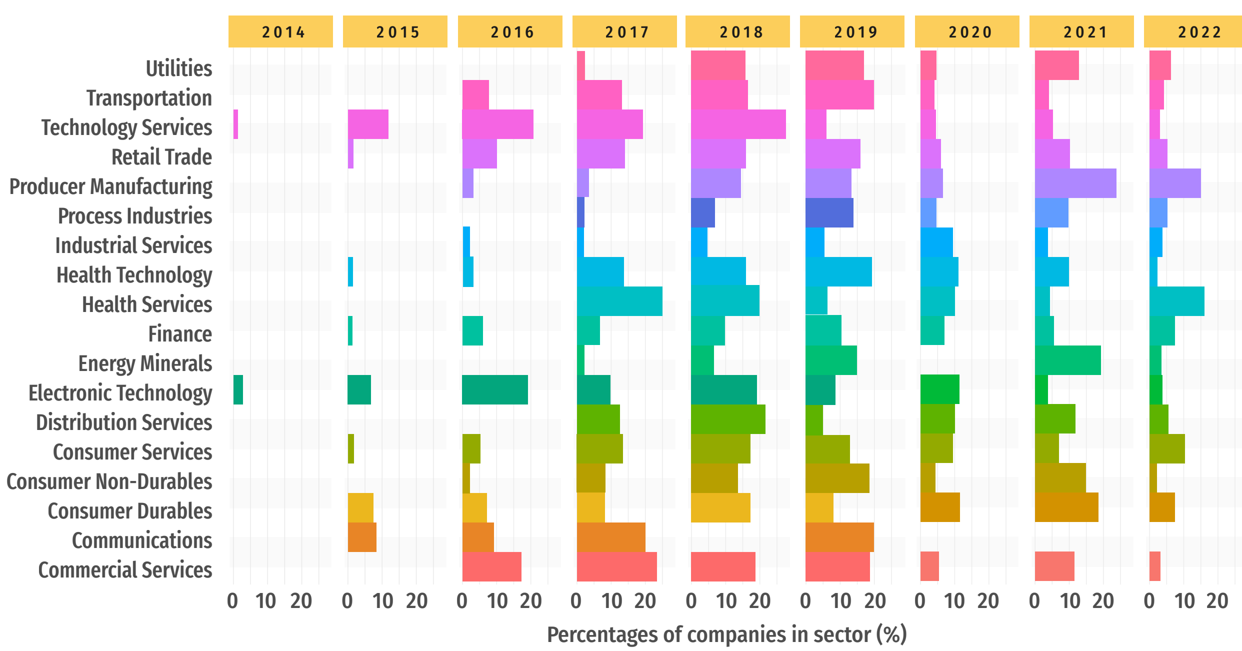


FIGURE 4. Lifetime of the novel skill Kubernetes across different sectors. *Source: RavenPack, January 2023*

1 A one-year initial buffer is employed from the start of the archive to generate a list of consolidated skills of a company. Similarly, a one-year buffer is applied when a new company is incorporated into our Top 1,000 US trading universe.

The central hypothesis of this study is that companies that continuously adopt novel technology skills are likely to exhibit higher levels of innovation and superior investment performance than their peers.

Note, however, that the signal we have created is always positive and that low scores in technology adoption should not be immediately interpreted as a sign of underperformance. Other key factors contributing to technological innovation, such as reskilling or upskilling existing employees, are not considered in this analysis.

The signal analyzed in this study may be particularly useful in investment strategies that allocate higher weight to innovative companies and lower weight to those with less technology adoption. We evaluate the signal using a long-only trading strategy relative to sector.

To illustrate the lifetime of a novel skill, in Figure 4 we show the example of Kubernetes[2] using its sector penetration over time, i.e., the percentage of companies per sector hiring that skill as novel. In 2014/2015, early adopters of Kubernetes were in the Technology Services and Electronic Technologies sectors.

However, over time, its use became widespread across all sectors. Currently, Kubernetes remains in high demand as a new skill in the Health Services and Product Manufacturers sectors.

2 RP_ENTITY_ID = 'C309EF'

4. Portfolio construction and backtesting

Our strategies are based on out-of-sample backtests from April 2014 through December 2022. Prior to this date, job descriptions were not available. To remove potential duplicates of job postings, we only count job posting events with event similarity days and title similarity days greater than or equal to one day.

As mentioned in the previous section, the technology adoption score is evaluated using a long-only strategy relative to sector. Performance is evaluated in excess-to-sector returns to provide a more accurate representation of the risk characteristics of each sector. The relative weights of each sector are proportional to their market cap and the portfolio rebalance is carried out daily, 30 minutes before market close, ensuring path-independence of the results.

FIGURE 5 shows the cumulative log returns of the strategy using a rolling window span, Δ, of a month. The strategy provides 2.8% Annualized Excess Returns relative to sector, with a 1.1 Information Ratio. The average Portfolio Size is large, with around 580 names, and an effective holding period of 18 days (5% daily turnover).

It's important to assess the stability of the signal against changes in parameters, despite its established robustness over time. **FIGURE 6** illustrates the impact of decreasing the portfolio's cross-section span from 100% to 10%. We observe an overall increase in per-trade returns, which indicates higher value for the larger scores. However, the reduced cross-section span also leads to a loss of diversification, resulting in a lower Information Ratio.

The choice of innovation period, Δ, has a significant impact on the signal's performance. To ensure representativeness of the adoption scores in the cross section, it is crucial that the selected time period is of adequate length, given that companies post job advertisements at varying frequencies. We find that the use of a one-month timescale for aggregation of job-based analytics is appropriate as it balances performance, portfolio size, and turnover. Values of Δ

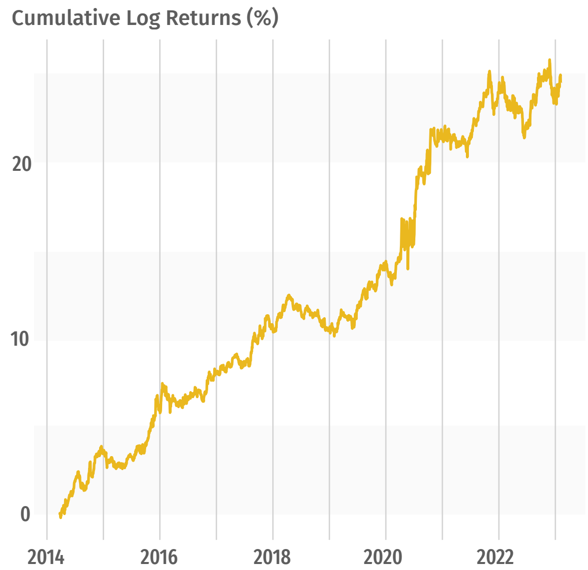


FIGURE 5. Cumulative log returns for the technology adoption signal using a one-month window for U.S. mid/large-cap companies. The strategy is long-only and is evaluated using excess to sector returns. *Source: RavenPack, January 2023*

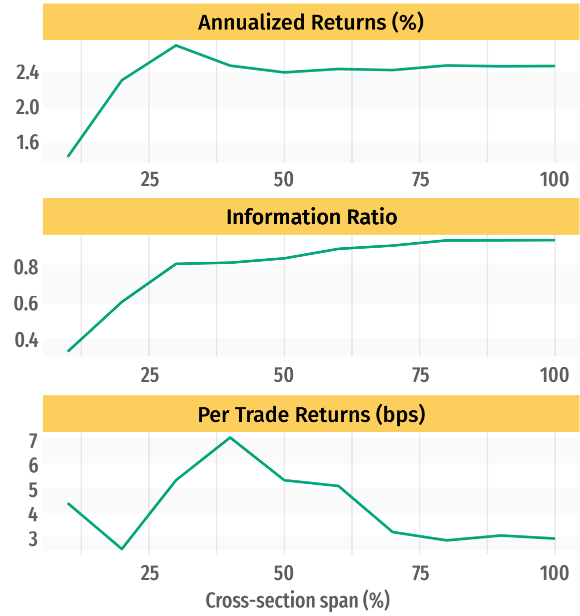


FIGURE 6. Effect of reducing the cross-section span on the performance of the technology adoption signal.
Source: RavenPack, January 2023

of less than one month yield insufficient performance. Extending the time window from one month to three months results in a decreased performance as the signal slows down beyond the one-month mark, as shown in **FIGURE 7**.

The alpha-generating potential of the strategy is evaluated using a conventional risk factor model.[1] The results, shown in **FIGURE 8**, indicate that alpha remains strong even when accounting for various risk factors. Here, the Information Ratio increases from 1.1 to 1.2 while the Annualized Excess Returns only decrease from 2.9% to 2.7%.

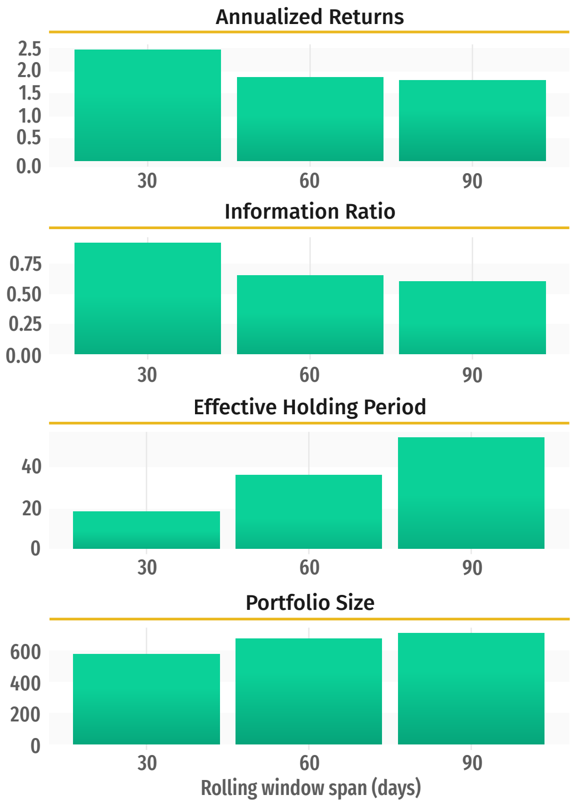


FIGURE 7. Effect of the rolling window △ on the performance of the technology adoption signal.
Source: RavenPack, January 2023

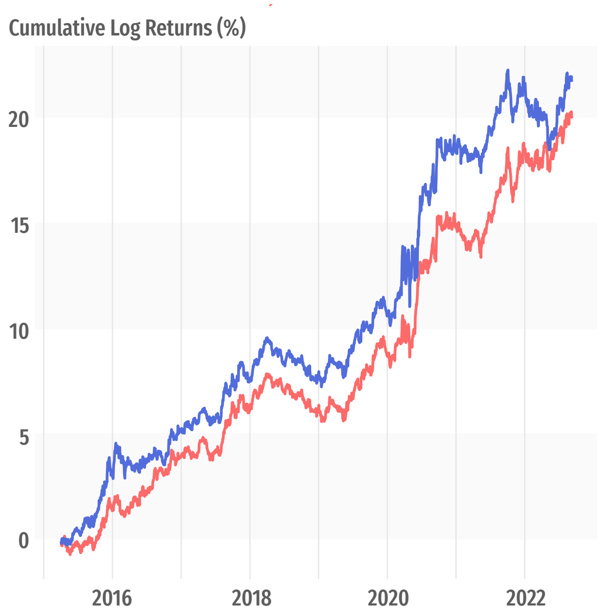


FIGURE 8. Cumulative log returns for the raw and factor-adjusted performance of the technology adoption signal for U.S. mid/ large-cap companies. *Source: RavenPack, January 2023*

1 We employ an in-house risk-factor model that uses an exponentially-weighted least squares dynamic regression of 10 common factors (Growth, Quality, Yield, Profitability, Investment, Market, Low Vol, Low Size, Momentum and Value). The raw vs. adjusted comparison is carried out from April 2014 to September 2022.

5. Combination with hiring growth

In **SECTION 3**, we noted that companies with more job postings are more likely to advertise for new skills. It was initially thought that the technology adoption signal would be highly correlated with the monthly hiring growth signal first introduced by Hafez et al.[1] However, our examination shows that the correlation is relatively weak, at around 15%, making it attractive to combine both signals for improved performance. We introduce an alternative implementation of the monthly hiring growth signal, which is assessed through a long-short, sector-neutral strategy. This implementation takes into account both the magnitude and direction of the signal after subtracting the cross-sectional median, and assigns relative weights between sectors based on market capitalization instead of signal volume. The limited correlation between the technology adoption and monthly hiring growth signals is supported by and enhanced combined performance[2], as demonstrated by an Information Ratio of 1.4 (vs. 1.0) and Annualized Excess Returns of 3.4% (vs. 2.3%) with a small decrease in Turnover when compared to the Hiring growth strategy, see **FIGURE 9** and **TABLE 1**. The large portfolio size, as summarized in **TABLE 1**, offers a chance to boost performance by targeting the signal's extreme values. This is demonstrated in **FIGURE 10**, which displays performance when selecting various quantities of the top (N/2) and bottom (N/2) values in the daily cross section, with a clear monotonic increase in returns when going more extreme in the signal selection.

	Hiring Growth	Tech Adoption	Combined Signal
Annualized Excess Return (%)	2.3	2.8	3.4
Information Ratio	1.0	1.1	1.4
Portfolio Size	708	581	733
Effective Holding Period (days)	6.3	18.3	7.4

TABLE 1. Performance of the backtesting strategy of Hiring Growth, Tech Adoption, and Combined Signal. U.S. mid/large-cap companies. Excess to market returns.
Source: RavenPack, January 2023

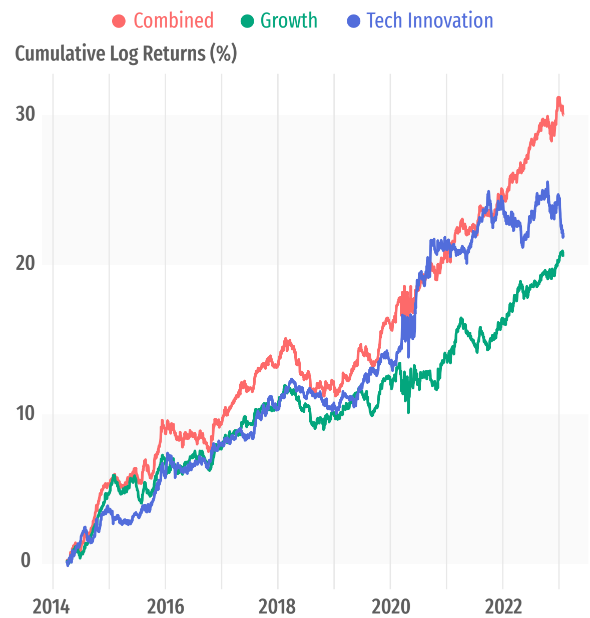


FIGURE 9. Cumulative log returns for the technology adoption, monthly hiring growth, and combined portfolio for U.S. mid/large-cap companies. Excess to market returns.
Source: RavenPack, January 2023

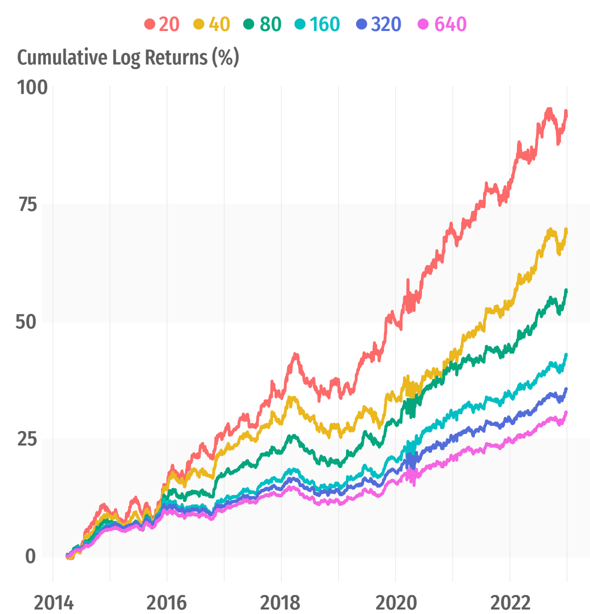


FIGURE 10. Cumulative log returns for the combined portfolio for selecting various quantities of the top (N/2) and bottom (N/2) values in the daily cross section. U.S. mid/large-cap companies. Excess to market returns. *Source: RavenPack, January 2023*

1 Hafez, P. et. al., Alpha Generation from Job Analytics, RavenPack Quantitative Research, 2022

2 To do this, we simply average the allocations of the two strategies, followed by a daily cross-sectional rescaling to ensure 50% long and 50% short exposure.

6. Conclusions

In this study, we used RavenPack Job Analytics and the Job Taxonomy framework to demonstrate the importance of employees' technology skills in predicting a company's investment performance. By quantifying companies' technology adoption, we were able to generate strong and robust alpha. A long-only strategy incorporating this signal achieved an Information Ratio of 1.1 and Annualized Excess Returns of 2.8% relative to sector, for a close-to-monthly effective holding period (5% daily turnover). By taking advantage of the low correlation between technology skills and monthly hiring growth and combining the two signals, we were able to achieve improved performance and generate an Information Ratio of 1.4 and Annualized Excess Returns of 3.4%.

The Job Taxonomy proved to be useful in measuring technology adoption and its use has laid the foundation for further exploration of the hiring landscape and changing hiring trends and its impact on company performance, which could provide valuable insights for investors, human resources, and technology companies.

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