Deutsche Bank
Markets Research

Global

Quantitative Strategy

Signal Processing

Date
19 May 2015

Macro and Micro JobEnomics

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Gleaning alpha and macro insights from job postings

What would you do if?

What would you do if you had access to over 44m unique job postings representing approximately 28,000 distinct private and public companies with over 32,000 new jobs posted daily as well as 16bn words captured in job posting descriptions?

Job postings and equity alpha

In this novel research piece, we utilize the LinkUp job posting dataset in search of new sources of alpha. We find that accounting and quant factors based on the job posting data set provide incremental and uncorrelated alpha. We also find that the textual or word components in job posting descriptions are indicative of current industry trends and fads.

Job postings and macro indicators

We further find that job postings are correlated to various job-centric macroeconomic indicators such as non-farm payrolls and the unemployment rate. Job postings can even assist portfolio managers with sector rotation strategies.

A rare and insightful dataset

As investment managers are continually in search of new and distinct sources of alpha, we think it's worthwhile to investigate the job posting dataset as a differentiated source of stock specific and macro alpha. We hope you enjoy the remainder of the report.

Source: gettyimages.com

Deutsche Bank Securities Inc.

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A letter to our readers

The monster of job postings

Recently, job and employment numbers have become a critical and highly scrutinized economic data point. This is because employment-related data is being closely monitored by the FED as they continually battle with the decision of when to raise the Federal Funds Target Rate. As such, investors are highly anticipatory and anxious of any changes in employment-related numbers and forecasts. Investor's attention has rotated to closely watching any employment-related indicators.

One issue with the traditional macroeconomic employment indicators is that they tend to be backward looking. They typically only measure whether individuals are currently employed or not (i.e. non-farm payrolls, initial jobless claims, unemployment rate, etc). In our opinion, what would be more applicable to investors is the outlook on future employment prospects.

Systematically gauging future job prospects is a challenging feat which involves gathering new datasets that are potentially predictive of future job growth. Luckily, we have taken this challenge upon ourselves. We have obtained a new data source called LinkUp, one of the largest job engines in the market. LinkUp crawls thousands of company websites for job postings and other data. What better metric to gauge future job prospects than job postings?

We start our analysis by introducing and examining the LinkUp dataset. The novel feature about this dataset is that it has job postings for individual companies. And, as such, we can form and test various stock-specific strategies based on this dataset. Do company job postings contain any predictive ability in forecasting their future stock prices?

The LinkUp dataset also provides the textual job description for each posting. We utilize this textual component along with a natural language processing algorithms to ascertain the current trends and fads in the job marketplace. Maybe current job trends can shed some light on the sector or market trends?

Lastly, we aggregate company level job metrics to attempt to forecast various macroeconomic indices including employment-based economic indicators. In summary, this research piece introduces a new and differentiated dataset and shows how investors can potentially utilize job postings for stock selection and global macro.

In the coming months, we will be publishing a series of reports and studies on rare yet insightful datasets. So please stay tuned. We hope you enjoy the remainder of our report.

Regards,

Yin, Javed, George and the quant team
Deutsche Bank Quantitative Strategy

The Jobs dataset

Introducing job postings

LinkUp is one of the largest and fastest growing job search engines. The company uniquely sources job postings data from thousands of company websites. LinkUp is essentially the backend service provider for various job search engines. Currently, the dataset is more focused on US companies; however, LinkUp is in the process of expanding its coverage globally.

LinkUp's search programs crawl the web to identify and archive job postings in real-time from companies' websites.

LinkUp's search programs crawl the web to identify and archive job postings in real-time from companies' websites. LinkUp also provides a multitude of detailed data analytics and predictive indicators. Figure 1 shows a sample of the job Meta data that is captured by LinkUp.

LinkUp provides the job posted/removed date along with the job title, category, location, website, as well as a unique job ID and employer/company code. LinkUp also provides the textual job description for each job posting (see Figure 2).

Figure 1: Sample job posting

Job Posting	Job Data
Date posted:	October 25, 2013
Date removed:	May 22, 2014
Company Name	DRW Trading Group
Job Title:	Software Engineer
Job Category:	Software Development
City, State, Zip Code, County:	Chicago, IL, 60602
Employer code:	8719
Job Category code:	152
Company URL:	http://www.drwtrading.com/

Source: LinkUp

Figure 2: Sample job textual description

Job Textual Description

DRW Trading Group is a principal trading organization, meaning all of our trading is for our own account, and all of our methods, systems and applications are solely for our own use. Unlike hedge funds, brokerage firms and banks, DRW has no customers, clients or investors. Using internally developed methods, models and technology, we trade across a wide range of asset classes both domestically and internationally. Founded in 1992, our mission is to empower a team of exceptional individuals to identify and capture trading opportunities in the global markets by leveraging and integrating technology, risk management and quantitative research. With that spirit, DRW has embraced the integration of trading and technology and has devoted extensive time, capital and resources to develop fast, precise and reliable infrastructure and applications. Our technology, along with our commitment and creativity, has greatly enhanced our ability to improve and expand our operations, solve complex problems and capture new opportunities.DRW is headquartered in Chicago, and has offices in New York and London, and employs over 450 people worldwide from many different disciplines and backgrounds.DRW is looking for exceptional individuals to become part of our dynamic organization. We are seeking undergraduate and graduate students for our full-time Software Engineer positions. Prior knowledge of financial markets is not required. Please note that you must apply for positions with DRW Trading Group through your University career services website and also directly on our company website at www.drw.com.Responsibilities:In-house proprietary software design, development, and testing focusing on data processing and analysis, research systems, and post-trade analysis. Work within a large-scale grid computing environment to minimize computation times and maximize throughput of research into algorithmic trading opportunities. Design and simulate prototype algorithmic trading strategies. Implement statistical and machine learning algorithms designed to perform efficiently on large data sets Work directly with Traders, ...

Source: LinkUp

Job postings have strong coverage

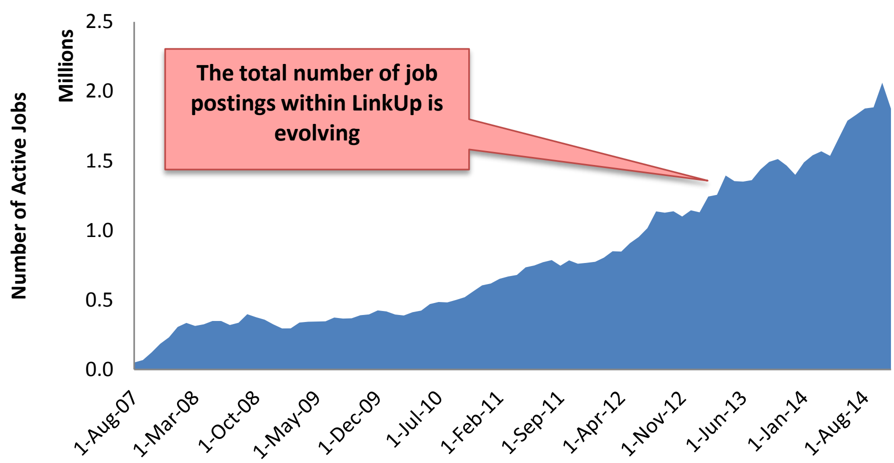
Prior to integrating and utilizing a new dataset, we need to understand the basic features of the dataset such as: coverage, sector, country or other effects that need to be accounted for when devising alpha strategies.

Using the LinkUp dataset, job postings can be classified into two broad categories: Jobs Created and Jobs Active. Jobs Created is simply the jobs created by a company and found by LinkUp on a daily basis. Active jobs are the job postings that are currently active and open (i.e. not filled or deleted).

Figure 3 shows the time series of the total number of active jobs in the LinkUp database. Note that this includes active jobs from public as well as private companies. The dataset commences August 1, 2007 and jobs postings are updated on a daily basis. The active job coverage is expanding. As of the end of 2014, LinkUp had approximately 2m active job postings.

As of the end of 2014, LinkUp had approximately 2m active job postings

Figure 3: Total number of active jobs for all companies in LinkUp

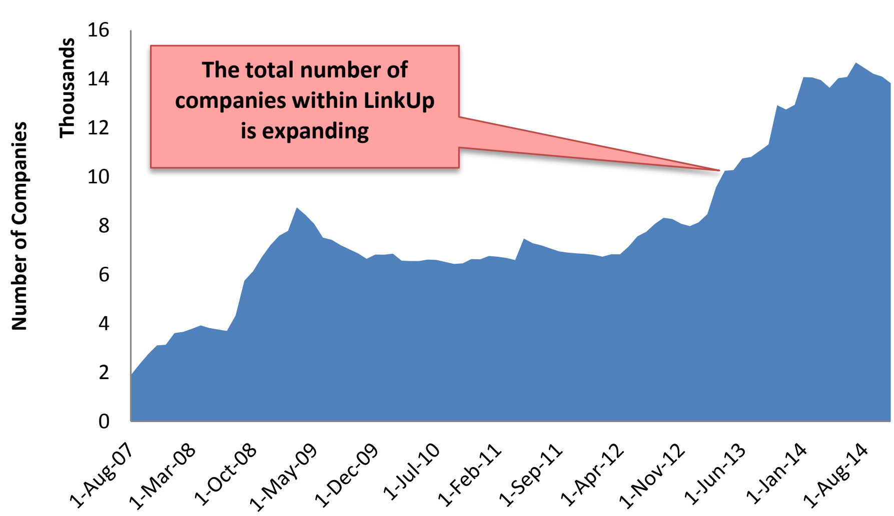


Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

One company can of course post multiple jobs. Figure 4 shows the time series of the number of unique public and private companies within the dataset. Again, the company coverage is expanding. At the end of 2014, LinkUp had approximately 14,000 unique companies in their database.

At the end of 2014, LinkUp had approximately fourteen thousand unique companies in their database

Figure 4: Total number of unique companies within LinkUp

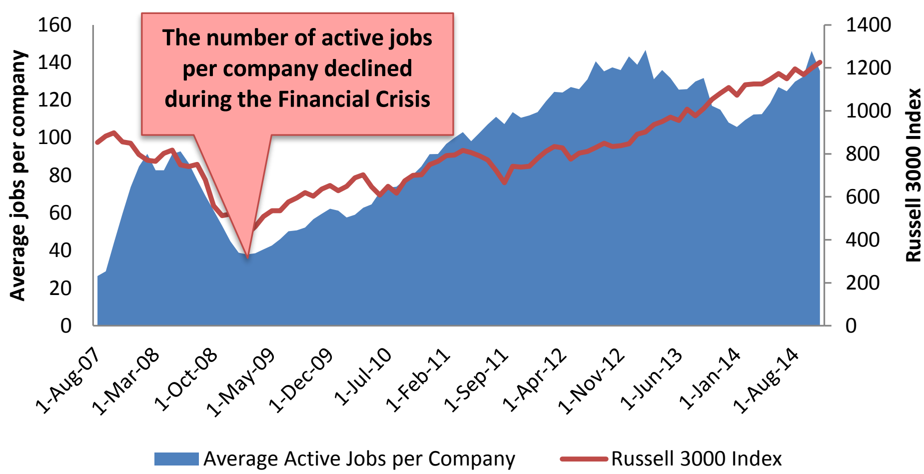


Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

The expansion in job postings and company coverage could be a result of an expanding dataset or continued economic job growth. To account for this duality, we also calculate the average active jobs per company. This is simply the total active jobs divided by the total number of companies (see Figure 5). This may be more representative of underlying economic job growth prospects. At a high level, we see that the average active jobs per company somewhat follow or mimic the equity market. In fact, during the financial crisis, the average active jobs per company were near an all-time low.

At a high level, we see that the average active jobs per company somewhat follows or mimics the market.

Figure 5: Average number of active jobs per company in LinkUp



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Although the LinkUp dataset contains both public and private job postings, investment manager may be more focused on job postings associated with public companies. After integrating the LinkUp dataset within our investment universe (i.e. the Russell 3000), we find the company coverage to be fairly strong.

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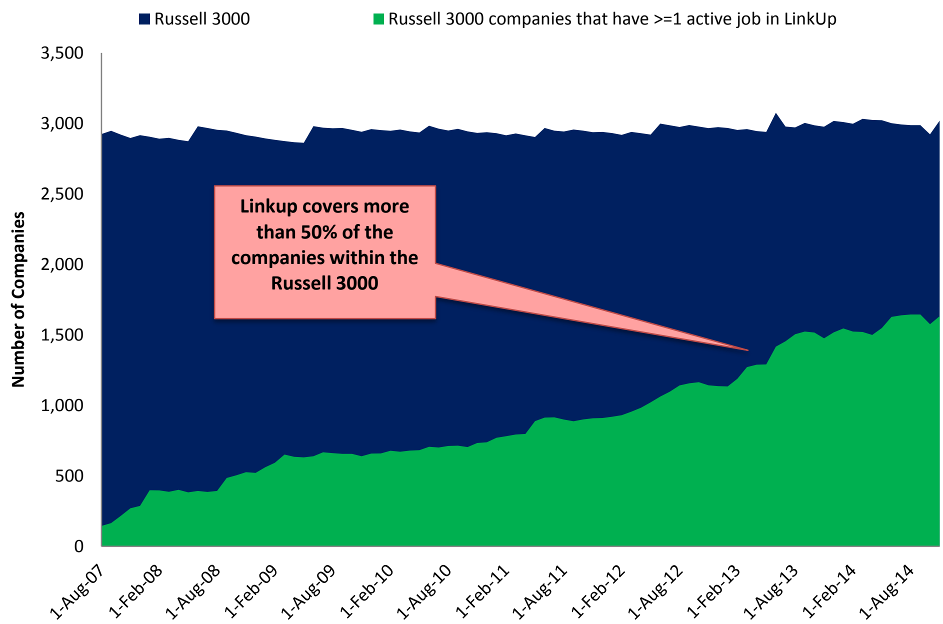
Figure 6 shows the time series coverage of companies with at least one job posting within the LinkUp dataset. As of the end of 2014, LinkUp covered over 50% of the companies within the Russell 3000. The company coverage continues to evolve within the US and globally.

LinkUp covers over 50% of the companies within the Russell 3000

Figure 6: Comparison of company coverage



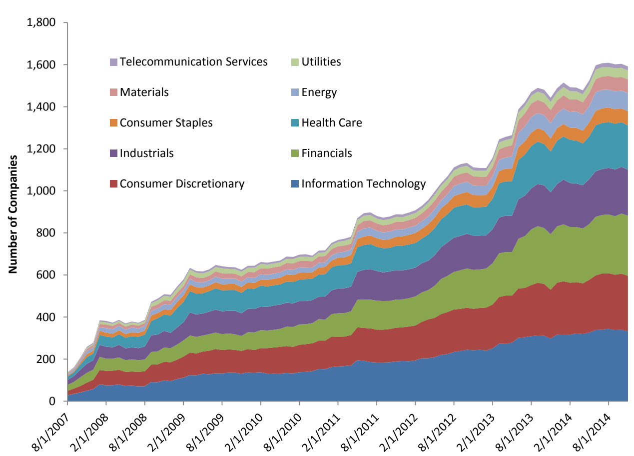
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Sectors are well represented

We find that the sector breakdown is fairly similar to the Russell 3000 constituents

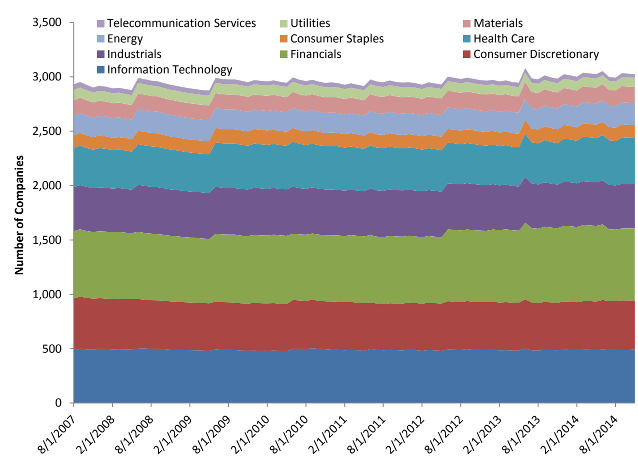
Next, we explore the sector coverage of all the companies within LinkUp that are a part of the Russell 3000 (Figure 8 and Figure 9). We find that the sector breakdown is fairly consistent with the Russell 3000 constituents. It is important to ensure that alpha is driven primarily by stock selection and not dominated by sector effects.

Figure 7: Number of companies by sector in LinkUp



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

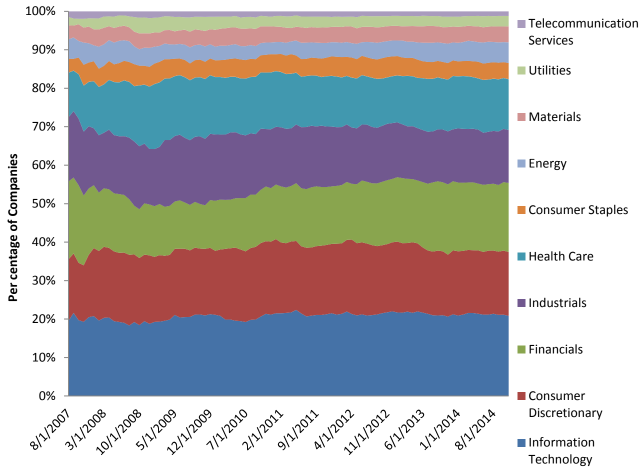
Figure 8: Number of companies by sector in Russell 3000



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

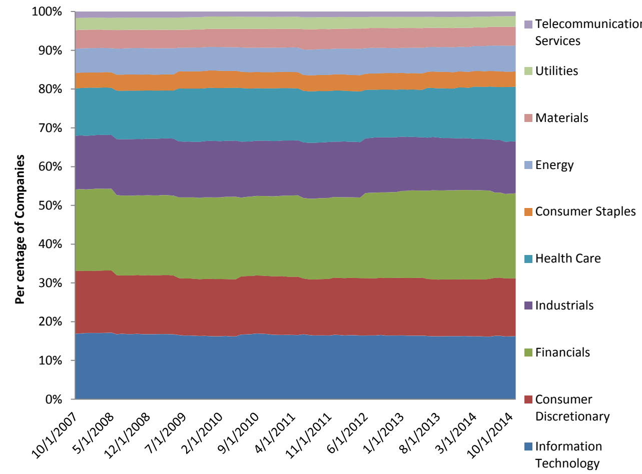
Figure 9 and Figure 10 show the same results but analyze the data as a percentage of sector breakdowns.

Figure 9: Percentage of companies by sector in LinkUp



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 10: Percentage of companies by sector in Russell 3000

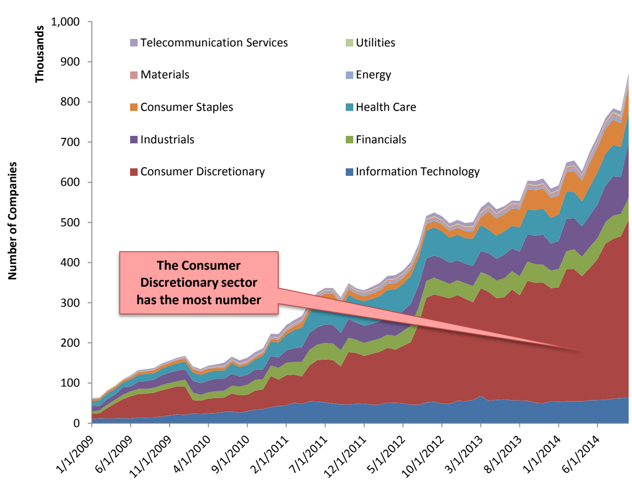


Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

It's also equally important to analyze the sector breakdown of active jobs. Figure 11 shows the sector breakdown of active jobs. Interestingly, most of the active jobs are dominated within the consumer discretionary sector. This is expected since service sectors are more labor intensive (Figure 12). This is an important finding to highlight. When we design factors or strategies based on the jobs data, we must keep in mind that depending upon the strategy; certain sectors may be favored. We discuss this in more detail later in the report.

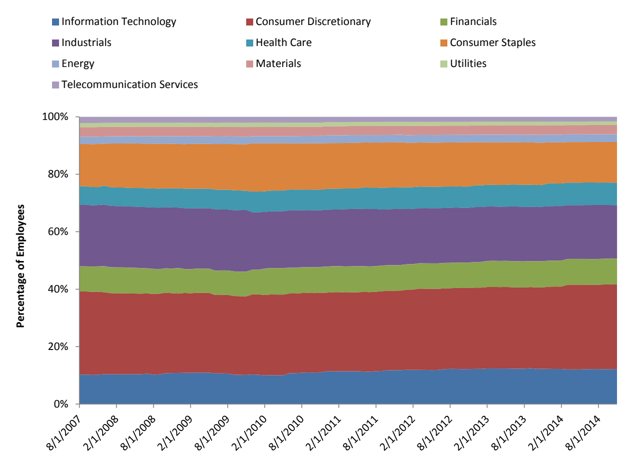
Interestingly, most of the active jobs are dominated within the consumer discretionary sector

Figure 11: Active jobs by sector in LinkUp



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 12: Percentage of employees by sector



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Job duration is increasing

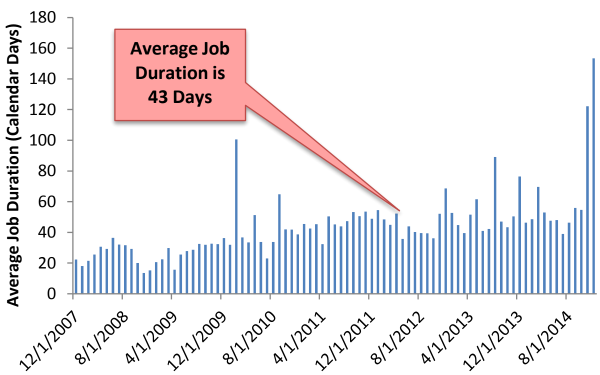
It takes on an average forty days to fill a job

Another interesting metric that can be derived from the jobs dataset is duration. Job duration is essentially the time (in days) required to fill a position.[1] The average job duration for companies within the Russell 3000 is approximately 40 days (see Figure 13). However, it seems that job duration is increasing.

Jobs within the consumer staples' sector take much longer to get filled whereas jobs in the financial sector get filled much quicker

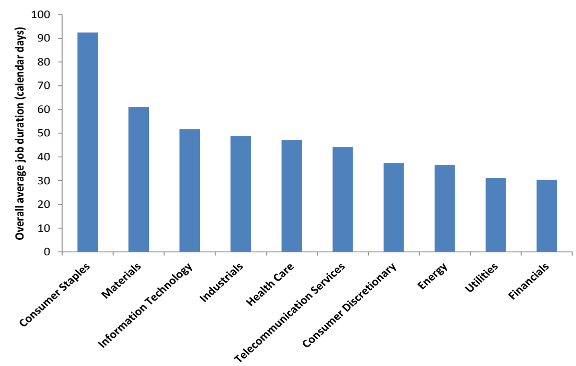
Interestingly, jobs within the consumer staples sector, (a relatively stable and low job turnover industry), take much longer to get filled whereas jobs in the financial sector (a more cyclical and high job turnover industry) get filled much quicker (see Figure 14).

Figure 13: Overall average job duration in Russell 3000



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 14: Average job duration by sector in Russell 3000

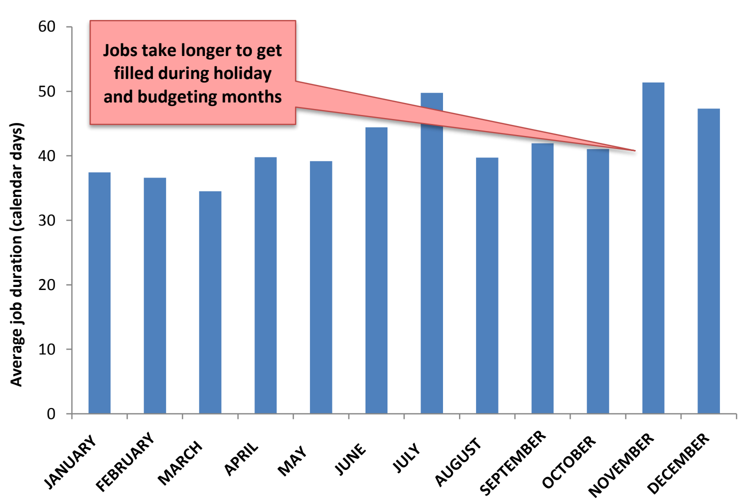


Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Understandably, jobs take longer to get filled during the summer months and at the end of the year

It's also interesting to analyze the average job duration by month. Interestingly, jobs get filled sooner during the first half of the year. Understandably, jobs take longer to get filled during the summer months and towards the end of the year. So, if you are looking for a new job, its best to kick start your search at the beginning of the year.

Figure 15: Percentage of active jobs by sector in DBEQS universe



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

[1] Note that our calculation of job duration does not distinguish between a job being filled and a job being deleted because it could not be filled.

Job trends and fads

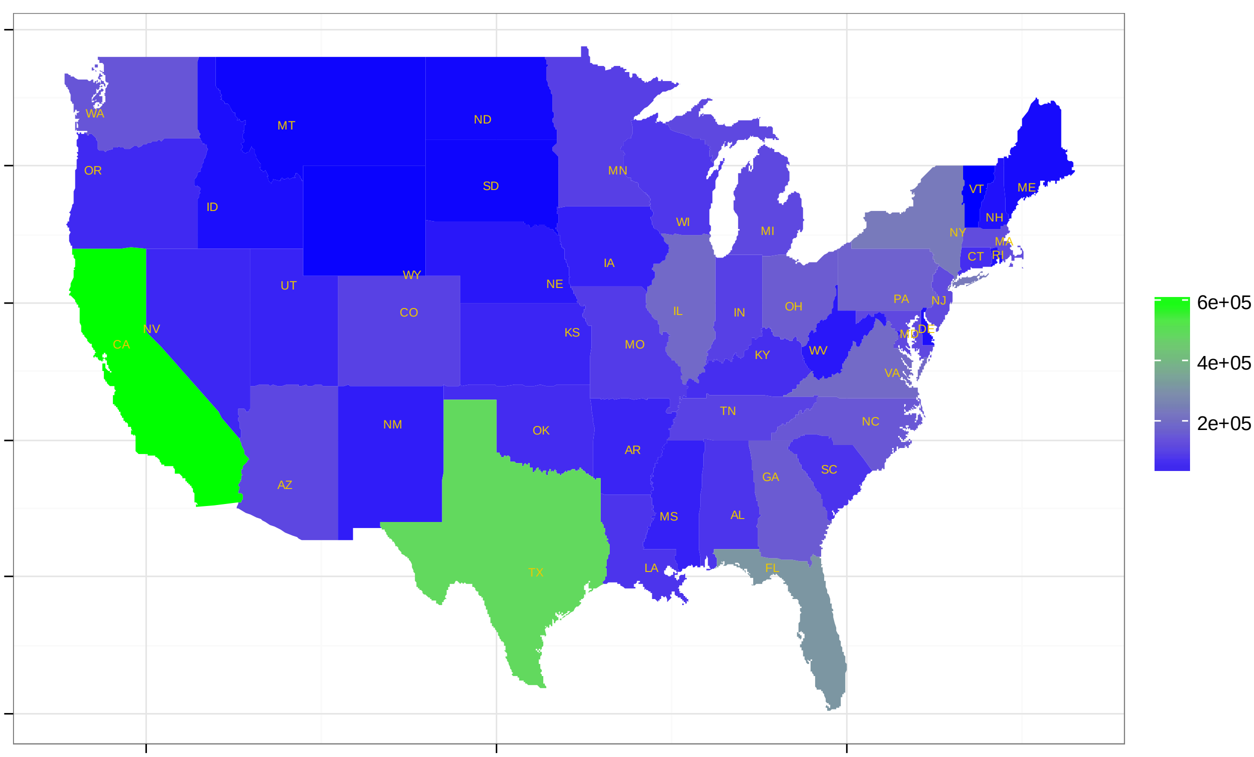
Geographical trends

As discussed earlier, the LinkUp jobs dataset also contains the location of the job (i.e. the state). We can utilize this information to glean some geographical information on job prospects. To start, we can simply chart the number of active jobs by state (Figure 16)[2].

This should be somewhat correlated to the population of each state. In fact, we find that the most populous states such as California, Texas, Florida, New York and Illinois have the most number of active jobs. The next logical question to ask is which states show the most significant job growth prospects?

In fact, we find that the most populous states such as California, Texas, Florida, New York and Illinois have the most number of active jobs

Figure 16: Average active jobs per state from 2010 to 2014



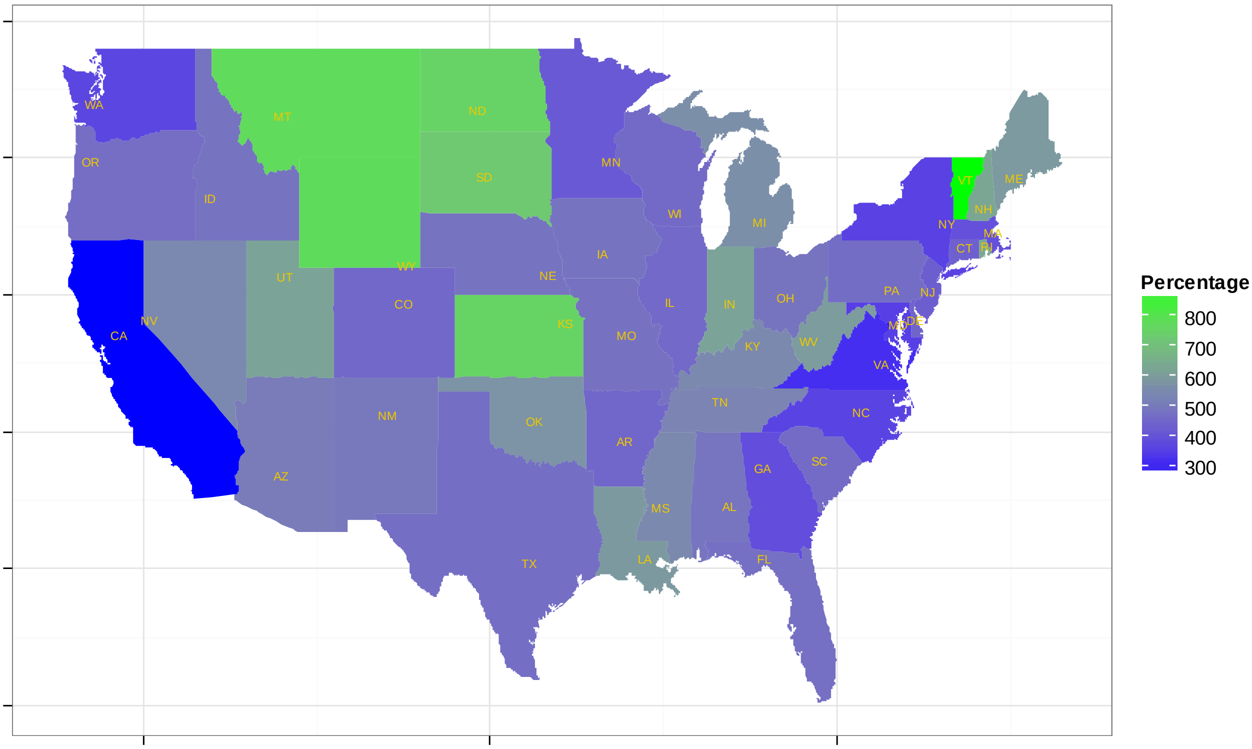
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 17 shows the active job growth from 2010 to 2014 by state. Essentially, this shows the number of jobs that have increased or decreased on a percentage basis over the past five years.

Interestingly, we see that job growth during the past five years has been primarily isolated in oil and agricultural rich states such as Wyoming, North Dakota, Montana, Oklahoma, Kansas, and Utah.

[2] Note that these are public company jobs that are a part of the Russell 3000 index.

Figure 17: Active job growth per state from 2010 to 2014



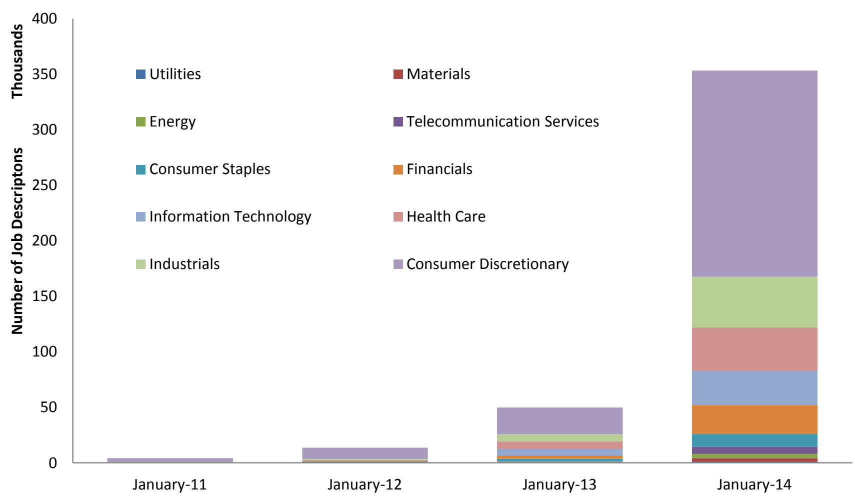
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Textual trends

As discussed earlier, the LinkUp dataset also contains the textual or word descriptions. This is intriguing for us as we can mine the textual job descriptions using natural language processing algorithms. This can potentially unravel key industry themes, trends and fads. The coverage of job descriptions is evolving. The vast majority of job descriptions contained in the LinkUp dataset commence from 2014 onwards (see Figure 18). Again, majority of the job descriptions are coming from the consumer discretionary sector.

We can mine the textual job descriptions using natural language processing algorithms

Figure 18: Coverage of textual job description by sector



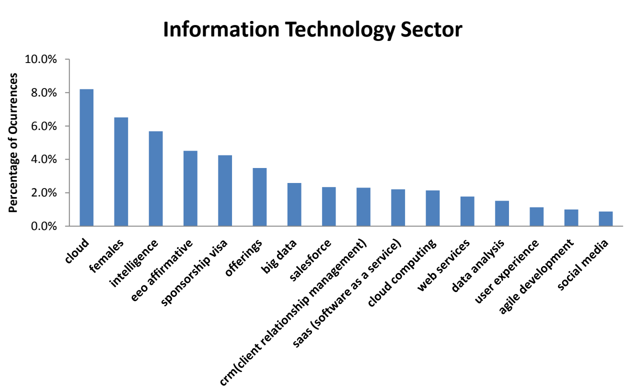
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Common words include: cloud computing, big data, CRM, SAAS, females, EEO affirmative…

After running the job descriptions through various language processing algorithms, we uncover some interesting themes. First, focusing on the information technology sector, some of the common technology themes we find are: cloud computing, big data, CRM, SAAS (software as a service), data analysis, agile development and social media (see Figure 19 and Figure 20). Interestingly, these are the current common trends occurring within the tech sector.

It is also worthwhile to point out the increased focused on employee diversity within the technology sector. Words such as females, EEO affirmative (equal opportunity and affirmative), and sponsorship visa also occur frequently in job postings.

Figure 19: Key words within the tech sector by occurrences



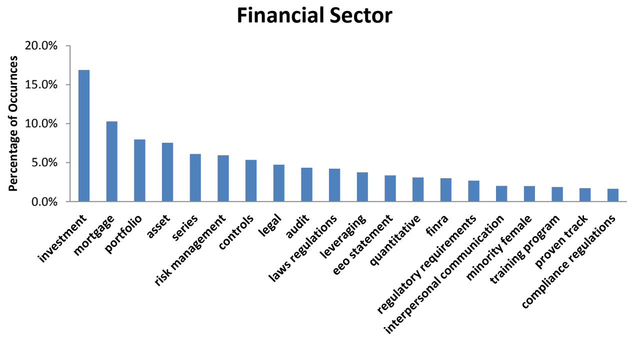
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 20: Visualize key words within the tech sector

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Next, we focus on the financial sector. Interestingly, words like mortgage, risk management, regulation, minorities, proven track record, females, and EEO statement are fairly popular.

Figure 21: Key words within the financial sector by occurrences



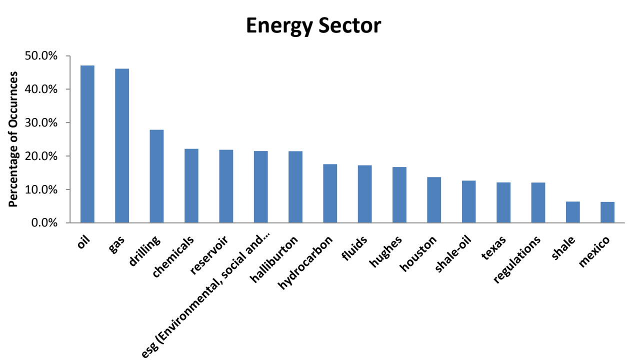
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 22: Visualize key words within the financial sector

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Transitioning to the energy sector, we find that the more popular words include: ESG (environmental, social, and governance), hydrocarbons, shale, shale-oil, and regulations (see Figure 23 and Figure 24). Again, this is in-line with the current industry trends within the energy sector.

Figure 23: Key words within the energy sector by occurrences



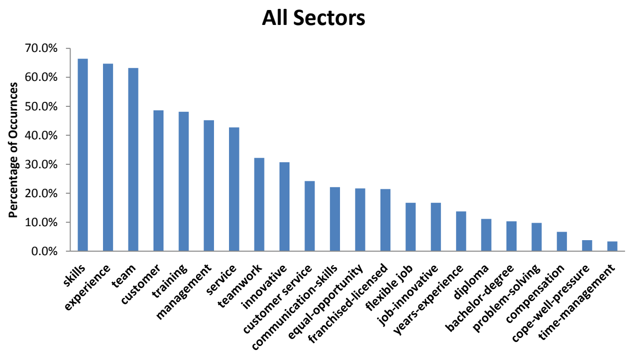
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 24: Visualize key words within the energy sector

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Analyzing the job descriptions for companies within the entire Russell 3000 universe unveils that many company are seeking employees with extensive job experience, team oriented, educated (with a bachelors degree) and innovated (see Figure 25 and Figure 26). The job posting data also reveals that most companies are equal opportunity employers.

Figure 25: Key words within all sectors by occurrences



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 26: Visualize key words within all sector

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Undoubtedly, more time series textual data would enable us to test whether word trends in job posting have some alpha selection ability. For example, sector rotation strategies may be correlated to job posting word trends. As the various job related datasets evolve and expand, we hope to do more of this type of research in the future.

Job micro alpha

Stock selection strategies and factors

Aside from the trends and fads in jobs, investment managers are concerned as to whether job posting related data contains any stock selection and return prediction ability. In this section, we explore in detail whether jobs posting data contains any untapped alpha.

We explore in detail whether jobs posting data contains any untapped alpha

To accomplish this, we form equity strategies or quant factors based on the jobs posting data. There are a numerous potential strategies that we can create based on the job posting data. We bucket these strategies into the following categories:

- Job Creation Factors: We develop various factors based on the number of jobs created per company within a month or year time frame. Since a larger company will likely create more jobs, we scale our job created factor by market cap, number of employees, total sales, total assets, and total earnings, respectively.[3]
- Growth in Job Creation: We develop various factors based on job creation growth. Essentially, we calculate the quarterly and annual growth in job creation per company. Additionally, we compare job creation growth versus earnings growth. The rationale is that if a company is hiring faster than its earnings growth, this could be a warning sign. We also compare job creation growth to growth in sales, total assets, and market cap.

We develop various factors based on job creation growth.

- Job Active Factors: We develop various factors based on the number of active jobs per company within a month or year time frame. Since a larger company will likely have more active jobs, we again scale our job created factor by market cap, number of employees, total sales, total assets, and total earnings, respectively.

We develop various factors based on the number of active jobs per company within a month or year time frame

- Growth in Active Jobs: We develop various factors based on active job growth. Essentially, we calculate the quarterly and annual growth in active jobs per company. Additionally, we compare active job growth versus earnings growth. Again, the rationale is that if a company has faster growth in active jobs than earnings or sales growth, this could be a red flag. We also compare active job growth to growth in sales, total assets, and market cap.
- Employment Growth: We develop various factors based on the number of total employees per company.[4] Since a larger company will likely have more employees, we again scale the number of employees by market cap, total sales, total assets, and total earnings, respectively. We also look at the year-over-year growth in the number of employees.

We develop various factors based on the number of total employees per company

Figure 27 provides a summary of all the factors we created. Next, we form equally weighted long/short portfolios based on these factors. We backtest these portfolios over a six-year period using monthly rebalancing. All the factors are backtested over the same period so that portfolio returns across all strategies are comparable.

[3] Note we also used an OLS regression to neutralize for size effects. These factors are denoted with a *.

[4] Note that the employee data is obtained from Compustat.

Figure 27: Potential job alpha factors

Description	Factor Groups	Backtesting Months	Description
Employee Number/Maket Cap	Employee Factors	72	EMP_to_MKTCAP
Employee Number/Total Assets		72	EMP_to_ATQ
Employee Number/Total Income		72	EMP_to_INCOME
Monthly Created Jobs /Number of Employees		72	JOBS_CREATED_MON_TO_EMP
Annual Employee Growth		72	EMP_YR_GROWTH
Annually Created Jobs/Number of Employees		72	JOBS_CREATED_YR_TO_EMP
Monthly Active Jobs /Number of Employees		72	JOBS_ACTIVE_MON_TO_EMP
Employee Number/Total Sales		72	EMP_to_SALES
Annually Active Jobs/Number of Employees		72	JOB_ACTIVE_YR_TO_EMP
Monthly Active Jobs/Total Asset	Active Job Factors	72	Monthly Active Jobs/Total Asset
Monthly Active Jobs /Number of Employees		72	Monthly Active Jobs /Number of Employees
Monthly Active Jobs/Net Income		72	Monthly Active Jobs/Net Income
Monthly Active Jobs/Market Cap		72	Monthly Active Jobs/Market Cap
Monthly Active Jobs/Total Sales		72	Monthly Active Jobs/Total Sales
Annually Active Jobs/Total Assets		72	Annually Active Jobs/Total Assets
Annually Active Jobs/Number of Employees		72	Annually Active Jobs/Number of Employees
Annually Active Jobs/Net Income		72	Annually Active Jobs/Net Income
Annually Active Jobs/Market Cap		72	Annually Active Jobs/Market Cap
Annually Active Jobs/Total Sales		72	Annually Active Jobs/Total Sales
Quaterly Active Job Number Growth	Active Job Growth Factor	72	Quaterly Active Job Number Growth
Annually Active Job Number Growth		72	Annually Active Job Number Growth
Active Job Growth Quaterly - Total Quaterly Asset Growth		72	Active Job Growth Quaterly - Total Quaterly Asset Growth
Active Job Growth Annually - Total Annually Asset Growth		72	Active Job Growth Annually - Total Annually Asset Growth
Active Job Growth Quaterly - Net Income Quaterly Growth		72	Active Job Growth Quaterly - Net Income Quaterly Growth
Active Job Growth Annually - Net Income Growth Annually		72	Active Job Growth Annually - Net Income Growth Annually
Active Job Growth Quaterly - Market Cap Quaterly Growth		72	Active Job Growth Quaterly - Market Cap Quaterly Growth
Active Job Growth Annually - Market Cap Annually Growth		72	Active Job Growth Annually - Market Cap Annually Growth
Active Job Growth Quaterly - Total Sales Quaterly Growth		72	Active Job Growth Quaterly - Total Sales Quaterly Growth
Active Job Growth Annually - Total Sales Annually Growth		72	Active Job Growth Annually - Total Sales Annually Growth
Active Job Growth Annually - Total Asset Quaterly Growth		72	Active Job Growth Annually - Total Asset Quaterly Growth
Active Job Growth Annually - Net Income Quaterly Growth		72	Active Job Growth Annually - Net Income Quaterly Growth
Active Job Growth Annually - Market Cap Quaterly Growth		72	Active Job Growth Annually - Market Cap Quaterly Growth
Active Job Growth Annually - Total Sales Quaterly Growth		72	Active Job Growth Annually - Total Sales Quaterly Growth
Monthly Created Jobs/Total Asset	Job Creation Factor	72	Monthly Created Jobs/Total Asset
Monthly Created Jobs /Number of Employees		72	Monthly Created Jobs /Number of Employees
Monthly Created Jobs/Net Income		72	Monthly Created Jobs/Net Income
Monthly Created Jobs/Market Cap		72	Monthly Created Jobs/Market Cap
Monthly Created Jobs/Total Sales		72	Monthly Created Jobs/Total Sales
Annually Created Jobs/Total Assets		72	Annually Created Jobs/Total Assets
Annually Created Jobs/Number of Employees		72	Annually Created Jobs/Number of Employees
Annually Created Jobs/Net Income		72	Annually Created Jobs/Net Income
Annually Created Jobs/Market Cap		72	Annually Created Jobs/Market Cap
Annually Created Jobs/Total Sales		72	Annually Created Jobs/Total Sales
Quaterly Created Job Number Growth	Job Creation Growth Factor	72	Quaterly Created Job Number Growth
Annually Created Job Number Growth		72	Annually Created Job Number Growth
Created Job Growth Quaterly - Total Quaterly Asset Growth		72	Created Job Growth Quaterly - Total Quaterly Asset Growth
Created Job Growth Annually - Total Annually Asset Growth		72	Created Job Growth Annually - Total Annually Asset Growth
Created Job Growth Quaterly - Net Income Quaterly Growth		72	Created Job Growth Quaterly - Net Income Quaterly Growth
Created Job Growth Annually - Net Income Growth Annually		72	Created Job Growth Annually - Net Income Growth Annually
Created Job Growth Quaterly - Market Cap Quaterly Growth		72	Created Job Growth Quaterly - Market Cap Quaterly Growth
Created Job Growth Annually - Market Cap Annually Growth		72	Created Job Growth Annually - Market Cap Annually Growth
Created Job Growth Quaterly - Total Sales Quaterly Growth		72	Created Job Growth Quaterly - Total Sales Quaterly Growth
Created Job Growth Annually - Total Sales Annually Growth		72	Created Job Growth Annually - Total Sales Annually Growth
Created Job Growth Annually - Total Asset Quaterly Growth		72	Created Job Growth Annually - Total Asset Quaterly Growth
Created Job Growth Annually - Net Income Quaterly Growth		72	Created Job Growth Annually - Net Income Quaterly Growth
Created Job Growth Annually - Market Cap Quaterly Growth		72	Created Job Growth Annually - Market Cap Quaterly Growth
Created Job Growth Annually - Total Sales Quaterly Growth		72	Created Job Growth Annually - Total Sales Quaterly Growth

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

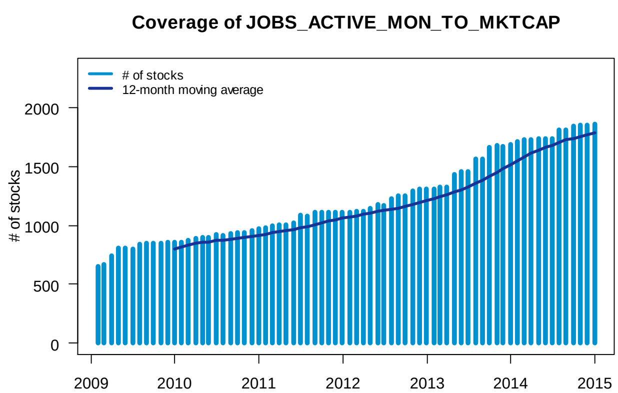
Before comparing the performance of all the factors, we examine the backtesting results of a select few job factors to better understand the return structure.

Individual strategy results

We start by analyzing the performance results for a specific factor: active jobs within the month scaled by market cap. Figure 28 shows the factor coverage which is expanding. More than half the stocks in the Russell 3000 are included within the LinkUp dataset. Figure 29 shows the factor quantile values. It shows that the long leg of the portfolio typically includes companies that have between 4% -10%percent of active jobs as a function of market cap.

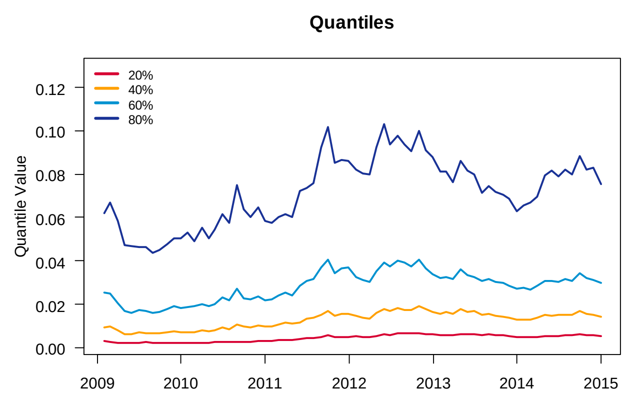
More than half the stocks in the Russell 3000 are included within the LinkUp dataset

Figure 28: Coverage - jobs created per year/market cap



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 29: Quantiles - jobs created per year/market cap

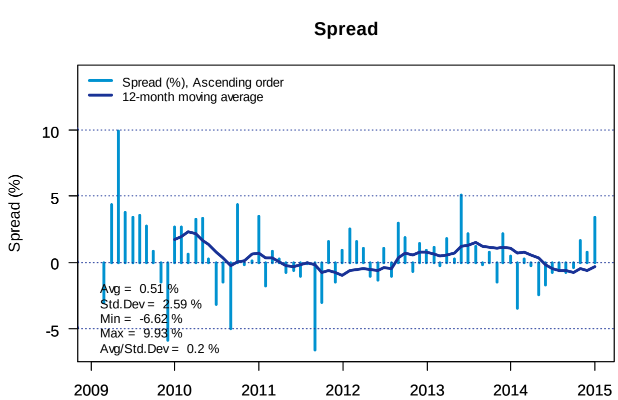


Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 30 shows the time series long/short monthly return of the job strategy. The performance is fairly strong with a monthly return of approximately 50 bps; albeit the strategy showed strong performance in 2009. Figure 31 shows the returns of each quintile portfolio. The return pattern is fairly monotonic meaning that companies with more hiring (adjusted for market cap) tend to show better performance.

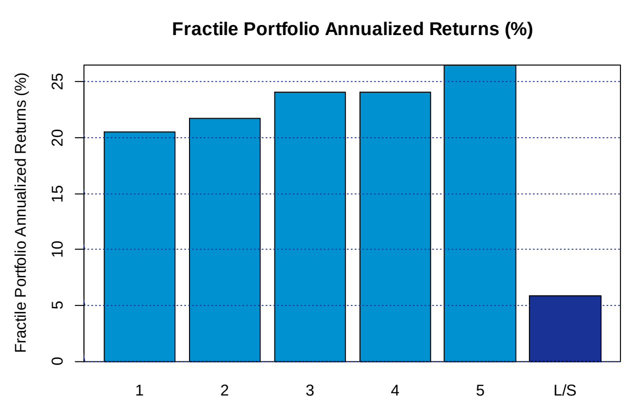
The performance is fairly strong with a monthly return of approximately 50 bps

Figure 30: Long/short spread - jobs created per year/market cap



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 31: Quintile returns - jobs created per year/market cap

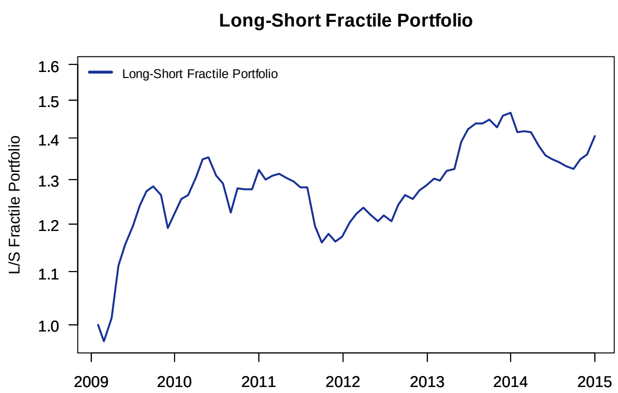


Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 32 shows the strategy's cumulative performance. We also find that the strong performance mostly comes from two periods: 2009 and 2012 to 2014. Lastly, the monthly two-way turnover of the strategy is modest at approximately 50%[5] (see Figure 33). This is a good finding as it implies that trading costs should not be too impactful on the strategy.

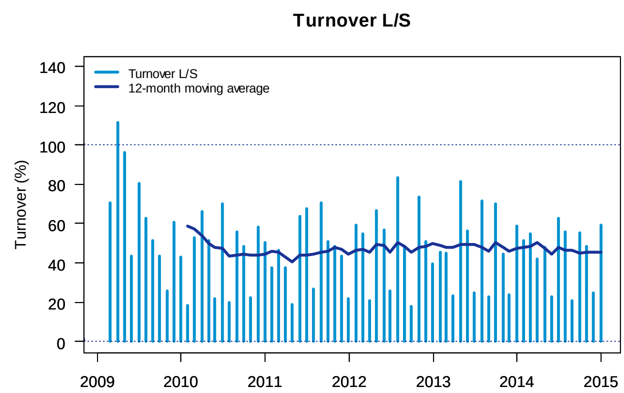
The turnover of the strategy is fairly low at around 50%.

Figure 32: Wealth - jobs created per year / market cap



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 33: Turnover - jobs created per year / market cap

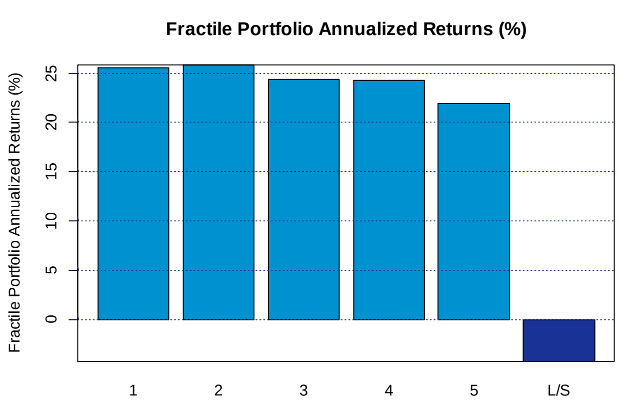


Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

We also briefly analyze the performance results for active job growth factors. To form this factor, we calculate the annual growth in active jobs per company. Next, we compare active job growth versus market cap growth. Again, the rationale is that if a company has faster growth in active jobs than its market cap, this could be a warning sign. The empirical results confirm our intuition. Figure 34 and Figure 35 show that companies that grow their active jobs faster than their market cap tend to underperform. Note that a portfolio strategy that utilizes this factor would essentially underweight or short companies where job growth outpaces market cap growth.

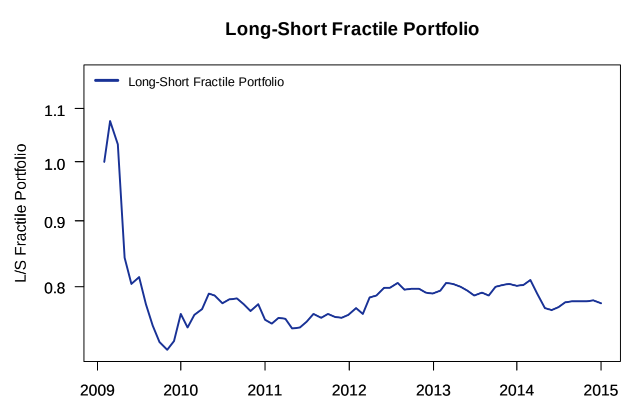
The rationale is that if a company has faster growth in active jobs than its market cap, this could be a red flag

Figure 34: Quintile returns – active annual jobs growth minus market cap growth



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 35: Wealth – active annual jobs growth minus market cap growth



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

[5] Note that the maximum turnover is 400%.

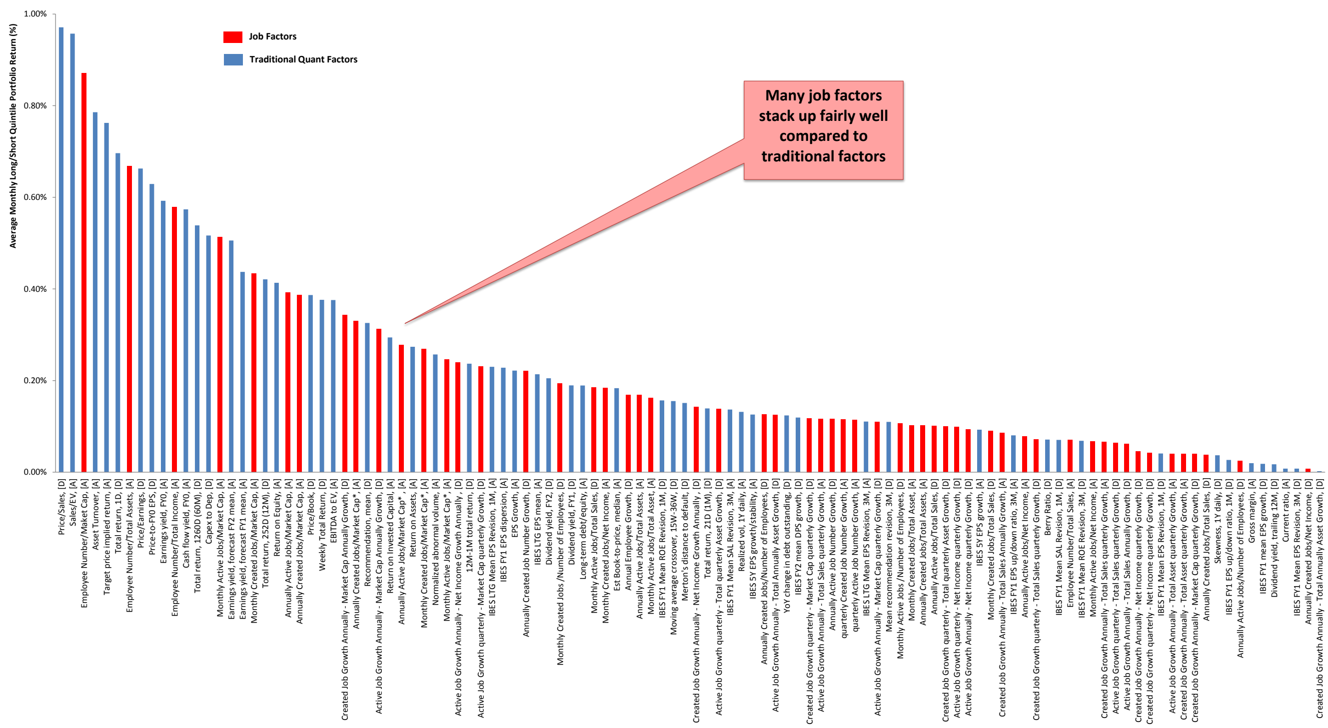
Now that we have briefly glimpsed the performance results for two job factors, next we analyze the performance of all the job factors and compare their performance to traditional quantitative factors.

Overall backtesting results

The job-based factors stack up fairly well compared to traditional quant factors backtested over the same period

Figure 36 shows the monthly return of the job factors alongside the traditional quant factors. The results are promising. The job-based factors stack up fairly well compared to traditional quant factors backtested over the same period. In fact, most of the employee, job creation, and active job-based factors showed good relative performance. Job growth factors showed moderate performance as well.

Figure 36: Long/short monthly quintile return spread of traditional and job factors



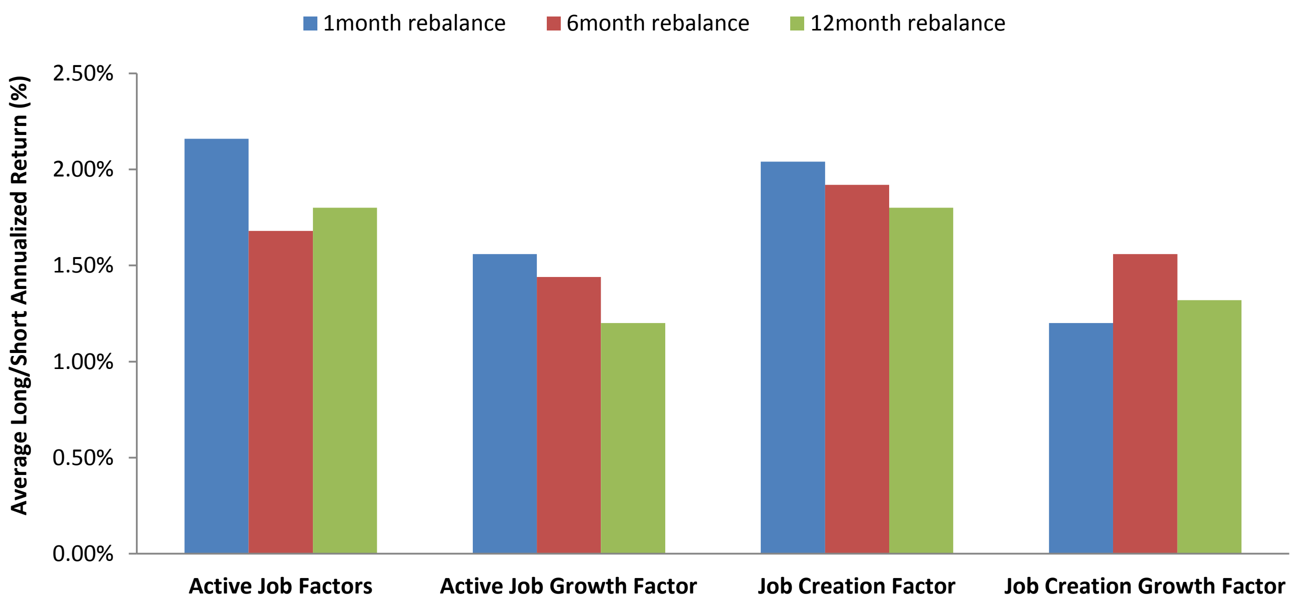
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

We would hypothesize that companies may reap the benefits off added innovation, productivity, revenue etc… that coincide with employee growth, several months after jobs are posted and new employees commence

Thus far we have backtested our portfolios using a one-month rebalance frequency. However, we would hypothesize that companies may reap the benefits of added innovation, productivity, revenue etc., that coincide with employee growth, several months after jobs are posted and new employees commence. As such, we re-test our job growth factors using longer rebalance frequencies. In particular, we test using a one-month, six-month, and 12-month rebalance frequency.

Figure 37 compares the performance of all the job factors using a one-month, six-month, and 12-month rebalance frequency. The results are interesting. The one-month rebalance frequency still beats most other rebalance frequencies. However, we still see strong performance with less frequent portfolio rebalances. In fact, most job growth factors show even better returns using longer rebalance frequencies (i.e. six or 12 month).

Figure 37 Long/short monthly quintile return spread of job factors using various rebalance frequencies

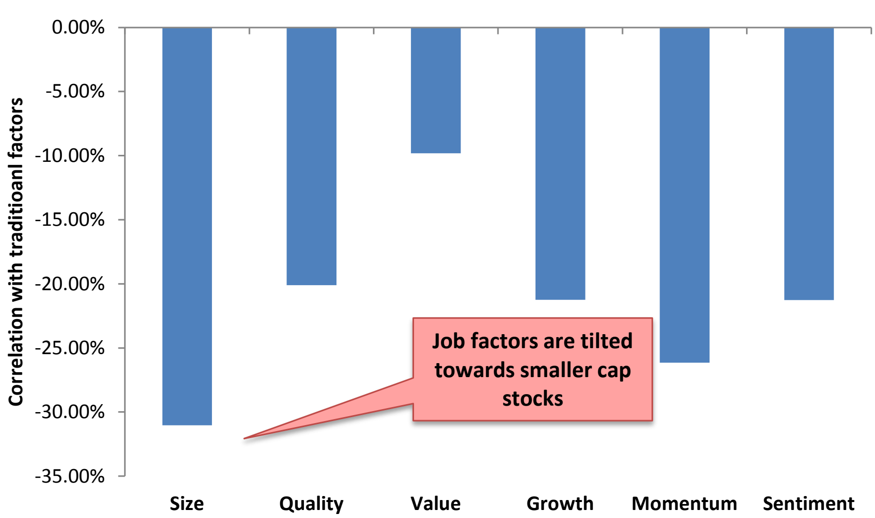


Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 38 shows the correlation between the active jobs per month factor and typical quantitative factor portfolios.[6] Interestingly, the job factor is negatively correlated to typically quantitative strategies. This is a promising finding as it suggests that the inclusion of the job factor into a multi-strategy portfolio is likely to improve diversification. It is also important to note that the job factor has a small cap tilt.

Interestingly, the job factor is negatively correlated to typically quantitative strategies. This is a promising finding as it suggests that the inclusion of the job factor into a multi-strategy portfolio will improve diversification

Figure 38: Overall correlation between job and traditional quant factors



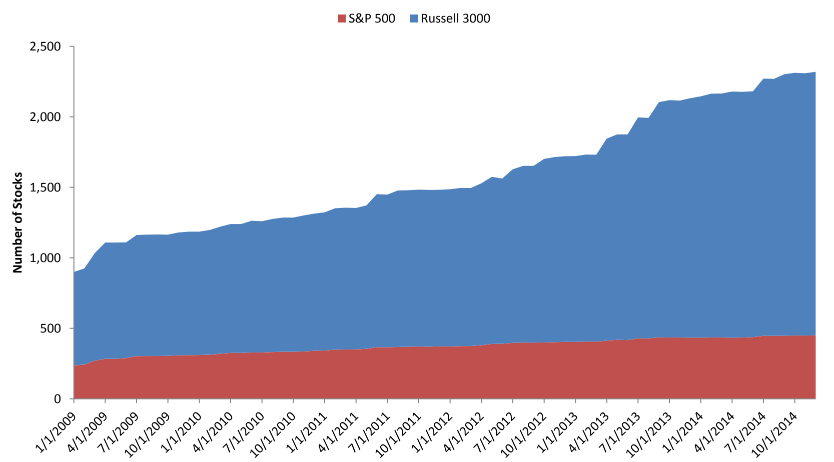
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

[6] Note that the job factor for this analysis is active jobs within the month scaled by market cap. The market cap scaling is done by using an OLS regression.

The next logical question to ask is whether these job factors perform well in a larger cap universe. This should provide some insight into whether the small cap size tilt is the main driver and source of alpha. Recall that LinkUp currently covers more than 50% of the stocks within the Russell 3000 universe and approximately 90% of the stocks in the S&P 500 (see Figure 39).

Is the small cap size tilt (or other anti-quant tilts) the main drivers and sources of alpha? Or is there incremental alpha in job-related postings?

Figure 39: Job factor coverage in different universes

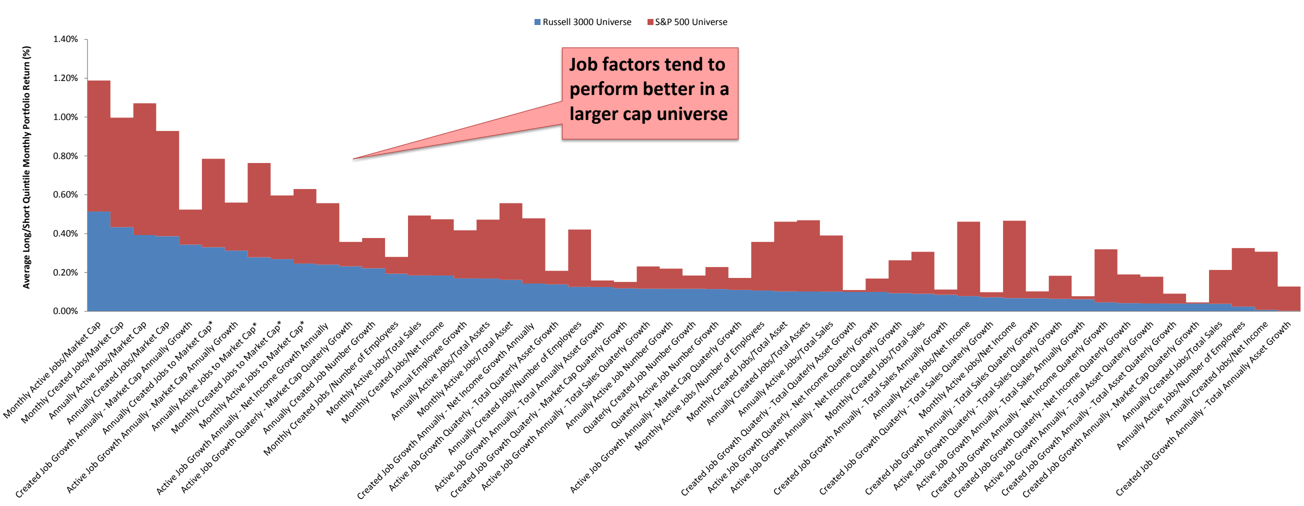


Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Next, we backtest the performance of the jobs factors within the S&P 500 universe and analyze the portfolio quintile return performance (Figure 40). Interestingly, we find that the job-related factors perform better in a large-cap universe.

Interestingly, we find that the job related factors perform slightly better in a large-cap universe

Figure 40 Long/short monthly quintile return spread of job factors using different investment universes

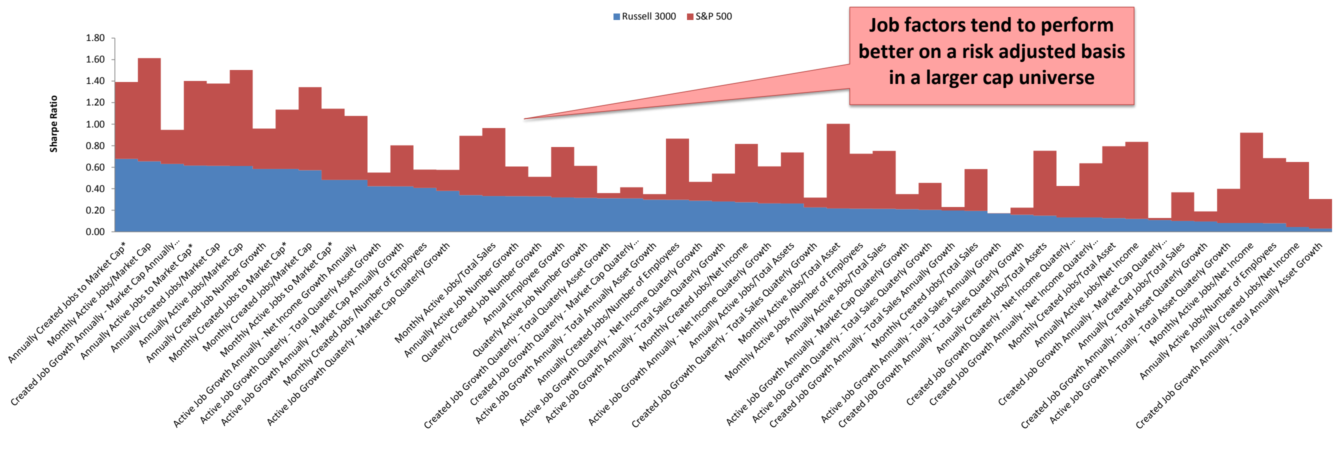


Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Simply comparing the long/short quintile portfolio return performance may be somewhat inappropriate since the portfolios have different number of stocks. A better measure may be to analyze the Sharpe ratio of each factor (Figure 41). Interestingly, we find similar results. Job-related factors perform slightly better in a large-cap universe on a risk adjusted basis. This is a promising finding, since most traditional quant factors struggle to add alpha within a large cap universe.

Job-related factors perform slightly better in a large-cap universe on a risk adjusted basis

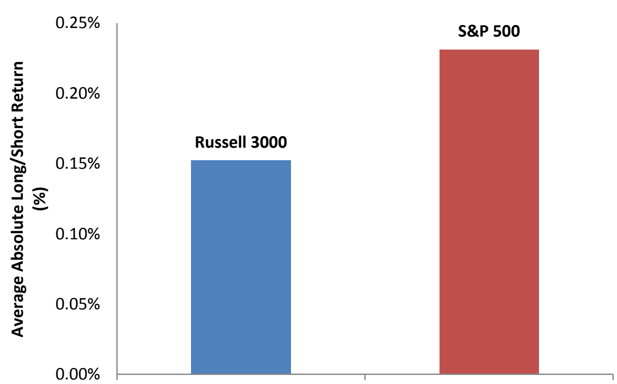
Figure 41 Information ratio of job factors using different investment universes



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

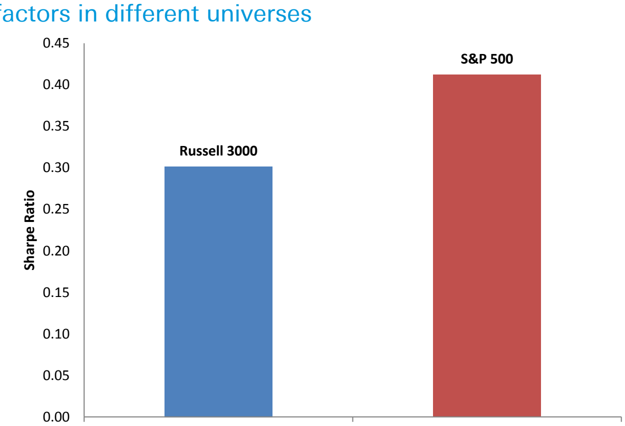
Figure 42 and Figure 43 summarize our findings and reiterate that job related factors tend to perform better within a large cap universe.

Figure 42: Compare average long/short spread of all jobs related factors in different universes



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 43: Compare average Sharpe of all jobs related factors in different universes



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Job macro alpha

In the previous section, we showed that the job posting dataset has some underlying stock selection ability. Motivated by Choi and Varian [2011], who use Google Trends data to predict the unemployment rate, in this section, we explore whether the job posting dataset can be "employed" to aid in the forecasting of macroeconomic indicators respectively, including employment indicators.

Macroeconomic indicators

We start by compiling a small set of macroeconomic indicators that we intuitively think can be forecasted using the jobs posting dataset. The unemployment rate, jobless claims, and non-farm payrolls are the obvious choices. However, undoubtedly, job growth has a multiplier effect and can hence benefit other industries.

As such, we attempt to forecast the Cash-Shiller national home price index, the purchasing managers index (PMI-an indicator of the overall economic cycle), retail sales, and consumer sentiment. Figure 44 shows all the macroeconomic indicators in our study.

Figure 44: Various macro-economic indicators tested

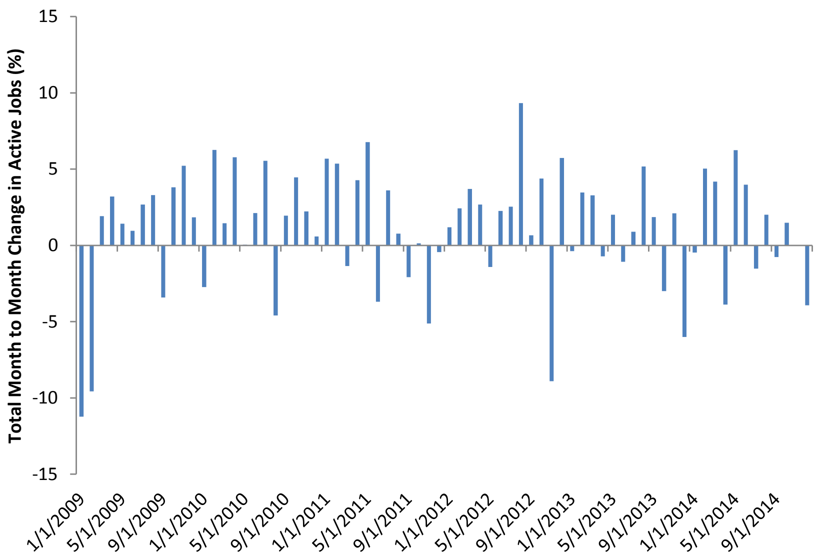
Macro-Economic Indicators	Description
Case-Shiller U.S. National Home Price Index	A leading measures of U.S. residential real estate prices, tracking changes in the value of residential real estate both nationally
Total Nonfarm Private Payroll Employment	A statistic researched, recorded and reported by the U.S. Bureau of Labor Statistics intended to represent the total number of paid U.S. workers of any non-farm business
Civilian Unemployment Rate	The unemployment rate represents the number of unemployed as a percentage of the labor force. Labor force data are restricted to people 16 years of age and older, who currently reside in 1 of the 50 states or the District of Columbia, who do not reside in institutions (e.g., penal and mental facilities, homes for the aged), and who are not on active duty in the Armed Forces.
PMI Composite Index	An indicator of the economic health of the manufacturing sector. The PMI index is based on five major indicators: new orders, inventory levels, production, supplier deliveries and the employment environment. A PMI reading above 50 percent indicates that the manufacturing economy is generally expanding; below 50 percent that it is generally declining.
Initial Claims	A measure of the number of jobless claims filed by individuals seeking to receive state jobless benefits. This number is watched closely by financial analysts because it provides insight into the direction of the economy.
Consumer Price Index	A measure of the average monthly change in the price for goods and services paid by urban consumers between any two time periods. It can also represent the buying habits of urban consumers. This particular index includes roughly 88 percent of the total population, accounting for wage earners, clerical workers, technical workers, self-employed, short-term workers, unemployed, retirees, and those not in the labor force.
Real Retail and Food Services Sales	An aggregated measure of the sales of retail goods over a stated time period, typically based on a data sampling that is extrapolated to model an entire country
University of Michigan: Consumer Sentiment	A consumer confidence index published monthly by the University of Michigan and Thomson Reuters. The index is normalized to have a value of 100

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, FRED, Deutsche Bank Quantitative Strategy

Are job postings correlated to macro indices?

To test the predictive ability of utilizing job postings to forecast macroeconomic indicators, we first calculate the number of active jobs for a basket of companies. Next, for that same basket of companies, we calculate the number of active jobs in the following month. Lastly, we compute the percentage change in the number of active jobs. Figure 45 shows percentage change in active job postings.[7]

Figure 45: Month-over-month percentage change in same company active jobs



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

We then analyze the relationship between the percentage change in active jobs and the percentage change in a select group of macro-economic indicators to determine if the two metrics are correlated. Please note that most economic data series have reporting lags. For example, NFP data for March 2015 was released during the first week of April 2015. For all predictive analysis, we use the month end job data to predict the subsequent month's economic data which may be released in later months. For correlation analysis, we analyze month end jobs data with economic data that is released after the month end.[8]

We can clearly see that changes in active jobs are highly positively correlated to changes in non-farm payrolls

Figure 46 shows the correlation between changes in active jobs and changes in non-farm payrolls from one to 12 months ahead[9]. The results are promising. We can clearly see that changes in active jobs are highly positively correlated to changes in non-farm payrolls. And, changes in active jobs can potentially forecast changes in non-farm payrolls several months in to the future. The changes in active jobs factor has a positive serial correlation.[10] Additionally, job postings take time to fill and as such, the impact to payrolls may be seen a few months after jobs are posted.

Figure 47 shows the correlation between changes in active jobs and unemployment rate. Interestingly, the correlation is predominantly negative. This is expected, since an increase in active jobs should intuitively lead to a lower unemployment rate.

---

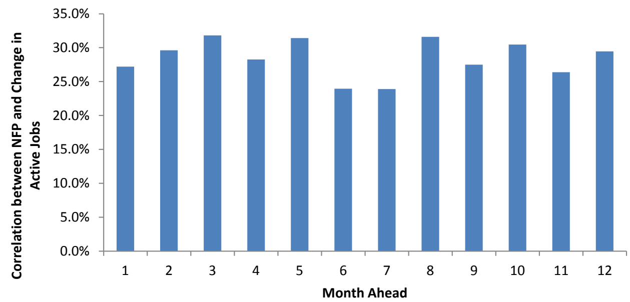
[7] Note this is in effect the month-over-month, percentage change in same company active jobs.

[8] For example, for correlation analysis, we compute the correlation between end of March's jobs data from Linkup and March's macroeconomic data which is released in early April Note that Linkup's job data is released at the end of March.

[9] Note that all the analysis with macroeconomic variables is based on the initial first reported data instead of the revised numbers. In Luo, et al [2010], we discuss in detail about the restatement bias in macroeconomic data in asset return prediction. The NFP number is seasonally adjusted.

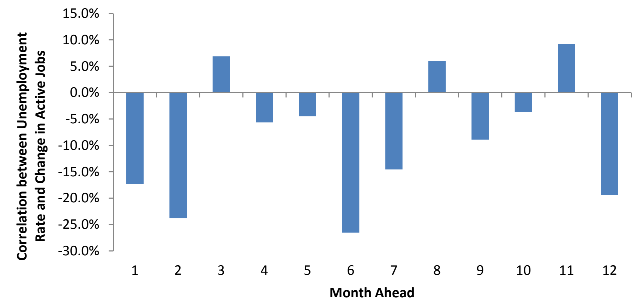
[10] Note that the correlation is formed using a limited number of data points, specifically from end of January 2009 onwards using a monthly frequency.

Figure 46: Correlation of non-farm payrolls and average active jobs per company



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, FRED, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 47: Correlation of unemployment rate and average active jobs per company

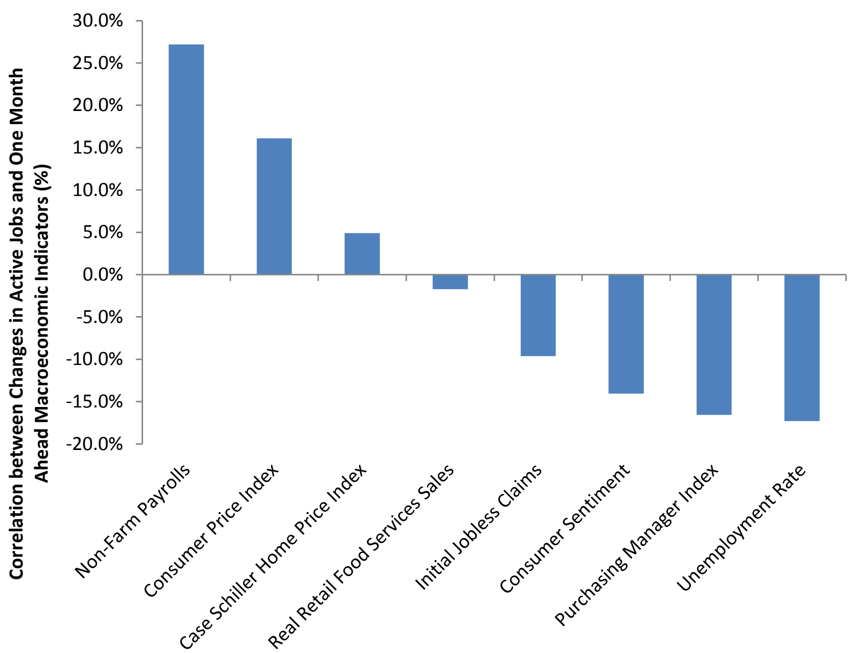


Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, FRED, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 48 shows the one-month ahead correlation between changes in active jobs and various economic indicators. We find that changes in non-farm payrolls are highly correlated to changes in active jobs whereas the unemployment rate has the most negative correlation.

We find that changes in non-farm payrolls are highly correlated to changes in active jobs whereas the unemployment rate has the most negative correlation

Figure 48: Correlation between changes in active jobs and one-month ahead macro indices



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, FRED, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

In summary, we found that the job posting dataset is most strongly correlated to changes in NFP. Next, we explore whether we can utilize the job posting dataset to develop a better and more accurate forecast of NFP.

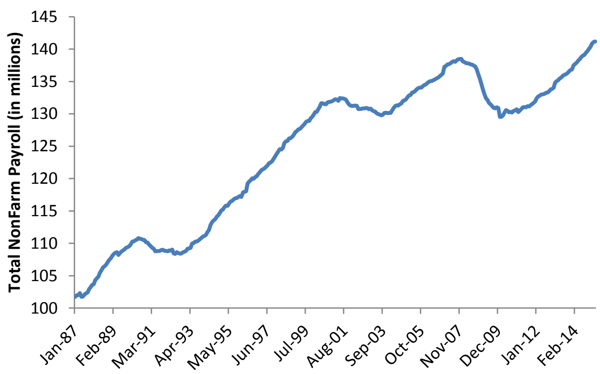
Forecasting non-farm payrolls

Devising systematic forecasts for non-farm payrolls

In this section, we investigate whether we can devise a better or more accurate prediction of NFP using jobs data. Figure 49 shows the total NFP values from 1987 onwards. NFP has been steadily increasing since the late 1980s, albeit there are some bouts where NFP drops sharply. Investors are generally focused on the monthly changes in NFP (Figure 50)

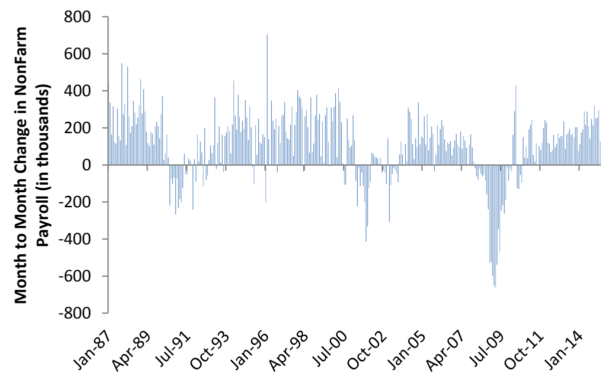
NFP has been steadily increasing since the late 1980s albeit there are some bouts where NFP drops sharply

Figure 49: Time series of total NFP (monthly)



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Haver, Deutsche Bank Quantitative Strategy

Figure 50: Month-over-month changes in NFP

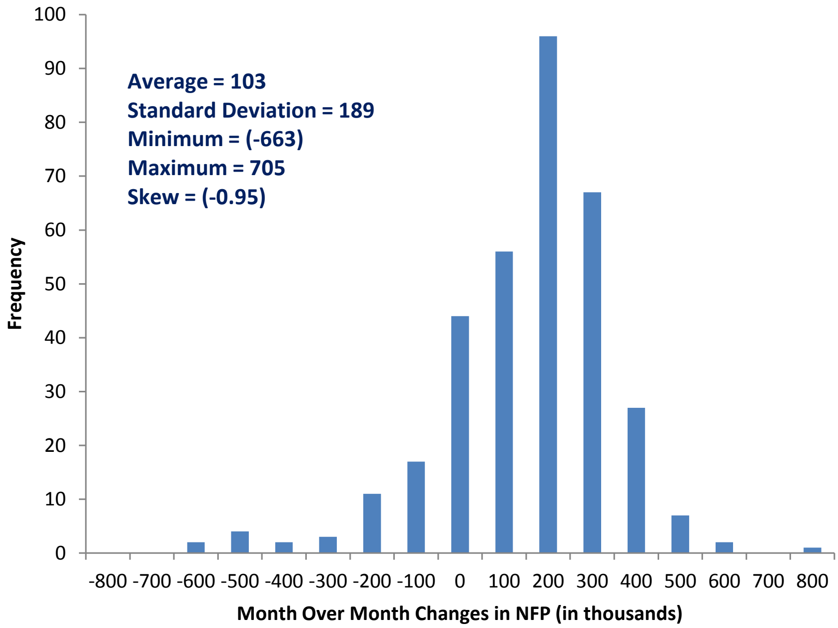


Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Haver, Deutsche Bank Quantitative Strategy

A deeper analysis of the changes in NFP (Figure 51) shows the average change in NFP is approximately 100,000 jobs. The month-over-month range in changes in NFP is approximately between -650,000 and 700,000. We find that changes in NFP are negatively skewed. This means that changes in NFP are predominantly positive; however, there are a few instances where month-over-month changes in NFP are significantly negative.

We find that changes in NFP are negatively skewed. This means that changes in NFP are predominantly positive; however, there are a few instances where month over month changes in NFP are significantly negative

Figure 51: Histogram of month over month changes in NFP (in thousands)



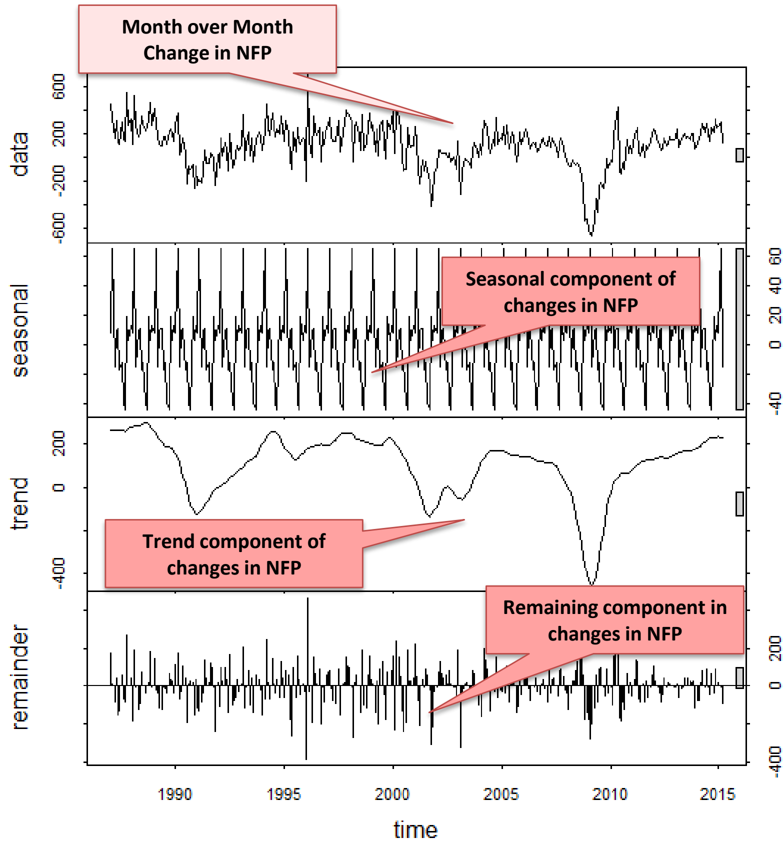
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Haver, Deutsche Bank Quantitative Strategy

We can further analyze changes in NFP by performing a decomposition. A signal decomposition simply isolates certain characteristics of a dataset to better understand its nature and structure. A signal can be decomposed into a trend, seasonal, and residual component. Figure 52 shows the signal decomposition of month over month changes in NFP.

The analysis shows the changes in NFP has a significant trend component. Changes in NFP also have a seasonal pattern. Interestingly, the "residual" or remainder component (i.e. the part of the signal that is not explained by trend or seasonality) is fairly significant. This may imply that changes in NFP can have a significant surprise factor.

This may imply that changes in NFP can have a significant surprise factor. This will likely make it trickier to forecast changes to NFP

Figure 52: Decomposition of NFP into trend, seasonality, and remainder



Source: : Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Haver, Deutsche Bank Quantitative Strategy

Forecasting NFP using NFP

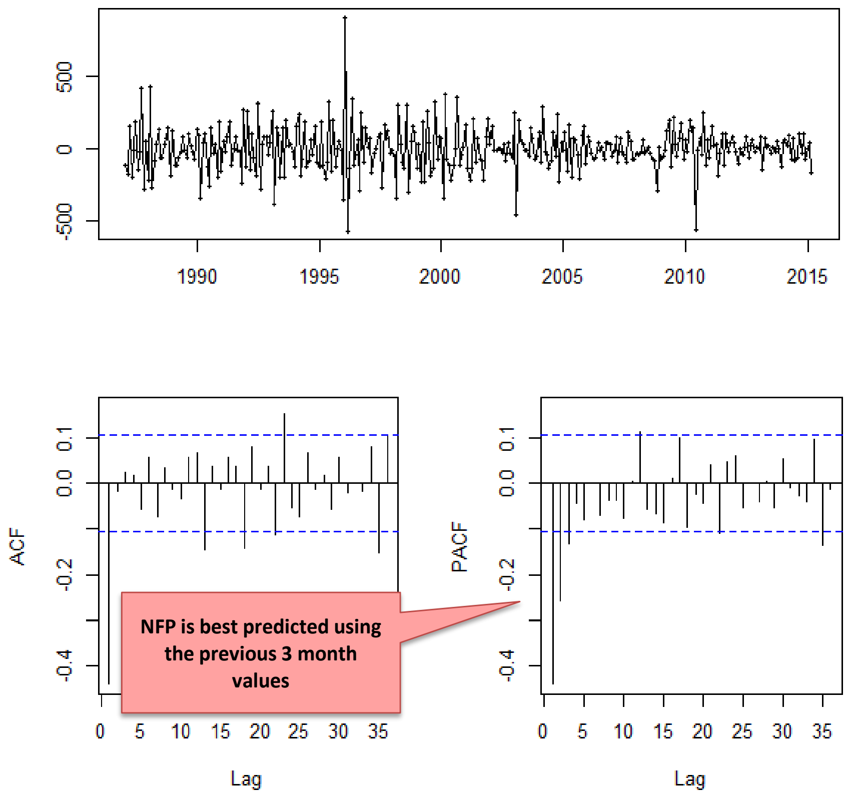
There are many methods investors can employ to forecast time-series data. One common method is to utilize an ARIMA model.[11] The inherent assumption underlying ARIMA model forecasting is that there is autocorrelation in the signal. Broadly speaking, an ARIMA model utilizes a combination of past signal values to forecast the future signal value. Deciding which combination of previous signal values to employ in the forecast requires some deeper analysis. A partial correlation chart aids with this analysis.

Broadly speaking, an ARIMA model utilizes a combination of past signal values to forecast the future signal value

Figure 53 shows the partial correlation plots for changes in NFP. The partial correlation chart shows the autocorrelation in the signal after remove the effects of other time lags. The chart shows that month over month changes in NFP are highly correlated or best forecasted using the previous 3 month values for NFP changes.

[11] ARIMA stands for Autoregressive Integrated Moving Average models

Figure 53: Autocorrelation and partial autocorrelation analysis



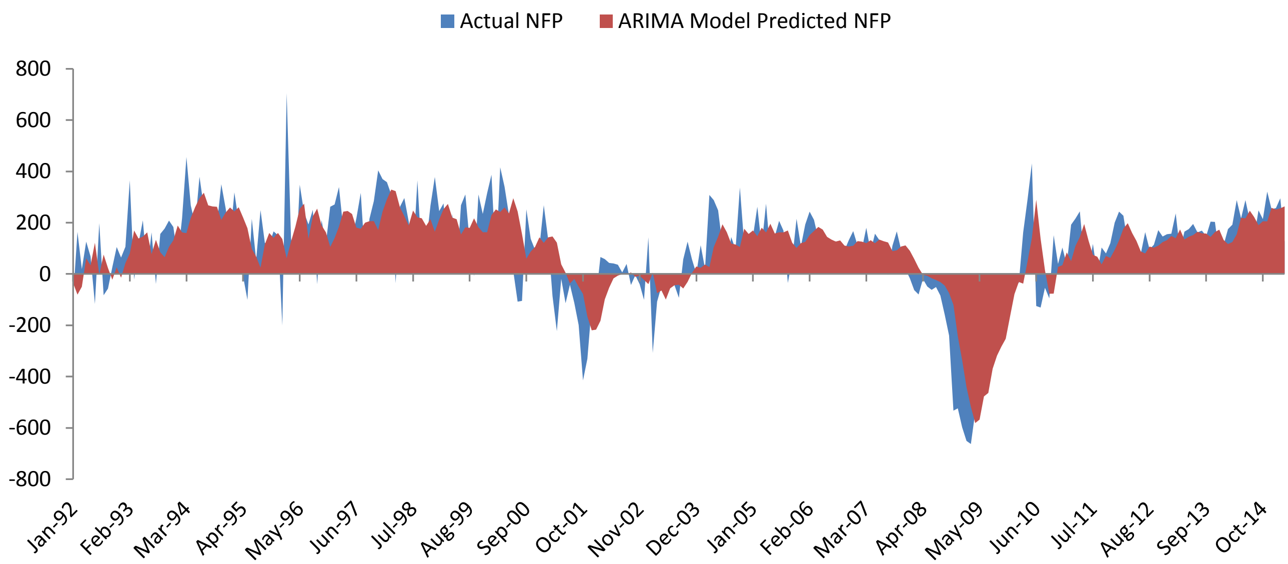
Source: : Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Haver, Deutsche Bank Quantitative Strategy

After further analysis and testing various models, we determined that the ARIMA(3,1,1) model is most accurate utilizing a 60 month training window.[12] Figure 54 compares our ARIMA forecast versus the actual NFP changes. On the surface, the ARIMA model seems to be performing moderately well.

On the surface, the ARIMA model seems to be performing moderately well

[12] The ARIMA (3,1,1) model had the lowest Akaike information criterion (AIC).

Figure 54: Actual NFP change versus ARIMA forecast



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Haver, Deutsche Bank Quantitative Strategy

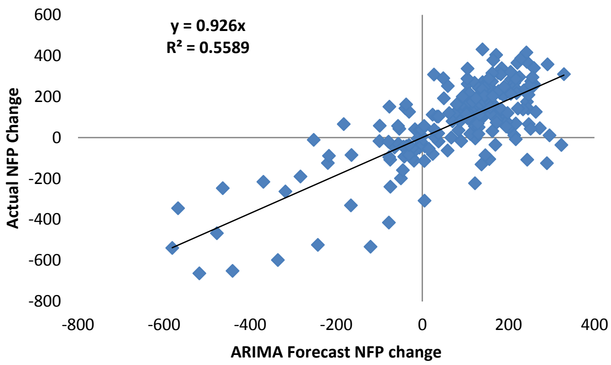
Figure 55 shows a scatter plot of our ARIMA forecasted NFP versus the actual NFP numbers. A perfectly accurate model would fit a line with a slope and R^2 of one. The ARIMA model performs reasonably well. Figure 56 shows a scatter plot of the Bloomberg consensus NFP forecasts versus the actually NFP numbers. The consensus Bloomberg forecast appears to be more accurate than our ARIMA model based on the slope and R^2 values.[13] However, comparing the accuracy of our ARIMA model against Bloomberg consensus forecasts is not entirely fair.

The consensus Bloomberg forecast appears to be more accurate than our ARIMA model. However, comparing the accuracy of our ARIMA model against Bloomberg consensus forecasts is not entirely fair

This is because the ARIMA model determines the NFP forecast one month prior to when the actual NFP number is published. However, the Bloomberg consensus NFP forecast is a more current estimate. Bloomberg consensus NFP forecasts can be updated days prior to when the actual NFP numbers are released. This of course gives a significant advantage to the consensus Bloomberg estimates over our ARIMA model.

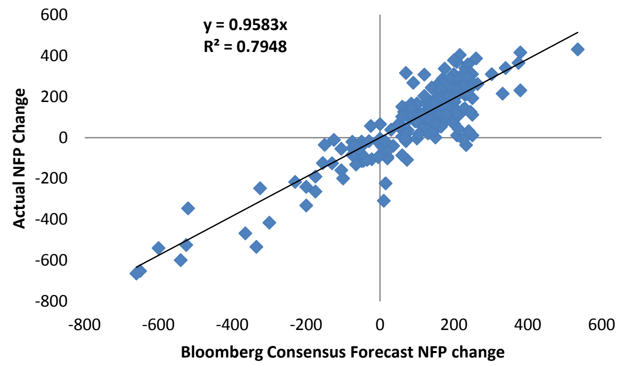
[13] Note that for both of the scatter plots, we have forced the intercept term to zero.

Figure 55: Actual NFP versus ARIMA forecast NFP



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Haver, Deutsche Bank Quantitative Strategy

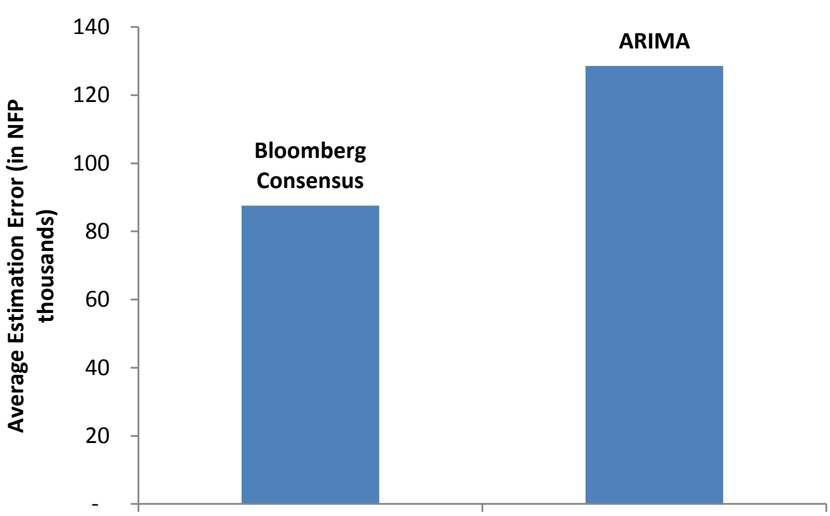
Figure 56: Actual NFP versus Bloomberg consensus forecast NFP



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Haver, Deutsche Bank Quantitative Strategy

Another method to gauge the accuracy of our AIRMA model versus consensus Bloomberg estimates is to compute the mean squared estimation error. We find that the Bloomberg consensus estimates have smaller estimation error than our ARIMA model. Again, this is expected since Bloomberg consensus estimates are more timely than our ARIMA model.[14]

Figure 57: Average estimate error for Bloomberg consensus and ARIMA



Source: : Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Haver, Deutsche Bank Quantitative Strategy

[14] Note that Bloomberg estimates could also be more accurate because the underlying analysts' estimates are more accurate than our systematic ARIMA model.

Unfortunately, we do not have a point-in-time daily running estimate of Bloomberg consensus NFP forecasts so that we can make a more fair comparison. However, we do have LinkUp jobs database which does provide current data on active jobs. Perhaps we can utilize changes in active jobs to provide more timeliness to our NFP estimates. We explore this next.

Unfortunately, we do not have a point-in-time daily running estimate of Bloomberg consensus NFP forecasts so that we can make a more fair comparison. However, we do have LinkUp jobs database which does provide current data on active jobs

The optimal NFP forecast – Bridging job postings

We compare the performance of various models to see if adding the job postings data can add incremental value and improve the accuracy of the forecasts. We compare the results of various models:

- Bloomberg Consensus: Our baseline benchmark is the Bloomberg consensus forecast of NFP. All subsequent models will be assessed against our baseline benchmark model.
- ARIMA: This is the time series model discussed in the previous section
- ARIMA + Change Active Job Postings: This model combines the ARIMA model with the change in active job postings, approximately a month prior to the economic release date.[15] We utilize the month prior job change so that posted jobs have an opportunity to be filled and impact payroll. We use the forecast from the ARIMA model and the change in active jobs, a month prior, to predict NFP using a bivariate OLS regression. The inclusion of the active jobs dependant variable in the regression adds more timeliness to our ARIMA forecast.[16]
- ARIMA + Change in Active Job Postings + Bloomberg Consensus: Here we also add the Bloomberg consensus NFP forecasts. The combination of all of our models may show some additional forecasting ability.[17]

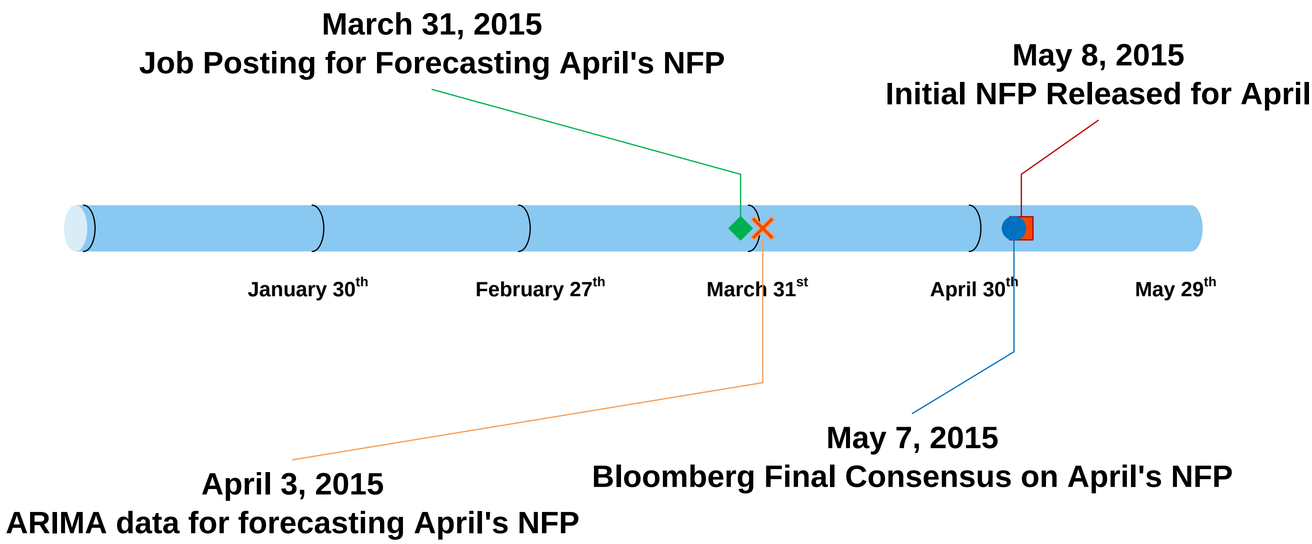
Figure 58 shows the timeline of each data series used in our various predictive models.

[15] To predict March's NFP which is released in early April, we utilize end of February's job numbers from Linkup.

[16] The job postings data utilized in the model begins in January 2009. Note that this model uses a 48 month training window. Therefore our out of sample results are over a two year period. The change in active job postings is a total absolute change not a percentage change.

[17] Note for this model, the Bloomberg forecast employed is the day prior to the actually NFP release.

Figure 58: Timeline example of data sets used in our forecasting models

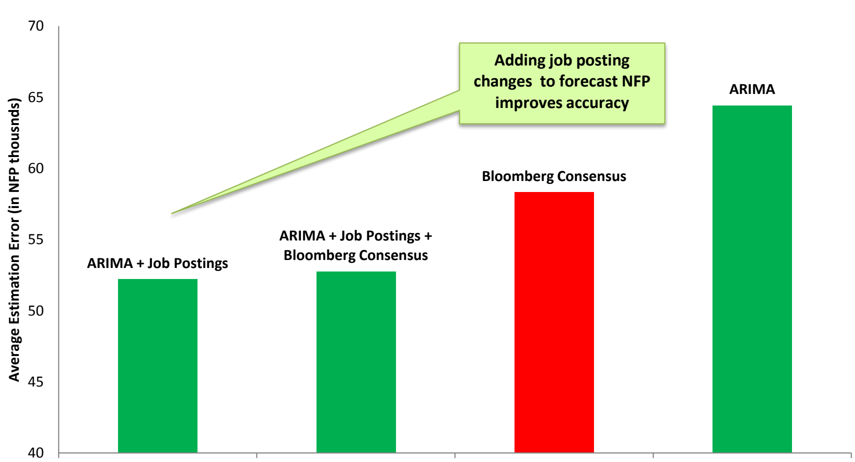


Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Haver, Deutsche Bank Quantitative Strategy

Figure 59 shows the estimation error of each model. This is used to assess the accuracy of the model. Adding the job posting dataset to our ARIMA model reduces the estimation error thereby improving the accuracy of the model and more importantly, it outperforms the Bloomberg estimates based on the estimation error. In fact, all models utilizing the job posting dataset improve the accuracy of the NFP forecast and outperform the Bloomberg consensus forecast. This outperformance is achieved by using data as of the previous month end whereas Bloomberg estimates are updated a few days prior to the release of NFP.

This outperformance is achieved by using data as of the previous month end whereas Bloomberg estimates are updated a few days prior to the release of NFP

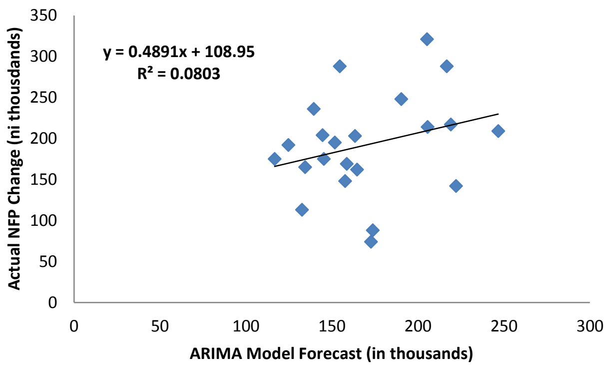
Figure 59: Average estimation error of all our backtested models



Source: : Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Haver, Deutsche Bank Quantitative Strategy

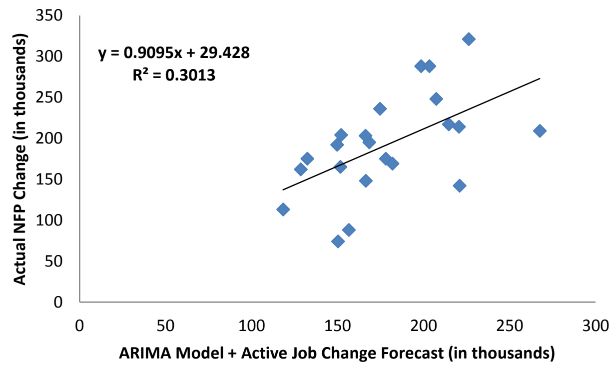
Lastly, to better gauge the accuracy of the models, we form various scatter plots of our forecasted models versus actual NFP numbers (Figure 60 to Figure 63). A perfectly accurate model would fit a line with a slope and R^2 of one. Again, we see that inclusion of the job posting dataset beats the Bloomberg consensus estimates. We note that there are few data points for this analysis. However, as more jobs posting related data becomes available, we can extend the training dataset and show performance results over a longer time period in the future.

Figure 60: Actual NFP & ARIMA forecast NFP



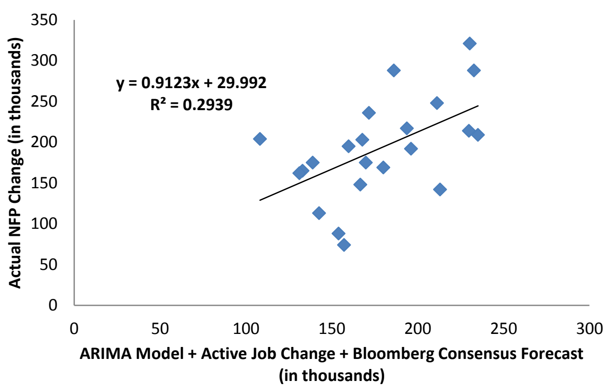
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Haver, Deutsche Bank Quantitative Strategy

Figure 61: Actual NFP & ARIMA + Jobs



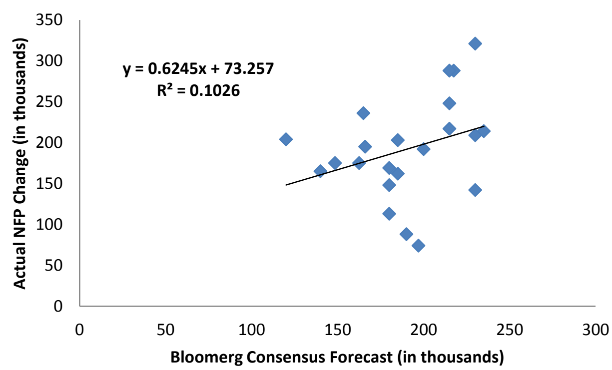
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Haver, Deutsche Bank Quantitative Strategy

Figure 62: Actual NFP & ARIMA + Jobs + Bloomberg



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Haver, Deutsche Bank Quantitative Strategy

Figure 63: Actual NFP & Bloomberg



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Haver, Deutsche Bank Quantitative Strategy

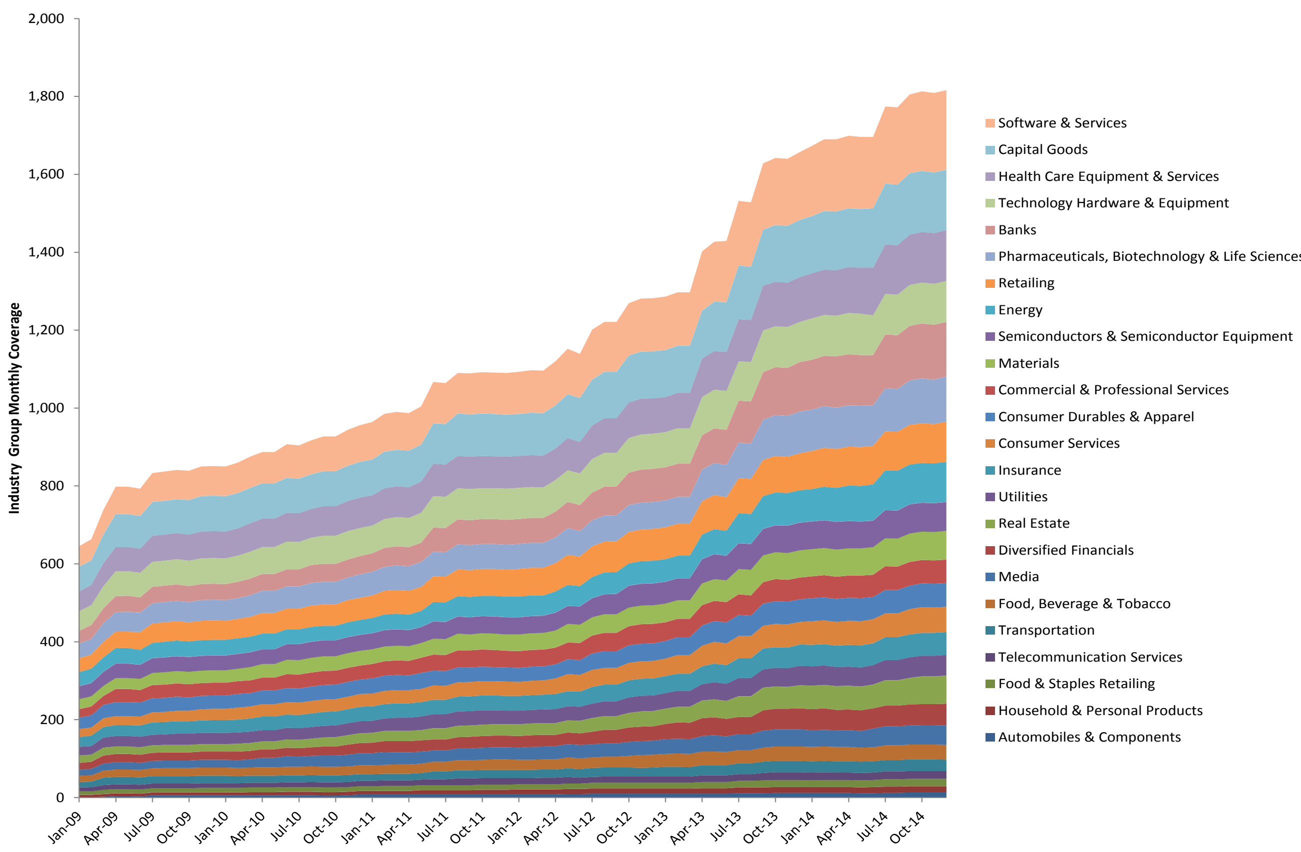
Sector rotation using jobs

Forecasting industry groups

In this brief section, we analyze whether the job posting dataset has the ability to predict industry returns. Figure 65 shows the coverage of companies within the job posting dataset by industry group. The coverage within each of the 24 industry groups is reasonable and as such we can attempt to devise a sector rotation strategy based on industry groups.

The coverage within each of the 24 industry groups is fairly good

Figure 64: Time series coverage of GICS industry group within jobs dataset



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

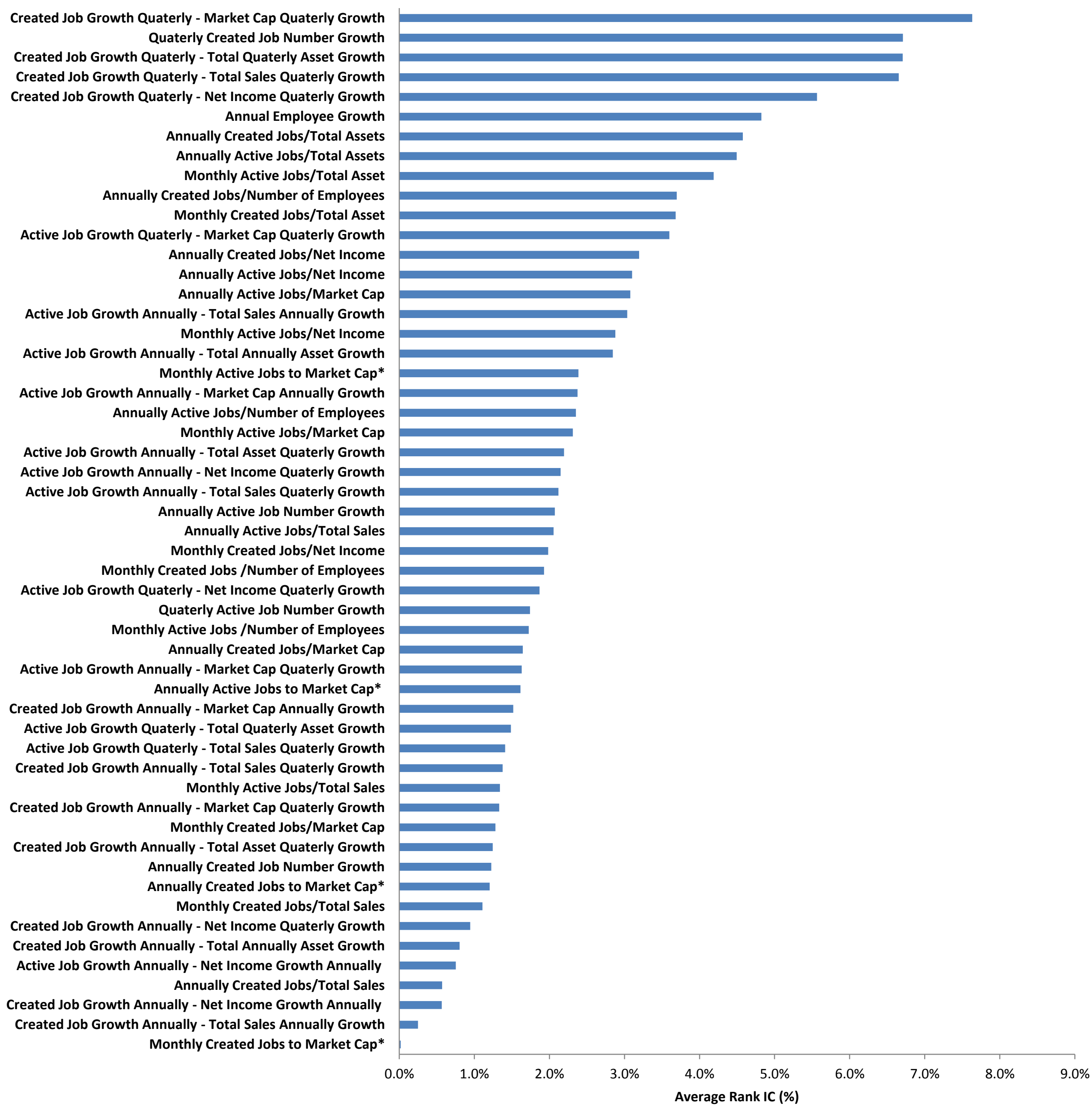
Our strategy involves aggregating the company level job factors discussed in the previous sections to an industry group level. We aggregate the company level job factors by simply computing the average factor value within each industry group. Next, we form an industry portfolio by longing the top and shorting the bottom industries based on the average factor value. We track the performance of the portfolio overtime.[18]

We aggregate the company level job factors by simply computing the average factor value within each industry group

[18] Note that the performance of each industry is based on the equally weighted average return of companies within that industry.

Figure 65 shows the performance of our industry rotation strategy for each job factor. Note that the results show the factor rank information coefficient (rank IC). An industry rotation strategy based on the job factor performs reasonably well. Some of the top performing factors have a rank IC of between 7% and 8%.

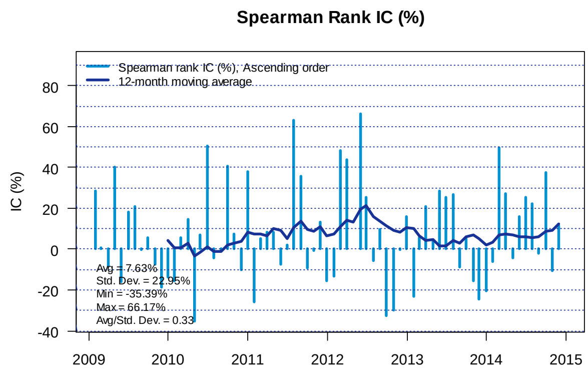
Figure 65: Average monthly performance (absolute Rank IC) of industry rotation strategies using jobs factors



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

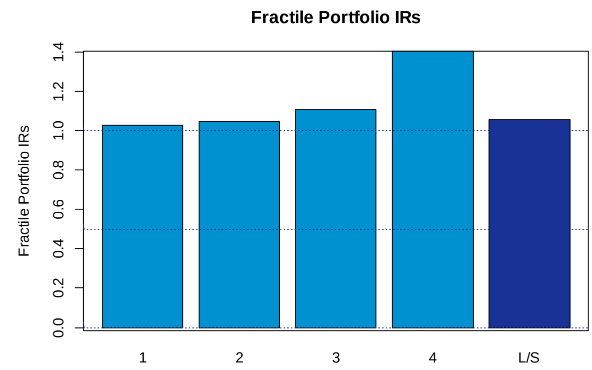
Taking a closer look at a particular job factor (quarterly job growth minus market cap growth) we find that the time-series rank IC is fairly strong (see Figure 66). In addition, the long/short portfolio has a Sharpe ratio of approximately 1.0x (see Figure 67). More interestingly, at the company level, firms with high job growth, exceeding market cap growth, tend to produce lower subsequent returns (i.e. the so-called asset growth anomaly – see Cooper, et al [2009]). However, at the industry level, industry groups with strong job growth (above market cap growth) actually lead to higher returns in the following month.

Figure 66: Rank IC of quarterly jobs created growth minus market cap growth



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Figure 67: Sharpe of quarterly jobs created growth minus market cap growth



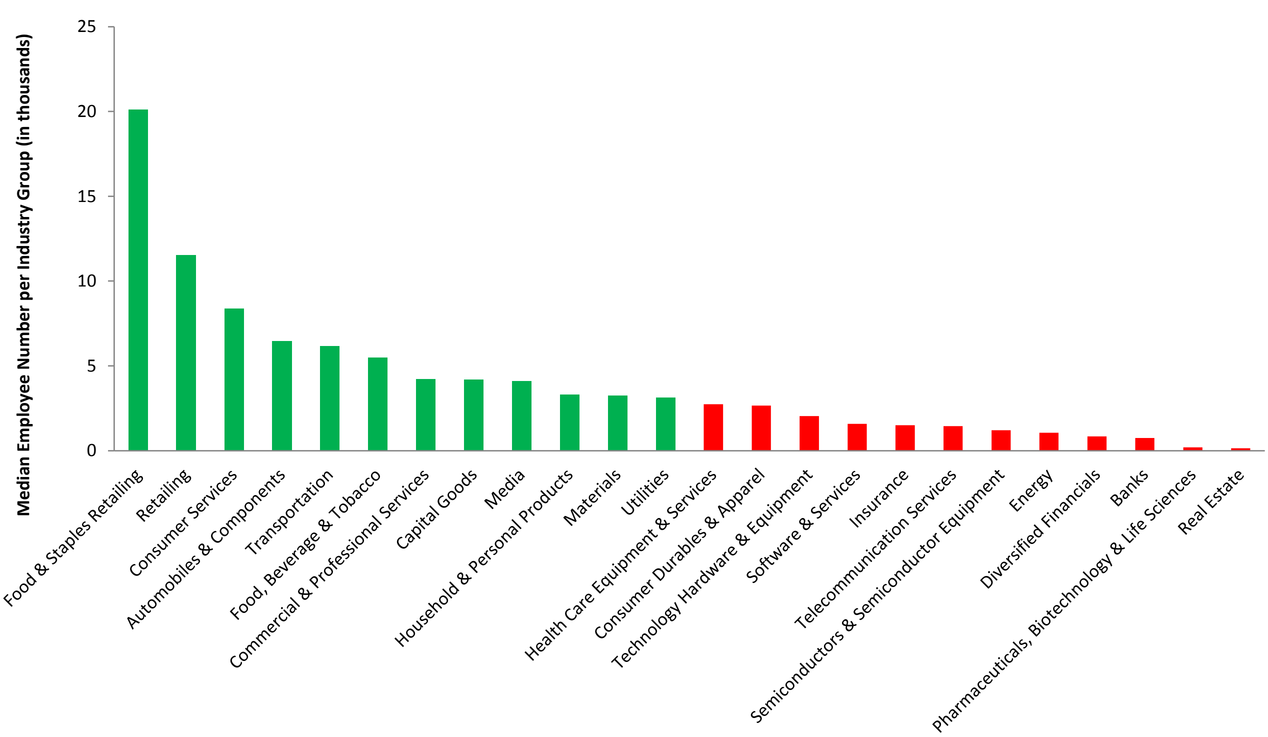
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

Labor intensive industries

Lastly, we test whether our industry rotation strategy performs better in labor force intensive sectors like retailing. To do this, we re-run our industry rotation strategy only within labor intensive industries. We define labor intensive industries as the top 12 industries ranked by the highest median number of employees per company in that industry group. Figure 68 highlights (in green) the top 12 industry groups with the highest number of employees.

Lastly, we test whether our industry rotation strategy performs well in labor force intensive sectors like retailing

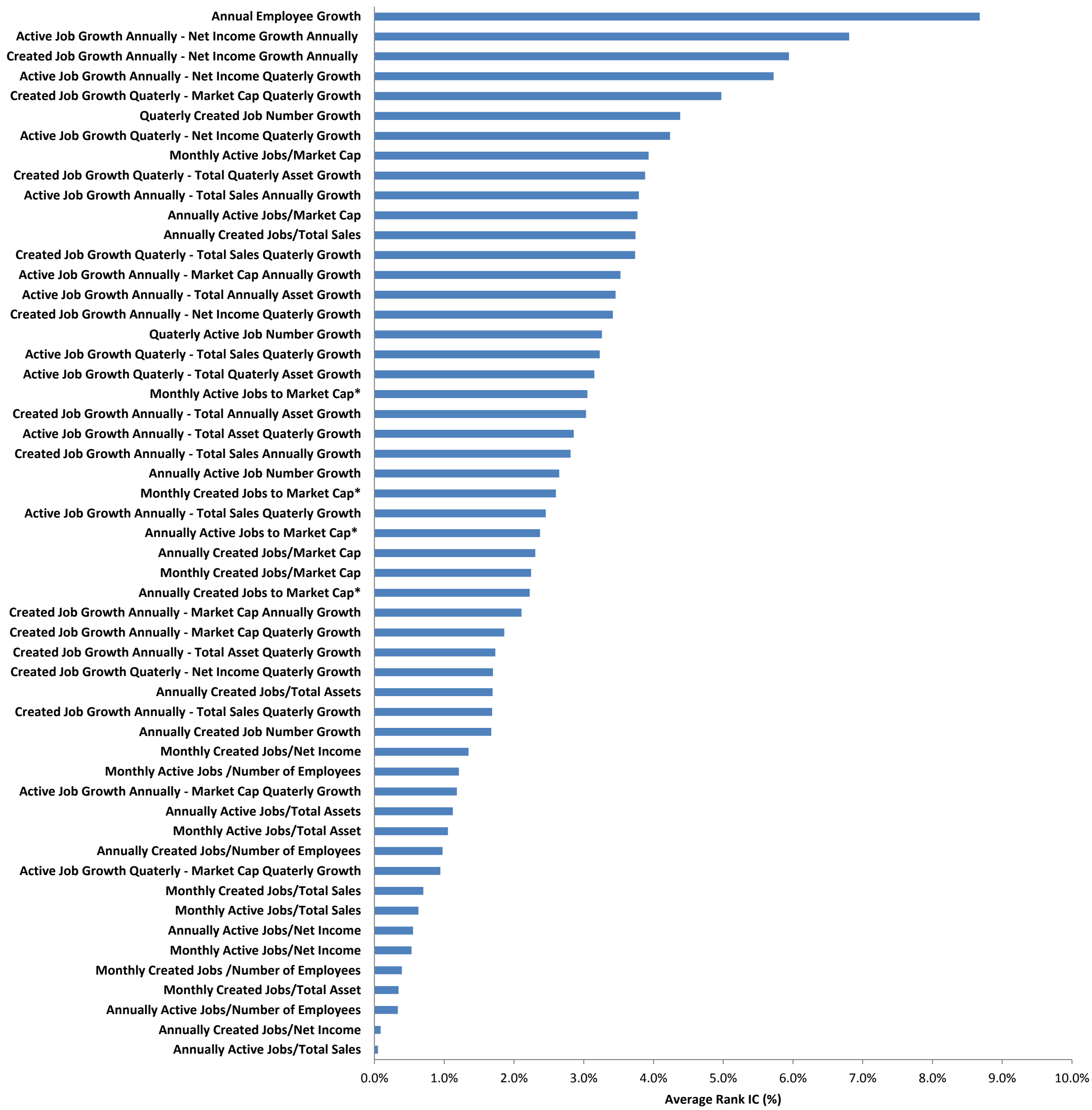
Figure 68: Median number of employees per industry group



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

We backtest the industry rotation strategy discussed previously but just within these 12 industries. Again the results are reasonable (see Figure 69). Some of the top performing factors have a rank IC of between 7% and 9%.

Figure 69: Average monthly performance (absolute Rank IC) of sector rotation strategies in labor intensive industries



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, LinkUp, Deutsche Bank Quantitative Strategy

References

Dayton, T. [2012], "Leveraging The LinkUp Index To Predict Future U.S. Job Growth", LinkUp job search engine, June 2012

Dayton, T. [2015], "A Bullish, Hands-Free NFP Forecast For Friday's Jobs Report", LinkUp job search engine, May 2015

Luo, Y., Cahan, R., Jussa, J. and Alvarez, M. [2010]. "Signal Processing: Style rotation", Deutsche Bank Quantitative Strategy, 7 September, 2010

Cooper, M.J., Gulen, H., and Schill, M.J. [2009]. "The Asset Growth Effect in Stock Returns", SSRN Working Paper, http://ssrn.com/abstract=1335524, 31 January, 2009

Choi, H., and Varian, H. [2011], "Predicting the Present with Google Trends", http://people.ischool.berkeley.edu/~hal/Papers/2011/ptp.pdf, 18 December, 2011

Appendix 1

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GRCM2015PROD034049