Do MBAs Pick Winning Stocks When Choosing Their First Job? *

Monica Bhole† Paul Oyer‡

November 17, 2016

Abstract

Every Summer and Fall, freshly minted MBAs and MBA Summer Interns take new positions at companies. We analyze whether their choices have any predictive power on the success of those companies. We show that MBAs tend to join companies that have been successful in the time leading up to the beginning of employment. These companies’ stock, on average, continues to substantially outperform the broader market in the year after new MBAs join. Most, if not all, of this outperformance after hiring can be explained by the fact that the employers tend to be high beta, or higher risk, firms. Adjusting returns for a factor model, we still find that excess returns are higher in the year leading up to the start of employment. Excess returns are mean reverting in the following year and are much smaller. We go on to show that the relationship between MBA hiring and stock returns is similar to that for other non-executive employee hires but very different from CEOs.

---

*PRELIMINARY/INCOMPLETE – Please do not distribute. We thank Brianna Cardiff, Kenneth Wong, Laura Tao, Hailey Kwon, and William Vijverberg for research assistance. We appreciate the comments we received from Daniel Ferreira and participants in numerous seminars.

†Department of Economics, Stanford University, mdbhole@stanford.edu.

‡Stanford University Graduate School of Business and NBER, pauloyer@stanford.edu.
1 Introduction

Shortly after graduating, MBAs from top schools are often given a fair amount of authority to act on their firms’ behalf in making investments and other decisions. Before they can act on the behalf of their new employers, these students and the firms that hire them have to make another large investment decision – which employer and employee should each match with? Working within the constraints of the other side of the labor market, students and firms make important choices with large financial ramifications.

In this paper we ask two empirical questions. The first is whether an investor can make money by investing on the basis of where MBAs go to work. The second question we address is whether returns of firms that hire MBAs differ systematically from firms that hire other employees. By analyzing the first job of new MBAs from one of the leading American business schools, we test whether the jobs they take have any predictive power for the stock market returns of the firms that hire them. We might expect that, having spent a great deal of time interviewing with a variety of companies in a variety of industries, these students have gathered useful information about which companies are poised to do well. In addition, we might expect that firms that have private information that their prospects are bright would choose to invest in talented people to complement those opportunities. If either or both of these inside information stories is important, firms that hire new MBAs should outperform the market in the period after they hire the new workers.

On the other hand, there is a great deal of anecdotal evidence of MBAs flooding into certain types of businesses right before things went sour. For example, the hot job market for new MBAs was investment banking in 1986 and 1987, internet-based businesses in 1999 and 2000, and private equity around 2007.1 Similarly, perhaps firms that hire MBAs could find more talented or lower cost sources of employees, indicating bad use of personnel resources.

A strictly efficient stock market would find no predictive power based on where MBAs take jobs, at least not using the type of public data we use in this analysis. In fact, we find no abnormal return for the stocks of firms where MBAs take new jobs, nor those where they go to work as Summer Interns. We also find that a student accepting a full-time job at the company that employed him for a summer internship does not provide inside information about the company’s future stock performance. We show that the raw returns of firms MBAs join are several percentage points higher in the year after new MBA graduates (or Summer Interns) take positions at a firm. However, this

---

1In a slightly different look at the relationship between MBA hiring and stock returns, consultant Roy Soifer has argued that the stock market in general does poorly whenever a large fraction of Harvard Business School graduates take jobs in the financial sector.
excess return can be fully explained by a market model – the new firms tend to have high betas, or are more volatile than the market.

We do find, however, that new MBAs are hired by firms that have just gone through a period of large abnormal returns. Firms outperform the market in the year leading up to MBAs starting their new positions and they have high alphas, or excess returns, based on average returns over the previous five years. Unless a market participant has the ability to predict who will take jobs at these firms, however, there is no way to profit from this relationship.

We then show that the fact that MBAs choose firms that are doing well during the recruiting process is because they pick (or are picked by) firms in industries that are doing well. The firms that MBAs go to are in industries that are outperforming the market but those firms are not, on average, outperforming others in the same industries.

For much of the analysis, the part each of these entities plays is difficult to separate. We only see completed employment agreements between workers and firms. We see neither the outside options of either party nor the opportunities either would have preferred. As a result, our ability to determine whether supply or demand drives the relationships we see is limited. As Kuhnen and Oyer (2013) show, MBAs receive more job offers in years where the economy is doing well. We take advantage of the fact that, over the period of our sample, there are some very good years for MBA graduates and some years where the job market is quite tight. We make inferences along these lines by comparing our results during bad economic times (when students have fewer options, suggesting firms’ preferences play a more important role) and good economic times (when students have more leeway to choose their job), as well as by looking at firms that recruit MBAs but do not successfully hire any. First, we show that the positive pre-graduation returns and the zero market-adjusted post-graduation returns are consistent during good and bad markets. That is, the firms MBAs will go to outperform the market in the year leading up to the job starting, and they keep pace with the market in the year after hiring, whether the overall market is doing well or poorly. This is suggestive that firms drive the process because MBAs do not seem to focus on better-performing firms in good times when they have more choice. We also find that firms that recruit on campus in a given year, but do not successfully hire anyone from the school in that year, have no excess returns in the year during which they recruit and don’t hire – that is, they neither outperform or underperform the market. If this is because students shun firms that are not doing as well, this suggests students do have a role in the relationships we show. It could also be the case that firms that recruit and don’t hire do not make offers, however.

Our analysis of firms that recruit but do not hire also turned up an unexpected and anomalous finding. While these firms neither outperform nor underperform the market in the recruiting year,
these firms outperform the market in the year after they recruit unsuccessfully. The pattern among these firms is the opposite of what we find among firms that hire overall and during booms. During bust periods we find that excess returns of these firms are similar in the year before and after students graduate. This suggests that either students, or firms themselves, are backward looking when making new employment decisions. Given this pattern, an investor could, in principle, profit from this surprising relationship. But, given out inability to determine the roots of this pattern, caution is warranted.

Finding that MBAs go to firms that are doing well, but that these firms do not outperform the market after the MBAs begin working there, seems sensible in terms of market efficiency. In addition, these findings are largely consistent with patterns in stock returns of firms that hire more generally. Belo, Lin, and Bazdresch (2014) show that firms that go on a wide-scale hiring spree tend to underperform the market a year after taking on many new employees. Though we find no such post-hiring negative excess return for firms hiring MBAs, several of our results mirror those for more general hiring. For example, we find that firms hiring MBAs have above average betas, as Belo, Lin, and Bazdresch (2014) find for firms that hire workers more generally. In addition, our pre-hiring excess returns for firms hiring MBAs are similar to those of firms that hire all types of workers. However, this is contrary to firms hiring new top executives – as Brickley (2003) shows, firms are more likely to hire a new outside CEO after a period of negative excess returns.

In the following section we describe our data. Section 3 describes our empirical methodology and section 4 presents the main results of this paper. Finally, section 5 concludes.

2 Data

Our sample consists of new graduates of the Kellogg School of Management at Northwestern University between 1980 and 2005. Each year, the school’s Career Management Center publishes a “Placement Report” that lists the employer of each graduating MBA, as well as the Summer Internship employer of each student who has finished the first year of the two-year program. Students volunteer this information to the Career Office which then publishes the report. While the Summer Internship samples consists entirely of students that are halfway through a traditional two academic year Kellogg MBA program (though a small subset of these are in a joint MBA/Engineering program), the graduating students are made up of several groups. Most are finishing the second year of the full-time MBA program or the two-year joint MBA/Engineering program. Some students get an MBA in one calendar year (the Kellogg One-Year MBA program), some are finishing a part-time MBA program or have transferred from that program into the traditional MBA program,
and others are completing a four-year JD/MBA program. In 2000, for example, there were a total of 794 graduates of whom 526 students had been in a two-year full-time program (MBA or joint MBA/Engineering), 82 were Four Quarter program graduates, 14 were JD/MBAs, and 172 were finishing the part-time program or were graduating having transferred from that program into the MBA program. Of these 794 students, 552 had accepted positions that they reported to the Career Office and are included in the published report.

Earlier placement reports do not always provide such detail on the breakdown of students by program and none of the reports specify which students came from which program. This is probably because, at least in the earlier years of our sample, the full-time MBA was dominant. Part-time students are only allowed to use the recruiting office if their current employer allows them to do so, or if they are paying their own tuition. Though we do not have hard numbers on this, anecdotal reports suggest that self-sponsored students have become more common in the part-time program. This has led to part-time program students making up a larger fraction of our sample over time and has simultaneously brought down the fraction of graduates reporting their first employer. This is because most part-time students already hold a job and are generally in less of a rush to find a position.

Table 1: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Full Time Positions</th>
<th>Summer Internships</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Number of Students</td>
<td>12,237</td>
<td>10,296</td>
</tr>
<tr>
<td>Students in Public Companies</td>
<td>6,060</td>
<td>5,781</td>
</tr>
<tr>
<td>Students with “Rolling” β</td>
<td>4,900</td>
<td>4,632</td>
</tr>
<tr>
<td>α</td>
<td>0.0047 (0.0095)</td>
<td>0.0048 (0.0095)</td>
</tr>
<tr>
<td>β</td>
<td>1.055 (0.5106)</td>
<td>1.058 (0.5120)</td>
</tr>
<tr>
<td>Volatility</td>
<td>0.0725 (0.0293)</td>
<td>0.0736 (0.0303)</td>
</tr>
<tr>
<td>Cumulative Return Before Join</td>
<td>0.224 (0.434)</td>
<td>0.244 (0.467)</td>
</tr>
<tr>
<td>Cumulative Market Return Before Join</td>
<td>0.133 (0.143)</td>
<td>0.123 (0.147)</td>
</tr>
</tbody>
</table>

Note: Return and Market Return are less the risk free rate. α and β are those from the Rolling CAPM model.

Table 1 reports summary statistics for our sample. Over the twenty-five years for which we have data, we have a total of 12,237 accepted full-time positions and 10,296 accepted Summer Internships. The difference is due to the fact that the part-time and one-year programs do not include time for a Summer Internship.
We can only analyze the stock returns of students who take jobs at publicly-traded companies. We use the placement reports to match students with firm stock return data from CRSP. We include students for whom we have enough data about their employer to estimate stock volatility and the parameters of CAPM and Fama-French models. We therefore limit the sample in all our analysis to companies students joined that were publicly-traded at some point in the 12 months before or after they started working. This includes a little under half (49.5%) of the full-time jobs and 56.1% for internships. Some of our analyses are further limited to people who work for firms for which we have sixty months of pre-graduation return data to use in our calculations of volatility and market model parameters. In these cases, 44.1% of full-time positions and 49.7% of internships are included.

When a student’s employer is taken over, we attempt to continue measuring the employer’s stock return. As long as the takeover is by another publicly-traded firm for which we can estimate a market model, the stock return data can continue seamlessly.

As the table shows, stock volatility and returns are high in our sample. We measure volatility as the root mean squared error from a Capital Asset Pricing Model using monthly data for the sixty months prior to the observation. For the central panel of the table an observation is June of the year of graduation for full-time positions or June at the start of a Summer Internship. Volatility of about 0.07 is a bit higher than blue chip volatility such as (using June 2000 figures) at 3M Company (0.063), Allstate (0.059), and General Electric (0.043). Volatility varies greatly within the sample, with some extreme examples (again from 2000) such as Gateway Computers (0.144), Oracle (0.147), and Apple (0.152).

The raw returns are sizable relative to the market when we look at all months in the year before and after a student takes either type of job. We would expect these firms to outperform the market given the typical Beta is over 1. The table also shows that we are measuring our market models during periods that are typically very good for these stocks as they have sizable monthly alphas averaging about forty basis points.

Figure 1 depicts the cumulative raw returns of the hiring companies relative to the market return over the course of the year before and the year after graduation. Here we can see how much larger the average cumulative returns of companies that offer full-time positions are relative to the average market returns during the same time periods. Returns are higher both before and after graduates start working and they are consistent across full-time jobs and (though not shown in the graph) summer internships. These figures and statistics are our first indication that stocks of companies that hire MBAs perform quite well in the two years surrounding the acceptance of offers.

There is considerable time series variation in the types of companies students work for over the
twenty-six-year period we study. Figure 2 shows the fraction of graduating students who take jobs in Marketing (Brand and Product Management), Finance (Investment Banking, not Commercial Banking), Management Consulting, and High Technology. The two most significant trends among Kellogg graduates are the rapid and sizable increase in students taking positions with consulting firms and the decline of brand management as a career entry point. For example, two members of the Class of 1981 went to work for McKinsey, Bain, Boston Consulting Group, or Booz, Allen, and Hamilton while ninety members of the Class of 2000 went to work for one of these four firms. Other less dramatic trends include a larger fraction of the class going into Investment Banking and at least a temporary jump in technology jobs around the time of the Internet Bubble in the late 1990’s.

The dotted line in Figure 2 shows the fraction of graduating MBAs that take jobs at publicly-traded firms. These graduates form the core of our sample, though some people who go to public
firms are not included because we do not have enough data to estimate a market model for their employer. The rise of consulting and decline of product management as first jobs led to a decrease in the fraction of MBAs going to public companies for most of the 1990's. However, the rise of investment banking and interest in high technology turned the trend around in the early 2000s.

Figure 2 shows the time series changes in alpha, beta, and volatility of MBA first jobs over the course of our sample. The alphas we estimate using CAPM change dramatically. Though always positive, on average, over the period we study, they become quite sizable in the mid-80’s and are more than sizable around 2000. The alphas of approximately 0.01, which are based on monthly returns, indicate that a typical student in our sample graduating around 2000 was going to work for a firm that outperformed the market by more than 10% per year in the five years leading up to graduation.

---

2 Alphas from the Fama French factor model are similar.
Figure 3: Alpha, Beta and Volatility

Note: In the first panel the Red line represents the Beta for Full Time positions, the Blue line represents the Beta for Summer Internships. The Purple line represents alpha for Full Time positions and the Green line represents the alpha for Summer Internships. In the second panel the Blue Line represents beta and the Red line represents volatility. Alphas and volatility are measured by the secondary axis on the right.

The betas are generally more than one, though they average less than one for a few years in the recessions of the early 1980’s and 2000’s. Average volatility is consistent for the entire sample except in the late 1990’s and early 2000’s, coinciding with the internet boom and bust. This is not entirely surprising given the jump in technology-related job placements shown in Figure 2.

3 Method

We use a “rolling” (that is, we update $\alpha$ and $\beta$ each month) version of the Fama-French four factor model to calculate each firm’s alpha and market factor betas. We match the stock data from CRSP to our sample of MBA students. For each firm that employs at least one student in any given year and for each month within one year of graduation (or the start of a Summer Internship), we calculate $\alpha$’s and $\beta$’s using data from the previous sixty months. As a result, each month has a different alpha and beta estimate and, because we require five years of return information to calculate the alphas and betas, we lose some observations.

As previously mentioned, incorporating acquisition information enables us to keep track of the companies with which each student is associated in the year before and after graduation (or starting an internship). When a student’s employer is acquired by another public firm, we use the new firm’s

---

3Our results are similar when we use a rolling version of the CAPM as well.
market beta, alpha, and return data for analysis.

We estimate the following version of the Fama and French (1992) model:

\[ R_{ij} - R_{fj} = \alpha_{it} + \beta_{it}(Rm_j - R_{fj}) + \theta_{1it}SMB_j + \theta_{2it}HML_j + \theta_{3it}MOM_j + \epsilon_{ij}. \quad (1) \]

The index \( j \) is defined as the period of months from \( t-59 \) to month \( t \). \( R_{ij} \) is defined as the return for firm \( i \) in period \( j \) and \( R_{fj} \) is the risk-free rate (the one month treasury bill rate). \( Rm_j \) represents market returns in period \( j \). The \( \beta_{it}, \theta_{1it}, \theta_{2it}, \theta_{3it} \) coefficients are estimating using monthly returns from the 60 months leading up to month \( t \). The market return is the value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ.\(^4\) The SMB and HMB factors are constructed using value-weighted portfolios based on size and book-to-market ratios. SMB (small minus big) is the average return of the difference between small and big portfolios, HML(high minus low) is the average difference between value and growth stocks, and MOM (momentum) reflects the difference in return between stocks that had high prior returns and those that had low prior returns. In some cases, we estimate the simpler CAPM model, which is equation (1) under the restriction that \( \theta_{1it}, \theta_{2it}, \theta_{3it} \) all equal zero.

We follow firms for the year before a newly hired student joined the firm and a year after. So for each class of students we define the month relative to graduation as 0 in June and index the periods of interest from \(-12\) to \(12\). This is done in the graduation year for full-time students. Similarly, for summer internships we define June of the year in which the internship takes place as 0, and again index the periods of interest from \(-12\) to \(12\). These indexes correspond to specific months (for a given year). For example, for full-time jobs for the class of 1980, June 1980 is indexed as 0 and May 1980 is indexed as \(-1\).

We then calculate the cumulative of the average (by student) return and excess return for the year leading up to the start of the job (months \(-12\) through \(-1\)) and the year following the start of the job (months 1 through 12). We predict the stock return for each firm in month \( t \) using parameters from the market model regression using the 60 months of data ending in month \( t \). We then define the “excess return” in month \( t \) as the actual return in month \( t \) minus the predicted return in month \( t \) plus \( \hat{\alpha}_{it} \).

\(^4\)See Ken French’s website for details.
4 Results

4.1 Excess Returns

We begin by looking at excess returns for those taking new full-time jobs. Figure 4 shows the cumulative average returns for $R_{mj} - R_{fj}$ (the market net of the risk-free rate), $R_{ij} - R_{fj}$ (firm return net of the risk-free rate), and the excess returns. The four parts of the graph show this for four different samples, as discussed below.

As we saw in Figure 1, the raw returns of the firms that MBAs join (now net of the risk-free rate) are higher than those of the market. The top left graph in Figure 4 shows the excess returns of all students taking full-time jobs. In the months leading up to graduation, the firms students join perform much better, on average, than the rest of the market. The excess returns are positive, economically large, and significant indicating that these firms are outperforming the market, even adjusting for risk and market factors, in the pre-hiring “event window”.

In the year after graduation, however, excess returns are essentially zero. These firms continue to have large and positive alphas (which evolve slowly given we measure them over a sixty-month period) but their total excess returns revert to the mean. On average, the firms that MBAs join perform as a market model would predict in the year after hiring.

The top right and bottom left graphs in Figure 4 show that these same patterns hold regarding Summer Internships. The top right graph shows returns for the year leading up to the June of the start of the Summer in which the internship is held and year following the start of the internship. Just as with full-time jobs, these firms outperform the market significantly in the year leading up to the start of the internship but, on a risk-adjusted basis, return to average performance in the year after the start of the internship (that is, during the internship and the students’ second year of the MBA program).

The bottom left graph of Figure 4 suggests that there is no market-relevant private information in the typical Summer Internship. It shows returns for the same full-time sample as in the top left graph, but it limits the sample to students whose full-time job is with their Summer Internship employer from the previous year. The results are identical to those for the broader sample.

In each of the Kellogg Placement Reports from which we gather our data, there is a listing of all the companies that recruit Kellogg students through the school’s on-campus recruiting system. From this, we are able to generate a list of companies each academic year that recruit Kellogg students but do not succeed in hiring any for either a full-time or Summer Internship position. The final (bottom right) graph in Figure 4 compares companies that hire MBAs to those that recruit but do not hire.
The logic behind this analysis is that it is a plausible way to separate the supply and demand side of the market. That is, if we make the (strong but not outrageous) assumption that firms that recruit on campus but do not hire anyone wanted to, in fact, hire people, then we can think of these as firms that MBAs chose not to join. The figure shows the stock return information for these non-hiring firms focusing on June of the end of the academic year in which the firms recruited on campus but did not successfully hire anyone. This figure is analogous to the top left graph in Figure 4 (firms that hire full-time workers) but looks quite different.

There are at least three noteworthy features of the bottom right graph in Figure 4 as compared to the top left graph. First, as we might expect, the firms that recruit but do not hire perform, on average, on a par with the market in the year during which they are recruiting with no success. So, though they are not performing as well as firms that successfully recruit and hire MBAs, the
firms that recruit with no success are at least keeping pace with the market overall. An investor could not make money betting against these firms, even if he had advance notice that the firm’s recruiting would be fruitless. Second, these firms are lower market risk (lower beta) firms than the firms that successfully recruit. This is consistent with the notion that MBAs prefer higher risk firms when possible. Third and potentially of most interest, the firms that recruit unsuccessfully beat the market in the year after they fail to hire. That is, if a firm recruits at this school during academic year \( t \) without success, it will, on average, outperform the market in year \( t+1 \). This excess return relative to the market is approximately the same magnitude as the amount by which firms that successfully recruit outperform the market in the year of the recruiting. Since the excess return for the unsuccessful recruiters comes a year after the recruiting, one could plausibly profit from this market difference.

It’s hard to say exactly why firms would do well after failing to recruit. This result is, on its face, consistent with a “Winner’s Curse” in the MBA hiring market, except firms that successfully recruit do not underperform the market. It could also reflect the idea that, in broader samples, firms that do not hire tend to outperform the market (Belo, Lin, and Bazdresch (2014)).

We now analyze the numbers underlying Figure 4 more formally to determine which, if any, are statistically significant and which are statistically distinct from one another. Table 2 shows the average cumulative excess return for the one year period before and after June for each of the four samples in Figure 4.

Specifically, for each graduate who takes a full-time job at a publicly-traded firm, we calculate the excess return in each month from the June of the year before the student graduates through June of the year after graduation. We then cumulate these returns over the twelve month period ending June 1 of graduation year (“Pre-June” row) and over the twelve month period starting July 1 of graduation year (“Post-June” row). The averages are displayed in the “Full-time Positions” and “Returning Summer Intern” columns.

Similarly, for each student starting a new Summer Internship, we calculate the excess return in each month from the June of the year before the person starts the Summer Internship through June of the year of the internship. We then cumulate these returns over the twelve month period ending June 1 of the internship year (“Pre-June” row) and over the twelve month period starting July 1 of the internship year (“Post-June” row). The averages are displayed in the “Summer Internships” column.

The final column shows the excess returns of firms in each month of the year in which they recruit on campus without hiring anyone (“Pre-June” row) and over the twelve month period after that academic year (“Post-June” row).
### Table 2: Cumulative Excess Returns

<table>
<thead>
<tr>
<th></th>
<th>Full-Time Positions</th>
<th>Summer Internships</th>
<th>Returning Students</th>
<th>Recruit - do not hire</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-June</td>
<td>0.0383</td>
<td>0.0476</td>
<td>0.0252</td>
<td>0.0241</td>
</tr>
<tr>
<td></td>
<td>(0.2559)</td>
<td>(0.2581)</td>
<td>(0.2476)</td>
<td>(0.2489)</td>
</tr>
<tr>
<td></td>
<td>[4,880]</td>
<td>[4,622]</td>
<td>[857]</td>
<td>[1,218]</td>
</tr>
<tr>
<td>Post-June</td>
<td>0.0173</td>
<td>0.0140</td>
<td>0.0193</td>
<td>0.0413</td>
</tr>
<tr>
<td></td>
<td>(0.2441)</td>
<td>(0.2405)</td>
<td>0.2392</td>
<td>(0.2633)</td>
</tr>
<tr>
<td></td>
<td>[4,918]</td>
<td>[4,645]</td>
<td>[869]</td>
<td>[1,208]</td>
</tr>
</tbody>
</table>

Note: Standard deviations are in parentheses and number of observations are in brackets. The estimates are from the rolling Fama French model.

The coefficient 0.0383 for pre-June full-time jobs means that, after adjusting for the four Fama-French factors, the average student goes to a firm that outperforms the market by about 3.83% in the year before the student graduates. This is much larger than the 1.73% in the year after graduation. Both of these estimates are statistically different from zero at any reasonable confidence level. We can also reject that the post-graduation return equals the pre-graduation return with greater than 99% confidence. The magnitudes are slightly different for Summer Internships but the message is very similar and, again, the averages are statistically different from zero and from one another.

### Table 3: Cumulative Excess Returns: All firms that hire

<table>
<thead>
<tr>
<th></th>
<th>(1) Cumulative Returns</th>
<th>(2) Cumulative Returns</th>
<th>(3) Cumulative Returns</th>
<th>(4) Cumulative Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post</td>
<td>-0.0266***</td>
<td>-0.0269***</td>
<td>-0.0270***</td>
<td>-0.0273***</td>
</tr>
<tr>
<td></td>
<td>(0.00725)</td>
<td>(0.00721)</td>
<td>(0.00721)</td>
<td>(0.00717)</td>
</tr>
<tr>
<td>Class FE</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry FE</td>
<td></td>
<td></td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>6078</td>
<td>6078</td>
<td>6077</td>
<td>6077</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.002</td>
<td>0.014</td>
<td>0.028</td>
<td>0.038</td>
</tr>
</tbody>
</table>

Note: Standard deviations are in parentheses. Excess returns measured using estimates from the rolling Fama French model. Sample consists of all firms that hired MBAs (both ones that recruited and did not recruit). Robust standard errors.

Tables 3 and 4 expand upon the results in Figure 4 and Table 2. Using the calculated excess returns in the year before students join their firms and the year after, we estimate difference in excess returns among firms in the post period. Table 3 shows that among firms that hire, excess returns are about 2 percentage points (pp) lower than they were in the pre period. This result is statistically significant at the 5% level and is robust to controlling for class fixed effects as well as industry fixed effects. Industries in this table are defined based on their 2-digit SIC code.
As we might expect, workers are drawn to firms during periods where they are performing well and, on average, the firm’s stock performance mean reverts in the period after the student begins working. Returns are clearly higher leading up to taking a job than they are after the job begins. If a trader had information about which firms MBAs would join as full-time employees or as Summer Interns one year in advance, he or she could earn approximately a 3% risk-adjusted excess return. However, once the student graduates or starts as an intern, the firms’ returns are nearly equal to the market return (on average) in the subsequent year. Neither betting on the firms MBAs go to work for, nor betting against them, at the time of graduation is a winning investment strategy.

The right column of Table 2 is the most surprising. As the earlier graph suggested, firms that recruit MBAs and fail to hire them perform slightly better than the market in the year of the failed recruiting. But these firms outperform the market by over 4% in the following year. This excess return is as large as the excess returns of firms that successfully recruit in the year of the actual recruiting and it is statistically different from zero and the prior year for these same firms. This finding requires more investigation and suggests a tradable arbitrage opportunity similar to many other finance “anomalies”.

Similarly, panel (a) of Table 4 indicates that among firms that recruit but do not hire, excess returns are nearly 2pp higher in the post period. This result is robust to controlling for class fixed effects. The result also holds once industry fixed effects are incorporated, and are statistically significant at the 10% level. These results indicate that even after controlling for class specific characteristics and the industries students work in, the difference in excess returns are different in the pre and post periods for firms that hire as well as those that recruit but do not hire.

We investigate the results from the right column of Table 2 more closely in panels (b) and (c) of Table 4 which estimate the difference in excess returns between firms that recruit but do not hire, and those that recruit and do hire in the pre- and post- periods. Specification 4 in panel (b) of Table 4 indicates that in the pre-period firms that recruit but do not hire have excess returns that are nearly 2pp lower than those that recruit and do hire when controlling for class and industry fixed effects. This result is statistically significant at the 5% level. Panel (c) of Table 4 estimates the differences in cumulative excess returns in the post-period between firms that recruit and hire and those that recruit but do not hire. The results are almost the inverse of those in panel (b). In the post period, panel (c) of Table 4 shows that firms that recruit but do not hire have excess returns that are 1.8pp higher on average. Interestingly, this result is robust to controlling for class and industry fixed effects, though it is only statistically significant at the 10% level when incorporating both. These results suggest that given information about the firms that recruit and hire MBAs, one may be able to earn excess returns over the course of the following year.
Table 4: Cumulative Excess Returns: Recruiting firms

(a) Firms that don’t hire: pre vs. post periods

<table>
<thead>
<tr>
<th></th>
<th>(1) Cumulative Returns</th>
<th>(2) Cumulative Returns</th>
<th>(3) Cumulative Returns</th>
<th>(4) Cumulative Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post</td>
<td>0.0208**</td>
<td>0.0210**</td>
<td>0.0198*</td>
<td>0.0198*</td>
</tr>
<tr>
<td></td>
<td>(0.0103)</td>
<td>(0.0103)</td>
<td>(0.0102)</td>
<td>(0.0101)</td>
</tr>
<tr>
<td>Class FE</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry FE</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>2515</td>
<td>2515</td>
<td>2513</td>
<td>2513</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.002</td>
<td>0.021</td>
<td>0.048</td>
<td>0.068</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(b) Non-hiring vs. hiring firms in pre period

<table>
<thead>
<tr>
<th></th>
<th>(1) Cumulative Returns</th>
<th>(2) Cumulative Returns</th>
<th>(3) Cumulative Returns</th>
<th>(4) Cumulative Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recruit no hire</td>
<td>-0.0174**</td>
<td>-0.0176**</td>
<td>-0.0186**</td>
<td>-0.0199**</td>
</tr>
<tr>
<td></td>
<td>(0.00885)</td>
<td>(0.00873)</td>
<td>(0.00934)</td>
<td>(0.00919)</td>
</tr>
<tr>
<td>Class FE</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry FE</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>3362</td>
<td>3362</td>
<td>3360</td>
<td>3360</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.001</td>
<td>0.026</td>
<td>0.036</td>
<td>0.062</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(c) Non-hiring vs. hiring firms in post period

<table>
<thead>
<tr>
<th></th>
<th>(1) Cumulative Returns</th>
<th>(2) Cumulative Returns</th>
<th>(3) Cumulative Returns</th>
<th>(4) Cumulative Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recruit no hire</td>
<td>0.0189**</td>
<td>0.0167*</td>
<td>0.0213**</td>
<td>0.0182*</td>
</tr>
<tr>
<td></td>
<td>(0.00904)</td>
<td>(0.00904)</td>
<td>(0.00935)</td>
<td>(0.00935)</td>
</tr>
<tr>
<td>Class FE</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry FE</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>3343</td>
<td>3343</td>
<td>3342</td>
<td>3342</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.001</td>
<td>0.025</td>
<td>0.032</td>
<td>0.057</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Excess returns measured using estimates from the rolling Fama French model. Robust standard errors. In panel (a) the sample consists of all firms that recruited but did not hire. In panel (b) the sample consists of excess returns in the pre-period among all firms that recruited, including those that hired an employee and those that did not. In panel (c) the sample consists of excess returns in the post-period among all firms that recruited, including those that hired an employee and those that did not.
If we assume that the firms that recruited on campus but did not hire actually wanted to hire but were not attractive enough to be successful, then we can conclude that the fact that firms do well in the year in which they hire employees is driven by students choosing successful firms rather than firms whose stock is going up choosing to hire more. That is, the relationship between stock returns and hiring would be driven by labor supply rather than labor demand.

This conclusion would be invalid if firms recruit and determine whether or not to make offers once they observe how they are doing in that particular year. To further probe the supply-vs-demand issue, we now look at how hiring firms’ returns differ depending on the state of the job market.

Career options for MBA students may be restricted by the prevailing economic conditions. Over the 26 years of our sample there are some good years for MBA students and there are also some tougher years. During good years MBA students are likely to receive more job offers which would allow students to choose a more optimal starting job. Similarly, in recession years a tight labor market is likely to restrict students’ options. It is not obvious whether the patterns we have documented thus far are consistent during good and bad economic times and we might expect them to be slightly different in periods where MBAs have less freedom to choose their employers.

Following Oyer (2008), we define good and bad periods for new MBAs based on the return on the S&P 500 during the two-year period while the students are in the MBA program. Specifically, we define a student as graduating in a “boom” if the S&P 500 increases by more than 20% from July 1 of the year the person enters the program through June 30 of graduation year. We say a student graduated in a “bust” period if the S&P return is less than 20% in this two-year period. This categorizes eleven of the twenty-six graduating classes as “bust” classes and the other fifteen as “boom” classes.

Figure 5 reproduces the top left graph in Figure 4, showing returns in the year before and after graduation separating new MBAs into boom and bust groups. The graph shows that, while the level of returns is obviously different for the two periods, the returns relative to the market are consistent. In either good times or bad, students go to work for firms that have raw returns that are greater than those of the broader market in the year before and after graduation. These firms have positive excess returns in the period leading up to graduation and roughly zero average excess returns in the year after graduation, regardless of the state of the overall market.\(^5\)

The patterns in Figure 5 indicate that students are no better at picking “winners” in good times or in bad times. Regardless of the state of the overall market, they go to firms that have been outperforming the market in the time leading up to the new jobs starting and they roughly

---

\(^5\) Again, these results are consistent for the year leading up to and after June of the summer in which MBAs intern.
Figure 5: Performance during Booms v. Bust (Full Time positions)

“Booms”

“Busts”

Note: Figure depicts results using the rolling Fama French estimates. Results are similar using the rolling CAPM model.

parallel market returns in the year after. This means that, when students have a wider choice of job options (“boom” periods), they are no more likely to pick a “winner” than when they have a more limited set from which to choose. It also means that neither the ability to attract new MBAs in more competitive (“boom”) periods nor demanding new MBAs when others do not (“bust”) predicts anything, on average, about a firm’s performance relative to the broader market.

So, while the low returns of firms that recruit but fail to hire are suggestive that students’ choices drive the relationship between hiring and the high returns during recruiting, the fact that this relationship is stable across boom and bust periods suggest it is driven more by firms’ labor demand. Further work is required to better parse out the supply and demand effects.

Figure 6 reproduces the bottom right graph in Figure 4, showing returns in the year before and after graduation among firms that recruit and do not hire. Similar to Figure 5 we separate these firms into boom and bust groups. During booms, the pattern from Figure 4 persists and the excess returns among firms that recruit but do not hire are higher in the post period than in the period before students start work. Interestingly, the pattern during bust periods is somewhat different. Excess returns among firms that recruit but do not hire in bust periods exhibit neither higher nor lower returns in the following year.
4.2 Gender Effects

We now consider how the relationship between MBA hiring and stock returns varies by gender. Knowing the name is enough information to determine gender in almost all cases.\(^6\)

There are some differences by gender in terms of the types of firms MBAs go to work for. While 30\% of our sample (both full-time and internships) is comprised of women, 33\% of those taking an internship at a public company and 34\% of those taking a full-time job at a public company are women. Put another way, 49\% of the women in our sample take a full-time job at a public company (or at least one for which we can run the full market model) while 42\% of men go to work for such a company.

Conditional on taking a job at a public company, men tend to work for riskier companies. The average beta (using the basic CAPM model) for men is 1.09 while it is 0.98 for women and the average volatility at men’s employers is about 4\% (0.4 percentage points) higher than women’s employers. So, as we might expect (Eckel and Grossman 2008), women appear to be more risk averse in their selection of employers. One reason for the gender difference in our sample is that they are less likely to go into the financial services industry (and, as Bertrand, Goldin, and Katz

\(^6\)We also looked at differences for students that received a competitive merit scholarship but, perhaps because the sample size is small, we cannot draw strong conclusions. We found no evidence that the scholarship students chose (or were chosen by) relatively more successful companies.
(2010) show with a sample of MBAs from another top school, they have different career trajectories after graduation).

While the types of firms chosen differ by gender, neither gender makes better decisions in terms of the stock return of their employers. As Figure 7 shows, the pre- and post-graduation stock returns for women look essentially identical to the returns for all graduates. The same is true for Summer Interns (graph not displayed).

![Figure 7: Performance of Firms MBA Women Join Full Time.](image)

Note: Figure depicts results using the rolling Fama French estimates. Results are similar using the rolling CAPM model.

4.3 Is it Just the Industry?

MBAs go to work for firms that are doing well. This could be because they choose (and are chosen by) firms that are performing well, or because they simply work in industries with relatively good fortunes. In this section we address that issue by comparing the returns of the industries in which
MBAs take jobs to the overall market return and by comparing returns of individual firms where MBAs work to their industries’ returns.

To do this, we use all firms that are in the merged CRSP/Compustat dataset to generate industry indexes by two-digit SIC codes. For each month, we calculate the average return for all stocks and the average return for all stocks in each two-digit industry. We drop industries in any given month for which we do not have least six firms from which to calculate an index. We have done this both on an equal-weighted and value-weighted basis and the results are similar both ways. So we focus on equal-weighted indexes.

We run the simple CAPM (one factor) model for each industry. That is, we calculate

$$R_{ij} - R_f = \alpha_{it} + \beta_{it}(R_m - R_f) + \epsilon_{ij}. \quad (2)$$

for each industry, $i$, in each month, $j$.

Then, similar to our earlier graphs of individual firm returns, we mimic an investment of $1 in the industry index corresponding to the job taken by each MBA. We calculate the cumulative returns of the industry in the year leading up to the MBA taking a job there and the year after the MBA starts the job. Figure 8 shows the returns for the market average, for the industry indexes (weighted by how many MBAs take a job there), and the risk-adjusted excess return of the industry relative to the market.

The graph shows several noteworthy differences compared to the corresponding graph for individual companies (Figure 8). The returns of the industry and the overall market are almost exactly identical, on average. However, while the individual firms that MBAs go to have, on average, high betas, the industry indexes of these same firms are, on average, less than one. As a result, though the raw returns are the same for the index and the market as a whole, the risk-adjusted returns of the industry indexes are positive.

So, in the year leading up to MBAs taking a full-time job, the firms they will join are outperforming the market, despite the extra risk they impose and the industries of these same firms are outperforming the market because they have similar returns at lower risk. Figure 8 also shows that, unlike the individual stocks, the industry returns are similar in the year before and the year after graduation. This suggests that, over the period we study, MBAs go to work for firms in industries that are doing well over a sustained period.

Within these industries, Figure 9 provides no evidence that MBAs sort into firms that are doing particularly well at a given time. This graph shows the industry return, the individual return, and the excess return, all weighted by the number of students going to work in a given firm or industry in our sample. It appears that the firms MBAs go to perform about as well as their industry in
the year before and after hiring. The cumulative excess returns do not differ from zero for either period. Overall, we conclude that MBAs are attracted to industries that are doing well and/or that firms in industries that are doing well are heavily recruiting MBAs rather than that MBAs are particularly drawn to firms that are outperforming their industry peers.

5 How Firms Hiring MBAs Compare to Firms that Hire Others

We have shown that firms that hire MBAs, at least those from one leading program, outperform the rest of the stock market in the year leading up to the time of the hiring, are higher risk (higher beta) than the rest of the market, and have risk-adjusted returns on par with the market in the year after the MBA is hired. Belo, Lin, and Bazdresch (2014), using a comprehensive dataset of all firms in CRSP, come to seemingly different conclusions about firms that hire employees more
generally. First, they find that firms that do relatively more hiring in a given year have noticeably negative returns (relative to the market) the following year. Second, they find that some of this can be explained by the fact that firms with low hiring rates have higher market risk and, therefore, have to earn a larger risk premium. That is, they find that hiring in year $t$ predicts low stock returns in year $t+1$ and that firms that hire many people are, on average, low beta firms. This suggests noteworthy differences between firms hiring MBAs and those hiring other employees given we find that firms hiring MBAs have high market risk and no excess returns in the year after hiring.

To explore this in more detail, we now compare stock returns at firms hiring MBA to those at a broader sample of hiring firms. We use all firms in the CRSP/Compustat merged dataset for the same years as our MBA analysis (1980-2005). We generated a dataset of monthly stock returns for each firm, limiting the sample to firms with a calendar fiscal year for consistency. We then broke the firms into quartiles based on their annual employment growth (fractional increase
in employment) in a given year, adjusted for year fixed effects. Companies in the bottom quartile all decreased their employment, those in the second quartile decreased employment slightly or held employment essentially steady, those in the third quartile increased their employee base modestly, and the fourth quartile consists of companies that increased their employment by more than ten percent from one year to the next.

Figure 10: Performance of Firms by Employment Growth: Raw Returns

Figure 10 shows the stock returns for firms in the four quartiles. The graph is centered around the end of the fiscal year (which is always December 31 in this sample) for year $t$. The graph shows, on the left, the cumulative stock return during year $t$. Recall that the quartiles of employment growth are based on this same fiscal year “year $t$”). The right side of the graph shows the cumulative stock return during year $t+1$.

As with our MBA sample, stock returns are positively related to hiring within a year. Firms in the top hiring quartile of year $t$ hiring have the highest year $t$ stock return, the second highest
quartile has the second highest returns, and so on. While these are raw returns, not adjusted for risk, the difference across the quartiles is quite dramatic. The typical firm in the top hiring quartile outperforms the typical firm in the lowest hiring quartile by approximately 25% over the course of year $t$. Top-hiring firms outperform the average firm by about 10%, suggesting that knowing in advance that a firm will go on such a hiring binge is even more valuable than knowing in advance that the firm will hire an MBA.

The right side of the graph shows a very different story for these firms in year $t+1$. The raw returns are not dramatically different across the quartiles and the differences, to the extent that they exist, are not obviously correlated with employment growth. The highest returns are in the two middle quartiles.

Figure 11 replicates Figure 10 using excess returns based on the Fama French four factor model. The patterns from Figure 10 persist and are even more obvious in this chart. Firms that are in
the bottom quartile of hiring, or that are reducing their work force, exhibit negative excess returns while those in the top quartile have the highest excess returns. In the following year firms that reduced their labor generate the highest excess returns. Firms in the top two quartiles are nearly indistinguishable and have lower excess returns than those in second quartile as well.

![Figure 12: Performance of Firms Hiring MBAs by Employment Growth](image)

In this chart we replicate Figure 10 using only the firms that hire Kellogg MBAs. We categorize these firms into quartiles based on regular employment growth. The graph is centered around the month relative to graduation. The lowest quartile represents firms with the lowest growth in employment. Firms are weighted by the number of MBAs hired. The graph using excess returns yields a similar pattern.

Overall, Figures 10 and 11 suggests more similarities than differences in the stock performance of firms hiring MBAs and those hiring other workers. For firms hiring MBAs, and firms that hire more employees in general, strong relative stock returns in the period leading up to and right around hiring are followed by returns that, on average, mimic the overall market in the period after hiring.\textsuperscript{7}

\textsuperscript{7}We attempted to more closely replicate our “invest $1 in each new hire” strategy from Figure 4 for the broader
We now do a similar analysis of the relationship between employment growth and stock returns for firms hiring MBAs in our sample. We divided the sample of firms hiring MBAs into quartiles by total employment growth (that is, using the same measure we used for the broader sample rather than some MBA-specific metric) in year \( t \). We then look at stock return for the four quartiles in years \( t \) and \( t+1 \) in Figure 12. As the graph shows, stock returns in year \( t \) are increasing in employment growth as in the broader sample. The excess stock return of the highest employment growth quartile is especially pronounced in this sample. As the right part of the graph shows, the trend in year \( t \) largely continues into year \( t+1 \). The highest quartile of employment growth firms outperforms the lowest quartile by more than 5% in the year after the hiring.

Figure 12 suggests that firms that hire MBAs are different from other firms in the same hiring quartile. Unlike the broader negative association between employment growth and future stock returns documented by Belo, Lin, and Bazdresch (2014), there is a positive relationship between employment growth and future stock returns for firms that hire MBAs. This is likely because this sample selects on a group that is generally growing and healthy, so the firms that are cutting employees (and seeing future positive returns) are largely removed from the sample. Though there is not likely enough of an abnormal return to profit, Figure 12 does indicate that MBA hiring, when considered in the context of overall firm hiring, is potentially informative about future stock returns.

Finally, note that all our results, including the basic findings in Figure 4, suggest that firms hiring MBAs are very different from firms hiring new top executives. As Brickley (2003) explains, it is well established that top executives are replaced (that is, new executives are hired) during and after a period of bad firm performance. Whereas growing and thriving firms are likely to hire new employees and new MBAs, firms that are not doing as well are likely to hire new executives. So, if a person knew in advance that a firm was going to replace its executives, that would have very different implications than knowing it was going to hire new MBAs or other employees.

6 Conclusions

We analyzed the stock returns of firms that hire new graduates of MBA programs and MBA students doing Summer Internships. We showed that investing money in the firms that hire these students in the year leading up to the student taking the job would be a profitable trading strategy sample of firms. However, mergers and divestitures, which often involve sharp stock movements, seemed to dominate our attempted measures of new hires.

\(^8\)The result is similar when we use excess returns
if it were feasible. But investing in these firms starting at the time of graduation is not as valuable—firms outperform the market in the year after students start these jobs but only because the firms have relatively high betas. These results are consistent for full-time hires and Summer Interns, as well as during good and bad periods in the stock market and the broader economy. We also showed suggestive evidence of an anomaly whereby firms that recruit MBAs and do not successfully hire any outperform the market in the subsequent year.
References


