Competition Links and Stock Returns

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ABSTRACT

This paper demonstrates that value-relevant information about a firm appearing in regulatory disclosures of other firms is overlooked by investors. Firms highly mentioned in the 10-K competition section of other firms tend to outperform with risk-adjusted returns of up to 9% annually. Outperformance is concentrated in firms whose competition references are made in the context of targeting rather than admiration. Consistent with investor inattention, abnormal returns stem from cross-sector competition mentions as well as firms with low-analyst coverage. Moreover, highly mentioned firms exhibit improved fundamentals in subsequent years, further signifying they are underpriced.

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JEL Classifications: G12, G14

The information content of corporate financial statements has been explored for many years. Early studies focus on the effect of unexpected net income on stock returns (e.g., Ball and Brown 1968; Beaver, Clarke, and Wright 1979), followed by a deeper look at the accounting numbers such as discretionary accruals (e.g., Sloan 1996). More recently, studies apply advanced learning techniques such as textual analysis to gauge economic insight (e.g., Hoberg and Phillips 2010, 2016; Garcia and Norli 2012; Cohen, Malloy, and Nguyen 2020). The common objective of these studies is to assess what investors can learn about a certain company from the information embedded in its own financial statements.

This paper presents a different learning approach. Instead of focusing on firm-produced information, we show that relevant information about the value of a given firm can be obtained by analyzing the financial statements of all other firms. Such releases typically include a competition section in which the company can list and discuss the firms it views as competitors. We use textual analysis to identify competitor lists in the cross-section of financial statements. The number of times each firm is mentioned by other firms in their most recent annual reports is then recorded and updated monthly.

We postulate that a firm appearing in the competition discussions of many other firms is likely viewed as a strong competitor, and as such, is expected to perform relatively well in the future. Consistent with this conjecture, we find that highly mentioned firms subsequently exhibit an increase in profitability. It does not necessarily imply, however, that investors realize in a timely manner the competition strength of the firm, as viewed by other firms. Because measuring competition links of every firm requires obtaining and analyzing large amounts of information (embedded in the 10-Ks of all other firms), we hypothesize that due to either investor limited attention or computation complexity, these links might not be fully understood by investors. This can result in underpricing of highly mentioned stocks, reflected in abnormally high future returns.

We note that the competition-mention measure seems to capture a different type of information than other measures of competitiveness introduced in the literature. First, the competition-mention measure is not assessed merely based on own-firm characteristics, such as firm size or product market share. Rather, the competition-mention measure requires the collective view of all other firms. Most significantly, the traditional definition of competition is a symmetrical one by nature, i.e., a pair of firms are assumed competitors. Competition links however are directional—a mentioning of a firm as a competitor by another firm does not necessarily imply the reverse mentioning. In fact, the percentage of mutual mentioning over our sample period is only 5.67% (and 3% if restricted to the same year). Indeed, while a set of existing measures of firm competitiveness (Li, Lundholm, and Minnis 2013; Hoberg, Phillips, and Prabhala 2014; Bustamante and Donangelo 2017) are related to competition mentions, their average correlation with competition mention is about 2%. This suggests that the mentions appearing in the competition sections span a different type of information set than existing measures.

The first test documents the association between competition mentions and future stock returns. We find that competition mentions positively predicts stock returns; an investment strategy that buys highly mentioned firms and shorts low-mention firms generates a monthly 6-factor alpha of 0.54% (value-weighted portfolios). Performance is robust to various subsamples and investment horizons, and is confirmed using Fama-MacBeth (1973) regressions with various controls. Also, given the positive correlation between competition mention and firm size, the paper includes various tests to alleviate the possibility that the results are merely a manifestation of firm size.

One aspect overarching the results is the endogenous nature of a firm's decision to mention another firm, which can shed light on the mechanism that drives the potential mispricing of highly mentioned firms. In this regard, 10-K mentions are classified into two types. The first represents 'admiring' mentions, which occur when a firm is mentioned by smaller firms; the second represents 'targeting' mentions, which occurs when a firm is mentioned by larger firms. We hypothesize that targeted firms are more likely underpriced than admired ones. An admired firm has likely established a strong reputation, which drives smaller firms to recognize it in their reports. The high reputation, as well as the transparency of admired firms, leaves less room for stock misvaluation. The case is different, however, for targeted firms. For example, if a large firm such as Google mentions a smaller firm outside the technology sector as a competitor, it might indicate that Google finds the business environment of the given firm promising. The outperformance of the mentioned firm in this case is consistent with prior underpricing based on inferior information as it is updated slowly by investors to include Google's informationally-superior views. The evidence shows a clear difference between admired and targeted firms. Both portfolio sorting analyses and Fama-MacBeth regressions indicate that highly mentioned targeted firms significantly outperform highly mentioned admired firms. This outperformance remains significant while controlling for firm size and other firm characteristics related to the admiring/targeting classification.

To provide further support for the explanation of return predictability as a result of mispricing stemming from investor inattention, the paper studies cross- and within-sector predictability. Specifically, we produce cross-sector mentions, which consider only mentions of firms that operate in different sectors than the filing firm, and within-sector mentions, which consider only mentions of firms from the same sector as the filing firm. The analyses demonstrate that the main results are significantly stronger for cross-sector mentions than for within-sector mentions, which is consistent with the tendency of investors to focus on a particular sector, not recognizing the information produced about a given firm by other firms outside its sector. Similarly, we hypothesize that it is more likely that competition-mention information about a given firm will be known to investors if the financial analysts that cover the firm also cover multiple sectors, and specifically the sectors of the mentioning firms. We find that this scenario indeed reduces the return predictability of competition mentions, supporting the conjecture that highly mentioned firms are underpriced.

We also study real effects—if the high returns to highly mentioned firms represent their high business potential, then these firms should, on average, exhibit significant improvement in fundamentals in subsequent years. The paper provides evidence consistent with this prediction. We compute the growth of total sales and operating income over one, two, and three years post-mention (adjusted to the median growth rates of comparable firms). We find that while, in general, the mentioned firms experience positive performance, the extent of the growth largely depends on two dimensions. The first dimension is whether the mention is cross-sector or within-sector, and the second dimension is whether the mention is in the context of targeting or admiring. For cross-sector mentions, ‘targeted’ firms display, on average, significantly larger growth in fundamentals than ‘admired’ firms. The patterns however are different for within-sector mentions, where targeted firms experience lower growth rates than admired firms, especially in sales.

These results are consistent with the premise that when leading organizations reach out of sector to identify a competitor (the mentioned firm), it indicates significant business opportunities for that competitor, which are not fully understood yet by market participants. In turn, this leads to positive stock returns for the competitor/mentioned firm as market participants slowly incorporate the information about the mentioned firm business opportunities, which are later realized, as indicated by the positive changes in firm fundamentals post-mentioned. When targeting is within-sector, however, it may also indicate that the leading firms in that sector are trying to ‘protect’ their business from smaller firms in the same sector, resulting in increased competition pressure and ultimately relatively lower future fundamentals. In addition, being mentioned as a target in 10-K filings is shown to significantly increase the likelihood of the firm to be acquired over the subsequent twelve months. This further supports the conjecture that, to the extent investor inattention to competition mentions generates mispricing, targeted firms are likely underpriced.

An alternative explanation to stock mispricing might be that competition mentions identify an element of a firm’s risk profile. If many companies recognize a certain firm as a competitor, they are likely to adjust their strategies to compete more vigorously with that firm. A firm’s high mentions may suggest therefore that the firm might face strong competition by major competitors, which can increase the uncertainty about the firm’s future performance and value. If this risk is undiversifiable, say an overall market environment of technological disruption, then the outperformance of highly mentioned firms might manifest compensation for risk. We explore the risk-based explanation by two types of systematic pricing of competition mentions. First, we study the systematic pricing of exposure to the mention return spread. We find that firms whose stock returns exhibit a high beta with respect to this spread do not subsequently outperform low such beta stocks, on average. Therefore, mention beta is an unlikely explanation for the return predictability of competition mention.

Second, we borrow intuition from theories in industrial organization (IO) that relate expected returns and competition in the product market (see, e.g., Hou and Robinson 2006; Hou 2007; Peress 2010). In particular, these works advance that firms operating in competitive industries are more adversely affected by systematic shocks and therefore earn higher expected returns than those operating in concentrated industries that are better able to weather aggregate shocks (other works, such as Gaspar and Massa (2006) and Irving and Pontiff (2009) point to a positive relation between a firm’s competitive product-market environment and idiosyncratic return volatility). Bustamente and Donangelo (2017) expand the theoretical framework to offer two separate effects determining the relation of competition to expected returns: operating leverage and threat of entry. Following that paper, we estimate operating leverage and concentration at the sector and industry levels.

Regression analyses confirm that competition mentions remains statistically significant while controlling for these variables as well as their interactions with competition mentions (none of the interaction terms are significant).

We conclude that existing systematic-risk-based explanations for the performance of competitive/concentrated sectors do not explain the outperformance of competition-mentioned stocks. Perhaps this is not entirely surprising, because, as discussed earlier, a firm being mentioned by other firms indicates a different type of competitiveness than that discussed in the literature. In particular, this paper advances that competition mentions is indicative of profitable future business opportunities (particularly for targeted firms), and that the return predictability is largely consistent with mispricing, as investors are slow to adjust for valuable information in financial statements.

Recent literature introduces several other measures of firm links, such as product similarity, as in Hoberg and Phillips (2010, 2016), media co-mentions, as in Scherbina and Schlusche (2015), and shared analysts, as in Ali and Hirshleifer (2020). This paper advances that literature in several aspects. First, as pointed out above, while these other measures are predicated on a symmetric relation between linked firms, competition links are asymmetric/directional. To demonstrate the importance of this asymmetry, we show that, in contrast to the abnormal performance of a highly mentioned firm (the main finding), a firm that mentions many competitors in its own report does not earn abnormal returns. Second, the correlations between competition mention and other variables are not particularly strong. For example, the overlap between competition mention and Hoberg and Phillips' product similarity measure is roughly 50%; moreover, the performance of highly mentioned firms is similar for mentions made by similar-product firms and non-similar-product firms. Finally, multiple-regression analysis confirms that the return predictability of competition links remains significant while controlling for the aforementioned firm-links in the literature.

Finally, the paper studies an augmented measure of competition mention, one that overweights mentions made by firms that themselves receive more mentions by other firms. Estimating such a measure requires it to be simultaneously estimated for all firms. This is accomplished using a Google PageRank-type algorithm in the manner of Page et al. (1999), applied to competition links in the most recent annual reports of all firms in each month. The results using this augmented measure are qualitatively similar to those using the simple mention count. To ease interpretation, the latter measure is maintained throughout the paper.

Overall, the results in this paper highlight a distinct source of mispricing stemming from the slow reaction of investors to information about potentially profitable business opportunities of a given firm as pointed out by the other firms.

1. Competition mentions

Our procedure to measure competition mentions of a given firm is based on the entire cross-sectional pool of financial statements. Each month we observe the most recent annual report of each firm (if available) over the past twelve months. That is, all companies are represented in the competition mention count each month. Using textual analysis, the companies that are listed as competitors by each firm are recorded (Appendix A describes the text analysis procedure). This provides a system of links between all firms in each month, where each firm can both mention other firms and be mentioned by other firms.

1.1. Distribution and correlations

We observe a total of 119,785 10-Ks filed by 11,304 firms over the period 1995-2017, out of which 68,952 reports (58%) include a competition section. The number of firms that are mentioned as competitors in a single report's competition section ranges between zero (61 percent of the reports) to 35. Also, most firms, about 69 percent, are not mentioned at all in other reports. The company with the most mentions at a given time is IBM Corp. ('IBM') which was recognized as a competitor by 136 companies in the annual reports filed during 1997, followed by Microsoft Corp. ('MSFT') with 113 mentions in the reports filed during 1999. Figure 1 presents the distributions of the number of firms mentioned as competitors in a report's competition section, and the number of reports in which a firm is mentioned as a competitor. Figure 2 further shows that the percentage of firms with no competition mentions has steadily decreased over the sample period. We produce the simple mention count measure for each firm in each month over the period 1995-2017. Our sample includes 939,863 firm-month observations. The competition-mention measures for each month are based on the available annual financial reports as of three months earlier (allowing three months for the release of the reports).

A reasonable question regarding our competition-mention measure is whether it simply captures the market capitalization of a firm, as larger firms are typically more recognized as competitors. We confirm that competition-mention contains information that is incremental to firm size in several ways. We show that the largest companies in the market at a given time are not necessarily the ones with most mentions at that time. We control for the effect of firm size in all of our tests, using several specifications for size to demonstrate that lack of meaningful effect on the conclusions. Moreover, we find that high number of competition mentions is associated with high stock returns, which goes against the size effect. Finally, following Hou, Xue, and Zhang (2020) who show that many documented asset pricing anomalies are driven by microcap stocks, we exclude such stocks (stocks with market cap below the 20th percentile of NYSE breakpoint) from all analyses, and also run tests to mitigate the impact of small stocks (between the 20th and 50th percentiles).

Appendix B presents the five companies with most competition mentions over the period 1995-2017, as well as the largest companies over the same period. The competition-mention leaders exhibit an interesting pattern, where IBM has been the most mentioned company in 20 out of the 23 years of the sample period. Microsoft was the top mentioned firm in 2000 and 2009, and Pfizer Inc. ('PFE') in 2017. Comparing the top mentioned firms to the list of the largest companies indicates indeed that very large firms are often highly mentioned, as several firms appear in both lists. Yet this association does not seem extremely strong as some of the largest firms in the market do not have the equivalent competition recognition. For example, General Electric Co. ('GE') had the largest market capitalization in eight years between 1995 and 2005, yet it was in the top five mentioned firms only once during these years, in 1995. Similarly, Exxon Mobil Corp. ('XOM') had been constantly the largest company between 2006 and 2011, but was never in the group of the top five mentioned firms. This provides a first indication that our competition-mention measure contains information that is not captured by firm size.

We further assess the relation between competition mention and firm size, market beta, as well as other firm characteristics: market-to-book ratio, past stock return, profitability, investment intensity, and idiosyncratic volatility. All market and accounting data are obtained from CRSP and COMPUSTAT. Table 1 shows descriptive statistics for four portfolios sorted by the number of annual reports in which the firm is mentioned as a competitor over the past twelve months: 0, 1, 2, and 3+ mentions. We first calculate the cross-sectional mean and median across stocks for each portfolio, and then report the time-series averages of these means/medians. We also report the time-series averages of monthly cross-sectional correlations between (log of 1+) competition mentions and each firm characteristic.

As expected, there is a positive relation between competition mention and firm size, as both the mean and median firm size increase monotonically from the zero-mention to the 3+ mentions portfolio. The correlation, however, does not indicate an extremely strong relation, with a time-series average of 0.36 for the full sample, and 0.33 when excluding microcap stocks. This is consistent with the results in Appendix B, indicating that competition mention represents a firm characteristic that is not entirely captured by the size of the firm. To a lesser extent, highly mentioned firms also seem to represent more growth firms than value firms, as indicated by their relatively high market-to-book ratios, with a positive correlation of 0.13 for all stocks, and 0.07 without microcap stocks. Highly mentioned firms are also more profitable and with lower idiosyncratic volatility, yet all average correlations for these and the other characteristics are fairly low, especially without the microcap stocks. This suggests that competition-mention is not likely representing any of these risk factors.

1.2. Competition mentions and competitiveness

The competition-mention measure is derived solely from the textual content of competition sections in 10-K filings, thus naturally contains information related to the competitive strength of a firm. However, it is not clear whether it can be viewed as a measure of the degree of firm 'competitiveness' in the manner discussed in the literature. First, the competition-mention measure is not based on own-firm characteristics, such as firm size or product market share, or even more detailed information embedded in the firm's financial statements, news releases, executive conference calls, etc. Rather, it requires the collective view of all other firms. More important, the traditional definition of competition is a symmetrical one by nature, i.e., a pair of firms are assumed competitors. The competition links however are directional—a mentioning of a firm as a competitor by another firm does not necessarily imply the reverse mentioning. In fact, the percentage of mutual mentioning over our sample period is only 5.67% (and 3% if restricted to the same year). That is, for the vast majority of cases, when Firm A believes that it is in competition with Firm B, Firm B does not share the same view.

We empirically assess the relation between competition mentions and other existing measures of competitiveness, at both firm and industry levels. The first firm-level measure is based on Li, Lundholm, and Minnis (2013) who estimate the competitiveness of a firm as the percent of competition-related words in its 10-K ('PCT COMP'). We obtain this measure from Feng Li's website. The second measure is based on Hoberg and Phillips (2010, 2016) who analyze the product description section in 10-Ks to measure the similarity between the products of each pair of companies. Following Li, Lundholm, and Minnis (2013), we measure the competitiveness of a firm by the sum of the pairwise product similarity scores between the firm and all other firms ('Similarity COMP'). In addition, we use product market fluidity introduced by Hoberg, Phillips, and Prabhala (2014). This measure captures changes in rival firms' product descriptions in their disclosures relative to the firm's product description. We obtain data on product similarity and fluidity from Hoberg and Phillips data library. Competitiveness in the firm's business environment is gauged using two measures following the study of Bustamante and Donangelo (2017). The first is industry operating leverage, defined as the average ratio of the sum of operating costs and administrative expenses to total assets (see also Novy-Marx 2011). The second is industry concentration, estimated by the Herfindahl-Hirshman index for market share of sales. We implement these measures using both the eleven GIC sector and Fama-French 48 industry classifications.

Table 2 reports competition measure means within competition-mention portfolios, differences in means across portfolios, as well as the correlations between the competition measures and competition mentions. Competition-mention exhibits a positive relation with the other measures of competition (except for the concentration measures), and the differences in the other measures are statistically significant across extreme competition-mention groups (for example, 3+ mentions minus no mentions), which suggests competition mention is statistically significantly related to other measures of competition. However, the average correlation between competition mentions and the other measures is quite low, at about 2%.

The 10-K competitiveness (PCT COMP) displays the lowest mean for the zero-mentioned firms, and overall correlation of 4.9% with competition mention. This means that firms that are highly mentioned as competitors in other reports are not necessarily the ones who use more "competitive" language in their own reports. Product market fluidity exhibits the clearer relation with competition mentions, where the means are generally increasing monotonically when one moves from the zero-mention to the 3+ mention portfolio, yet the relation is quantitatively weak with a correlation of 5.7%. The weak relation between competition mentions and product market fluidity may have a natural interpretation. On the one hand, when a firm shares product similarity with many other firms, it can indicate that the firm operates in a competitive environment. Yet, when the firm is less dynamic than its peers in changing its products (high fluidity), its business can be perceived as less attractive by other firms, attracting therefore fewer competition mentions.

The operating leverage ratio shows an interesting pattern, where the firms with low mentions (1 and 2) have higher mean ratios than both the zero-mentioned and the highly mentioned groups. A plausible explanation for this result is that the mentioning firms are interested in dynamic and growing competitive environments, yet not "too competitive," so they can maintain a fair chance of entry and success. The differences in sector/industry concentration are very small across the mention-portfolios, where the zero-mentioned firms show the highest means and medians, which is reflected in small negative correlations of -0.9% and -4.1%. This may suggest that in concentrated industries that are led by a few leading organizations, most of the firms do not have high growth prospects, and are thus not mentioned much by other firms.

The results in Table 2 suggest that while the competition-mention measure shares aspects of competition with some of the other measures, its relation to the other measures is rather weak. Then, what does competition mention capture? We argue that competition mentions indicate profitable future business opportunities. When a firm mentions another firm as a competitor in its report, it is often because the mentioning firm finds the business environment of the given firm attractive (especially when the mentioning firm is relatively large and from a different sector—we elaborate on this later in the paper). Consistent with this conjecture, we show in this study that highly mentioned firms subsequently exhibit an increase in profitability and are also more likely to be taken over. Therefore, in contact to other works in the IO literature (discussed below), advancing that expected returns are related to competition as a result of market equilibrium, we postulate that future returns are caused by investor inattention. That is, competition mentions signify future growth, yet this information is slowly reflected in asset prices. Indeed, we show below that when investors pay more attention to the mentioned firms, the future stock returns of these firms are lower than mentioned firms with low investor attention.

1.3. Portfolio sort analysis

An important feature of the competition-mention measure, namely the number of 10-Ks in which the firm is mentioned as a competitor, is that it is not an independent assessment based on observed firm-specific characteristics, such as firm size or product market share, or even the competitive nature of the text in the firm's 10-K (Li, Lundholm, and Minnis 2013). Rather, the competition-mention measure reflects the collective view, across all companies, regarding important competitors in the marketplace. This feature therefore raises the question of whether investors fully understand the information about a given firm, as recognized by its competitors. Thus, we study whether highly mentioned firms are mispriced at a given point in time by examining whether competition mentions subsequently lead to high stock returns.

We begin with a portfolio sort analysis. Each month over the period 1995-2017 all firms are sorted into four portfolios by number of mentions (0, 1, 2, and 3+). The portfolios are value-weighted and held for one month, and, as discussed above, do not include microcap stocks. Panel A of Table 3 reports the monthly returns on each portfolio, as well as the difference between the 3+ and 0 mention portfolios, and the difference between the 3+ and 1 mention portfolios. In addition to reporting the average return in excess of the risk-free rate, we also report the alpha from a 6-factor model. The factors are the Fama and French (2015) factors augmented with a momentum factor. All factor returns are downloaded from Ken French's website. All returns and alphas are in percent per month and numbers in parentheses denote the corresponding *t*-statistics.

The results show that the highly mentioned firms (3+ mentions) earn higher mean excess returns than firms with zero mentions and firms with one mention, yet the return gaps are not highly significant: mean excess returns of 0.1% and 0.21% per month, respectively, with *t*-statistics of 0.68 and 1.46. Controlling for risk factors yields significant differences: 6-facor alphas of 0.32% for the difference between 3+ and zero mentions (*t*-statistic=2.64) and 0.45% for the difference between 3+ and one mention (*t*-statistic=3.53). The latter return difference is meaningful as it demonstrates that the predictability of competition mentions over stock returns is not solely driven by firms with no competition mentions at all, which account for most firms.

Note that the return predictability of competition mentions is not driven by firms in a particular sector. In Figure 3 we show that removing from the sample all firms from one sector at a time (using the eleven GIC sector classifications), as well as all firms that they mention, yields a significant value-weighted 6-factor alpha for each case; monthly alpha point estimates range from 0.36% (when excluding communication services) to 0.54% (when excluding healthcare).

To verify that the positive effect of competition mentions on stock return does not capture the size effect, we perform a double-sort analysis. We first sort all stocks equally into three groups based on firm size (measured by the market value of equity). Within each size group, the stocks are further sorted into the four competition mention groups as in the single sort. Panel B of Table 3 shows the mean excess monthly stock returns and 6-factor alpha for the four mention portfolios as averaged across the three size groups. The double-sort results are even stronger than those of the single-sort, as both mean excess returns and 6-fsctor alphas of the hedge portfolios are higher in all cases and are all statistically significant. For example, the 6-factor alpha of the 3+ minus zero-mention portfolio is 0.70% a month (*t*-statistic=4.43), and is 0.54% (*t*-statistic=3.62) when comparing 3+ mentions and one-mention portfolios. The results in Panel B thus confirm that the high stock returns to highly mentioned firms are not captured by the size effect.

Figure 4 shows the cumulative return of the competition-mention hedge portfolios over the period 1995-2017. While the effect seems stronger in the early years, it is consistently upward sloping over the sample period. Robustness tests presented later in the paper confirm that the return spreads are statistically significant in both the early and recent periods.

2. Admiring versus targeting mentions

One important aspect underpinning the results is the decision of the firm to mention other firms in the competition section of its 10-K filings. As this decision is endogenous by nature, we attempt to identify some potential motivations, which further help us understand the performance of highly mentioned firms. We break the competition mentions into two types based on the relative size (as measured by market capitalization) of a given firm and the firms by which it is mentioned. When a firm is mentioned as a competitor by a far smaller firm, it is more likely to represent admiration or aspiration of the small firm to become or to be perceived as similar to the larger firm. When the mentioning firm is much larger than the firm it mentions, however, it is more likely to indicate that the mentioning firm sees high potential in the business environment of the mentioned firm, consistent with targeting-like behavior.

We hypothesize that firms that are ‘targeted’ in 10-K competition sections are more likely to be underpriced than ‘admired’ firms in these sections. It is fair to assume that an admired firm has established a strong reputation already, which drives smaller firms to recognize it in their reports. The high reputation, as well as the transparency of admired firms, leave less room for stock misvaluation. The case is different, however, for targeted firms. A large company that finds the business environment of a smaller firm attractive likely uses information tools that are typically not possessed by the average investor. This can result in a temporary underpricing of the mentioned firm.

It is important to note that although the distinction between admired and targeted firms is based on relative firm size, the future performance of admired/targeted firms is not a manifestation of the size effect. The series of tests conducted in this section control for size in a variety of ways.

To test our hypothesis, we classify firms that are mentioned in other reports as competitors into two categories. The ‘admired’ group includes the firms that are larger (by equity market value) than the average firm that mentions them, and the ‘targeted’ group includes the firms that are smaller on average than their mentioning firm. We perform the portfolio sort analysis separately for mention-admired and mention-targeted firms. Firstly, the results reported in Table 4 show that there are much more admired firms than targeted firms; average monthly portfolio sizes of 472 and 115 firms, respectively. This is not surprising given the natural ambition of small firms to chase the success of the leading firms. More interestingly, consistent with our hypothesis, mention-targeted firms earn higher return than mention-admired firms. The 6-factor alpha of targeted firms with at least three mentions is 0.84% a month, compared to only 0.20% a month for admired firms with three or more mentions. The alpha of the hedge portfolios is also higher for targeted firms, especially when comparing highly mentioned firms to zero-mention firms.

We further examine the association between competition mentions and subsequent returns, and specifically targeting versus admiring, using Fama-MacBeth (1973) regressions. Beyond serving as an additional diagnostic check, these regressions offer the advantage of controlling directly for well-known determinants of the cross-sectional patterns in returns and thus check for the marginal influence of competition mentions on our results. Accordingly, we run these cross-sectional regressions and report the results in Table 5. The dependent variable is the excess stock return and the main independent variable is the number of 10-Ks in which the firm is mentioned as a competitor over the past twelve months. This variable refers to all mentioned firms, and separately to targeted and admired mentioned firms. To isolate the difference in return between mentioned and non-mentioned firms, the regressions include a dummy variable that equals one for non-mentioned firms, and one for mentioned firms. The control variables are log market capitalization, log market-to-book, past six-month return, profitability, investment intensity, market beta, and idiosyncratic volatility. All independent variables are winsorized at the 1% and 99% levels to reduce the impact of outliers. All reported coefficients are multiplied by 100 and Newey-West (1987) corrected (with twelve lags) *t*-statistics are reported in parentheses.

The results show that the number of times a firm is mentioned as a competitor has a significantly positive impact on stock return, with a regression coefficient of 0.34 (*t*-statistic=3.12). The coefficient of the zero-mention dummy is negative, yet weakly significant (*t*-statistic=-1.52). These results suggest that the effect of competition mentions on stock returns does not stem only from the difference between non-mentioned and mentioned firms, but it is also present within mentioned firms, which is consistent with the portfolio sort results. We further show in the table that the regression results remain significant without the Newey-West correction and when removing small firms.

Running the same regressions for targeting mention classification yields stronger results where the coefficient of mentions is roughly twice as high (0.71), albeit with a lower *t*-statistic (2.02), perhaps due to the smaller sample of targeted firms. Admiring mentions however yields a lower impact on stock returns, with a coefficient of 0.27 and borderline statistical significance (*t*-statistic=1.72). The regression results therefore corroborate the portfolio sort analysis, indicating that high competition mentions are associated with high expected stock returns, and support our conjecture that targeted firms are more likely underpriced than admired firms.

3. Evidence of limited attention

A relation between firm characteristics and future returns, not captured by documented risk factors (size, value, etc.), can signify temporary mispricing. As we argue above, if a group of large companies point to a smaller firm as a competitor (targeting mentions), it might indicate that they find the business environment of that firm attractive, more than currently valued by investors. The outperformance of highly mentioned firms in this case is consistent with mispricing—these firms gradually grow in value as investors slowly digest the information.

3.1. Cross- and within-sector mentions

To provide further support for the explanation of return predictability as mispricing stemming from investor limited attention, we study the cross- and within-sector predictability. Because investors tend to focus on particular sectors, they are less likely to pay attention to information produced about a given firm by other firms outside its sector. We thus expect a stronger return predictability for competition links across sectors than within sectors. This prediction is tested by dividing all 10-K competition mentions into two groups: mentions outside the sector of the filing firm (cross-sector mentions) and mentions within the sector of the filing firm (within-sector mentions). We use two sector/industry classifications. The first is the eleven GIC sectors and the second is the Fama-French 48 industries.

As we outline above, most firms in the sample are not mentioned at all as competitors, and the percentage of zero mentions is even higher when considering cross-sector and within-sector mentions separately. That is, dividing mentioned firms into groups of cross- and within-sector mentions and further dividing these groups by the number of mentions leaves even smaller portfolio sizes. Therefore, instead of sorting firms by the number of cross- and within-sector mentions, we consider all firms with at least one cross-sector mention as one group and all firms with at least one within-sector mention as another group. We then further analyze the types of mentions in each group, that is either 'targeting' mentions (when the mentioning firms are larger, on average, than the mentioned firm) or 'admiring' mentions (when the mentioning firms are smaller, on average, than the mentioned firm). We find stark differences between cross- and within-sector groups. Table 6 reports that for GIC classifications, the 6-factor alpha of cross-sector targeting mentions is 0.98% per month, compared to 0.23% for cross-sector admiring mentions. The corresponding alphas for within-sector mentions are far lower, 0.35% and 0.15%, respectively. Using the Fama-French 48 industry classification yields similar results. The 6-factor alpha of cross-sector targeting mentions is 1.00% per month, compared to 0.20% for cross-sector admiring mentions, whereas the corresponding alphas for within-sector mentions are lower at 0.52% and

0.18%, respectively. This analysis thus identifies that firms targeted by other firms from different sectors earn the largest returns, providing further evidence consistent with the explanation that limited attention drives the high expected returns to highly mentioned firms.

Given the high return predictability driven by cross-sector links, we further examine the structure of these links. Appendix C reports the sectors with most cross-mentioning, and the sectors that are mostly mentioned by them. The sector with the most cross-sector mentioning is Information Technology (32% of all cross-sector links), and the top three sectors it mentions are: Industrial, Consumer Discretionary, and Communication Services. We perform a similar analysis using the Fama-French 48 industries. The results highlight the heterogeneity (and complexity) of competition links across the various businesses. While some competition links may be more intuitive than others (for example, Business Services mentioning Computers and Electronic Equipment, and Pharmaceutical Products mentioning Medical Equipment), overall, all sectors are linked to all other sectors, which further emphasizes the difficulty of gathering all value-relevant information of any given company.

3.2. Analyst coverage

Presumably, a significant amount of information across firms and industries flows through analyst reports. Therefore, we can further test the mispricing hypothesis by tracing the analyst links along with the competition links. If a given firm is recognized as a competitor by many other firms outside its sector—a recognition that indicates potentially profitable business opportunities—then it is more likely that this information will be known to investors if the financial analysts that cover the given firm also cover many sectors, and especially the sectors of the mentioning firms.

We utilize data on analyst coverage (obtained from IBES dataset) to test for mispricing due to slow diffusion of information. Specifically, we classify five groups of firms that represent different types of sector-analyst coverage (using the GIC classification), and perform the competition-mention portfolio sort analysis separately within each group. Table 7 reports the 6-factor alpha of each mention portfolio as well as the hedge portfolios. The differences in alphas across the analyst coverage groups are consistent with stock mispricing. We focus on the alpha figures for the 3+ minus one-mention portfolio, where the 3+ minus zero-mention portfolio exhibits similar pattern.

First, partitioning firms into those with and without analyst coverage shows that the latter group displays higher alpha (0.30% vs 0.66% per month, respectively). For firms with analysts that cover only one sector, the effect is even higher, 1.77% per month; yet this figure should be interpreted with some caution as the average portfolio size is quite small in this case. When the firm's analysts cover multiple sectors, the alpha is still positive at 0.24% per month, yet weakly significant (*t*-statistic=1.55). Finally, when the firm's analysts cover multiple sectors, including those of the mentioning firms, the return predictability of competition links disappears. This pattern seems consistent with the flow of relevant information about competition links through analysts, supporting the notion that investor inattention to competition links can explain their return predictability.

4. Real effects

The evidence presented thus far suggests that firms that are highly mentioned as competitors in other firms' 10-Ks subsequently earn positive returns, especially if the mentioning firms are larger than the mentioned firm and operate in a different sector. This result is consistent with the conjecture that larger firms recognize small firms as competitors typically when they identify high business potential, and that these recognitions receive less attention when they are generated from outside the sector. To better establish the direction of mispricing advanced in this paper, that is highly mentioned firms are underpriced, we examine the changes in the fundamentals of mentioned firms along the two dimensions of cross/within-sector and targeting/admiring mentions.

The real effects of competition mentions are examined by studying subsequent changes to total firm sales and operating income (before depreciation and amortization). We compute growth (percent change) of total sales and operating income in the next one, two, and three years. The growth rates are adjusted to the median of comparable firms, those in the same 3x3 size/market-to-book group within the same GIC sector. All growth rates are winsorized at the 1st and 99th percentiles. Figure 5 displays the average cumulative adjusted-growth rates (and *t*-statistics) of sales and operating income during each of the subsequent three years. The sample includes only firms that are mentioned by competitors, which are further divided into targeted and admired firms for cross- and within-sector mentions.

The results show that while, in general, mentioned firms experience positive performance, the extent of the growth largely depends on the type of the mention. For cross-sector mentions, targeted firms display, on average, larger growth in fundamentals than admired firms in all horizons. The differences in sales growth range between 1.1% and 2.1%, and is statistically significant for the first two years, and insignificant in the third year (*t*-statistic=1.09). The differences in operating income growth are larger, ranging between 2.7% and 5.8%, and are all statistically significant (*t*-statistics range between 2.32 and 2.60). The patterns however are different for within-sector mentions, where targeted firms experience lower growth rates than admired firms, with statistical significance for sales.

These results are consistent with the premise that when leading organizations reach out of sector to identify a competitor (the mentioned firm), it indicates significant business opportunities for that competitor, which are not fully understood yet by market participants. In turn, this leads to positive future stock returns for the competitor/mentioned firm as market participants slowly incorporate the information about the mentioned firm business opportunities, which are later realized, as indicated by the positive changes in firm fundamentals. When the targeting is within-sector, however, it may also indicate that the leading firms in that sector are trying to 'protect' their business from smaller firms in the same sector, resulting in increased competition pressure and ultimately relatively lower future fundamentals.

To further explore the intention of competition mentions in 10-Ks, i.e., admiring or targeting mentions, the paper examines their ability to predict future takeovers. If a firm being mentioned by larger firms signifies a 10-K-targeting behavior, then the likelihood that this firm will be acquired should be higher than that of admired firms. To test this prediction, we obtain takeover data from Thomson One Banker. Our sample contains 7,962 merger target announcements over the sample period.

We run logit regressions for the sample of all mentioned firms, and separately for cross- and within-sector mentions. The dependent variable equals one if the firm has been announced as a merger target in the next twelve months, and zero otherwise. The independent variable of interest equals one if the firm is targeted in 10-Ks, and zero if admired as defined above. To control for the firm's unconditional probability of being taken over, we use the model of Billett and Xue

(2007). This model relies on a set of merger-related characteristics, such as firm size, profitability, leverage ratio, and others. The regression also includes firm and time fixed effects.

The regression results reported in Table 8 indicate that being recognized by larger firms as a competitor increases the likelihood of being acquired in the short run. This effect is statistically significant for all three samples. To assess the economic significance of this effect, we look at the change in takeover probability as implied by the logit model when changing the targeting dummy variable from 0 (10-K admiring) to 1 (10-K targeting), while keeping the Billett and Xue's model value at its mean. The probabilities are displayed in Figure 6. Considering all mentions, an admired firm has a probability of 2.63% to be acquired during the next twelve months, where the probability of a targeted firm is 4.88%. This means an increase in probability of about 85%. The cross- and within-sector mention samples also show significant results, where consistent with the fundamental changes analysis, cross-sector targeting mentions have a stronger impact on the probability of takeover: increases of 122% and 77%, respectively. Being mentioned as a target in 10-Ks, therefore, not only leads to higher stock returns than admired firms, but also significantly increases the likelihood to be merged. This further supports the conjecture that targeted firms are more likely underpriced.

5. Testing for systematic risk

As discussed above, the return predictability of competition mentions may reflect underpricing of highly mentioned firms driven by investors not fully aware of these firms' attractive business opportunities as recognized by other companies. Yet, the high stock returns earned by highly mentioned companies can also be consistent with a risk-based explanation. That is, being identified by strong companies as a competitor imposes uncertainty as to the firm's future performance and value. To the extent that this type of risk is systematic and recognized by the market, it should be compensated by high expected stock returns. We explore the risk-based explanation in two ways. First, we study the systematic pricing of competition mentions; second, we explore whether the return predictability of competition mentions is related to competition risk factors offered in the literature.

To explore systematic pricing, we produce a competition-mention factor and examine whether stocks that are more sensitive to this factor gain higher returns than stock that are less sensitive to the factor. We estimate the monthly mention-factor as the return spread of 3+ mentions minus one-mention portfolios, as appeared in Table 3. For each stock every month, we compute a 'mention-beta' using rolling regressions over the past 36 months of the firm's excess return on the mention-factor. The regressions control for the Fama and French (2015) five factors and the momentum factor. Every month we sort all stocks into five equal-sized portfolios based on their mention-beta. The portfolios are value-weighted and are held for one month.

The results reported in Panel A of Table 9 do not show any significant differences in returns/alphas along the mention-beta quintiles. Because the return predictability is largely driven targeting mentions, we further perform this exercise when the mention-factor is generated from targeting mentions only. The results in Panel B shows even smaller differences, where the 6-factor alphas are virtually zero for all mention-beta quintiles. These results therefore do not support systematic risk as the driving the high expected returns to highly mentioned firms.

We next turn to examine the association of our findings to theories that relate expected returns and competition in the product market (see, e.g., Hou and Robinson 2006; Hou 2007; Peress 2010). In particular, these works advance that firms that operate in competitive industries are more adversely affected by systematic shocks and therefore earn higher expected returns than those operating in concentrated industries that are better able to weather aggregate shocks (other works, such as Gaspar and Massa (2006) and Irving and Pontiff (2009) point to a positive relation between a firm's competitive product-market environment and idiosyncratic return volatility). Bustamente and Donangelo (2017) expand the theoretical framework to offer two separate effects determining the relation of competition to expected returns: operating leverage and threat of entry.

To explore this potential explanation, we follow Bustamante and Donangelo (2017) to measure operating leverage and concentration at the industry level (as described in Section 1.2), and study whether these channels can explain the outperformance of mentioned stocks. Table 10 presents results of Fama-MacBeth regressions, the same as those presented in Table 5 with four additional explanatory variables: industry operating leverage and concentration and their interaction with mentions. The regressions include all control variables as in Table 5, where to reduce the clutter in the table, only the coefficients of interest are reported.

The results indicate that none of the variables associated with industry-wide competition risk are significant, while the coefficient of number of mentions remains significant. When estimating the regressions separately using targeting mentions and admiring mentions, all specifications except one yield insignificant coefficients on the four aforementioned additional variables. (The one specification is that yielding a negative and significant coefficient on the interaction of targeting mentions and sector operating leverage, consistent with the results and interpretation of Bustamante and Donangelo.) Despite the low power of these regressions due to a low number of firms with non-zero targeting/admiring mentions, the number of mentions remains significant for most specifications.

We conclude that the existing systematic-risk-based explanations for the performance of competitive/concentrated sectors do not explain the outperformance of competition-mentioned stocks. Perhaps this is not entirely surprising, because, as discussed above, a firm being mentioned by other firms may capture additional information over and beyond the notion of competitiveness advanced in the literature. Specifically, this paper advances that competition mentions signal profitable future business opportunities (particularly for targeted firms).

6. Controlling for other firm links

As discussed in the introduction, recent studies attempt to identify pairwise connectivity between companies, typically by comparing the contents in the disclosures of each pair of companies. Our study presents a different learning approach. Instead of focusing on firm-produced information, we show that relevant information about the value of a given firm can be obtained by analyzing the financial statements of all other firms. Nevertheless, in this section we verify that our competition-link classification does not capture other documented peer metrics, and in addition, that the return predictability of competition mentions remains significant while controlling for other firm-link characteristics.

Hoberg and Phillips (2010, 2016) analyze the product description section in 10-Ks to measure the similarity between the products of each pair of companies, creating thereby a network of peers to each firm. Because presumably firms are more likely to compete with each other when producing similar products, we begin our analysis by examining the manner by which competition links interact with Hoberg-Phillips (HP) peers. We do so in two ways. First, we assess the overlap between competition links and HP peers. In particular, we classify each competition link as ‘similar’ if it connects between two firms that are peers by HP classification, and ‘not similar’ if the two firms are not HP peers. The percentage of the competition links that are 'similar' thus reveals the overlap between competition links and the HP product similarity peers. We find that the overlap is 53%, that is, when firms list competitors in their 10-Ks, only for about half of the cases these competitors are peers by HP classification. Furthermore, we find a quite low correlation (5%) between the number of times a firm is mentioned as a competitor and its cross-sectional average HP distance score. These findings suggest that competition links capture information that is not particularly embedded in product similarity.

Second, we examine whether the competition-link results interact with the HP peer classification by comparing portfolio return of 'similar' and 'not similar' competition mentions, as described above. The results (Table 11) show that the competition-link effect is significant in almost all cases, where mentions between HP peers generate higher returns. At first glance, this result might seem to contrast those using traditional industry classification to proxy for product similarity, such as the eleven GIC sectors and Fama-French 48 industries, where cross-sector competition mentions yield stronger returns that within-sector mentions. However, a plausible explanation is that HP-similar-product firms are better informed than non-HP-similar-product firms about future opportunities of their competition-linked firms. Yet, in contrast to the more traditional sector/industry classifications, investors may not be able to estimate or even ignore the HP metric. This can lead to higher portfolio return spreads for similar-product linked firms than for non-similar-product linked firms.

Rauh and Sufi (2012) and Lewellen (2015) use the product market competition from Capital IQ ('CIQ'). This dataset classifies product market competition peers by collecting data from different sources including SEC filings, and in that aspect it is similar to the data underlying our competition-link system. There are several differences between the CIQ and our competition links, most are related to nuances of the mechanism of the textual learning process. Yet a key distinction is that while CIQ (and also Hoberg-Phillips for that matter) is a symmetric peer dataset (i.e., firms A and B are identified as a competitor pair), our competition link system, as discussed in the previous section, is not symmetric, as it is based on the direction from one firm to another. This is a very important feature in our study because it allows us to build a uniform measure of competition at the firm-level based on the extent to which competition links are directed at each firm. To demonstrate this asymmetry, we show (Table 12) that in contract to the main finding of this paper (that firms mentioned by many other firms significantly outperform), firms that mention many competitors in theirs10-Ks do not outperform. This suggests that the competition status of a firm cannot be fully assessed by examining the firm's own statement, but rather requires the view of other firms.

Other studies identify links between firms that contain information for subsequent returns. Scherbina and Schlusche (2015) study the cross-predictability of stock returns of firms linked via their co-mentioning by the media. Ali and Hirshleifer (2020) find a connected-firm momentum for firms that are covered by the same analysts. Another related paper is Cohen, Malloy, and Nguyen (2020) who introduce the concept of "lazy prices" by showing that textual changes in 10-Ks predict stock returns. This raises the question whether the return predictability of competition mentions we document is driven by adding/removing competitors in 10-K reporting.

We examine the interaction between competition links and the other firm links in a cross-sectional regression similar to that presented in Ali and Hirshleifer (2020). We run Fama-MacBeth regressions with our main variable of competition mentions and add three measures based on the aforementioned studies. The first variable indicates a change in competition mentions over the past year, which captures the notion of lazy textual composition highlighted in Cohen et al. (2020); specifically, the 'mention change' variable equals 0, 1, and 2 for negative change, no change, and positive change in the number of mentions over the past twelve months, respectively. The second measure is the shared analyst coverage of Ali and Hirshleifer (2020). This variable is of key importance because, as shown in Ali and Hirshleifer, it dominates all other link-based measures examined in that paper. Following this study, for each firm in every month we compute the average return of the firms that are covered by the same analysts, where the average return is weighted by the number of shared analysts (see Eq. 1 in Ali and Hirshleifer). The third measure is news co-mention used in Scherbina and Schlusche (2015). Due to the complexity involved in generating this measure, we were able to generate values only for the period 2011-2017, nevertheless it yields results consistent with Scherbina and Schlusche.

Similar to our approach with the HP dataset, we first examine the overlap between competition links and the shared analysts and news links. We find that the overlap is rather low, 16% and 15%, respectively, suggesting that competition links across 10-Ks are not fully captured by analyst coverage or co-mentioning in the media. The regression results are reported in Table 13. The change in competition mentions does not seem to predict stock returns, suggesting that the level of competition links is not subsumed by the 'lazy' mentions. The shared analyst and news co-mention display positive and significant stock-return predictability, consistent with their respective original studies. Most importantly, the coefficient of competition mentions remains positive and significant in the presence of these three controls.

The collective results in this section confirm therefore that the high stock returns to highly mentioned firms are not captured by alternative firm links.

7. Additional tests

We perform a series of tests to validate the robustness of the return predictability of the competition-mention measure. We replicate the main results for different subsamples and investment horizons, and using a modified measure of competition mentions.

7.1. Sample splits and longer horizons

We replicate the portfolio sort analysis in Panel A of Table 3 for different subsamples and longer investment horizons. Table 14 reports the 6-factor alpha for each portfolio. To facilitate comparison with the main results, we also report the full-sample results in the first row of the table. In addition, we report also the equal-weighted alpha for each hedge portfolio. We consider four different kinds of subsamples. In the first we exclude small stocks, defined as stocks with equity market value of between the 20th and 50th percentiles by NYSE breakpoints (see Fama and French 2008). The second simply tabulates results when excluding the month of January. The third subsample excludes recession periods. We use the NBER recession dummy as an indicator of the health of the economy for this exercise. Fourth, we tabulate the results separately for the early years (1995-2006) and the late years (2007-2017). For the sub-periods we also show the results of double-sort by size and mentions as in Panel B of Table 3.

Panel A of the table shows that the competition-mention return spread is larger without small stocks; the monthly value-weighted 6-factor alpha is 0.51% with a *t*-statistic of 3.78. This result is consistent with the regression results in Table 5, verifying that the return predictability of competition mentions is not driven by small stocks. The spread is somewhat lower when excluding January, but is still significant; a value-weighted alpha of 0.40% with a *t*-statistic of 3.09. The results seem insensitive to the state of the economy, as excluding recessions shows a significant value-weighted 6-factor alphas of 0.41% (*t*-statistic=3.18). Consistent with Figure 4, the effect of competition mentions is stronger in the early years, yielding a value-weighted alpha of 0.77% with a *t*-statistics of 3.70, yet is still significant in the recent years with an alpha of 0.26% (*t*-statistic=2.13). When controlling for size, both alphas are larger, 0.84% in the early years (*t*-statistic=3.24) and 0.43% in the late years (*t*-statistic=3.34). The equal-weighted alpha of the main result is lower than the value-weighted alpha, yet statistically significant, as well as the equal-weighted alphas of all subsamples.

We look at the return predictability of competition mentions over longer investment horizons in Panel B of Table 14. We consider holding periods of 3, 6, 12, and 18 months. This means that we have overlapping portfolios. We take the equal-weighted average of these overlapping portfolios similar to the approach of Jegadeesh and Titman (1993). The 6-factor monthly alphas of the competition-mention hedge portfolio are positive and statistically significant for horizons up to 18 months, although decline monotonically as we increase the horizon, from a value-weighted alpha of 0.45% for a one-month horizon to 0.27% for a 18-month horizon. All portfolio sort results are therefore robust to different subsamples and investment horizons.

7.2. Alternative mention-based measure

We examine the robustness of the results to an alternative measure of firm competition-mention. While our simple count measure gives the same weight to each mentioning firm, we study an augmented measure of competition mention, one that overweights mentions made by firms that themselves receive more mentions by other firms. Estimating such a measure requires it to be simultaneously estimated for all firms. We accomplish this using a Google PageRank-type algorithm in the manner of Page et al. (1999), applied to competition links in the most recent annual reports of all firms in each month.

Each month we run a PageRank-type algorithm that iteratively solves a system of n (where n is the number of unique-firm reports) simultaneous equations to produce a firm-level competition-mention rank, which we refer to as 'C-Rank'.[1] (Appendix D provides a simple example to illustrate

[1] We use a damping factor of 0.7 in applying the algorithm. The results remain similar when using different damping factors between 0.5 to 0.9. See Page et al. (1999) for details on the PageRank algorithm.

this algorithm.) As with the simple mention count, to make sure that all firms participate in calculating monthly C-Ranks, for each month we use the most recent annual report of every firm over the past twelve months.

We find first that although the C-Rank is a more complex metric and utilizes additional information to that captured by a simple mention count, the two measures are highly correlated; the time-series average of the monthly cross-sectional correlations between the two measures is 0.76. To compare the return predictability of the two measures, we run the portfolio sort analysis using C-Rank instead of simple mention count as the primary sorting variable.

Each month we sort all firms into four portfolios. The first portfolio, 'No Mentions' includes all firms that have not been mentioned as competitors by any other firm in the past twelve months and thus get the lowest C-Rank value in the current month. The mentioned firms are divided equally into three portfolios according to their C-Rank in the current month ('Low', Mid', and 'High'). The portfolios are value-weighted and held for one month. Table 15 reports the mean excess returns and factor-model alphas of the C-Rank portfolios, as well as the hedge portfolios, both for single-sort by C-Rank, and for double-sort by size/C-Rank as in Table 3. The return predictability of C-Rank is consistent with that of the simple mention count. The single-sort results (Panel A) show that the high C-Rank firms gain higher mean excess returns than firm with zero mentions and firms with low C-Rank, yet the differences are not statistically significant, whereas the factor-model alphas of both differences are positive and statistically significant. Controlling for size (Panel B) yields higher returns/alphas of the hedge portfolios, all are statistically significant. And perhaps somewhat surprising, for most cases the returns/alphas of the C-Rank sorted hedge portfolios are lower than those achieved by the simple mention count.

Given the high correlation between the simple mention count and C-Rank and the quantitatively similar results they produce, to ease interpretation, the simple count measure is maintained throughout the paper. The simple measure still requires the scanning of all 10-Ks constantly to detect all competition mentions, but it saves the task of calculating the C-Rank for the cross-10-K-link system. This also simplifies many other tests conducted in the paper.

8. Conclusions

We produce a dynamic measure of a firm's competition-mention from the financial disclosures of all other firms. The main result of this paper indicates that firms that are highly mentioned as competitors in other firms' reports tend to outperform. Returns are significant after controlling for firm size and other common risk factors, and are robust to various econometric procedures and subsamples. The high return associated with competition mentions mainly stems from targeting-driven mentions from other sectors. This result is largely consistent with investor underreaction to firm business opportunities identified by other firms. Utilizing data on analyst coverage lends further support for this conjecture.

Abnormal changes in firm fundamentals in subsequent years reveal patterns consistent with the return predictability. Additional tests suggest that the high return to highly mentioned firms is not associated with competition-based systematic risk, and is not driven by alternative documented classifications of firm links. We further demonstrate the robustness of the results to an augmented measure of competition-mention, one that overweights mentions made by firms that themselves receive more mentions by other firms.

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Appendix A. Text analysis of competition sections in 10-Ks

Dataset

We match company tickers to CIKs, identifiers used by SEC-Edgar, and download from SEC-Edgar the 10-K filings. We observe a total of 119,785 10-Ks filed by 11,304 firms over the period 1995-2017. The focus of this paper is Part I / Item 1 – Business of the 10-K form. Although reporting firms are not required to designate a competition section in Item 1, we find that 68,952 of the forms used in this study (58%) include a designated section for competition. And about 39% of these competition sections include names of the company's competitors.

The example below is an extract from the 2017 10-K form filed by Alphabet Inc., parent company of Google. In Part I / Item 1 – Business, Alphabet designates a section to discuss its competitive environment. In this section it lists both the areas in which it faces competition (e.g., general search engines, vertical search engines, social networks, etc.) and the companies it considers as competitors in each of the areas.

Competition

Our business is characterized by rapid change as well as new and disruptive technologies. We face formidable competition in ever aspect of our business, particularly from companies that seek to connect people with online information and provide them with relevar advertising. We face competition from:

- General purpose search engines and information services, such as Baidu, Microsoft's Bing, Naver, Seznam, Verizon's Yahoo, an Yandex.
- Vertical search engines and e-commerce websites, such as Amazon and eBay (e-commerce), Kayak (travel queries), LinkedIn (jo queries), and WebMD (health queries). Some users will navigate directly to such content, websites, and apps rather than go throug Google.
- Social networks, such as Facebook, Snap, and Twitter. Some users increasingly rely on social networks for product or servic referrals, rather than seeking information through traditional search engines.
- Other forms of advertising, such as billboards, magazines, newspapers, radio, and television. Our advertisers typically advertise i multiple media, both online and offline.
- Other online advertising platforms and networks, including Amazon, AppNexus, Criteo, and Facebook, that compete for advertiser that use AdWords, our primary auction-based advertising platform.
- Providers of digital video services, such as Amazon, Facebook, Hulu, and Netflix.
- Companies that design, manufacture, and market consumer electronics products, including businesses that have develope proprietary platforms.
- Providers of enterprise cloud services, including Alibaba, Amazon, and Microsoft.
- Digital assistant providers, such as Amazon, Apple, and Microsoft.

Competing successfully in our advertising-related businesses depends heavily on our ability to deliver and distribute innovative product and technologies to the marketplace so that we can attract and retain:

- Users, for whom other products and services are literally one click away, primarily on the basis of the relevance and usefulness of ou search results and the features, availability, and ease of use of our products and services.
- Advertisers, primarily based on our ability to generate sales leads, and ultimately customers, and to deliver their advertisements in a efficient and effective manner across a variety of distribution channels.

5

In total Alphabet lists twenty individual companies as competitors. These include domestic US firms such as Verizon and Microsoft, foreign firms (e.g., Baidu), and also private companies and private subsidiaries of public companies such as Hulu and Yahoo respectively. Some of the listed competitors appear multiple times as Alphabet considered them as competitors in multiple areas. Amazon, which is mentioned five times, is considered by Alphabet as a competitor in e-commerce search, online advertising, digital video, enterprise cloud, and digital assistance services.

Identifying firms in competition section

Once a designated competition section is found on a 10-K filing, our process attempts to identify which specific companies it lists. Since competitors are referred to by names using natural language, matching listed firms to security identifiers requires some additional text and language processing. We use an open-source natural language processing (NLP) tool, StanfordNER,[2] which is designed to label names of "things" in sequences of words. Each of the 68,952 designated competition sections is passed to the StanfordNER tool which is required to provide a list of text parts that are likely names of organizations. We consider each name of organization as a potential public company by matching against databases of public companies.

We apply a matching process that first searches for organization name on Edgar-SEC database, then on company name column of the CRSP master file, and finally we search Wikipedia using suspected organization names and in the cases of public companies parse the ticker following a "traded as" tag.[3] On average, we find 1,940 unique firms mentioned on 10-K filings of other companies each year.

[2] Jenny Rose Finkel, Trond Grenager, and Christopher Manning. 2005. Incorporating Non-local Information into Information Extraction Systems by Gibbs Sampling. Proceedings of the 43nd Annual Meeting of the Association for Computational Linguistics (ACL 2005), pp. 363-370. http://nlp.stanford.edu/~manning/papers/gibbscrf3.pdf https://nlp.stanford.edu/software/CRF-NER.shtml

[3] To increase the probability of matching suspected names of organizations to public companies we remove generic strings and suffixes such as Corp., LTD, LLC, etc. which are often used prior to processing the matching algorithm. We then use the standard text matching algorithms Sequence Matcher and Levenshtein Distance.

Appendix B. Top mentioned companies

The left panel of the table below shows the companies with most competition mentions each year over the sample period. The right panel shows the largest companies (by equity market value) for the same period.

	Most competition mentions					Largest firms				
Year	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
1995	IBM	HPQ	MSI	GE	NOVL	GE	T	XOM	KO	MRK
1996	IBM	MSFT	HPQ	MSI	INTC	GE	KO	XOM	INTC	MSFT
1997	IBM	MSFT	HPQ	MSI	LU	GE	KO	MSFT	XOM	MRK
1998	IBM	MSFT	HPQ	LU	MSI	MSFT	GE	INTC	WMT	XOM
1999	IBM	MSFT	LU	MSI	HPQ	MSFT	GE	CSCO	WMT	XOM
2000	MSFT	IBM	LU	HPQ	MSI	GE	XOM	PFE	CSCO	C
2001	IBM	MSFT	MSI	LU	CSCO	GE	MSFT	XOM	C	WMT
2002	IBM	MSFT	MSI	HPQ	CSCO	MSFT	GE	XOM	WMT	PFE
2003	IBM	MSFT	CSCO	HPQ	JNJ	GE	MSFT	XOM	PFE	C
2004	IBM	MSFT	CSCO	HPQ	WMT	GE	XOM	MSFT	C	WMT
2005	IBM	MSFT	PFE	CSCO	HPQ	GE	XOM	MSFT	C	PG
2006	IBM	MSFT	PFE	CSCO	HPQ	XOM	GE	MSFT	C	BAC
2007	IBM	MSFT	PFE	CSCO	JNJ	XOM	GE	MSFT	T	PG
2008	IBM	MSFT	PFE	JNJ	GE	XOM	WMT	PG	MSFT	GE
2009	MSFT	IBM	GE	JNJ	CSCO	XOM	MSFT	WMT	AAPL	JNJ
2010	IBM	MSFT	CSCO	GE	JNJ	XOM	AAPL	MSFT	GE	WMT
2011	IBM	MSFT	GE	WMT	PFE	XOM	AAPL	MSFT	IBM	CVX
2012	IBM	MSFT	PFE	GE	WMT	AAPL	XOM	WMT	MSFT	GE
2013	IBM	MSFT	GE	WMT	PFE	AAPL	XOM	GOOGL	MSFT	GE
2014	IBM	MSFT	GOOGL	PFE	JNJ	AAPL	XOM	MSFT	JNJ	WFC
2015	IBM	MSFT	GOOGL	PFE	JNJ	AAPL	MSFT	XOM	AMZN	GE
2016	IBM	PFE	MRK	GOOGL	CSCO	AAPL	MSFT	XOM	AMZN	JNJ
2017	PFE	IBM	MRK	GOOGL	MSFT	AAPL	MSFT	AMZN	FB	JNJ

Appendix C. Cross-sector mentions

Panel A ranks the eleven GIC sectors from the most mentioning to the least mentioning one by percentage (left column) and the three sectors they mostly mention by percentage (right three columns). Panel B shows the percentages for the top ten mentioning Fama-French 48 industries.

Panel A. GIC Sectors

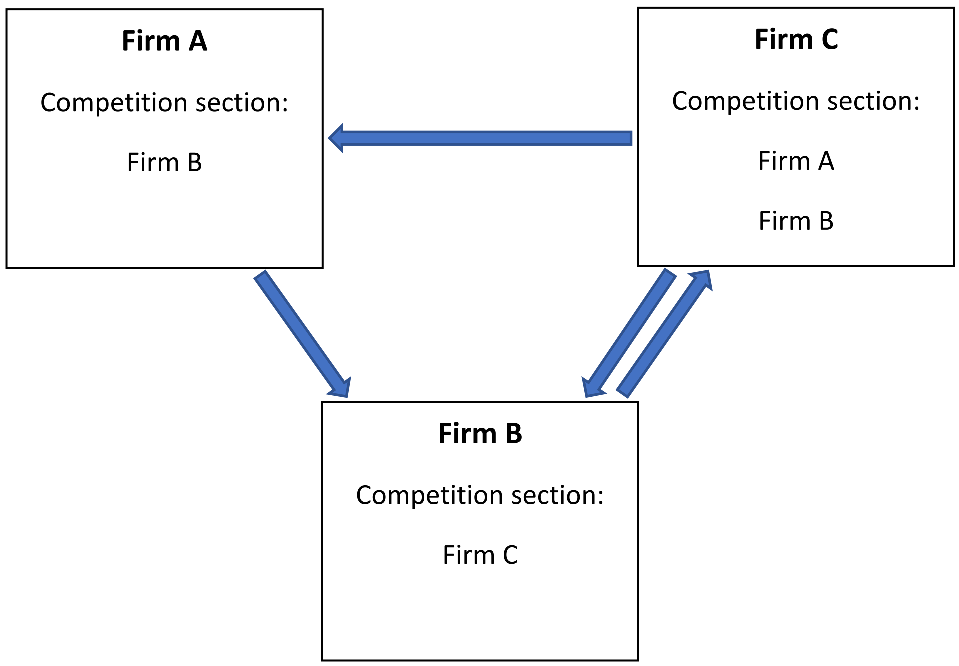
Mentioning sector		**Mentioned sector**	
Information Technology 32.5%	Industrials 43.0%	Consumer Discretionary 18.7%	Communication Services 15.4%
Consumer Discretionary 17.1%	Information Technology 30.4%	Consumer Staples 21.9%	Industrials 16.4%
Industrials 17.0%	Information Technology 47.5%	Consumer Discretionary 18.9%	Health Care 8.2%
Health Care 10.4%	Information Technology 37.3%	Industrials 35.7%	Consumer Staples 7.5%
Financials 5.6%	Information Technology 32.3%	Industrials 23.7%	Consumer Discretionary 9.3%
Communication Services 5.3%	Information Technology 56.4%	Consumer Discretionary 22.3%	Health Care 10.9%
Materials 3.4%	Industrials 30.0%	Energy 20.4%	Information Technology 17.7%
Consumer Staples 2.6%	Health Care 40.5%	Consumer Discretionary 38.6%	Information Technology 5.8%
Energy 2.5%	Industrials 45.4%	Information Technology 16.7%	Health Care 10.7%
Real Estate 2.5%	Consumer Discretionary 32.4%	Information Technology 32.2%	Industrials 10.5%
Utilities 0.9%	Industrials 30.5%	Energy 23.4%	Materials 15.6%

Panel B. Fama-French 48 industries

Mentioning industry		**Mentioned industry**	
Business Services 17.9%	Computers 34.9%	Electronic Equipment 14.0%	Communication 8.6%
Computers 13.4%	Business Services 52.6%	Electronic Equipment 27.5%	Wholesale 4.5%
Electronic Equipment 10.7%	Computers 35.2%	Business Services 18.9%	Measuring and Control Equipment 10.9%
Pharmaceutical Products 5.8%	Medical Equipment 41.9%	Measuring and Control Equipment 22.6%	Wholesale 8.1%
Medical Equipment 5.4%	Pharmaceutical Products 59.1%	Electronic Equipment 9.9%	Measuring and Control Equipment 5.0%
Measuring and Control Equipment 4.3%	Electronic Equipment 15.5%	Pharmaceutical Products 14.4%	Machinery 12.3%
Machinery 3.5%	Measuring and Control Equipment 18.6%	Electronic Equipment 15.2%	Computers 7.8%
Trading 3.4%	Business Services 23.5%	Banking 18.6%	Electronic Equipment 11.4%
Wholesale 3.3%	Business Services 29.0%	Retail 20.3%	Pharmaceutical Products 11.5%
Electrical Equipment 3.0%	Electronic Equipment 36.3%	Measuring and Control Equipment 15.3%	Machinery 14.1%

Appendix D. Applying the PageRank algorithm to competition links

We present a simple example to illustrate the use of the PageRank algorithm developed by the founders of Google, Larry Page and Sergey Brin (Page et al. 1999) to measure firm competition status. Consider three firms, named A, B, and C, where each firm includes a competition section in its 10-K. Firm A mentions only Firm B as a competitor, Firm B mentions only Firm C as a competitor, and Firm C mentions both Firms A and B as competitors. The following figure shows the competition links across the three firms.



Applying the PageRank algorithm solves a system of linear equations for each firm C-Rank (CR):

$$CR(A) = \frac{1-d}{N} + d \times \frac{CR(C)}{2}$$

$$CR(B) = \frac{1-d}{N} + d \times \left[CR(A) + \frac{CR(C)}{2}\right]$$

$$CR(C) = \frac{1-d}{N} + d \times CR(B)$$

Where N denotes the number of firms, which is 3 in this example, d is a damping factor that assures that firms that are not mentioned at all will not converge all C-Rank values to zeros, and each firm's C-Rank on the right-hand-side is scaled by the number of firms it mentions (i.e., CR(A) and

CR(B) are scaled by 1 and CR(C) is scaled by 2), such that all C-Rank values are summed to 1. Assuming a damping factor of 0.7 yields the following C-Rank values: $CR(A) = 0.2314$, $CR(B) = 0.3933$, and $CR(C) = 0.3753$. That is, Firm B gets the highest C-Rank as it is mentioned by both Firms A and C, and Firm C gets a higher C-Rank than Firm A as it is mentioned by a stronger firm (B and C, respectively).[4]

[4] When the system includes entities that do not point at all to other entities and/or entities that are not pointed at by other entities (as in our 10-K sample), the algorithm is a little more complex, requiring an iterative process of equation solving.

Table 1. Competition mentions and firm characteristics

Each month we sort all firms into four portfolios by the number of annual reports in which the firm is mentioned as a competitor over the past twelve months: 0, 1, 2, and 3+ mentions. The table presents descriptive statistics for each portfolio, where all variables are winsorized at the 1st and 99th percentiles. For each variable, we first calculate the cross-sectional mean and median across stocks for each portfolio. We then report the time-series averages of these means/medians. Firm size is computed as stock price multiplied by the number of shares outstanding (in billions of dollars). Market-to-book ratio is the market value of equity divided by the book value of equity. Past return is based on monthly stock returns over the last six months skipping the most recent month (see Jegadeesh and Titman 1993). We estimate profitability by return on equity (ROE), computed by the annual income before extraordinary items divided by the previous year's book equity value. We estimate investment by the annual change in gross property, plant, and equipment, plus the change in inventories, scaled by lagged book value of assets. Market beta is estimated using a regression of a firm overlapping 3-day log return on the equivalent market return over the past year (see Frazzini and Pedersen (2014) for a similar procedure). We calculate idiosyncratic volatility for each month by the standard deviation of the residuals of regression of daily stock returns on the daily Fama and French (1993) three factors. The table also shows the time-series averages of monthly cross-sectional correlations between (log of 1+) the number of competition mentions and each variable. We report the results for the full sample of stocks and when excluding microcap stocks, defined as stocks with market value of equity below the 20th percentile by NYSE breakpoints and share price below $5. The sample period is 1995-2017.

		All stocks					Excluding microcaps				
		# Competition mentions					# Competition mentions				
		0	1	2	3+	Correlation	0	1	2	3+	Correlation
	# Firm-months	728,626	120,721	42,474	48,042		263,849	72,042	30,069	41,368	
Size	Mean	1.136	2.416	3.377	6.284	0.362	3.355	4.678	5.836	10.691	0.331
	Median	0.236	0.848	1.484	4.972		1.410	2.072	2.771	6.747	
Market-to-book	Mean	2.457	3.002	3.274	3.421	0.127	3.240	3.560	3.738	3.804	0.072
	Median	1.679	2.180	2.456	2.717		2.314	2.621	2.874	2.972	
Past return	Mean	0.047	0.058	0.055	0.063	0.015	0.100	0.101	0.092	0.085	-0.028
	Median	0.024	0.031	0.031	0.044		0.071	0.070	0.064	0.061	
Profitability	Mean	0.009	0.019	0.035	0.076	0.056	0.126	0.122	0.124	0.130	0.008
	Median	0.084	0.093	0.101	0.127		0.133	0.133	0.137	0.144	
Investment	Mean	0.056	0.057	0.055	0.052	-0.020	0.072	0.068	0.061	0.056	-0.077
	Median	0.034	0.038	0.036	0.034		0.045	0.045	0.041	0.036	
Market beta	Mean	1.082	1.296	1.370	1.344	0.102	1.080	1.203	1.259	1.269	0.083
	Median	0.953	1.188	1.280	1.250		0.988	1.113	1.165	1.180	
Idio. volatility	Mean	0.027	0.025	0.024	0.021	-0.112	0.018	0.019	0.019	0.018	-0.008
	Median	0.022	0.021	0.020	0.017		0.016	0.016	0.017	0.016	

Table 2. Competition mention and measures of competitiveness

Each month we sort all firms into four portfolios by the number of annual reports in which the firm is mentioned as a competitor over the past twelve months: 0, 1, 2, and 3+ mentions. The table presents the means of measures of competitiveness for each portfolio, where all measures are winsorized at the 1st and 99th percentiles. The sample does not include microcap stocks, defined as stocks with market value of equity below the 20th percentile by NYSE breakpoints and share price below $5. For each competitiveness measure, we first calculate the cross-sectional mean across stocks for each portfolio, and report the time-series averages of these means. The competitive measures are the percent of competition-related words in 10-K ('PCT COMP') of Li, Lundholm, and Minnis (2013), the sum of the pairwise product similarity scores between a firm and all other firms ('Similarity COMP') based on Hoberg and Phillips (2010, 2016), the product market fluidity of Hoberg, Phillips, and Prabhala (2014), the operating leverage in the GIC sector/Fama-French 48 industry, defined by the average ratio of the sum of operating costs and administrative expenses to total assets, and the sector/industry concentration, estimated by the Herfindahl–Hirshman index for market share of sales. The table also shows the differences between the 3+ and 0 mention portfolios and the 3+ and 1 mention portfolios, where '*', '**', and '***' indicate statistical significance at the 0.1, 0.05, and 0.01 levels, respectively, as well as the time-series averages of monthly cross-sectional correlations between (log of 1+) the number of competition mentions and each measure. The sample periods are 1995-2009 for 10-K competitiveness, 1997-2017 for product market fluidity, and 1995-2017 for all other measures.

	Number of competition mentions						
	0	1	2	3+	3+ minus 0	3+ minus 1	Correlation
PCT COMP	0.470	0.504	0.524	0.511	0.041*	0.007	0.049
Similarity COMP	4.182	3.843	3.994	4.436	0.254***	0.593***	0.009
Product fluidity	6.677	6.703	6.872	7.301	0.624***	0.598***	0.057
GIC Operating leverage	0.908	0.946	0.965	0.947	0.038***	0.001	0.045
FF48 Operating leverage	0.935	0.982	1.002	0.976	0.041***	-0.006	0.041
GIC Concentration	0.044	0.042	0.041	0.040	-0.004***	-0.002***	-0.041
FF48 Concentration	0.083	0.082	0.080	0.080	-0.003***	-0.001**	-0.009

Table 3. Returns of portfolios sorted on competition mentions

Panel A shows single sort portfolio returns. Each month we sort all firms into four portfolios by the number of annual reports in which the firm is mentioned as a competitor over the past twelve months: 0, 1, 2, and 3+ mentions. The portfolios are value-weighted and held for one month. Panel A shows the mean excess monthly stock returns (in excess of the risk-free rate) and alpha from a 6-factor model for each of the four portfolios as well as for the differences between the 3+ and 0 mention portfolios and the 3+ and 1 mention portfolios. The factors are the Fama and French (2015) factors augmented with a momentum factor. Panel B shows double sort portfolio returns. We first sort all stocks equally into three groups based on firm size, measured by market value of equity. Within each size group, the stocks are further sorted into the four competition mention groups as in the single sort. The panel shows the mean excess monthly stock returns and 6-factor alphas for the four mention portfolios as averaged across the three size groups. The 'Avg portfolio size' is the average number of firms in the mention and size/mention monthly portfolios. All returns and alphas are in percent per month and the corresponding *t*-statistics are in parentheses. The sample period is 1995-2017.

Panel A. Single sort by # mentions						
	Number of competition mentions					
	0	1	2	3+	3+ minus 0	3+ minus 1
Avg portfolio size	1,011	236	125	225		
Mean excess return	0.64	0.53	0.76	0.74	0.10	0.21
	(2.38)	(1.76)	(2.51)	(2.56)	(0.68)	(1.46)
6-factor alpha	-0.12	-0.25	-0.06	0.21	0.32	0.45
	(-1.83)	(-2.75)	(-0.66)	(3.16)	(2.64)	(3.53)
Panel B. Double sort by size/ # mentions						
	Number of competition mentions					
	0	1	2	3+	3+ minus 0	3+ minus 1
Avg portfolio size	338	79	42	76		
Mean excess return	0.80	0.90	0.99	1.28	0.48	0.38
	(4.39)	(3.98)	(4.16)	(4.96)	(2.39)	(2.43)
6-factor alpha	0.00	0.16	0.26	0.70	0.70	0.54
	(0.06)	(1.58)	(2.22)	(5.00)	(4.43)	(3.62)

Table 4. Portfolio returns of targeting and admiring competition mentions

We classify all firms that are mentioned as competitors in other reports into two groups; 'targeted' includes all firms with size (equity market value) smaller than the average size of its mentioning firms, and 'admired' includes all firms with size larger than the average size of its mentioning firms. The table presents the value-weighted 6-factor alpha of portfolios sorted on competition mentions, as described in Table 3, separately for targeted and admired mentioned firms. All alphas are in percent per month and the corresponding *t*-statistics are in parentheses. The sample period is 1995-2017.

		Number of competition mentions					
		0	1	2	3+	3+ minus 0	3+ minus 1
Targeted	Avg portfolio size	1011	52	29	34		
[Mentioned < Mentioning]	6-factor alpha	-0.12	0.16	0.00	0.84	0.95	0.68
	T-statistic	(-1.83)	(0.84)	(0.00)	(3.00)	(3.41)	(2.13)
Admired	Avg portfolio size	1011	184	96	192		
[Mentioned > Mentioning]	6-factor alpha	-0.12	-0.28	-0.07	0.20	0.32	0.48
	T-statistic	(-1.83)	(-3.01)	(-0.83)	(3.03)	(2.57)	(3.64)

Table 5. Fama-MacBeth regressions

We run cross-sectional Fama and MacBeth (1973) regressions each month of excess stock returns. The independent variables are the number of annual reports in which the firm is mentioned as a competitor over the past twelve months, a dummy variable that equals one if the firm has not been mentioned by any other firm in the past twelve months, and zero otherwise, and other firm characteristics as described in Table 1. The regression coefficients are multiplied by 100 and Newey-West corrected *t*-statistics (with twelve lags) are in parentheses. In the lower panel we show the coefficient of the number of competition mentions from the same regressions without the Newey-West adjustment, and when excluding small stocks, classified as stocks with market cap between the 20th and 50th percentiles of NYSE breakpoints. The sample period is 1995-2017.

	All mentioned firms	Targeted Mentioned	Admired mentioned
Intercept	3.46	5.11	3.15
	(4.18)	(3.16)	(3.50)
# Mentions	0.34	0.71	0.27
	(3.12)	(2.02)	(1.72)
No mention dummy	-0.81	-2.49	-0.51
	(-1.52)	(-1.58)	(-0.86)
Log(size)	-0.21	-0.37	-0.18
	(-3.33)	(-2.95)	(-2.93)
Log(size) x No mention dummy	0.07	0.24	0.05
	(1.92)	(2.18)	(1.23)
Log(market-to-book)	-0.13	-0.13	-0.13
	(-0.94)	(-0.97)	(-0.96)
Past return	0.26	0.25	0.25
	(0.66)	(0.63)	(0.64)
Profitability	0.02	0.02	0.01
	(0.08)	(0.07)	(0.04)
Investment	-1.66	-1.75	-1.75
	(-3.30)	(-3.41)	(-3.42)
Market Beta	0.06	0.07	0.07
	(0.35)	(0.40)	(0.39)
Idiosyncratic volatility	3.76	4.51	4.32
	(0.50)	(0.59)	(0.57)
# obs	344,541	326,323	326,323
Mean R-Square	0.081	0.083	0.082
Coefficient on # mentions using alternative specifications			
Without NW adjustment	0.34	0.71	0.27
	(3.41)	(2.09)	(1.90)
Excluding small stocks	0.31	1.03	0.34
	(2.77)	(2.09)	(1.95)

Table 6. Portfolio returns of cross- and within-sector competition mentions

The table shows value-weighted 6-factor alphas on portfolios sorted by cross-sector and within-sector competition mentions, using either the eleven GIC sector classification or the Fama-French 48 industry classification, as described in Section 3.1. A mentioned firm is classified as 'targeted' ('admired') if its size is smaller (larger) than the average size of its mentioning firms. All alphas are in percent per month and the corresponding *t*-statistics are in parentheses. The sample period is 1995-2017.

			GIC		FF48	
		All firms	Cross-sector	Within-sector	Cross-sector	Within-sector
Not mentioned	Avg portfolio size	1,011	1,473	1,140	1,403	1,266
	6-factor alpha	-0.12	-0.10	-0.15	-0.11	-0.14
	T-statistic	(-1.83)	(-2.03)	(-2.36)	(-2.46)	(-2.72)
All mentions	Avg portfolio size	586	165	495	263	401
	6-factor alpha	0.11	0.24	0.15	0.21	0.19
	T-statistic	(2.56)	(3.05)	(2.67)	(3.14)	(3.20)
Targeted	Avg portfolio size	115	21	101	39	78
[Mentioned < Mentioning]	6-factor alpha	0.37	0.98	0.35	1.00	0.52
	T-statistic	(2.31)	(3.46)	(2.01)	(4.18)	(2.90)
Admired	Avg portfolio size	472	144	394	224	324
[Mentioned > Mentioning]	6-factor alpha	0.11	0.23	0.15	0.20	0.18
	T-statistic	(2.41)	(2.89)	(2.60)	(2.99)	(3.08)

Table 7. Competition-mentions return predictability by analyst sector coverage

The table reports value-weighted 6-factor alphas of portfolios sorted by competition mentions, as described in Table 3, for different subsamples representing different types of sector-analyst coverage. The first row shows the baseline results for the full sample as appear in Table 3. The second row shows the results for firms that are not covered by analysts. The third row shows the results for firms that are covered by analysts. The fourth row shows the results for firms whose all analysts cover only firms in the same GIC sector. The fifth row show the results for firms with analysts that cover multiple sectors. And the sixth row shows the results for firms with analysts that cover multiple sectors including those of their mentioning firms. All alphas are in percent per month and the corresponding *t*-statistics are in parentheses. The sample period is 1995-2017.

		Number of competition mentions					
		0	1	2	3+	3+ minus 0	3+ minus 1
Baseline results	Avg portfolio size	1,011	236	125	225		
	6-factor alpha	-0.12	-0.25	-0.06	0.21	0.32	0.45
	T-statistic	(-1.83)	(-2.75)	(-0.66)	(3.16)	(2.64)	(3.53)
Firms with no analyst coverage	Avg portfolio size	762	105	54	93		
	6-factor alpha	-0.15	-0.43	-0.01	0.24	0.39	0.66
	T-statistic	(-2.04)	(-2.95)	(-0.05)	(2.22)	(2.61)	(3.48)
Firms with analyst coverage	Avg portfolio size	250	130	72	132		
	6-factor alpha	-0.03	-0.09	-0.06	0.21	0.24	0.30
	T-statistic	(-0.35)	(-0.81)	(-0.52)	(2.56)	(1.70)	(2.06)
The firm's analysts cover a single sector	Avg portfolio size	40	16	10	15		
	6-factor alpha	-0.16	-0.36	0.22	1.41	1.57	1.77
	T-statistic	(-0.41)	(-0.65)	(0.34)	(2.43)	(2.36)	(2.29)
The firm's analysts cover multiple sectors	Avg portfolio size	226	121	66	124		
	6-factor alpha	-0.03	-0.07	-0.04	0.17	0.19	0.24
	T-statistic	(-0.34)	(-0.58)	(-0.35)	(2.03)	(1.38)	(1.55)
The firm's analysts cover the sectors of the mentioning firms	Avg portfolio size	13	32	30	92		
	6-factor alpha	0.31	0.15	0.15	0.14	-0.17	-0.01
	T-statistic	(0.78)	(0.63)	(0.75)	(1.15)	(-0.42)	(-0.03)

Table 8. Logit regressions of future takeovers on target-mentioned firms

The table shows the results of logit regressions for the sample of all firms that are mentioned as competitors in 10-Ks in the past twelve months. The dependent variable equals one if the firm has been announced as merger target in the next twelve months, and zero otherwise. The first independent variable equals one if the firm is targeted in 10-Ks, and zero if admired. A firm is classified as targeted (admired) if its size is smaller (larger) than the average size of the firms that mention it. The second independent variable is the firm's takeover probability estimated by the model of Billett and Xue (2007). We report the results for the sample of all mentions, and for subsamples of mentions only from outside of the sector and only from the same sector. The regressions include firm and time fixed effects. The *p*-value of the coefficients are reported in parentheses. The full sample contains 7,962 merger target announcements over the period 1995-2017.

	All mentions	Cross-sector	Within-sector
Intercept	-4.14	-4.32	-4.10
P-value	(<.001)	(<.001)	(<.001)
Targeted	0.64	0.83	0.59
P-value	(<.001)	(<.001)	(<.001)
Billett and Xue's model	11.93	12.26	11.89
P-value	(<.001)	(<.001)	(<.001)

Table 9. Returns of portfolios sorted by competition-mention factor beta

For each firm in each month, we run a rolling regression over the past 36 months of the firm's excess returns (in excess of the risk-free rate) on the competition mention factor, which is the mean excess return of the hedge portfolio of 3+ minus 1 competition mentions, as described in Table 3. The regressions also control for the Fama and French (2015) five factors and the momentum factor. Referred to the coefficient of the competition mention factor as 'competition beta'. Each month we divide all stocks into five equal-sized portfolios according to their competition beta. The portfolios are value-weighted and held for one month. The table shows the portfolios' mean excess monthly stock returns and 6-factor alphas. In Panel A the competition beta is based on all mentions and in Panel B the beta is based on targeting mentions only (i.e., the cases where the size of the mentioned firm is smaller than the average size of its mentioning firms). All returns and alphas are in percent per month and the corresponding *t*-statistics are in parentheses. The sample period is 1998-2017.

Panel A. All mention beta						
	1-low beta	2	3	4	5-high beta	high-low
Mean excess return	0.65	0.58	0.53	0.36	0.25	-0.40
	(1.80)	(2.06)	(2.09)	(1.21)	(0.56)	(-1.26)
6-factor alpha	-0.14	-0.11	0.03	0.01	-0.06	0.08
	(-0.84)	(-1.21)	(0.39)	(0.08)	(-0.32)	(0.27)

Panel B. Targeting mention beta						
	1-low beta	2	3	4	5-high beta	high-low
Mean excess return	0.52	0.47	0.48	0.52	0.45	-0.07
	(1.40)	(1.61)	(1.78)	(1.84)	(1.11)	(-0.34)
6-factor alpha	-0.03	-0.04	-0.01	0.00	-0.01	0.02
	(-0.22)	(-0.45)	(-0.07)	(-0.03)	(-0.07)	(0.11)

Table 10. Industry-wide competition risk

We run cross-sectional Fama and MacBeth (1973) regressions each month of excess stock returns. The independent variables are defined as follows. '# Mentions' is the number of annual reports in which the firm is mentioned as a competitor over the past twelve months, as described in Table 5. 'Ind Operating leverage' is the average operating leverage in the industry, defined by the ratio of the sum of operating costs and administrative expenses to total assets. 'Ind Concentration' is the Herfindahl–Hirshman index for market share of sales in the industry (see, e.g., Bustamante and Donangelo 2017). Both industry measures are applied to the eleven GIC sector and the Fama-French 48 industry classifications. The regressions also include the control variables in Table 5. A mentioned firm is classified as 'targeted' ('admired') if its size is smaller (larger) than the average size of its mentioning firms. All coefficients are multiplied by 100 and Newey-West corrected *t*-statistics (with twelve lags) are in parentheses. The sample period is 1995-2017.

All mentions						
		GIC			FF48	
# Mentions	0.34	0.36	0.38	0.50	0.35	0.50
	(1.82)	(3.47)	(2.15)	(2.82)	(2.62)	(2.30)
Ind. Operating leverage	0.03		0.05	0.06		0.05
	(0.21)		(0.33)	(0.35)		(0.32)
# Mentions x Ind. Operating leverage	0.00		-0.01	-0.14		-0.14
	(0.00)		(-0.06)	(-1.34)		(-1.25)
Ind. Concentration		1.39	1.46		-0.30	-0.20
		(0.74)	(0.80)		(-0.76)	(-0.45)
# Mentions x Ind. Concentration		-0.79	-0.96		0.14	0.10
		(-0.53)	(-0.67)		(0.18)	(0.12)
# obs	231,744	231,744	231,744	218,615	218,615	218,615
Mean R-Square	0.095	0.099	0.104	0.098	0.093	0.100
Targeted [Mentioned < Mentioning]						
		GIC			FF48	
# Mentions	1.61	0.73	1.34	1.33	0.77	1.27
	(3.25)	(1.75)	(2.16)	(2.60)	(1.58)	(2.17)
Ind. Operating leverage	0.10		0.11	0.04		0.04
	(0.68)		(0.78)	(0.29)		(0.26)
# Mentions x Ind. Operating leverage	-0.87		-0.63	-0.60		-0.52
	(-2.37)		(-1.38)	(-1.56)		(-1.25)
Ind. Concentration		0.82	0.93		-0.15	-0.08
		(0.46)	(0.54)		(-0.43)	(-0.18)
# Mentions x Ind. Concentration		3.61	2.84		-0.79	0.25
		(0.68)	(0.57)		(-0.23)	(0.07)
# obs	231,744	231,744	231,744	218,615	218,615	218,615
Mean R-Square	0.095	0.099	0.104	0.098	0.094	0.101
Admired [Mentioned > Mentioning]						
		GIC			FF48	
# Mentions	0.44	0.27	0.50	0.52	0.25	0.43
	(1.99)	(1.65)	(1.92)	(2.17)	(1.49)	(1.80)
Ind. Operating leverage	0.09		0.11	0.05		0.05
	(0.61)		(0.77)	(0.32)		(0.30)
# Mentions x Ind. Operating leverage	-0.17		-0.19	-0.19		-0.18
	(-1.12)		(-1.15)	(-1.36)		(-1.28)
Ind. Concentration		1.15	1.28		-0.36	0.76
		(0.60)	(0.68)		(-1.02)	(0.81)
# Mentions x Ind. Concentration		0.03	-0.43		0.88	-0.25
		(0.02)	(-0.23)		(0.93)	(-0.60)
# obs	231,744	231,744	231,744	218,615	218,615	218,615
Mean R-Square	0.094	0.098	0.103	0.097	0.093	0.100

Table 11. Competition mentions and Hoberg-Phillips product similarity

We classify each competition mention as ‘similar’ if it connects between two firms that are peers by the Hoberg and Phillips (2010) product similarity score, and ‘not similar’ if the two firms are not peers. The table shows value-weighted 6-factor alphas on portfolios of similar/not similar competition mentions. A mentioned firm is classified as ‘targeted’ (‘admired’) if its size is smaller (larger) than the average size of its mentioning firms. All alphas are in percent per month and the corresponding *t*-statistics are in parentheses. The sample period is 1995-2017.

		All firms	Similar	Not similar
Not mentioned	Avg portfolio size	1,011	1,293	1,203
	6-factor alpha	-0.12	-0.11	-0.11
	T-statistic	(-1.83)	(-2.38)	(-2.10)
All mentions	Avg portfolio size	586	372	355
	6-factor alpha	0.11	0.26	0.13
	T-statistic	(2.56)	(3.31)	(2.34)
Targeted	Avg portfolio size	115	80	50
[Mentioned < Mentioning]	6-factor alpha	0.37	0.61	0.36
	T-statistic	(2.31)	(3.05)	(1.70)
Admired	Avg portfolio size	472	292	304
[Mentioned > Mentioning]	6-factor alpha	0.11	0.25	0.12
	T-statistic	(2.41)	(3.18)	(2.22)

Table 12. Returns of mentioning firms

We replicate the portfolio sort analysis in Panel A of Table 3 where instead of sorting on the number of 10-Ks a firm is mentioned as a competitor, we sort on the number of competitors the firm is mentioning in its report: 1, 2, and 3+ competitors. We further split the sample into targeting and admiring mentioning firms. A mentioning firm is classified as targeting (admiring) if it is larger (smaller) on average than the firms it mentions. The table shows the value-weighted 6-factor alpha of each portfolio as well as for the differences between the high and low mentioning portfolios. All alphas are in percent per month and the corresponding *t*-statistics are in parentheses. The sample period is 1995-2017.

	Number of competition mentioning			
	1	2	3+	3+ minus 1
All mentions	0.37	-0.26	0.31	-0.07
	(1.69)	(-1.32)	(1.95)	(-0.26)
Targeting	0.13	-0.32	0.37	0.24
[Mentioning > Mentioned]	(0.53)	(-1.41)	(2.24)	(0.82)
Admiring	0.34	-0.21	0.32	-0.02
[Mentioning < Mentioned]	(1.01)	(-0.71)	(1.22)	(-0.04)

Table 13. Controlling for other firm links

We run cross-sectional Fama and MacBeth (1973) regressions each month of excess stock returns. The independent variables are defined as follows. '# Mentions' is the number of annual reports in which the firm is mentioned as a competitor over the past twelve months, as described in Table 5. 'Mention change' indicates negative change, no change, and positive change in the number of mentions over the past twelve months, equals 0, 1, and 2, respectively. We follow Ali and Hirshleifer (2020) to measure shared analyst coverage; for each firm in every month we compute the average return of the firms that are covered by the same analysts, where the average return is weighted by the number of shared analysts (see Eq. 1 in Ali and Hirshleifer (2020)). We follow Scherbina and Schlusche (2015) to measure the news co-mention; for each firm in every month we compute the average return of the firms that are mentioned in the news together with a given firm, where the average return is weighted by the co-mentioning score. The regressions also include the control variables in Table 5. All coefficients are multiplied by 100 and Newey-West corrected *t*-statistics (with twelve lags) are in parentheses. The sample period is 1995-2017 except for the regressions with news co-mention that cover the period 2011-2017.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
# Mentions	0.34		0.30		0.42		0.19	0.17
	(3.12)		(2.98)		(2.39)		(3.04)	(2.13)
Mention change		-0.02	-0.07					0.00
		(-0.44)	(-1.32)					(-0.01)
Shared analyst coverage				4.47	3.20			3.55
				(2.39)	(1.43)			(1.93)
News co-mention						11.26	11.58	14.01
						(3.67)	(3.18)	(2.88)
# obs	344,541	344,541	344,541	130,012	52,841	33,731	29,617	18,008
Mean R-Square	0.081	0.082	0.086	0.066	0.151	0.064	0.077	0.103

Table 14. Subsamples and investment horizon

We replicate the portfolio sort analysis in Panel A of Table 3 for different subsamples and longer investment horizons. The first subsample excludes small stocks, classified as stocks with market cap between the 20th and 50th percentiles by NYSE breakpoints. The second subsample does not include the month of January. The third subsample excludes recession periods, based on NBER recession dummy. The fourth and fifth subsample break the full sample period into two subperiods, for which we also show the results of double-sort by size and mentions as in Panel B of Table 3. The holding period is increased to 3, 6, 12, and 18 months. We also show the equal-weighted (ew) alphas on the hedge portfolio in the rightmost column. All alphas are in percent per month and the corresponding *t*-statistics are in parentheses.

	1	2	3+	3+ minus 1	ew 3+ minus 1
Full sample	-0.25	-0.06	0.21	0.45	0.33
	(-2.75)	(-0.66)	(3.16)	(3.53)	(3.39)
Subsamples					
Excluding small stocks	-0.30	-0.07	0.20	0.51	0.48
	(-3.22)	(-0.81)	(3.09)	(3.78)	(4.37)
Excluding January	-0.21	-0.02	0.19	0.40	0.23
	(-2.34)	(-0.17)	(2.82)	(3.09)	(2.33)
Excluding Recessions	-0.24	-0.05	0.17	0.41	0.32
	(-2.70)	(-0.51)	(2.42)	(3.18)	(3.23)
1995-2006	-0.37	-0.01	0.40	0.77	0.56
	(-2.46)	(-0.04)	(3.65)	(3.70)	(3.41)
Size neutral	0.17	0.38	1.01	0.84	0.92
	(0.91)	(1.78)	(3.96)	(3.24)	(4.45)
2007-2017	-0.16	-0.12	0.11	0.26	0.18
	(-1.75)	(-1.34)	(2.00)	(2.13)	(2.09)
Size neutral	0.08	0.14	0.51	0.43	0.41
	(0.87)	(1.25)	(4.09)	(3.34)	(3.39)
Longer investment horizons					
3 months	-0.19	-0.06	0.20	0.39	0.31
	(-2.25)	(-0.70)	(3.04)	(3.15)	(3.34)
6 months	-0.16	-0.03	0.19	0.35	0.30
	(-1.96)	(-0.32)	(2.80)	(2.87)	(3.32)
12 months	-0.15	-0.01	0.18	0.33	0.27
	(-1.91)	(-0.06)	(2.64)	(2.69)	(3.11)
18 months	-0.12	0.02	0.15	0.27	0.23
	(-1.50)	(0.21)	(2.34)	(2.20)	(2.76)

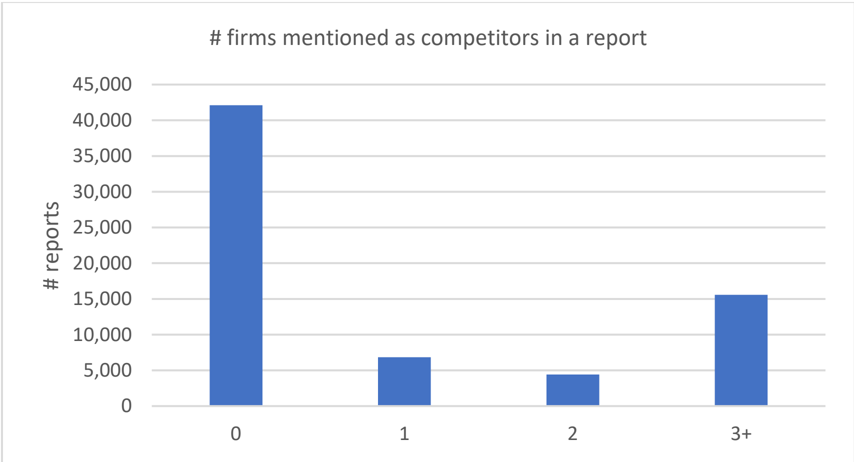
Table 15. Returns of portfolios sorted on C-Rank

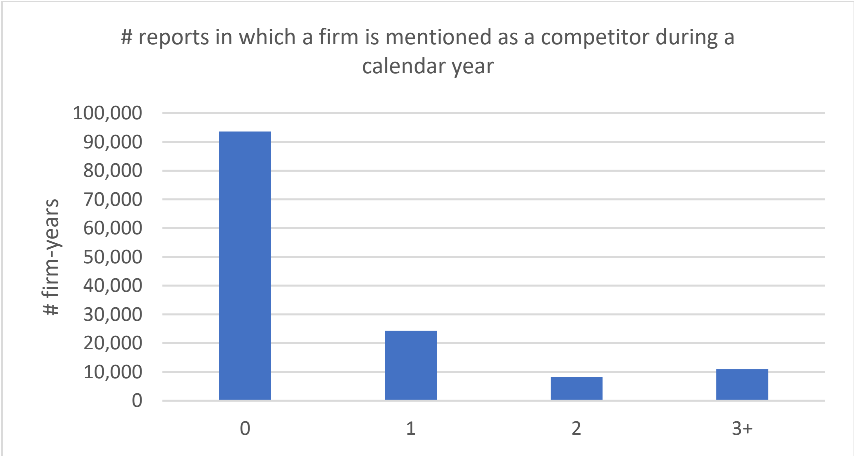
Panel A shows single sort portfolio returns. Each month we sort all stocks into four portfolios. The first portfolio, 'No Mentions' includes all stocks of firms that have not been mentioned as competitors by any other firm in the past twelve months and thus get the lowest C-Rank value in the current month. The stocks of the mentioned firms are divided equally into three portfolios according to their C-Rank in the current month ('Low', Mid', and 'High'). The portfolios are value-weighted and held for one month. Panel A shows the mean excess monthly stock returns (in excess of the risk-free rate) and alpha from a 6-factor model for each of the four portfolios as well as for the differences between the 'High' and 'No Mentions' portfolios and the 'High' and 'Low' mention portfolios. Panel B shows double sort portfolio returns. We first sort all stocks equally into three groups based on firm size, measured by market value of equity. Within each size group, the stocks are further sorted into four C-Rank groups as in the single sort. The panel shows the mean excess monthly stock returns and 6-factor alpha for the four C-Rank portfolios as averaged across the three size groups. All returns and alphas are in percent per month and the corresponding *t*-statistics are in parentheses. The sample period is 1995-2017.

Panel A. Single sort by C-Rank			C-Rank			
	No Mentions	Low	Mid	High	High-No	High-Low
Avg portfolio size	1,011	216	216	216		
Mean excess return	0.64	0.51	0.72	0.75	0.11	0.24
	(2.38)	(1.52)	(2.44)	(2.65)	(0.80)	(1.47)
6-factor alpha	-0.12	-0.16	0.04	0.19	0.31	0.36
	(-1.83)	(-1.55)	(0.56)	(3.00)	(2.58)	(2.53)
Panel B. Double sort by size/C-Rank			C-Rank			
	No Mentions	Low	Mid	High	High-No	High-Low
Avg portfolio size	337	72	72	72		
Mean excess return	0.80	0.89	1.03	1.18	0.37	0.29
	(4.49)	(3.55)	(4.72)	(5.16)	(2.76)	(2.03)
6-factor alpha	0.00	0.23	0.31	0.48	0.49	0.25
	(-0.05)	(1.97)	(3.15)	(4.44)	(4.43)	(2.11)

Figure 1. Distribution of 10-K competition mentions

The upper figure shows the distribution of the number of firms mentioned as competitors in a report for a total of 68,952 10-Ks with competition sections over the period 1995-2017. The middle figure shows the distribution of the number of reports in which a firm is mentioned as a competitor during a calendar year for a total of 135,921 firm-years. The bottom figure shows the joint distribution.





% reports in which a firm is mentioned

% firms mentioned

	0	1	2	3+	Total
0	50.48	5.60	2.12	2.89	61.09
1	8.37	0.95	0.30	0.32	9.94
2	5.13	0.76	0.30	0.24	6.43
3+	15.54	3.25	1.63	2.14	22.56
Total	79.52	10.56	4.35	5.59	100.00

Figure 2. Time-series percentage of no competition mentions

The figure shows the percentage of firms that have not been mentioned as competitors in any 10-K in the past twelve months over the sample period.

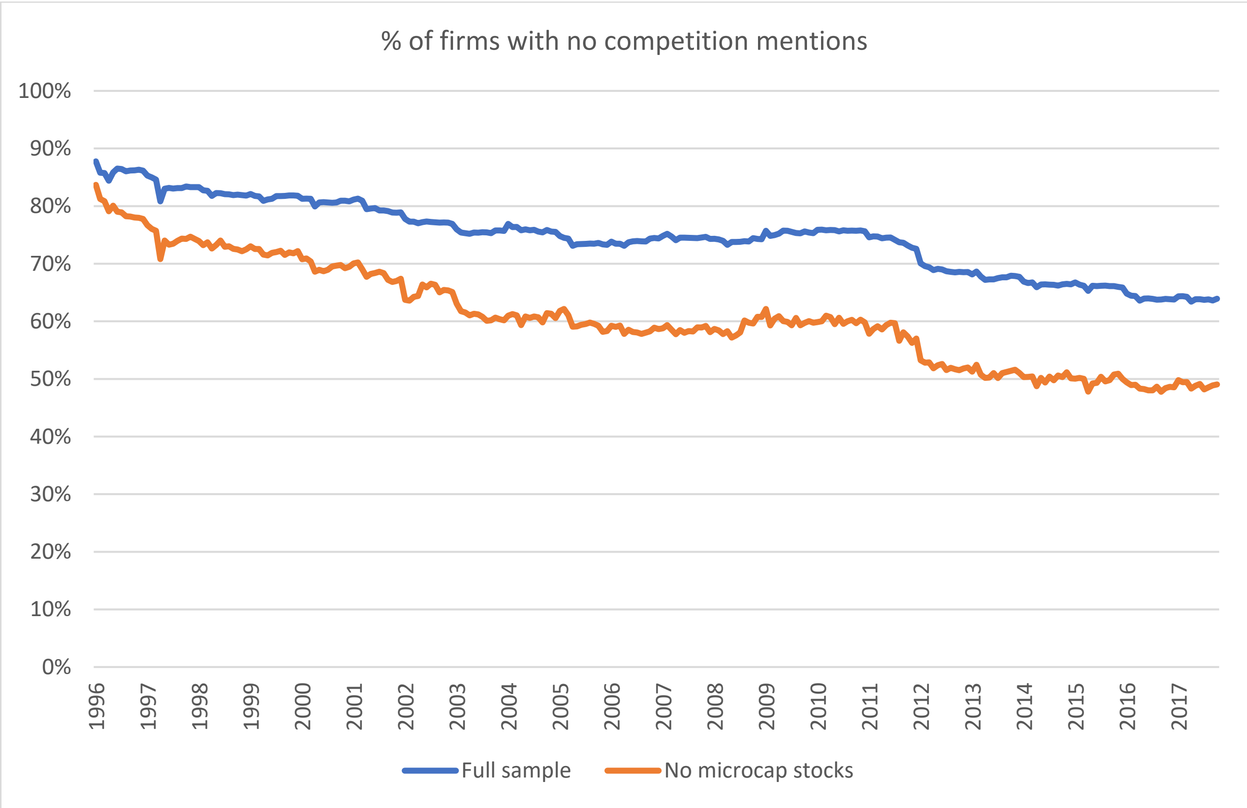


Figure 3. Competition-mention portfolio spreads excluding specific sectors

We replicate the portfolio sort analysis in Panel A of Table 3 when removing from the sample all firms from one sector at a time, as well as all firms that they mention. The leftmost bar shows the monthly value-weighted 6-factor alpha (left axis) and *t*-statistic (right axis) of the 3+ minus 1 competition mentions portfolio as appear in Table 3. The rest of the bars show the alphas and *t*-statistics of the hedge portfolios excluding each of the eleven GIC sectors.

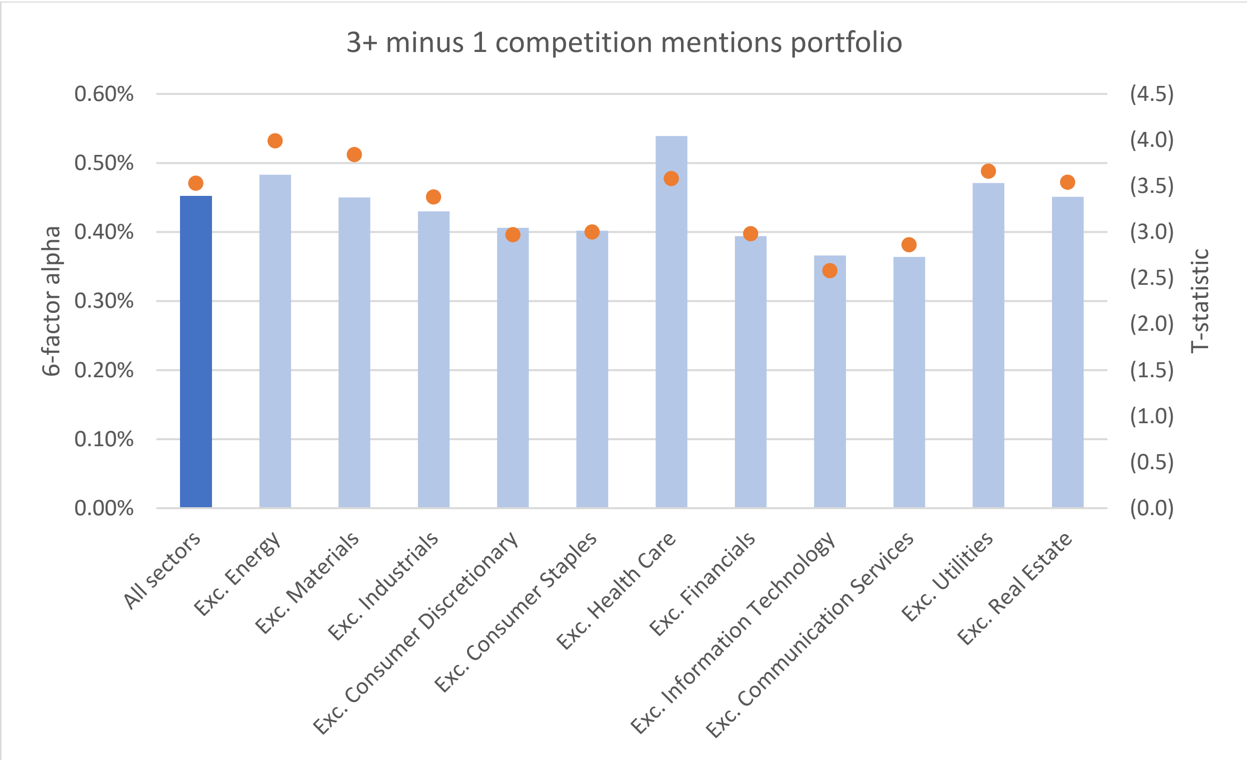
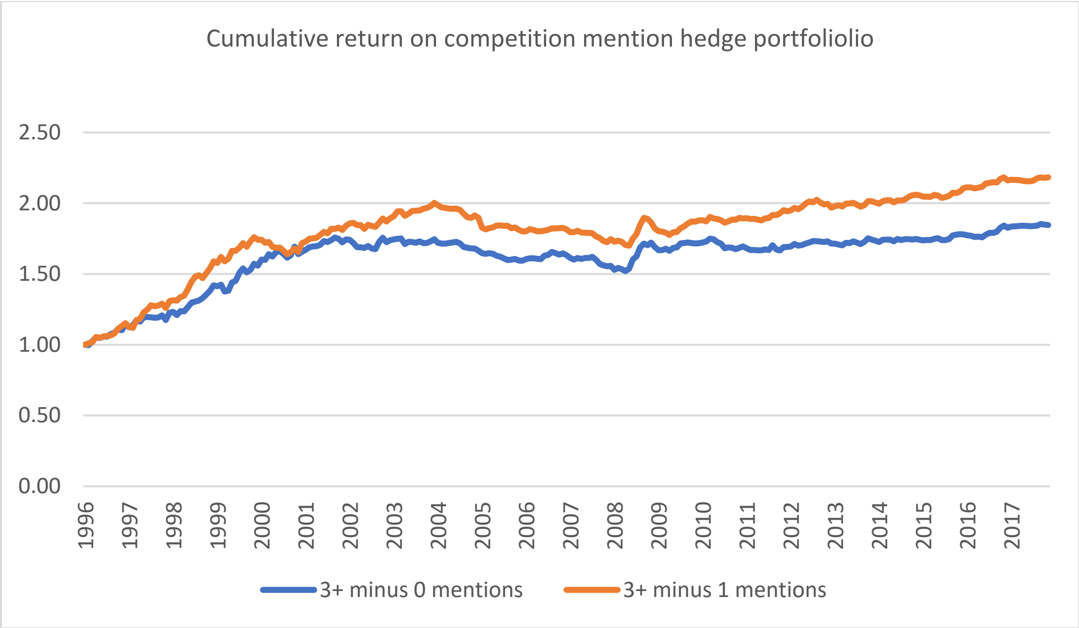


Figure 4. Cumulative return of competition-mention portfolio spread

The figure plots the cumulative value-weighted 6-factor alpha of the zero-investment strategy that buys stocks with 3+ competition mentions and shorts stocks with either no mentions or one mention. The upper figure refers to the single sort mention portfolios, and the lower figure to the double-sort size/mention portfolios, corresponding to Panels A and B, respectively, in Table 3.



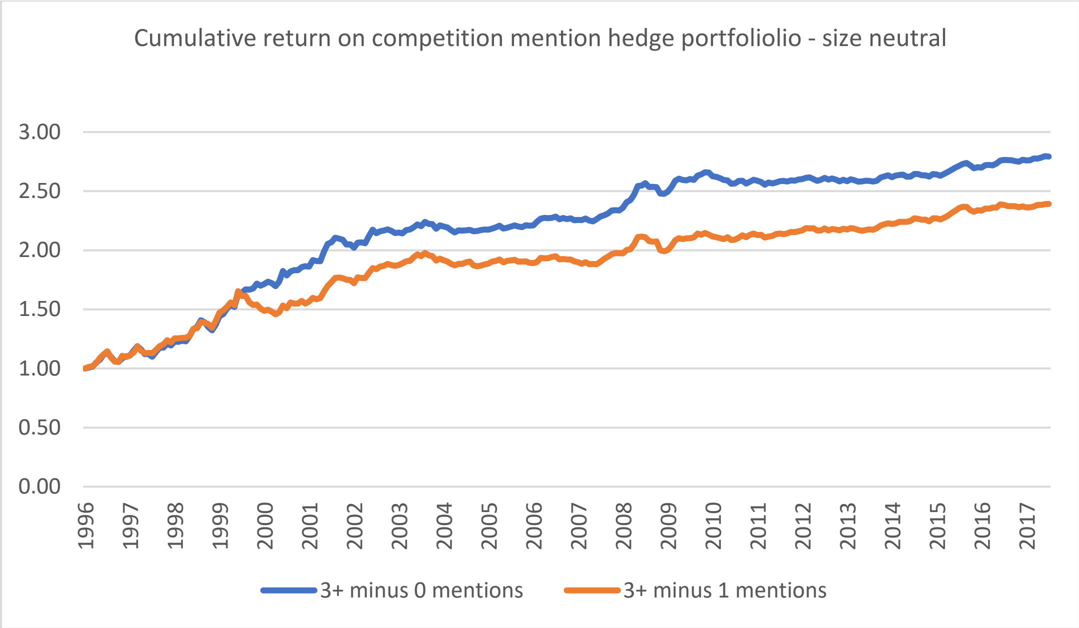


Figure 5. Competition mentions and real effects

The figure shows long-term growth in sales and operating income of firms that are mentioned in 10-K competition sections. A mentioned firm is classified as 'targeted' ('admired') if its size is smaller (larger) than the average size of its mentioning firms. This classification is determined every month based on the 10-Ks over the past twelve months. We report the percent change of sales and operating income in the next one, two, and three years, all are adjusted to the median of firms in the same 3x3 size/market-to-book group within the same GIC sector, and all are winsorized at the 1st and 99th percentiles. The figure also shows the *t*-statistic of the difference between the targeted and admired sample growth rates, based on Newey-West corrected standard errors. The upper figures show the mean growth rates for competition mentions outside the GIC sector, and the lower figures for mentions from the same GIC sector. The sample period 1995-2017.

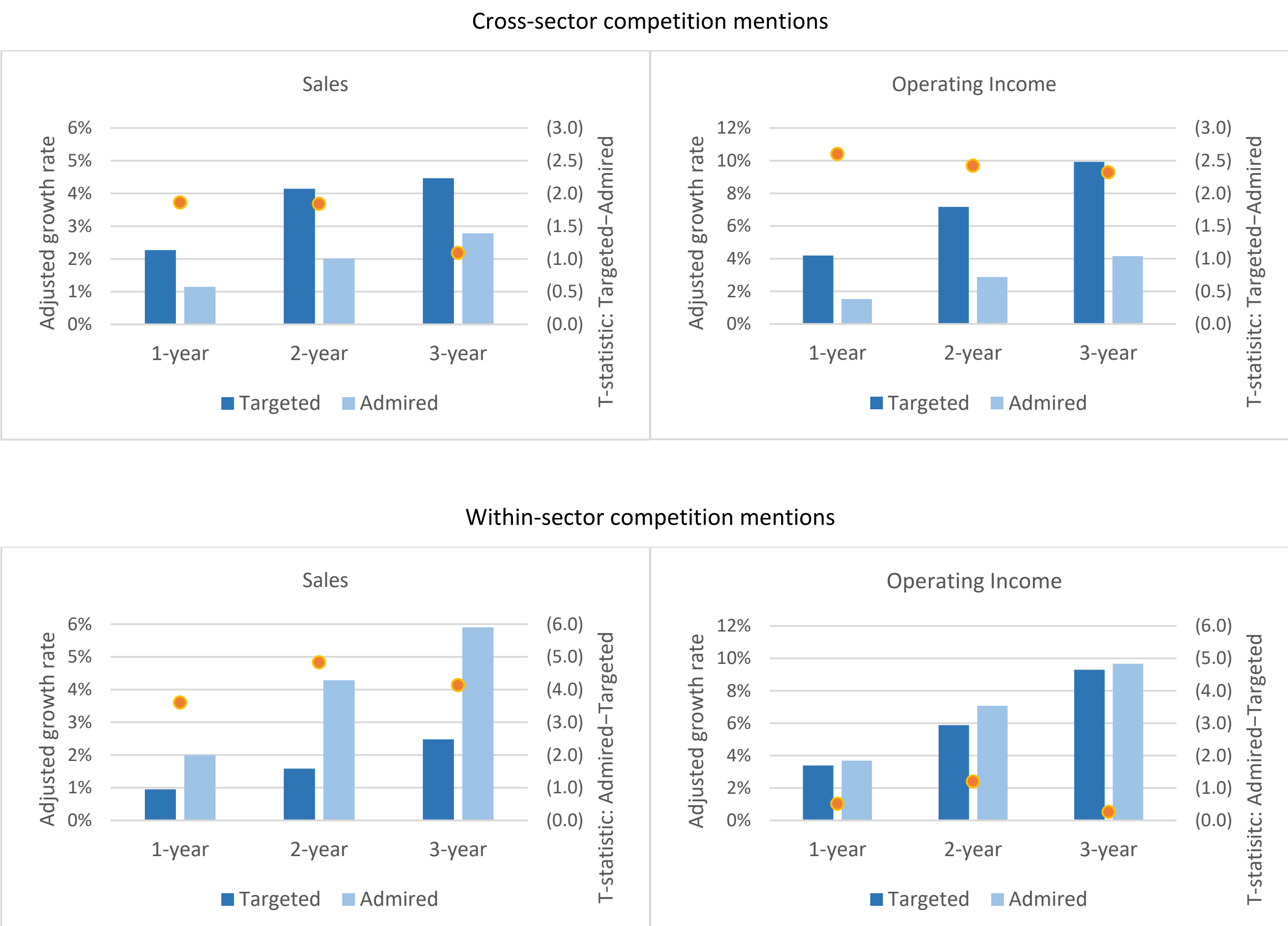


Figure 6. Target-mentioning and future takeover

The figure shows takeover probabilities derived from the logit regression models in Table 8: $Prob(Takeover) = e^{\hat{\alpha}+\hat{\beta}'X}/(1 + e^{\hat{\alpha}+\hat{\beta}'X})$ where X includes the 10-K targeting dummy variable and the Billett and Xue's model value. The impact of 10-K targeting (indicated by the percentage in the upper bars) is assessed by changing the value of the targeting dummy from 0 (the percent in the lower bars) to 1 (the percent in the full bars), while keeping the Billett and Xue's model value at its mean.