Salience and Neglected Risk[*]

Yolanda Yulong Wang

Shenzhen Audencia Financial Technology Institute

Shenzhen University

yolanda.wang@szu.edu.cn

Long Yi (Jason)

School of Business

Hong Kong Baptist University

jasonyi@hkbu.edu.hk

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Abstract

A long-short strategy that sells supplier stocks of superstar firms with high crash risk and buys those that do not generate a monthly excess return of 48 basis points that is not explained by prominent factors. The portfolio generates positive returns in 31 out of 42 years in the sample period. The pattern is consistent with the salience theory of asset pricing in which investors overweight upside potential associated with salient features, but neglect risk associated with non-salient features. We show that the premium associated with stocks having salient features disappears once a stock loses its salient features. Those that maintain their salient features do not exhibit negative excess returns compared with similar stocks. These results are consistent with the neglect of crash risk leading to the observed lower return of stocks with salient features. The results of this paper provide supporting evidence that salience plays an important role in inducing investors to neglect risk.

Keywords: Mispricing; Salience; Neglected Risk.

JEL Codes: G41; D91

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Abstract

A long-short strategy that sells supplier stocks of superstar firms with high crash risk and buys those that do not generate a monthly excess return of 48 basis points that is not explained by prominent factors. The portfolio generates positive returns in 31 out of 42 years in the sample period. The pattern is consistent with the salience theory of asset pricing in which investors overweight upside potential associated with salient features, but neglect risk associated with non-salient features. We show that the premium associated with stocks having salient features disappears once a stock loses its salient features. Those that maintain their salient features do not exhibit negative excess returns compared with similar stocks. These results are consistent with the neglect of crash risk leading to the observed lower return of stocks with salient features. The results of this paper provide supporting evidence that salience plays an important role in inducing investors to neglect risk.

1. Introduction

While the neglect of the crash (tail) risk by investors has been put forward as an explanation for the financial crisis (Gennaioli, Shleifer, and Vishny, 2012), direct empirical evidence in support of that is scarce. In this paper, we study whether investors neglect crash risk by focusing on a group of supplier firms with concentrated sales to dominant customers like Apple Inc. or Microsoft. These supplier firms provide us a chance to examine if investors neglect crash risk as supplier firms with concentrated sales to one firm are embedded with crash risk. For instance, according to Financial Times[1], Imagination Technologies, a U.K.-based chipmaker, saw a more than 70% decline in its market value when the chipmaker revealed that Apple Inc., a customer accounting for about half of the company's revenue, may dwindle its association with the firm.

What makes this firm unique is that it is a supplier of a superstar firm, Apple Inc., which is a salient feature[2]. According to the salience theory of asset pricing, investors tend to neglect crash risks with the presence of salient features (Bordalo, Gennaioli, and Shleifer, 2012, 2013, 2022). Being a supplier of a superstar firm satisfies this condition. One cannot, however, easily pinpoint that 70% drop in price to investors neglecting crash risk. Investors may be well aware of the crash risk associated with Imagination Technologies, and the 70% decline may simply be the manifestation of idiosyncratic risk, which can be diversified away if the investor holds a portfolio of firms similar to Imagination Technologies. In another word, investors holding a portfolio of firms should not be surprised to observe some of the holdings in their portfolio lose their prominent feature and should correctly price the portfolio to begin with. To see if it is the case, we focus on a group of firms like Imagination Technologies in this paper. Namely, we focus on suppliers of superstar firms (superstar suppliers). First, connection with superstar firms is a salient feature. Second and more importantly, superstar suppliers differ in their concentration of sales from superstar firms, which means the crash risk of these suppliers varies. Therefore, these superstar suppliers provide us a chance to see whether investors

[1] https://www.ft.com/content/3d49b76a-1b76-11e7-a266-12672483791a

[2] Salience requires contrast with other firms. The association with a superstar firm is an eye-grabbing feature, it satisfies the definition of salience. For instance, the suppliers of Apple Inc., a superstar firm, are widely covered. The search of the term "Apple Supplier" generates 17,400 news articles on Google. See Bordalo, Gennaioli, and Shleifer (2022) for a review of the literature.

neglect crash risk. This is also the primary reason that we focus on the suppliers, instead of superstar firms themselves in this paper.

We define superstar firms following De Loecker, Eeckhout, and Unger (2020). Superstar firms are defined as those with high sales but could still maintain a high markup. These firms are corporate behemoths like Apple Inc. or General Motors. We focus on the suppliers of these firms. Those suppliers are salient compared with otherwise similar firms because of the superstar supplier status. In addition, those with concentrated sales to superstar firms are subject to high crash risk when superstar firms opt to cease their relationship. The salience theory of asset pricing would predict investors focusing more on the upside potential of these suppliers (i.e., superior performance resulting from the association with superstar firms, a salient feature) and may ignore crash risk of these stocks, leading to the overvaluation of these stocks.

Indeed, we find evidence consistent with the overvaluation prediction. A long-short strategy that buys superstar suppliers with a low degree of concentration of sales with superstar firms and short-sells superstar suppliers with a concentrated sales (suppliers with crash risk) generates an equal-weighted monthly CAPM alpha of 49 basis points. Prominent factor models do not reduce the size of the alpha. We find a Fama-French (1993) three-factor alpha of 47 basis points and a four-factor alpha of 48 basis points when we add the Carhart (1997) momentum factor. The results are also not explained by firm characteristics such as market capitalization, book-to-market ratio, momentum, investment, or profitability.

To identify if salience drives the finding, we conduct a placebo test: instead of focusing on superstar suppliers, we construct a sample based on large non-superstar firms and their suppliers. Compared with superstar firms, large non-superstar firms have high sales within an industry but do not sustain high margins. These firms are intuitively less visible to investors compared with superstar firms. As such, supplier firms of these large non-superstar firms are less salient. Thus, we would expect a weaker overvaluation for these suppliers of large non-superstar firms if the salience effect drives the finding. Characteristic-wise, suppliers of large firms are very similar to superstar suppliers. Using this sample of stocks, we are not able to find an overvaluation effect. This result suggests potentially that the salience feature of a strong connection with superstar firms generates the overvaluation of these stocks.

While salient superstar suppliers benefit from the blessings of high sales growth and stock price appreciation (upside potential), it comes with crash risk. As such, there are two potential sources of overvaluation. First, investors may have overestimated the upside potential of superstar suppliers with strong ties to superstar firms as salient superstar suppliers potentially benefit from their strong association with firms that are performing well (Wang and Yi, 2022). Alternatively, investors may ignore the crash risk associated with these suppliers. To pin down the source of the overvaluation, we focus on superstar suppliers with concentrated sales to superstar firms only (i.e., those with high crash risk). Then, we examine their return differences when some lose their strong connection with superstar firms (i.e., the connection crashes). If investors overestimate the upside potential, the overvaluation will weaken with the new information's arrival irrespective of whether the connection crashes. This predicts lower returns for all these superstar suppliers, irrespective of whether these superstar suppliers can maintain the superstar connection or not[5]. On the other hand, if investors ignore the crash risk, we expect to observe low returns for superstar suppliers that lose their connection with superstar firms only while there should not be any negative returns for those who maintain the relationship. We find when a superstar supplier is no longer strongly connected with superstar firms, the premium (overvaluation) associated with the connection goes away. These stocks have low returns that prominent factor models cannot explain. For superstar suppliers that maintain their strong relation with superstar firms, we do not observe subsequent low returns, nor are their returns much different from those of superstar suppliers with weak connections. These results suggest that the overvaluation of salient superstar suppliers is likely due to investors ignoring crash risk of these stocks instead of investors overestimating the upside potential of these stocks.

We are closely related to papers investigating how salience relates to behavioral biases. It has been shown that salience impacts the trading behavior of both individual and mutual funds. Hartzmark (2015) shows a "rank effect": how a stock's performance compared with other stocks in an investor's portfolio affects the tendency to trade. The "rank effect" is consistent with the salience theory in which contrast matters regarding investor attention. Frydman and Wang (2020) document how the rank effect can be affected by the salience of information. When the salience of the purchasing price of stocks increases exogenously, they find a stronger disposition effect. The "rank effect" can explain the finding, suggesting salience indeed affects investor behavior. We contribute to this line of literature by providing empirical support for the salience theory of asset pricing that salience is associated with investors neglecting risk.

[5] Of course, the returns are even lower for those that lost the connection.

This study also provides empirical support for the salience theory of asset pricing. Prior studies on the salience theory of asset pricing using return-based salience measures find weak support for the salience theory because 1) the return reverses within a year; 2) the effect is only robust in microcap stocks; 3) the effect exists only in volatile markets. In contrast to the previous finding that overpricing fades using annual portfolios, our portfolio strategy is based on annual rebalancing. We also show that the salience effect exists outside of microcap stocks using our measure. The magnitude of the overvaluation is similar between samples based on microcap stocks and non-microcap stocks. In terms of time-series variation of the effect, we find our portfolio strategy yields positive returns in 31 out of 42 years of the sample. Moreover, we show that mispricing has become stronger in recent years, potentially due to the advancement of technology that makes information more accessible, which enables investors to discover salient stocks more easily.

Not only is this study in support of the salience theory of asset pricing, but this paper also shows that the overvaluation of salient stocks is more related to investors neglecting crash risk than them overestimating the future performance of these stocks. It has been documented in various papers that investors sometimes ignore crash risk (Barberis, Shleifer, and Vishny, 1998; Gerardi, Lehnert, Sherlund, and Willen, 2008; Coval, Jurek, and Stafford, 2009; Reinhart and Rogoff, 2009). Gennaioli and Shleifer (2010) formalize that investors may ignore certain contingencies to explain judgment biases. Gennaioli, Shleifer, and Vishny (2012) apply this idea to explain how financial innovation caters to investors neglecting risks, which explains financial fragility. However, few have empirically investigated under what circumstances investors tend to neglect crash risk. In this line of research, Baron and Xiong (2017) find evidence that investors tend to forget about crash risk in credit expansions. We contribute by providing empirical evidence that salience is closely related to the neglect of risk.

This one also contributes to the broad literature on how investor behavioral biases affect stock returns. For example, the seminal work of prospect theory by Kahneman and Tversky (1979) indicates that investors value gains and losses differently. Specifically, investors have loss aversion. Because of this loss aversion, investors would transform the objective probability distribution of stock returns to a subjective one, leading to the overweight of crash risk.[6] Under the prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), stocks of suppliers with crash risk should be undervalued because of loss aversion and probability overweighting on crash risk (Barberis and Huang, 2008; Barberis, 2013; Barberis, Jin, and Wang, 2021). On the other hand, the salience theory of asset pricing (Bordalo, Gennaioli, and Shleifer, 2012, 2013) predicts investors neglecting crash risk if investors are distracted by other salient features. Ours provides empirical support for the prediction from the salience theory.

2. Data and Variables

We obtain supply chain data through COMPUSTAT segment files. The data, which records major customers of supplier firms, is available from 1978 through 2019. Supplier firms are required to disclose information for major customers that makes up more than 10% of total sales. Therefore, the information is readily available to investors. We then obtain stock return data from the Center for Research in Security Prices (CRSP) and

[6] see Barberis (2013) for a review of the literature.

associated accounting information from COMPUSTAT. We exclude American depositary receipts, real estate investment trusts, and units of beneficial interest and only include NYSE, Nasdaq, and Amex stocks with share codes 10 and 11. We also exclude penny stocks with prices less than $1 at the time of portfolio formation. Given the supply chain data's availability, this study's stock return data spans from January 1979 to December 2020.

Superstar firms are defined as those that satisfy the following conditions: 1) sales are ranked within the top three in the same two-digit SIC industry, and the sales number has to be at least three times the industry median; 2) markup is above the industry median. Markup is estimated using the method described in De Loecker, Eeckhout, and Unger (2020). We provide a list of superstar firms in 2019 in Table 1. The list of firms validates the definition of superstar firms as most of these firms are indeed ones as one would normally expect to be superstar firms.

[Insert Table 1 Here]

2.1 Superstar Supplier

What we are interested in this paper, however, is not superstar firms per se but their suppliers. As such, we utilize the supply chain data and define a superstar supplier as a supplier firm relates to at least one superstar firm as defined above. We do not include any superstar firms in the sample, even if they are connected with another superstar firm. We find, on average, 158 such superstar suppliers each year.

2.2 Superstar Concentration

The main variable of interest in this paper is the concentration of sales to superstar firms, or STAR_CON. For each superstar supplier firm, it is defined as the percentage of sales attributed to superstar firms. The variable, therefore, ranges from zero to one. Superstar suppliers with high values of STAR_CON tend to have higher crash risk.

2.3 Other Variables

We also calculate firm-level characteristics associated with stock returns: MKT_CAP is the market capitalization of firms. It is calculated as the product of share price and shares outstanding in millions at portfolio formation; SIZE is the natural log of MKT_CAP. BM, the book-to-market ratio, is the ratio of book value to market value. Book value is calculated as the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock[7] measured one year before portfolio formation. The associated market value is calculated at portfolio formation. MOM is momentum. It is calculated as the past twelve-month cumulative stock return. INV, investment, is the change in total assets. ROE, return on equity, is calculated as the ratio of income before extraordinary items to total common equity.

Each year in December, we sort superstar suppliers into three groups based on STAR_CON. We present their characteristics in Table 2. We have around 53 stocks in each portfolio on average. We find that firms with high STAR_CON are typically smaller in market capitalization and slightly less profitable than other star suppliers. However, they are not otherwise quite different.

[Insert Table 2 Here]

[7] Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of the preferred stock. Stockholders' equity is the value reported by COMPUSTAT, if it is available. If not, we measure stockholders' equity as the book value of common equity plus the par value of the preferred stock, or the book value of assets minus total liabilities (in that order).

3. Main Results

3.1 Superstar Concentration and Portfolio Returns

We start with portfolio return results. Each year in December, we sort superstar suppliers into three groups based on STAR_CON. We hold the portfolio for a year. We report both equal-weighted (EW) and value-weighted (VW) portfolio returns in Panel A of Table 3.

[Insert Table 3 Here]

In the first two columns, we report returns and associate t-statistics of EW portfolios formed by STAR_CON. We calculate excess returns (RAW) and risk-adjusted returns for each set of results under various asset pricing models. We include alpha based on the CAPM model, alpha based on the Fama-French (1993) three-factor (FF3) model, and alpha based on the three-factor plus the UMD factor of Carhart (1997) (FF4) model. The difference in excess return or alpha between suppliers with low STAR_CON and high STAR_CON is reported in bold. Given that the results are consistent, we focus our discussion on FF4 alpha. We observe that stocks with high STAR_CON earn significantly lower monthly returns than those with low STAR_CON. The difference in FF4 alpha is 0.48%, with a t-stat of 3.22, which translates into 5.76% annually. The difference is economically significant and is consistent with the salience theory of asset pricing prediction that salient stocks with high crash risk are overvalued, leading to lower subsequent returns[8]. To the best of our knowledge, we are the first to show a strong

[8] In later tests, we show it is unlikely the result of risk differences: 1) if anything, those suppliers with a high concentration of sales to star suppliers are riskier in the sense that the superstar firm may terminate their relation; 2) the overpricing is only associated with suppliers of superstar firms, we do not observe such pattern for suppliers of large firms; 3) the overpricing goes away once a star supplier lost its strong tie with a superstar firm.

salience effect using an annual rebalancing approach based on non-return-based salience measures.

We observe similar but stronger patterns when we turn to value-weighted (VW) returns in the next two columns. The FF4 alpha becomes 0.51% with a t-stat of 2.05. A caveat of the VW result is that due to the size distribution of the portfolio, the returns could be affected by a few disproportionately larger stocks. For this reason, we focus our discussion on EW results in this paper.

Panel B of Table 3 reports the associated loadings in the FF4 model for both the equal-weighted and value-weighted portfolios. Stocks with high STAR_CON have higher loading on SMB, given that these stocks are on average smaller when equal-weighted. However, when value-weighted, the loading on SMB becomes much smaller across all STAR_CON portfolios, confirming our conjecture that the size distribution and the existence of large star suppliers may dominate VW portfolios, making the VW results less reliable in our paper.

3.2 Fama-Macbeth Regression

To show our previous results not due to the heterogeneity of other popular firm characteristics, we use the following Fama-MacBeth regression:

$$EXRET_{i,t+1} = \alpha + \beta_1 H\_STAR\_CON_{i,t} + Controls, \tag{1}$$

where EXRET is the monthly excess returns in year $t + 1$. H_STAR_CON is a dummy variable that equals one in year t if a star supplier strongly ties with a superstar firm in the same year. i.e., it's STAR_CON is in the top tercile. Control variables include SIZE, the natural log of the market capitalization of firms. LOGBM is the book-to-market ratio in natural log. MOM is the past twelve-month cumulative stock return. INV is the change in total assets. ROE is the return on equity. The results are reported in Table 4.

[Insert Table 4 Here]

We report results with and without control variables in columns (1) and (2), respectively. We observe similar results. The coefficients on H_STAR_CON are positive and significant, with similar magnitude (-0.5%). This is indicative of our finding that star suppliers with a strong connection with superstar firms earn lower subsequent returns is unlikely driven by popular firm characteristics that are shown to affect stock returns.

3.3 Overestimate Fundamentals or Ignorance of Crash Risk

The results so far are consistent with the overvaluation of superstar suppliers with high crash risk because of the neglect of crash risk. However, the overvaluation can also be explained by investors overestimating the fundamentals of superstar suppliers. To examine which mechanism drives our results. We examine the return of superstar suppliers that have concentrated sales with superstar firms in year t but subsequently lose the connection in year $t+1$. If investors overestimate the fundamentals of superstar suppliers with crash risk, then the overestimation will go down with the arrival of new information that corrects investors' beliefs. This predicts the return will be lower for all superstar suppliers with crash risk, irrespective of whether a superstar supplier loses its connection with superstar firms. Of course, we expect to see even lower returns for those who lose the connection. On the other hand, if investors ignoring the crash risk of salient superstar suppliers is the source of overvaluation, we expect to see lower subsequent returns only for superstar suppliers that lose their strong connection with superstar firms. We report the results in Table 5.

[Insert Table 5 Here]

As seen from Table 5, irrespective of excess returns (RAW) or alpha from factor models (CAPM, FF3, FF4), we observe a significant negative return for salient superstar suppliers that lose their connection. On the other hand, the return of superstar suppliers that can keep their strong connection does not see a low excess return or alpha compared with the returns of firms with weak connections in Table 3. These results suggest the lower returns of superstar suppliers are mainly due to these stocks that lose their strong connection with superstar firms, suggesting the lower return we observed earlier is indeed due to the neglect of crash risk. These are also consistent with salient feature of stocks biases the judgment of investors, leading them to ignore the less salient crash risk of these stocks. Note that if investors were not neglecting the crash risk, the portfolio of high connection should not have negative abnormal returns although a lower return is expected to be observed for a stock lost its connection

4. Robustness Tests

4.1 A Placebo Test

Having established that superstar suppliers with strong connections with superstar firms have lower subsequent returns and the mechanism being the ignorance of crash risk, we provide a placebo test to validate that salience matters in this section. To that end, we focus on another set of supplier firms. Instead of focusing on suppliers of superstar firms, we examine the suppliers of large firms. The definition of large firms is similar to superstar firms except that we do not require the firm to have a high markup. In other words, large firms are industry leaders in terms of total sales, but the markup of these firms is low. These firms may not have state-of-the-art products but win the market through low margin. Presumably, these stocks are less attention-grabbing than superstar firms. Subsequently the suppliers of these firms are less standing out compared with other firms. This makes these stocks unlikely salient stocks. Investors may have less distorted expectations on supplier firms with concentrated sales with large firms. As a result, we expect to observe a weaker pattern focusing on these stocks.

To see if it is the case, we define large firm sales concentration, or LF_CON as the ratio of sales to large firms to total sales. Each year in December, we sort suppliers of large firms into three groups based on LF_CON. We present their characteristics in Panel A of Table 6. We observe that supplier firms with high LF_CON are typically smaller in market capitalization than other suppliers. However, they are not otherwise quite different. We have around 83 stocks in each portfolio on average. These characteristics are very similar to what we have observed in Table 2 for superstar suppliers.

[Insert Table 6 Here]

As previously, after sorting suppliers of large firms into three groups based on LF_CON each December, we form portfolios and hold the portfolio for a year. We report both equal-weighted and value-weighted portfolio returns in Panel B of Table 6.

In the first two columns, we report returns and associate t-statistics of equal-weighted (EW) portfolios formed by LF_CON. The difference in excess return or alpha between suppliers with low LF_CON and high LF_CON is reported in bold. We focus our discussion on FF4 alpha as the results are similar. We observe that stocks with high

LF_CON do not earn significantly lower monthly returns than those with low LF_CON. The difference in FF4 alpha is 0.07%, with a t-stat of 0.65. We observe similar patterns in the last two columns when portfolios are value-weighted (VW). These results suggest that salience is essential for us to observe the lower subsequent returns of supplier firms have strong connections with superstar firms.

4.2 Additional Factor Models

In this section, we show that our results are also robust to other popular factor models. To that end, we calculate the difference (DIFF) in equal-weighted returns between star suppliers with low and high STAR_CON and regress it on factor models including Fama and French (2015) 5-factor model, Hou, Xue, and Zhang (2015) q-factor model enhanced with the expected growth factor, and Stambaugh and Yuan (2017) mispricing model. The results are reported in Table 7.

[Insert Table 7 Here]

First, we observe that the alpha remains positive and significant. The magnitude is also not much different than what we observed earlier (48 basis points). The results suggest that current asset pricing models may not account for the mispricing caused by investors due to salience. Overall, the result in this table suggests existing asset pricing models do not capture the salient effect.

4.3 Sub-Period Analysis

In this section, we report the time-series variations of the overvaluation of superstar suppliers with crash risk. We first report the time-series of the equal-weighted portfolio returns of the long-short strategy that buys into stocks with low STAR_CON and sells stocks with high STAR_CON across the sample years in Figure 1. We can observe that the portfolio generates positive returns in most years (31 out of 42).

[Insert Figure 1 Here]

Next, we report the portfolio results of Table 3 with two sub-periods. Specifically, we cut the sample into two: the first contains portfolio returns from 1979 to 1999, and the second from 2000 to 2020. Finally, the results are ported in Table 8.

[Insert Table 8 Here]

First, we can see that the results are present in both sub-periods. Second, the strength of the effect is slightly stronger in the second half of the sample period. This could be because with the advancement of technology, it is easier for investors to figure out salient stocks.

4.4 Microcap Stocks

Although we have dropped penny stocks at portfolio formation, we conduct a further test to show that our results exist outside microcap stocks. Specifically, we divide our sample into two by whether a stock is classified as microcap or not. A stock is classified as a microcap if its market capitalization is below the 20^{th} breakpoint of the size distribution of NYSE stocks. The results are reported in Table 9.

[Insert Table 9 Here]

It can be seen from the table that our finding that star suppliers with strong connections with superstar firms underperform exists in both the microcap sample and the non-microcap sample, suggesting our finding is not confined to microcap stocks.

Moreover, the magnitude of the alpha is not a lot different. In contrast, Cakici and Zaremba (2022) document strong differences in portfolio returns between samples based on microcap stocks and non-microcap ones when past return characteristics are used to gauge the salience of a stock.

5. Conclusion

Focusing on suppliers of superstar firms, we provide empirical evidence that in the presence of salient features, investors tend to neglect the less salient crash risk. Although strong concentration of sales with superstar firms entails a higher crash risk, investors ignore this less salient feature. Investors' ignorance of crash risk leads to the overvaluation of these stocks. We find no such a pattern for suppliers of large non-superstar firms, suggesting the importance of salience in the overvaluation. We also show corroborative evidence for the ignorance of crash risk: we show that the premium associated with stocks having salient features goes away once a stock loses its salient features. Moreover, those that maintain their salient features do not exhibit negative excess returns compared with similar stocks. Overall, the results support the salience theory of asset pricing and provide evidence suggesting the salience feature is closely related to investors neglecting certain tail risks.

We differ from the previous literature on the salience theory of asset pricing in several ways. For example, first, we focus on a novel measure of salience that is not stock return-based. Second, our setting generates distinct results compared to those using return-based salience measures. For example, we find the salience effect using annual rebalancing portfolios, whereas tests using return-based measures are subject to return reversal within a year. We can also show a positive alpha in most of the years in our sample period and our results exist outside of microchips.

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Table 1. List of Superstar Firms in 2019

This table lists firms that are classified as superstar firms as of 2019. Superstar firms are defined as those that satisfy the following two conditions: 1) sales are ranked within the top three in the same two-digit SIC industry, and the sales number has to be at least three times the industry median; 2) markup is above the industry median. Markup is estimated using the method described in De Loecker, Eeckhout, and Unger (2020).

3M	MARTIN MARIETTA MATERIALS
ABBOTT LABORATORIES	MASTEC INC
AIRBNB INC	MATTEL INC
ALBERTSONS COS INC	MCDONALD'S CORP
AMAZON.COM INC	MICROSOFT CORP
APPLE INC	MOHAWK INDUSTRIES INC
AT&T INC	NETFLIX INC
AVIS BUDGET GROUP INC	NEWMONT CORP
BUILDERS FIRSTSOURCE	NEWS CORP
C H ROBINSON WORLDWIDE INC	NIKE INC
CARNIVAL CORPORATION & PLC	NORWEGIAN CRUISE LINE HLDGS
CHEVRON CORP	NOVELIS INC
CINTAS CORP	OWENS CORNING
CONOCOPHILLIPS	PEPSICO INC
CORTEVA INC	PFIZER INC
D R HORTON INC	PROCTER & GAMBLE CO
EXPEDIA GROUP INC	PUBLIX SUPER MARKETS INC
FORTUNE BRANDS HOME & SECUR	PULTEGROUP INC
GAP INC	PVH CORP
GENERAL MOTORS CO	ROYAL CARIBBEAN GROUP
HASBRO INC	SOUTHERN COPPER CORP
HERTZ GLOBAL HOLDINGS INC	STARBUCKS CORP
HONEYWELL INTERNATIONAL INC	SYSCO CORP
INTEL CORP	TAPESTRY INC
JACOBS ENGINEERING GROUP INC	VERIZON COMMUNICATIONS INC
JOHNSON & JOHNSON	VF CORP
KIMBERLY-CLARK CORP	VULCAN MATERIALS CO
LAS VEGAS SANDS CORP	WEYERHAEUSER CO
LENNAR CORP	XPO LOGISTICS INC
LIONS GATE ENTERTAINMENT CP	

Table 2. Superstar Concentration: Portfolio Characteristics

This table reports characteristics of the three portfolios constructed based on the level of superstar concentration. Each December from 1978 to 2019, stocks are sorted into three portfolios by STAR_CON, the percentage of sales attributed to superstar firms. OBS is the average number of observations for each portfolio. MKT_CAP is the market capitalization of firms. BM is the book-to-market ratio. MOM is the past twelve-month cumulative stock return. INV is the change in total assets. ROE is return on equity.

STAR_CON	OBS	MKT_CAP	BM	MOM	INV	ROE
Low	53	384.67	0.63	0.04	0.07	0.08
Mid	53	327.30	0.62	0.02	0.07	0.08
High	52	237.34	0.60	0.04	0.07	0.06

Table 3. Superstar Concentration: Portfolio Returns and Factor Loadings

This table reports equal-weighted (EW) and value-weighted (VW) excess returns (RAW) as well as (CAPM, FF3, FF4) risk-adjusted returns of the three superstar concentration portfolios constructed under various factor pricing models in Panel A. The associated loadings on FF4 factors are reported in Panel B. In each December from 1978 to 2019, stocks are sorted into three portfolios by STAR_CON, the percentage of sales that are attributed to superstar firms. The differences in returns between stocks with low and high STAR_CON and associated Newey-West t-statistics are reported in bold in Panel A.

Panel A. Portfolio Returns

STAR_CON	EW		VW	
	Return	t-stat	Return	t-stat
Low	1.29%	3.67	1.21%	3.60
Mid	1.27%	3.65	1.37%	4.13
High	0.81%	2.11	0.52%	1.38
RAW	**0.48%**	**3.20**	**0.69%**	**2.84**
Low	-0.03%	-0.13	-0.10%	-0.50
Mid	0.01%	0.06	0.11%	0.52
High	-0.51%	-2.30	-0.86%	-3.71
CAPM	**0.49%**	**3.27**	**0.75%**	**3.06**
Low	-0.04%	-0.32	-0.05%	-0.27
Mid	-0.04%	-0.27	0.14%	0.74
High	-0.51%	-3.48	-0.73%	-3.95
FF3	**0.47%**	**3.22**	**0.68%**	**2.82**
Low	0.13%	0.92	0.01%	0.04
Mid	0.11%	0.76	0.33%	1.80
High	-0.35%	-2.35	-0.51%	-2.77
FF4	**0.48%**	**3.22**	**0.51%**	**2.05**

Panel B. FF4 Factor Loadings

STAR_CON	**Factors**	**EW Loadings**	**t-stat**	**VW Loadings**	**t-stat**
Low	MKTRF	1.14	29.43	1.20	20.09
	SMB	0.96	16.04	0.53	5.96
	HML	-0.08	-1.16	-0.27	-2.90
	UMD	-0.22	-5.11	-0.07	-1.20
Mid	MKTRF	1.06	33.10	1.12	23.34
	SMB	1.03	16.08	0.43	4.42
	HML	0.05	0.77	-0.27	-3.26
	UMD	-0.18	-3.21	-0.23	-4.42
High	MKTRF	1.09	28.28	1.18	26.68
	SMB	1.21	17.62	0.67	9.64
	HML	-0.16	-2.20	-0.65	-7.14
	UMD	-0.21	-4.42	-0.28	-5.04

Table 4. Superstar Concentration: Regression Returns

This table presents Fama-MacBeth regression results where the dependent variable EXRET is the monthly excess return. H_STAR_CON is a dummy variable that equals one if the STAR_CON of a firms is within the top tercile at portfolio formation month. SIZE is the natural log of the market capitalization of firms. BM is the book-to-market ratio in natural log. MOM is the past twelve-month cumulative stock return. INV is the change in total assets. ROE is return on equity. Newey-West t-statistics are reported in parenthesis. *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.

VARIABLES	(1) EXRET	(2) EXRET
H_STAR_CON	**-0.005*** **	**-0.005*** **
	(-3.38)	**(-2.75)**
SIZE		-0.000
		(-0.58)
LOG_BM		0.002
		(0.80)
MOM		-0.003
		(-0.25)
INV		-0.009***
		(-3.76)
ROE		0.005
		(1.45)
Intercept	0.013***	0.018***
	(3.82)	(3.13)
# of Months	504	504

Table 5. Superstar Concentration: The Fall of Stars

This table reports equal-weighted excess returns (RAW) and (CAPM, FF3, FF4) risk-adjusted returns of the two superstar concentration portfolios constructed under various factor pricing models. In each December from 1978 to 2018, stocks are sorted into three portfolios by STAR_CON, the percentage of sales that are attributed to superstar firms. We keep stocks in the top tercile of STAR_CON. We then divide this portfolio into two depending on whether a stock continues to be classified in the top tercile of STAR_CON in the next year. The differences in returns between these two portfolios and associated Newey-West t-statistics are reported in bold.

High Star Concentration (t+1)	**Return**	**t-stat**
No	-0.09%	-0.19
Yes	1.42%	3.75
RAW	**-1.51%**	**-4.63**
No	-1.41%	-4.42
Yes	0.17%	0.66
CAPM	**-1.58%**	**-4.70**
No	-1.40%	-4.99
Yes	0.19%	1.06
FF3	**-1.59%**	**-4.85**
No	-1.16%	-4.12
Yes	0.29%	1.60
FF4	**-1.45%**	**-4.38**

Table 6. Large Firm Concentration: Portfolio Returns

This table reports characteristics, equal-weighted (EW) and value-weighted (VW) excess returns (RAW) as well as (CAPM, FF3, FF4) risk-adjusted returns of the three large firm concentration portfolios constructed under various factor pricing models in Panel A and Panel B, respectively. In each December from 1978 to 2019, stocks are sorted into three portfolios by LF_CON, the percentage of sales that are attributed to large firms. In Panel A, OBS is the average number of observations for each portfolio. MKT_CAP is the market capitalization of firms. BM is the book-to-market ratio. MOM is the past twelve-month cumulative stock return. INV is the change in total assets. ROE is return on equity. In Panel B, the differences in returns between stocks with low and high LF_CON and associated Newey-West t-statistics are reported are reported in bold.

Panel A. Portfolio Characteristics

LF_CON	OBS	MKT_CAP	BM	MOM	INV	ROE
Low	83	443.41	0.65	0.05	0.07	0.09
Mid	85	511.17	0.64	0.04	0.06	0.09
High	81	326.39	0.71	0.02	0.05	0.09

Panel B. Portfolio Returns

LF_CON	**EW**		**VW**	
	Returns	**t-stat**	**Returns**	**t-stat**
Low	1.17%	3.62	1.07%	4.46
Mid	1.07%	3.73	1.09%	5.16
High	0.99%	3.05	0.97%	3.23
RAW	**0.18%**	**1.57**	**0.10%**	**0.43**
Low	-0.08%	-0.48	-0.04%	-0.29
Mid	-0.11%	-0.75	0.14%	0.94
High	-0.20%	-1.11	-0.17%	-0.75
CAPM	**0.12%**	**1.12**	**0.13%**	**0.52**
Low	-0.13%	-1.29	-0.01%	-0.08
Mid	-0.16%	-1.73	0.20%	1.43
High	-0.25%	-2.10	-0.12%	-0.58
FF3	**0.11%**	**1.04**	**0.11%**	**0.46**
Low	0.02%	0.23	0.04%	0.28
Mid	-0.04%	-0.41	0.12%	0.82
High	-0.05%	-0.38	0.11%	0.48
FF4	**0.07%**	**0.65**	**-0.07%**	**-0.28**

Table 7. Superstar Concentration: Additional Factor Models

This table reports the regression results using additional factor pricing models, including Fama and French (2015) 5-factor model, Hou, Xue, and Zhang (2015) q-factor model enhanced with the expected growth factor, and Stambaugh and Yuan (2017) mispricing model. In each December from 1978 to 2019, stocks are sorted into three portfolios by STAR_CON, the percentage of sales that are attributed to superstar firms. DIFF is the differences in equal-weighted returns between stocks with low and high STAR_CON. Newey-West t-statistics are reported in parentheses. *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
VARIABLES	DIFF	DIFF	DIFF
Constant	**0.004****	**0.005*****	**0.005*****
	(2.36)	**(3.21)**	**(3.38)**
MKTRF	0.086**	0.050	0.031
	(1.99)	(1.14)	(0.64)
SMB	-0.211***	-0.244***	-0.268***
	(-3.05)	(-3.40)	(-3.53)
HML	-0.019		
	(-0.26)		
RMW	0.001		
	(1.50)		
CMA	0.002**		
	(2.04)		
R_IA		0.002**	
		(2.28)	
R_ROE		0.001	
		(1.52)	
R_EG		-0.002	
		(-1.64)	
MGMT			0.042
			(0.51)
PERF			-0.020
			(-0.44)
Months	504	504	456

Table 8. Superstar Concentration: Sub Period Analysis

This table reports equal-weighted excess returns (RAW) as well as (CAPM, FF3, FF4) risk-adjusted returns of the three superstar connection portfolios constructed under various factor pricing models for two sub-periods. Microcap stocks are those market capitalization falls under the 20th size breakpoint of NYSE stocks. In each December from 1978 to 1998 (1999 to 2019), stocks are sorted into three portfolios by STAR_CON, the percentage of sales that are attributed to superstar firms. The first (second) set of results are for the sub-period 1978 to 1998 (1999 to 2019). The differences in returns between stocks with low and high STAR_CON and associated Newey-West t-statistics are reported in bold for both sub-periods.

STAR_CON	**1979-1999**		**2000-2020**	
	Returns	t-stat	Returns	t-stat
Low	1.36%	2.98	1.23%	2.32
Mid	1.63%	3.58	0.91%	1.77
High	0.98%	1.84	0.64%	1.18
RAW	**0.38%**	**1.62**	**0.59%**	**3.10**
Low	-0.23%	-0.79	0.25%	0.99
Mid	0.08%	0.26	0.01%	0.03
High	-0.67%	-1.90	-0.31%	-1.15
CAPM	**0.44%**	**1.87**	**0.56%**	**3.01**
Low	-0.09%	-0.44	0.14%	0.76
Mid	0.22%	1.13	-0.14%	-0.76
High	-0.51%	-2.32	-0.44%	-2.39
FF3	**0.42%**	**1.84**	**0.58%**	**2.99**
Low	0.03%	0.13	0.22%	1.22
Mid	0.25%	1.26	-0.04%	-0.23
High	-0.50%	-2.32	-0.34%	-1.89
FF4	**0.53%**	**2.31**	**0.56%**	**2.84**

Table 9. Superstar Concentration: Microcap Stocks

This table reports equal-weighted excess returns (RAW) as well as (CAPM, FF3, FF4) risk-adjusted returns of the three superstar concentration portfolios constructed under various factor pricing models for microcap stocks and non-microcap ones. Microcap stocks are those market capitalization falls under the 20th size breakpoint of NYSE stocks. In each December from 1978 to 2019, stocks are sorted into three portfolios by STAR_CON, the percentage of sales that are attributed to superstar firms. The first (second) set of results further requires the stocks to be microcap (non-microcap). The differences in returns between stocks with low and high STAR_CON and associated Newey-West t-statistics are reported in bold for microcap stocks and non-microcap stocks.

STAR_CON	**Microcap**		**Non-Microcap**	
	Returns	t-stat	Returns	t-stat
Low	1.44%	3.44	1.14%	3.38
Mid	1.27%	3.17	1.37%	4.03
High	0.93%	2.29	0.65%	1.60
RAW	**0.51%**	**2.19**	**0.50%**	**2.12**
Low	0.09%	0.34	-0.20%	-1.06
Mid	0.05%	0.18	0.05%	0.26
High	-0.35%	-1.36	-0.77%	-3.12
CAPM	**0.44%**	**2.08**	**0.58%**	**2.48**
Low	0.03%	0.16	-0.18%	-1.12
Mid	-0.04%	-0.22	0.05%	0.35
High	-0.40%	-2.17	-0.69%	-3.41
FF3	**0.43%**	**2.01**	**0.50%**	**2.21**
Low	0.25%	1.09	-0.04%	-0.28
Mid	0.09%	0.42	0.22%	1.53
High	-0.24%	-1.26	-0.48%	-2.43
FF4	**0.49%**	**2.11**	**0.43%**	**1.92**

Figure 1. Superstar Concentration: Time Series of Portfolio Returns

This figure plots the time series of portfolio returns. Each December from 1978 to 2019, stocks are sorted into three portfolios by STAR_CON, the percentage of sales attributed to superstar firms. The annual differences in equal-weighted returns between stocks with low and high STAR_CON are plotted in the figure.