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# Do contented customers make shareholders wealthy? - Implications of intangibles for security pricing

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# Do Contented Customers Make Shareholders Wealthy? - Implications of Intangibles for Security Pricing*

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**Abstract**

We explore the relation between customer satisfaction and security returns. Firms with high customer satisfaction levels earn significant abnormal returns. This result is robust to variations of model specification and test methodology. Additional tests do not reveal evidence of systematic mispricing. Our results rather suggest that there are, consistent with the model of Eisfeldt and Papanikolaou (2013), sources of risk not covered by standard risk factors. We identify firm characteristics, such as the Hoberg et al. (2014) product market fluidity measure, and macro variables, such as patenting activity and aggregate R&D spending, that are related to these sources of risk.

**Keywords:** Intangible Capital, Customer Satisfaction, Innovativity, ESG-Investing
**JEL Classifications:** E22, G12, G14, M31

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Recent research in marketing suggests that stock returns of firms with high levels of customer satisfaction outperform the market on a risk-adjusted basis, and that a hedge fund which implements a customer satisfaction-based strategy generates significant abnormal returns (e.g. Aksoy et al. 2008, Fornell et al. 2006 and Fornell et al. 2016a). In this paper we address the link between customer satisfaction, intangible assets and security returns from a finance perspective. A link between customer satisfaction and stock returns may exist if either customer satisfaction is related to a source of systematic risk not controlled for, or if there is mispricing. We combine data from the American Customer Satisfaction Index (ACSI) with stock return data to test empirically whether standard risk factors capture the customer satisfaction premium. Our results imply that this is not the case. A trading strategy based on the ACSI yields significant abnormal returns even after controlling for a large number of factors. This finding is robust both to variations in the set of factors included in the regression, and to the test methodology. Specifically, we estimate time-series regressions, we employ characteristics-based matching, and we run Fama and MacBeth (1973) regressions.

We then investigate whether the significant abnormal returns are caused by mispricing. We find that the abnormal return is mainly due to the long leg of the strategy, that the stocks in the customer-satisfaction portfolio are large and have low idiosyncratic volatility, and that the turnover in the customer satisfaction portfolio is moderate. Thus, it should be easy for arbitrageurs to exploit and thereby eliminate mispricing. We further adopt a methodology pioneered by Tetlock et al. (2008) and subsequently adopted by Chen et al. (2014), Huang (2018) and Green et al. (2019) to test whether information revealed through earnings announcements is related to pre-announcement customer satisfaction scores. If these scores contained information on future cash flows not yet incorporated into stock prices, we would expect that they are positively related to earnings surprises. We find no evidence of such a relation. Overall, there is thus no indication that the abnormal return of the customer-satisfaction strategy is caused by mispricing. We then explore whether firms with high levels of customer satisfaction are exposed to specific risks that are not covered by standard risk factors. Based on theoretical considerations routed in the model of Eisfeldt and Papanikolaou (2013) we hypothesize that investments in customer capital (of which customer satisfaction is an output-based measure) are risky because innovations by competitors may devalue these investments. Consistent with this argument we find that the customer satisfaction premium is larger among firms with high equity duration, higher operating leverage, and higher levels of product market fluidity. The latter is a measure of competitive threats proposed by Hoberg et al. (2014). We also find that the return of the customer satisfaction strategy loads positively and significantly on factors related to measures of innovative activity, such as venture capital financing, aggregate R&D spending, or patenting activity. Overall, our evidence is thus supportive of a risk-based explanation for the customer satisfaction premium. However, the risk associated with higher levels of customer satisfaction is not captured by standard risk factors.

Our paper is related to several strands of the literature. Many papers analyzing return "anomalies" and the profitability of trading strategies built on them consider accounting-related firm characteristics. Recently, however, there has been growing interest in the role and valuation of intangible assets that do not appear on the balance sheet of the firm. Corrado and Hulten (2010) estimate that intangible assets account for 34% of firm value. Following the taxonomy proposed by Peters and Taylor (2017), the intangible assets of a firm are composed of its knowledge capital and its organizational capital. The latter, among other things, includes human capital and the value of customer relationships (or the customer capital, as Gourio and Rudanko (2014) name it). Previous papers have constructed input-based measures of customer capital from advertising expenses (Belo et al. (2014)). We argue (and provide supporting evidence) that the ACSI customer satisfaction index is an output-based measure of customer capital. Consequently, our paper contributes to the literature on the valuation of organizational capital and, more generally, of intangible assets.

Eisfeldt and Papanikolaou (2013) develop a formal model in which firms with higher levels of organizational capital are more risky and therefore should have higher expected returns. We argue that the logic of their model extends to customer satisfaction. Eisfeldt and Papanikolaou (2013) also present empirical results which are consistent with the predictions of their model. They show that the stocks of firms with high levels of organizational capital earn higher returns, a finding that is supported by the evidence presented in Belo et al. (2014) and Dou et al. (2020). However, there is also conflicting evidence. Tuli and Bharadwaj (2009) find that firms with higher levels of customer satisfaction have lower market risk and lower idiosyncratic risk. Larkin (2013) performs an empirical analysis of customer brand perception and finds that firms with stronger brand perception have less volatile cash flows and better credit ratings. It is thus unclear whether the high returns of firms with high levels of organizational capital are a compensation for risk. Several recent studies indeed provide evidence that stock prices fail to accurately reflect the value of intangible assets. Edmans (2011) finds that stock prices are slow in reacting to news about intangible assets. Specifically, he shows that stock prices do not fully incorporate readily available information on employee satisfaction.[1] Green et al. (2019) use data on employee-authored company reviews and show that changes in the employer ratings predict one-quarter ahead returns. Thus, consistent with Edmans (2011), stock prices are slow in incorporating that information. Huang (2018) employs Amazon ratings and shows that these consumer opinions predict one-month ahead stock returns. Customer reviews thus provide valuable information, and stock prices adjust slowly to this information.

Our paper contributes to this discussion. We shed light on the important question whether the abnormal returns earned by firms with high levels of organizational capital (and intangible capital in general) are a reflection of a different level of risk or evidence of mispricing. The finding that firms with higher levels of customer satisfaction earn significant abnormal returns relative to standard asset pricing models is consistent with the prior empirical evidence described above. However, our finding that there is no indication of mispricing is in contrast to the results presented by Edmans (2011), Edmans et al. (2020),

[1] Edmans et al. (2020) show that the effect holds also internationally for countries with flexible labor markets, but not for countries with rigid labor markets.

Green et al. (2019) and Huang (2018). The evidence we provide that firms with higher levels of customer satisfaction are more risky is supportive of the Eisfeldt and Papanikolaou (2013) model. We further add to the literature by identifying firm characteristics that are related to the source of risk we propose, and we show that there is a time-series relation between the customer satisfaction return premium and macro factors related to innovative activity.

The remainder of the paper is organized as follows. Section 1 provides a brief survey of the relevant literature and describes the theoretical background. In section 2 we describe our data set and present descriptive statistics. We put particular emphasis on the construction of the ACSI index, and on the characteristics of the firms that are included in the index. In section 3 we relate our measure of customer satisfaction to several measures of intangible asset value proposed in the recent literature. In section 4 we analyze the return of a customer-satisfaction-based investment strategy, including a battery of robustness checks. In section 5 we explore whether the abnormal return earned by the strategy is a reflection of an omitted source of risk or a reflection of mispricing. Section 6 concludes.

# 1 Literature and Theory

An extensive body of literature analyzes the profitability of investment strategies that are based on firm characteristics. This literature focuses almost exclusively on tangible assets, the value of which can be derived from the firm's balance sheet. A potential reason for this focus may be rooted in the neoclassical theory of investments. As Peters and Taylor (2017) point out, the theory has been developed in a time when firms were mainly holding tangible assets. Since then the structure of economies in developed countries has shifted significantly, with service and technology industries having the largest shares in GDP and market capitalization nowadays. At the same time intangible assets became increasingly important.

Several papers provide evidence on the importance of intangible assets for firm value. Corrado and Hulten (2010) estimate that intangible assets on average account for 34% of a firm's total capital. Vitorino (2013) reports that brand equity alone accounts for 23% of firm value, and Belo et al. (2018) estimate that, depending on the industry, brand capital on average accounts for 3.5% to 24% of a firm's market value. The management literature plainly considers human capital and brand value to be a firm's most valuable assets (e.g. Vomberg et al. (2015)). Li et al. (2017) show empirically that acquisitions made by acquirers with higher level of organizational capital are more profitable in terms of both abnormal stock performance and operational performance than acquisitions made by low organizational capital acquirers. These findings imply that organizational capital is a valuable resource. Corrado et al. (2009) explore the implications of investments in intangible assets for the growth of the US economy while Lim et al. (2016) analyze the extent to which intangible assets support debt financing. Peters and Taylor (2017) propose a modified Tobin's q that accounts for intangible assets and demonstrate that their measure, named Total q, is a better proxy for physical and intangible investment opportunities. Clausen and Hirth (2016) propose an indirect measure for intangible asset value, based on the intuition that a higher level of intangibles allows a firm to use its tangible assets more efficiently.[2]

Peters and Taylor (2017) categorize a firm's intangible capital into its knowledge capital and its organizational capital. The former comprises intellectual assets such as patents and the latter comprises, among others, market-based assets such as human capital, brand values, the value of customer relations and distribution systems. Customer satisfaction, in this categorization, is a component of a firm's organizational capital. R&D expenses are interpreted as an investment into the firm's knowledge capital while SG&A expenses (excluding R&D expenses) constitute an investment into organizational capital. Input-based estimates of knowledge capital and organizational capital can thus be obtained by capitalizing

[2]This view is consistent with Lev and Radhakrishnan (2015, p. 1) who define that "organization capital consists of business processes and systems [...] that enable tangible and intangible resources, such as patents, brands and human capital, [...] to be productive."

past R&D and SG&A expenses, respectively. Gourio and Rudanko (2014) propose a model in which the existence of search frictions in product markets provides an incentive for firms to invest in organizational capital.

Eisfeldt and Papanikolaou (2013) develop a theoretical model based on the assumption that a firm's organizational capital is embodied in "key talent". Key talent can be thought of as management and other personnel with specific knowledge that is essential to the firm. These persons have the option to leave the firm, which allows them to extract rents from the shareholders of the firm. Specifically, when the efficiency of organizational capital in other firms increases, the outside option of key talent improves and they can extract higher rents from the shareholders. Consequently, there is an important difference between investment in physical capital and in organizational capital. While shareholders can fully appropriate the cash flows generated by physical capital, this is not true for investment in organizational capital. The latter should thus be more risky and, consequently, the risk of a firm should depend on its ratio of organizational capital to physical capital. The risk associated with higher levels of organizational capital is systematic and thus should be rewarded in equilibrium. To test this hypothesis, Eisfeldt and Papanikolaou (2013) construct a measure of organizational capital from data on SG&A expenditures. They then estimate the ratio of organizational capital to physical capital (denoted the O/K ratio) and relate it to stock returns. They find that a portfolio that is long in firms with high O/K ratios and short in firms with low O/K ratios earns a 4.7% annual rate of return.

The intuition of the Eisfeldt and Papanikolaou (2013) model carries over to customer satisfaction, implying that firms with higher levels of customer satisfaction should be more risky.[3] There are three arguments to support this view. First, customer capital is a component of organizational capital, and customer satisfaction is an output-based measure of

[3]Eisfeldt and Papanikolaou (2013) use a concept that refers to capital that is embedded within the firm's employees, similar to Prescott and Visscher (1980). We can extend the theory to customer satisfaction if we build on the extended concept of intangible and organizational capital of Atkeson and Kehoe (2005). In their concept, organizational capital is not only employee-, but *firm-specific* and thus embedded within the firm as a whole. Eisfeldt and Papanikolaou (2014) also refer to this definition.

customer capital. Our analysis is thus complementary to Eisfeldt and Papanikolaou (2013) who use an input-based measure of organizational capital, namely, capitalized SG&A expenditures. Second, the "key talent channel" of Eisfeldt and Papanikolaou (2013) directly applies to our setting, because the level of customer satisfaction is related to the activity of key talent of the firm in the areas of product design and product development, marketing and distribution.[4] Finally and crucially, we argue that there is a "customer channel" that complements the key talent channel proposed by Eisfeldt and Papanikolaou (2013). Customers have the option to "leave the firm" (or to threaten to do so), i.e. to cease to buy its products, in response to product or marketing innovations in other firms. While *all* firms are exposed to that threat, those firms that invest more heavily in customer capital have more to lose because their shareholders may be unable to fully appropriate the cash flows associated with investments in customer capital. This argument implies that investments into customer capital (such as advertising) are more risky than investments into physical capital.

Several papers indeed find that stocks of firms with higher levels of customer satisfaction earn higher risk-adjusted returns (Fornell et al. 2006, Aksoy et al. 2008, and Luo et al. 2010).[5] This finding is confirmed by Fornell et al. (2016a). These authors show that a hedge fund that uses an ACSI-based long/short strategy significantly outperforms one-, three- and four-factor models. They further provide evidence that firms with higher levels of customer satisfaction subsequently have higher earnings and higher earnings surprises. Consistent results based on customer opinion data are provided in Huang (2018). Brand value (Madden et al. 2006 or Belo et al. 2014) and human capital (Edmans 2011 and Green et al. 2019) also appear to be positively related to risk-adjusted stock returns.

[4]Dou et al. (2020) characterize firms whose customer capital strongly depends on key talent as firms with high "inalienability of customer capital" (high ICC). Based on a theoretical model they argue that high ICC firms are vulnerable to financial distress and are therefore more risky. They then construct a survey-based measure of ICC and show that high ICC firms indeed have higher risk-adjusted returns.

[5]In contrast to the papers cited in the text, O'Sullivan et al. (2009) conclude that firms with high levels of customer satisfaction do not outperform standard three and four factor models. Jacobson and Mizik (2009) conclude that the outperformance of high customer satisfaction firms is limited to firms in the computer and internet industries.

However, there is little evidence so far that higher organizational capital intensity is associated with higher risk levels. In fact, several papers conclude that firms with higher levels of customer satisfaction are actually less risky (Gruca and Rego 2005, Tuli and Bharadwaj 2009, Fornell et al. 2016b, Huang 2018). Larkin (2013) considers customer brand perception rather than customer satisfaction and finds that more positive brand perception is associated with lower levels of risk. Anderson et al. (2004) and Fornell et al. (2006) find that firms with higher levels of customer satisfaction have higher Tobin's q and higher market capitalization, respectively; findings which are inconsistent with the notion that these firms are more risky. The evidence presented by Vomberg et al. (2015) points in a similar direction. These authors report that a score based on product quality perception and brand awareness is positively related to Tobin's q. The combined evidence of high returns and low risk suggests that either a relevant source of systematic risk is not accounted for (the "risk hypothesis"), or that the market may not be correctly valuing organizational capital (the "mispricing hypothesis"). Edmans (2011) and Green et al. (2019) show that stock prices do not fully incorporate readily available information on employee satisfaction and employer ratings, respectively, thus supporting the mispricing hypothesis. To the extent that these results carry over to other intangible assets, we might expect that firms with high level of customer satisfaction have positive alphas after controlling for known risk factors.

To summarize, while a positive relation between customer satisfaction and other measures of organizational capital and stock returns is well-established, it is much less clear why this relation exists. In this paper we analyze whether excess returns related to customer satisfaction are evidence of mispricing, or whether the excess returns are related to sources of systematic risk not accounted for in earlier studies, and hence constitute a risk premium.

## 2 Data

The data we use to measure customer satisfaction is taken from the American Customer Satisfaction Index (ACSI), introduced by Fornell et al. (1996). This index comprises customer satisfaction data for US-customers and is published regularly by ACSI LLC. It covers foreign and domestic firms that have a significant share in the US market. Figures (on a scale extending from 0 to 100) are released at the aggregate (i.e. US) level, at the industry level, and at the firm level. The scores can be obtained directly from the ACSI.[6] Each year around 180,000 customer evaluations are collected in order to determine the customer satisfaction values. The ACSI uses a cause-and-effect model which identifies customer satisfaction based on its drivers and outcomes. The final customer satisfaction (CS) value is determined such that it maximizes the explanatory power of the model. The final firm-level CS value is published once per year. For all firms in one industry scores are published at the same point in time. ACSI uses an industry classification based on NAICS codes. The industry level CS values include more firms than only those for which individual CS values are published. All firms for which not a minimum number of customer evaluations is available are summarized, separately for each industry, in the category "all others".

Our final sample comprises 33 industries that include at least 3 firms. Until May 2010 the data was published quarterly, since May 2010 it is published monthly. We obtain the exact announcement dates back until 2001. The announcement dates are the days on which the press releases of the scores take place. An affiliated group with subsidiaries can have more than one customer satisfaction value. We aggregate these values at the CRSP permco level.[7] We update the aggregate CS value for the firm whenever new information becomes available.[8]

[6] The data is available on www.theacsi.org

[7] Only at this level we can assign stocks to the firms in the ACSI dataset, although one firm may have multiple securities outstanding (multiple permnos).

[8] If the ACSI releases for all subsidiaries are made in the same month we still get one CS value per firm and year. If the releases are made in different months we obtain more frequent changes in the CS value of the firm.

Appendix A.1 provides a more detailed description of the way the data is gathered, the functioning of the cause-and-effect model and the industry definitions.

We construct four variables from the ACSI customer satisfaction scores. The first variable is simply the CS level as reported by the ACSI. Average customer satisfaction values vary across industries. What matters for a firm is its CS value relative to the values of other firms in the same industry, not relative to the values of firms in different industries. We therefore use as our main measure an industry-adjusted customer satisfaction level. We construct it by cross-sectionally demeaning the CS level by the respective industry CS score. By proceeding this way, we eliminate the inter-industry variation and only retain the intra-industry variation. Several previous studies have focused on changes in the level of customer satisfaction.[9] We therefore also construct the first differences of the raw CS scores and of the industry-adjusted CS scores. Our sample period extends from January 2001, the earliest date for which ACSI index announcement dates are available, until December 2018.

We merge the ACSI data with monthly CRSP stock market data by assigning the ACSI data to the CRSP data in the month subsequent to the announcement month. ACSI data is then retained until new information for the same firm is released. Moreover, we merge the data with accounting data from Compustat. We follow the usual convention in the literature and merge all accounting data with fiscal year end in calendar year t-1 to July of year t and keep this data until June of year t+1. We only keep firms with common stock (share code 10 or 11) that trade on either the NYSE, NASDAQ or AMEX. After filtering, we can link ACSI data to stock market and accounting data for a total of 230 firms. We do not have a complete time series for all sample firms. The final data set contains 132 firm-level observations per month on average.

A specific feature of our data set is that it contains information on both high and low customer satisfaction levels. This is in sharp contrast to data sources such as the "Best companies to work for" list (first used by Edmans (2011)), which only contain information

[9] E.g. Aksoy et al. (2008) or Jacobson and Mizik (2009).

on highly rated firms. From an asset pricing perspective it is desirable to have information on "good" and "bad" firms because this allows us to construct long-short portfolios of firms sorted based on the customer satisfaction scores.

Insert Table 1 here

Panel A of Table 1 shows summary statistics for the different customer satisfaction variables introduced above. The 0 to 100 scale is not exhausted. Rather, most CS level values are in the range from 56 to 87. The range of the industry-adjusted CS values is smaller, extending roughly from -12 to 9. These values imply that there is considerable intra-industry variation in customer satisfaction levels. Changes generally are not very large on average. However, there are incidences of extreme changes, as can be inferred from the values for the 1% and 99% percentiles. The finding that most changes are small is corroborated by the observation that the CS levels are highly persistent. A simple time-series model delivers an AR(1) coefficient of 0.88 for the CS levels.

Panel B of table 1 reports summary statistics for various firm characteristics. It differentiates between all firms in our ACSI sample and all firms in the CRSP/Compustat universe. The most noticeable difference between the two samples is that ACSI firms have a much higher market capitalization than the average CRSP/Compustat firm. This should come as no surprise, though, because the ACSI contains, by construction, only firms with a large US market share.

# 3 Intangible Capital and Customer Satisfaction

We have argued above that customer satisfaction is an output-based measure of customer capital. The finance and economics literature employs different proxy measures for different types of intangible capital. The most common procedure to estimate the value of intangible capital, or components thereof, relies on the perpetual inventory method based on a specific category of costs (e.g. research and development expenses for knowledge capital or advertising expenses for customer capital). This approach results in the formal model $IC_{it} = (1 - \delta_c)IC_{i,t-1} + investment_{it}$, where $IC_{it}$ is (a component of) intangible capital and $\delta_c$ is the depreciation rate. Eisfeldt and Papanikolaou (2013) estimate the level of organizational capital based on the assumption that 30% of a firm's selling, general and administrative (SG&A) expenses are an investment into organizational capital.[10] The costs are scaled by the value of the consumer price index, $SG\&A_{it}/cpi_t$. They further assume a depreciation rate $\delta_c$ of 20%.

We adopt the procedure of Eisfeldt and Papanikolaou (2013) to estimate the level of organizational capital for all firms included in the ACSI index. Specifically, we capitalize SG&A expenses (net of R&D expenses). Using a similar procedure, we also capitalize advertising expenses to obtain an input-based estimate of customer capital,[11] and staff expenses to obtain a measure that is related to employee satisfaction as analyzed by Edmans (2011) and Green et al. (2019). Finally, we follow Peters and Taylor (2017) and capitalize R&D expenses to obtain an estimate of the level of a firm's knowledge capital.[12] We assume that the initial capital stock is $IC_{i,0} = investment\ costs_{i1}/(g + \delta_c)$. This estimate is based on the assumption that the investment grows at a constant rate $g$. We assume $g$ to be 10%, which is the sample average of the growth of SG&A expenses and is also the value assumed by Eisfeldt and Papanikolaou (2013).

Moreover, we follow Lev and Radhakrishnan (2015) and decompose the market value of a firm's assets (measured by the sum of the market value of equity plus the book value of debt) into the levels of the firm's tangible and intangible capital and a residual. The tangible capital is the value of property, plant and equipment as provided in the balance

[10]Selling, general and administrative expenses include, among other things, advertising expenses, expenditures for distribution systems, staff expenses and expenses for other brand enhancement activities (see for instance Lev and Radhakrishnan (2005) for a more detailed summary). Based on prices paid for intangible assets in acquisitions, Ewens et al. (2019) estimate that 28% of SG&A expenses are an investment in organizational capital. The 30% estimate used by Eisfeldt and Papanikolaou (2013) is thus a good approximation to this value.

[11]This approach is similar to Belo et al. (2014).

[12]We use the industry-specific depreciation rates provided by Li and Hall (2016), table 4. If no rate is available for a particular SIC code we use 20%.

sheet. The value of intangible capital is the sum of our estimates of organizational and knowledge capital. The residual then is the difference between the observed market value and the estimates of the values of tangible and intangible capital and can be interpreted as the fraction of the market value left unexplained by these value estimates. A large residual may be indicative of a component of intangible capital that is not accounted for, or it may simply indicate that the cost-based estimates of intangible capital are inaccurate. In this case we would expect that customer satisfaction, which is an output-based measure of a component of intangible capital, is positively related to the unexplained fraction of market value.

In order to analyze how strongly the customer satisfaction score is related to input-based measures of intangible capital we use one-dimensional portfolio sorts. We sort the sample stocks into quintile portfolios according to their raw CS score (columns 1-5 in Table 2) and their industry-adjusted CS score (columns 6-10). According to the release frequency of the ACSI scores, we rebalance the portfolios quarterly until May 2010 and monthly thereafter. Table 2 shows time-series averages of the cross-sectional quintile portfolio means for various firm characteristics and for the input-based measures of intangible capital, scaled by the book value of assets.[13] Detailed definitions of the variables are provided in appendix A.2. The industry-adjusted CS scores are purged of inter-industry variation. To be consistent we therefore report standardized firm characteristics and intangible capital proxies in columns 6-10 of Table 2.[14]

Insert Table 2 here

The first lines in Table 2 report statistics for our four customer satisfaction variables: the raw and the industry-adjusted CS scores and their first differences. The level variables are, by construction, increasing across the CS quintile portfolios. The first differences also

[13]We obtain similar results when we use sales or PP&E to scale the intangible capital proxies.

[14]We standardize values of firm characteristics in case of industry-adjusted CS, as their mean values and distributions vary considerably across industries. Table A.1 in the internet appendix reports the non-standardized values.

increase monotonically, implying that firms with high customer satisfaction levels are more likely to experience further increases in customer satisfaction. The results further reveal that firms with higher CS scores have higher total q and lower financial and operating leverage. In this respect, the results are similar for sorts based on the raw and industry-adjusted CS scores.

An important observation is that firms with higher customer satisfaction scores tend to have higher cash flows. This relation holds for both cash flow measures we employ (the first one, denoted "cash flow" is based on balance sheet data while the second, denoted "free cash flow", is based on data from the cash flow statement, see appendix A.2 for details), and it is more pronounced for the quintile portfolios sorted by industry-adjusted CS scores. We further observe that firms in the top CS quintile have the highest cash holdings. This observation is in contrast to Larkin (2013) who finds that firms with better brand perception have lower cash holdings.

The raw customer satisfaction scores are positively related to the input-based measures of intangible capital. The relation holds for all measures but is strongest (as might be expected) for capitalized advertising expenses. In fact, capitalized advertising expenses are more than four times as high in the top CS quintile as compared to the bottom quintile (25.5% vs. 6.2%). Firms with high customer satisfaction apparently realize their CS level by (among other things) investing in advertising. These firms also invest more in R&D. Likewise, these firms have higher personnel expenses, which may be indicative of their attempt to retain key talents. The results are weaker for the industry-adjusted CS levels. However, it still holds that capitalized advertising and staff expenses are much higher in the two top CS quintiles than in the three bottom quintiles. For both the raw and the adjusted CS scores the fraction of the market value unexplained by the tangible and intangible asset estimates is highest in the top customer satisfaction quintile. This indicates that customer satisfaction may be related to a source of value not captured by the input-based measures of intangible asset value.

# 4 A Customer Satisfaction-Based Investment Strategy

In this section we analyze the profitability of an investment strategy based on the ACSI customer satisfaction scores. We proceed in four steps. We first present descriptive statistics and Sharpe ratios. We then estimate time series regressions in order to test whether the profitability of the customer satisfaction-based strategy persists when we control for known sources of systematic risk. We then compare the return of the CS-strategy to the return of a portfolio of stocks that do not belong to the ACSI universe but are similar with respect to relevant firm characteristics. Finally, we estimate cross-sectional regressions to test whether firms with higher customer satisfaction levels earn higher returns after controlling for other characteristics.

## 4.1 Descriptive Statistics

In order to test whether customer satisfaction scores are related to stock price performance we form a value-weighted long-short portfolios based on the extreme CS quintiles. The CS-based investment strategy is thus long in the quintile portfolio of high customer satisfaction stocks and short the quintile portfolio of low customer satisfaction stocks. We test four versions of this strategy, two based on the levels of the raw and industry-adjusted CS scores, respectively, and two based on first-differenced CS levels. Corresponding to the release frequency of the ACSI data, the portfolios are rebalanced quarterly until the first quarter of 2010 and monthly from May 2010 onwards.

Insert Table 3 here

Table 3 reports descriptive statistics and Sharpe ratios for the long-short portfolio returns. To put the results into perspective, the table provides the same information for other long-short portfolios that have been used as factors in recent empirical asset pricing tests. Among others, we include the factors of the Fama and French (2015) 5-factor model, the momentum factor, the Pástor and Stambaugh (2003) liquidity factor and the Frazzini and Pedersen

(2014) betting against beta factor. The industry-adjusted CS strategy clearly outperforms all other long-short portfolios. It has a higher mean return and a higher annualized Sharpe ratio (0.77) than any of the other portfolios.[15]

The industry-adjusted CS strategy performs much better than the strategies based on the raw CS score or on first-differenced scores. This finding is consistent with our earlier argument that what matters is customer satisfaction relative to other firms in the industry, not the CS score *per se*. We thus base our formal analysis, to be presented below, on the industry-adjusted CS strategy. Results for a CS strategy based on raw scores are relegated to the internet appendix. Figure 1 plots the cumulative returns of the CS-based strategies against the factors of the Fama and French (2015) 5-factor model and the momentum factor.[16] The graph confirms the result from Table 3 that the industry-adjusted customer satisfaction portfolio performs exceptionally well.

Insert Figure 1 here

## 4.2 Time-Series Regressions

The high mean return and Sharpe ratio of the CS-based strategy may be due to a high level of systematic risk. It may also be the case that the CS-based strategy is related to a known source of mispricing. In the following, we thus analyze whether factors that have been shown to be priced in recent empirical research can explain the return of the CS-based strategy. To this end, we regress the returns of the industry-adjusted CS strategy on various sets of factors using time-series regressions of the form

[15] Applying volatility scaling on momentum following Barroso and Santa-Clara (2015) and on the other factors following Moreira and Muir (2017) does improve the Sharpe ratio of momentum to 0.57, but does not significantly improve the Sharpe ratio of the other strategies.

[16] In the figure we represent the customer satisfaction strategy by a CS factor that is constructed along the lines of the Fama and French (1993) SMB and HML factors (the construction of this CS factor is described in more detail below). We use this specification in order to define all factors shown in the figure in a consistent way.

$$r_{it}^e = \alpha_i + \sum_{j=1}^{J} \beta_i^j Fac_t^j + \epsilon_i. \tag{1}$$

Specifically, we test the CAPM, the Carhart (1997) 4-factor model, the Fama and French (2015) 5-factor model, the Fama and French (2018) 6-factor model (FF5 and FF6, respectively, in the sequel), the Hou et al. (2015) q-factor model and the Hou et al. (2020) q5 model, the Stambaugh and Yuan (2017) mispricing factor model, the Barillas and Shanken (2018) 6-factor model and the Daniel et al. (2020) behavioral factor model. A further factor combination that we test comprises the Fama and French (1993) 3-factor model extended by the Asness et al. (2019) quality-minus-junk and the Frazzini and Pedersen (2014) betting-against-beta factor.

Insert Table 4 here

The results, presented in Table 4, are striking. All alphas are statistically significant at the 5% level and all but one are significant at the 1% level. The alphas for several popular models, namely the CAPM, the Carhart model, the Fama-French 5-factor model, the q-factor and q5 model, and the Barillas and Shanken (2018) 6-factor model, also take the hurdle, proposed in Harvey et al. (2016), of a t-value in excess of 3. The alphas are also economically significant. They range from 0.717 for the Fama and French (2018) 6-factor model to 1.094 for the Barillas and Shanken (2018) 6-factor model. Thus, none of the ten factor models is able to explain the performance of the value-weighted industry-adjusted CS strategy. The factor loadings reveal that the industry-adjusted CS strategy loads positively on the market, is size-neutral and loads negatively on the book-to-market factor. There is also evidence that it loads negatively on the investment factor and positively on the profitability factor. Further, it is significantly related to the Stambaugh and Yuan (2017) mispricing factors, the Daniel et al. (2020) financing factor (denoted FIN), and the Hou et al. (2020) expected growth factor (denoted EG).

We have constructed the CS portfolio as a value-weighted long-short portfolio. To check the robustness of our findings we test two additional specifications. The first is an equal-weighted long-short portfolio and the second is a factor constructed along the lines of the Fama and French (1993) HML factor and the Fama and French (2015) CMA and RMW factors. Specifically, we sort all firms included in the ACSI index into three portfolios according to their industry-adjusted CS scores using the 20% and 80% percentiles as break points. The firms are independently sorted by size using the median market capitalization as break point. We then calculate value-weighted mean returns for the two high-CS and the two low-CS portfolios. The CS factor is constructed as the difference between the equal-weighted mean of the two high-CS portfolios and the equal-weighted mean of the two low-CS portfolios. We regress the equal-weighted long-short portfolio returns and the CS factor returns on the same sets of factors used previously. The intercepts of the time-series regressions and their t-statistics are presented in Panels A and B, respectively, of Table 5.

Insert Table 5 here

The results for the equal-weighted long-short strategy (shown in Panel A of Table 5) are slightly weaker than those for the value-weighted strategy. The numerical values of the intercepts are smaller but still economically significant, with values ranging from 0.365 to 0.629. With one exception (the combination of FF3 with QMJ and BAB), all alphas are significant at the 5% level. The results for the CS factor (Panel B) are in between those for the equal-weighted and the value-weighted long-short portfolios. The alphas range from 0.520 to 0.758 and all alphas are statistically significant at the 5% level or better. We therefore conclude that the results for the CS-based strategy are robust, but that the value-weighted long-short portfolio delivers the highest and most significant alphas. Panel C of Table 5 shows the intercepts that we obtain when we regress the excess return of a value-weighted or an equal-weighted portfolio of all firms in the ACSI universe on the 10 sets of factors. While all but one of the alphas are positive, their numerical values are much smaller than those obtained for the long-short strategies, and less than 50% of the alphas are significant. The fact that almost all alphas are positive provides some evidence that the firms included in the ACSI index generally perform well. However, the low magnitude of the intercepts and the low significance levels indicate that a strategy that invests in all ACSI firms does not deliver results comparable to those of the CS-based long-short strategy.

While the models presented in Tables 4 and 5 capture those asset pricing models that are routinely used as benchmark models in contemporaneous research, many other factors have been proposed and have been shown to be significantly related to returns. To test whether any of these factors are able to explain the return of the value-weighted industry-adjusted CS strategy we proceed as follows: We regress the returns of the CS-strategy on the returns of the factor under investigation[17] and the market factor. We consider a total of 33 factors. Among them are factors based on idiosyncratic volatility (which proxies for limits to arbitrage), a tail risk factor based on Kelly and Jiang (2014), an operating leverage factor as in Novy-Marx (2011) and a GDP-mimicking portfolio as in Lamont (2001) and Vassalou (2003). We further include long-short portfolios formed on input-based measures of organizational capital. Specifically, we use estimates of total organizational capital (based on capitalized SG&A expenses), as well as estimates based on components of organizational capital obtained by capitalizing advertising expenses (similar to the approach proposed by Belo et al. (2014)), staff expenses, and pension expenses. We further use capitalized R&D expenses as a proxy for knowledge capital. For details on the construction of these factors we refer the reader to appendix A.2.

Insert Table 6 here

Table 6 shows the alphas and the associated t-statistics for each model. The industry-adjusted CS-portfolio outperforms all 33 models. All alphas are positive and economically significant (with values ranging from 0.617 to 1.092). They are all significant at the 10%

[17] In one case two factors, the short-term and long-term reversal factors as in Fama and French (1996) are considered jointly.

level, 29 are significant at the 1% level and 24 have a t-value in excess of 3. Thus, none of the 33 models is able to explain the return of the industry-adjusted CS portfolio.

The "ACSI Long/Short Equity" hedge fund is a fund that implements a customer satisfaction-based strategy and is also studied in Fornell et al. (2016a). We obtain the holdings of the fund company from the 13F-filings and find that the firms in the long leg of the hedge fund are similar to the firms in the top quintile portfolio of our industry-adjusted customer satisfaction level strategy. Moreover, the holdings in the long leg of the hedge fund are close to equal-weighted. We further obtain the return data of the hedge fund from Eurekahedge and test whether the returns can be explained by a set of relevant benchmark models. We test the ten factor models already used in Tables 4 and 5. In addition we also test the Fung and Hsieh (2004) 7-Factor hedge fund benchmark model. The results are shown in Table 7. We find positive and significant alphas with t-statistics in excess of 3 in each single case. This finding is consistent with our previous results and with those of Fornell et al. (2016a) and indicates that the CS-based strategy can be profitably implemented.

Insert Table 7 here

## 4.3 Characteristics-Based Matching

In this section we test whether the performance of the CS-based long-short strategy can be replicated by creating portfolios of firms outside of the ACSI universe that are similar to the firms in the CS long and short portfolios with respect to appropriately chosen characteristics. We refer to this procedure as characteristics-based matching. If the long-short portfolio of matched firms has a performance similar to that of the CS strategy, the performance of the CS portfolios has to be attributed to the selected firm characteristics rather than to customer satisfaction scores. The characteristics used for the matching procedure should capture determinants of expected returns. We select two sets of characteristics that are distinctly different. The first set is related to the Fama and French (2015) five-factor model, augmented by momentum. Specifically, we match on size, book-to-market, gross profitability, asset growth and prior return. The second set of characteristics we choose consists of size, Total q and idiosyncratic volatility and is intended to capture the effect of intangible asset value and idiosyncratic risk on firm value.

We proceed as follows. To each firm in the ACSI universe we match one firm from the remaining CRSP/Compustat universe. We use two alternative matching procedures, matching based on the propensity score and covariates matching with the Mahalanobis distance. We apply nearest neighbor matching without replacement in both cases. Moreover, we require the matched firms to be in the same industry as the ACSI firm.[18] This approach assigns, in each month, to each firm in the ACSI universe exactly one firm which is in the filtered CRSP/Compustat universe but not in the ACSI universe. We consider all four CS-based long-short strategies, i.e. those based on raw and industry-adjusted CS scores in both levels and first differences. In each month we identify the firms in the top and bottom CS quintile portfolios and then replace these firms by the matched firms. We then construct long-short portfolios of these matched firms (referred to as mimicking portfolios) and compare their return to the return of the original customer-satisfaction-based long-short portfolio. We consider both equal-weighted and value-weighted returns.

Insert Table 8 here

Table 8 shows the returns of the CS-based long-short portfolios and those of the mimicking portfolios. The industry-adjusted CS-level strategy delivers a value-weighted (equal-weighted) monthly mean return of 0.871% (0.486%). Both values are statistically different from zero and are also economically significant. The returns of the mimicking portfolios are much smaller. The value-weighted (equal-weighted) return of the best-performing mimicking portfolio is 0.062% (0.181%). The other three CS-based strategies (i.e. the strategy based on raw CS levels and the two strategies based on first differences) do not outperform the returns of the mimicking portfolios. These results are fully in line with our previous findings

[18] The ACSI industry classification is not available for the non-ACSI firms. Because the ACSI classification is based on NAICS codes we use the first NAICS digit to sort firms into industries.

and imply that the industry-adjusted CS portfolio delivers returns in excess of those of a portfolio of characteristics-matched firms.

In Panel B of Table 8 we compare the returns of equal-weighted and value-weighted portfolios of *all* ACSI firms to the return of the corresponding mimicking portfolios. The ACSI portfolios deliver returns that are significantly different from zero, at 0.548% (0.757%) for the value-weighted (equal-weighted) portfolio.[19] However, the performance of the mimicking portfolios is similar. Two conclusions follow from this finding. First, it is the sorting on industry-adjusted customer satisfaction that causes the abnormal returns generated by a CS-based strategy, not just the characteristics of the firms included in the ACSI universe. Second, our matching procedures works well. It is able to replicate the performance of the average ACSI firm. What it is not able to replicate is the superior performance of high industry-adjusted CS-level firms over low industry-adjusted CS-level firms.

## 4.4 Fama-MacBeth Regressions

All results presented thus far are based on time-series regressions. In this section we present results of Fama and MacBeth (1973) cross-sectional regressions. This approach allows us to include firm-specific control variables. The dependent variable is the one-month ahead excess return of all firms in the ACSI universe. We estimate nine model specifications. In model (1) the industry-adjusted CS level is the only independent variable.[20] In models (2) and (3) we further include total q (as calculated in Peters and Taylor (2017)), the market beta (estimated relative to the CRSP value-weighted index using 36 months of data), a measure of operating leverage, a measure of financial leverage and the free cash flow (based on the cash flow statement) as additional independent variables. We use two different measures of operating

[19]When interpreting these values it should be kept in mind that the portfolios consisting of all ACSI firms are long-only portfolios and, therefore, have considerable factor exposure. The returns shown in Panel A are returns of long-short portfolios that have much lower factor exposure. The factor exposure of the industry-adjusted CS-level strategy is shown in Table 4 above.

[20]We also estimated cross-sectional regressions using the raw CS level and the first-differenced CS and industry-adjusted CS levels. Table A.5 in the internet appendix shows results. The coefficients are (with only one exception) all positive, but rarely significant. Thus, and in line with our previous results, it is customer satisfaction relative to the industry mean that matters.

leverage, based on O'Brien and Vanderheiden (1987) (model 2) and based on Novy-Marx (2011) (model 3). In all subsequent models we retain the industry-adjusted CS level, market beta and operating leverage. We refer to these variables as the base variables. In models (4) and (5) we add size, the book-to-market ratio, profitability, asset growth, turnover, and idiosyncratic volatility (relative to the Fama and French (1993) three-factor model) to the base variables. These specifications thus include the firm characteristics contained in the Fama and French (2015) five-factor model. Models (6) and (7) include the base variables, size, idiosyncratic volatility, return momentum, and two input-based measures of organizational capital (capitalized SG&A expenses and capitalized advertising expenses). Models (8) and (9) include the base variables, size, return momentum, the two input-based measures of organizational capital, the cash-to-assets ratio, short interest (shares sold short scaled by shares outstanding), and the Kelly and Jiang (2014) measure of tail risk. T-statistics are based on Newey and West (1987) standard errors.

Insert Table 9 here

The results are shown in Table 9. The coefficient on the industry-adjusted CS level is always positive and significant (at the 5% level or better), with coefficient values ranging from 0.029 to 0.048. Thus, and in line with our previous results, firms with higher industry-adjusted customer satisfaction levels earn higher returns, independent of which additional variables we include. The effect is also economically relevant. The industry-adjusted CS level has a standard deviation of 3.88 (see Table 1). A coefficient such as 0.041 in model 1 thus implies that a one standard deviation increase in industry-adjusted customer satisfaction increases the monthly return by 0.16%.

# 5 Sources of Profitability

In this section we investigate into the causes of the profitability of the CS-strategy. In particular, we wish to analyze whether mispricing, combined with the existence of limits to arbitrage, explains the apparent profitability of the CS-based strategy. Limits to arbitrage arguably are more pronounced in the short leg of a strategy. We therefore analyze how the long leg and the short leg of the strategy contribute to the performance of the long-short portfolio. A proxy for limits to arbitrage frequently used in the literature is idiosyncratic volatility (see for instance Stambaugh et al. (2015)). We therefore analyze whether firms in the top or bottom quintile of the CS strategy display high idiosyncratic volatility. Limits to arbitrage may prevent the correction of mispricing but they do not cause the mispricing in the first place. Mispricing may emerge if the customer satisfaction scores contain information on firm fundamentals not yet incorporated into stock prices. Following Tetlock et al. (2008), Chen et al. (2014), Huang (2018), Engelberg et al. (2018), and Green et al. (2019) we therefore analyze whether CS scores predict subsequent earnings surprises.

## 5.1 Long Leg or Short Leg?

Our earlier finding that a portfolio of *all* stocks in the ACSI universe performs well suggests that the profitability is due to the long leg of the strategy. To test this hypothesis more formally we create equally-weighted and value-weighted portfolios of the stocks in the top CS quintile and the bottom CS quintile. As before, we rebalance the portfolios in accordance with the ACSI publication frequency (i.e. quarterly until 2010 and monthly thereafter). The excess return for the long leg is the return of the top CS portfolio minus the risk-free rate (proxied by the 1-month T-bill rate). The excess return for the short leg is the risk-free rate minus the return of the bottom CS quintile portfolio. We regress these excess returns on the same set of 10 factor models as before (see Tables 4 and 5).

Insert Table 10 here

The results are presented in Table 10. They demonstrate that the profitability of the customer satisfaction-based strategy is indeed largely caused by the long leg. The alphas for the long leg are statistically significant (at the 5% level or better in each single case) and economically large, with values ranging from 0.393 to 0.697. This finding holds irrespective of whether we consider the equal-weighted or the value-weighted portfolio. The alphas for the short leg are mostly insignificant. Only 5 (1) alphas are significant at the 10% (5%) level. In each single case the value of the alpha for the short lag is smaller than the corresponding alpha for the long leg. Interestingly, there is a pronounced performance difference between the value-weighted and the equal-weighted portfolio (only) for the short leg. The four significant alphas mentioned above are all for the value-weighted bottom portfolio.

Insert Figure 2 here

Figure 2, which plots the excess returns of the four portfolios against the market, confirms the findings. Consistent with the results shown in Table 10, the long leg of the CS-strategy outperforms the market by a large margin, irrespective of whether we consider the value-weighted or the equal-weighted portfolio. The short leg of the strategy performs worse, and there are marked differences between the performance of the equal-weighted and the value-weighted portfolios. The former slightly, but very consistently underperforms the market. The value-weighted short portfolio, on the other hand, performed remarkably well during specific periods (most notably during the first years of the century and during the financial crisis) but strongly underperforms the market otherwise.

Two conclusions can be derived from the analysis in this section. First, most of the profitability of the CS-based strategy is caused by the long leg, a finding which implies that a large fraction of the profits can be earned without engaging in short sales. Second, the performance difference between the value-weighted and the equally-weighted long-short strategies documented above (see Tables 4 and 5) is due to the short leg of the strategy.

## 5.2 Limits to Arbitrage

If the performance of the CS-based investment strategy were due to mispricing we should expect that there are some limits to arbitrage in place which prevent sophisticated investors from exploiting (and thereby eliminating) the mispricing. Short selling restrictions are an important impediment to arbitrage. However, we have shown in the previous section that the performance of the CS strategy is mainly caused by the long leg of the strategy. Therefore, investors can reap most of the benefits of a CS-based strategy without engaging in short sales. It is further worth noting that the stocks in the ACSI universe should be relatively easily shortable. As is shown in Table 1 the average ACSI stock is much larger and has higher institutional ownership (a commonly employed proxy for shorting supply, e.g. Asquith et al. 2005, Berkman et al. 2009, Nagel 2005) than the average stock in the CRSP universe. As can be seen in Table 2, the proportion of institutional ownership is essentially constant across the CS quintiles, ranging between 65.7% and 69.5%. As also shown in Table 2 the short interest is actually highest in the bottom CS quintile (i.e. in the short leg of the strategy). The observation that the stocks in the ACSI are large (with a median market capitalization of 15.2 billion USD, as shown in Table 1) implies that the transaction costs of trading these stocks are low. We further note that the turnover in the long-short portfolio is moderate. On average, 40% (45%) of the stocks in the long (short) leg of the strategy are turned over in a year.[21]

Another proxy for the existence of limits to arbitrage commonly employed in the literature is idiosyncratic volatility (see e.g. Stambaugh et al. (2015)). Tables 1 and 2 show the idiosyncratic volatility (relative to the Fama and French 3-factor model) for the firms in the CRSP universe, those in the ACSI universe and the firms in each of the CS quintiles. The average ACSI firm has much lower idiosyncratic volatility than the average CRSP firm (mean (median) 1.39 (1.07) as compared to 2.64 (1.94)). While idiosyncratic volatility is higher in the bottom CS quintile (mean 1.61) than in the other quintiles, it is still much lower than the idiosyncratic volatility of the average CRSP stock. Further, we have presented in Table 6 alphas of the CS-based long-short strategy relative to a two-factor model comprising the market factor and an idiosyncratic volatility factor. This model delivers a monthly alpha

[21] In case of the long-short portfolio based on unadjusted customer the turnover is only 30% in the long and short leg, respectively.

of 1.04% (the fourth largest of the 32 alphas shown in the table) with a t-statistic of 3.54. In addition, as was shown Table 8 above, a portfolio obtained by matching CRSP firms to the ACSI firms on idiosyncratic volatility is unable to replicate the return of the CS long-short strategy. Similarly, as shown in Table 9 above, idiosyncratic volatility is not significant in stock-level Fama and MacBeth (1973) regressions estimated for the firms in the ACSI universe. To summarize, limits to arbitrage do not appear to be very pronounced for the firms in the ACSI universe in general and those in the short leg of the strategy in particular.

### 5.3 Mispricing and Earnings Surprises

One potential reason why customer satisfaction scores affect stock returns is that the CS scores contain information on firm fundamentals that is not yet fully reflected in the stock price. To test whether this is the case, we adopt a methodology pioneered by Tetlock et al. (2008) and subsequently adopted by Chen et al. (2014), Huang (2018) and Green et al. (2019). We use a sample containing all ACSI firms and regress earnings surprises on the customer satisfaction scores and a set of control variables. If the CS scores contain information on future cash flows not yet reflected in the stock price, they should be positively related to the earnings surprises. We use four different specifications of the CS scores. The first is our main variable, the industry-adjusted CS score. In addition, we consider the raw CS score and the first differences of both the raw and the industry-adjusted scores.

The earnings surprise for firm $i$ in quarter $q$ is defined as actual earnings minus the median analyst earnings forecast, scaled by the stock price at the end of the preceding month. We obtain earnings announcement dates from the Compustat quarterly database and analyst earnings forecast data from I/B/E/S.[22] The independent variable of prime interest is the CS score. As control variables we include the log of the market value of equity, the book-to-market ratio, gross profitability, the investment rate, return momentum, capital-

[22] All firms in the ACSI universe have at least 2 analysts following. We therefore did not have to drop observations because of insufficient analyst coverage. On average, 15 analysts are following a firm in the ACSI universe.

ized advertising and SG&A expenses, operating leverage, market leverage, and idiosyncratic volatility.[23] All control variables are from the previous quarter. The simplest specification (models 1, 4, 7 and 10) includes time-fixed effects and no control variables. The extended specification (models 2, 5, 8 and 11) includes time- and firm-fixed affects and the control variables described above. Finally, to account for the critique of Gormley and Matsa (2014) with respect to unobserved heterogeneity, we additionally include specifications with industry-time fixed effects (models 3, 6, 9 and 12). Standard errors are clustered by firm and quarter.

Insert Table 11 here

The results are shown in Panel A of Table 11. The coefficients on the CS scores are small in magnitude and insignificant (none of the twelve coefficients is significant even at the 10% level). These result do not support the hypothesis that the CS scores contain valuable information on firm fundamentals not yet included in the stock price.

To assure the robustness of this result we also implement a variation of the approach suggested by Engelberg et al. (2018). We regress the earnings surprise (defined as above[24]) on a dummy variable that is set to 1 when a firm $i$ in quarter $q$ is in the top CS quintile portfolio and is zero else. We define an analogous dummy variable that indicates whether a firm is in the bottom CS quintile. With this procedure we aim to test whether the CS ranking of a stock (as measured by its inclusion in the top or bottom quintile portfolio) is related to earnings news. As before, we consider both the industry-adjusted and the raw CS scores in both levels and first differences. We include in our regressions all firms from the CRSP/Compustat universe for which all required data (including at least one analyst earnings forecast) is available. Following Engelberg et al. (2018), we include as control variables the number of analyst forecasts for firm $i$ in quarter $q$, a dummy variable set to 1 if only one analyst issued a forecast, and the standard deviation of analyst forecasts scaled

[23] Please see appendix A.2 for variable definitions.

[24] Engelberg et al. (2018) use the forecast error, which is the negative of the earnings surprise.

by the stock price (set to zero whenever only one analyst issued a forecast). The results are shown in Panel B of Table 11. They are fully consistent with those from Panel A. The coefficients on the CS dummy are, with only one exception, insignificant in all specifications. Thus, whether a firm is in the top or bottom CS portfolio in a quarter has no effect on the earnings surprise. This finding is, again, inconsistent with the notion that the CS ranking of a firm contains fundamental information not yet incorporated into stock prices.

## 5.4 The Customer Channel

Based on the model of Eisfeldt and Papanikolaou (2013) we have argued that investments in customer capital are more risky than investments in physical capital because customers have the option to "leave the firm" (or threaten to do so) in response to product or marketing innovations in other firms. In this section we explore whether there is empirical evidence supporting this view. To this end we identify firm characteristics that affect the riskiness of investments in customer capital. Specifically, we consider equity duration, operating leverage, and product market fluidity as introduced by Hoberg et al. (2014).

Firms with higher equity duration on average generate their cash flows in the more distant future, either from additional sales to current customers or from sales to new customers. Sales expected in the more distant future are more heavily exposed to the risk that innovations by competitors draw the customers away. Consequently, firms with high equity duration should be more exposed to the risk associated with investments in customer capital. We therefore expect a larger customer satisfaction premium in firms with high equity duration. Firms with higher operating leverage cannot easily adjust their costs when demand decreases and are therefore more exposed to risk caused by demand reductions. Consequently, the customer satisfaction premium should be higher among firms with higher operating leverage. Hoberg et al. (2014) propose product market fluidity as a measure of competitive threats.[25] It captures changes in the products of rival firms relative to the products of the reference

[25] We obtain the measure of product market fluidity from the Hoberg-Phillips data library at https://hobergphillips.tuck.dartmouth.edu/.

firm based on textual analysis of 10-K business descriptions. Consequently, higher levels of product market fluidity indicate that a firm is more exposed to the risk of product innovation by competitors. We conjecture that the customer satisfaction premium should be higher for firms with higher levels of product market fluidity.

For each of the aforementioned characteristics we sort firms into two groups. We use two different sorting procedures, industry-level sorting and firm-level sorting. For the industry-level sorting procedure we first calculate the mean value of the respective firm characteristic for each industry (based on the ACSI industry classification) and use the median industry as breakpoint. We then assign all firms in industries with above-median [below-median] values to group 1 [2]. For the firm-level sorting procedure we sort firms into two groups according to the median value across the firms in the CRSP/Compustat universe.

Within each of the two groups we then sort firms into terciles based on their industry-adjusted customer satisfaction levels. We then compute the customer satisfaction premium within each of the characteristics groups. Table 12 presents the time-series average of the customer satisfaction premium for the low and high characteristics groups as well as the difference between the two. The table further reports alphas relative to two benchmark models (the Fama and French (2018) 6-factor model and the Hou et al. (2020) q5 model) of the customer satisfaction long-short portfolios.

Insert Table 12 here

The customer satisfaction premium is indeed significantly higher among high equity duration firms as compared to low equity duration firms (0.837 as compared to 0.199 for the industry-level sort and 0.883 as compared to -0.122 for the firm-level sort). A portfolio consisting of high equity duration firms that is long in high customer satisfaction firms and short in low customer satisfaction firms has a positive and significant alpha, while a similar portfolio constructed from low equity duration firms does not. However, while the differences in the alphas are rather large, they are statistically significant only in one out of four cases (the q5 alpha for the firm-level sort). The results for operating leverage point in the same direction but are somewhat weaker. The customer satisfaction premium is positive and significant among high operating leverage firms, and it is higher than the premium among low operating leverage firms (0.679 as compared to 0.360 for the industry-level sort and 0.590 as compared to 0.381 for the firm-level sort). However, the difference between the premiums is not statistically significant. Similarly, all alphas are positive and are larger among high operating leverage firms than among low operating leverage firms, but the difference between the alphas for the two groups is insignificant.

The product market fluidity measure of Hoberg et al. (2014) in our opinion best captures the intuition underlying the customer channel because it is directly related to the risk that product innovations of rival firms devalue investments in customer capital. We indeed find that the customer satisfaction premium is larger among high than among low product market fluidity firms (0.690 as compared to 0.486 for the industry-level sort and 0.840 as compared to 0.227 for the firm-level sort). The difference is statistically significant for the firm-level sort. A portfolio of high product market fluidity firms that is long in high customer satisfaction firms and short in low customer satisfaction firms has an alpha that is economically large (with values ranging from 0.782 to 0.903) and statistically significant while the alpha of a similar portfolio constructed from low product market fluidity firms is insignificant. The difference in the alphas is significant in three out of four cases (the exception being the FF6 alpha for the industry-level sort). These results imply that, in line with our hypothesis, the customer satisfaction premium is earned by those firms that are more exposed to competitive threats.

Overall, the results presented in Table 12 provide support for the hypothesis that firms with high levels of customer satisfaction are indeed more risky. Essentially, these firms have more to lose when competitors innovate. This intuition suggests that there might be a time-series relation between the customer satisfaction premium and aggregate measures of innovative activity. To explore whether such a relation exists and to substantiate our results we use five different measures of innovative activity. The first is aggregate venture capital

(VC) financing (sourced from Refinitiv EIKON). The volume of VC financing should be positively related to the number of innovative start-ups seeking funding. We further employ three measures based on patent data from the USPTO.[26]. Patents are a direct measure of the output of innovative activity. We use the number of patents granted, the number of reissued patents and the monthly average number of patent applications over the last year. Finally, we employ R&D expenditures as an input-based measure of innovative activity. Specifically, we use the cross-sectional average of the ratio of R&D expenditure to total assets. To eliminate seasonal variation from the data we follow a similar approach to Grammig and Jank (2016) and first-difference these variables.

For each measure of innovative activity we estimate two regression specifications. First, we regress the return of the industry-adjusted CS long-short strategy return $R^{CS}$ on the respective measure and its first lag. Second, we augment the regression by the market return $MKT_t$ and the first lag of the industry-adjusted CS long-short strategy return $R^{CS}_{t-1}$. All regressions are estimated by OLS. Results are reported in Panel A of Table 13.

Insert Table 13 here

The argument presented above suggests that a positive shock to innovative activity is bad news for firms with high levels of customer satisfaction. We thus expect negative coefficient estimates for the innovative activity variables. We indeed make according observations. All ten coefficients are negative, and eight [two] are significant at the 10% [5%] level. The results are very similar for the two specifications. Thus, whether we include the market return and the lagged return of the CS long-short strategy does not materially affect the results.

The results presented in Panel A of Table 13 indicate that there is indeed a time-series relation between the return of the customer satisfaction-based investment strategy and aggregate measures of innovative activity. To explore this relation further we estimate time-series regressions of the customer satisfaction strategy returns on cross-sectional innovativity factors as proposed by Hirshleifer et al. (2013). To construct the factors we first assign to

[26]The data can be obtained on www.patentsview.org

the firms in the CRSP/Compustat universe all granted patents and all citations for patents granted by the USPTO.[27] We then sort firms into quintiles first based on the ratio of number of patents granted in the previous year to total assets and second based on the number of citations obtained in the previous year for patents granted in the last five years to market capitalisation. The cross-sectional innovativity factors are the returns of portfolios which are long in firms with the highest number of patents or citations, respectively, and short in the firms with the lowest number of patents or citations. We estimate two specifications for each of the two cross-sectional factors, one with and one without the market excess return as an additional factor. The results are shown in Panel B of Table 13. In line with our preceding findings the slope of the innovativity factor is positive and significant in all four cases, with values ranging from 0.422 to 0.470. These results imply that the innovativity factor indeed has explanatory power for the return of a customer satisfaction-based investment strategy. However, the innovativity factors do not fully explain the return of the CS strategy, as is evidenced by the large and significant intercepts.

In summary, the results in this section indicate that the customer satisfaction premium is more pronounced for firms for which the risk of investing into customer capital is higher, and that there is a time-series relation between the return of the CS strategy and measures of innovative activity. These results are consistent with our theoretical considerations, presented in section 1 and based on the model of Eisfeldt and Papanikolaou (2013). Investments in customer capital are associated with a systematic source of risk because customers may "leave the firm" in response to product or marketing innovations in other firms, in which case shareholders are unable to appropriate the return on investments in customer capital.

[27] We use the patent assignments from the GitHub repository (KPSS2017) which provides the data employed in Kogan et al. (2018).

# 6 Conclusion

This paper considers the link between intangible assets and security returns by documenting that firms with higher levels of customer satisfaction (as measured by the American Customer Satisfaction Index, ACSI) have higher risk-adjusted stock returns. This finding is robust to a large number of model specifications and test methodologies (time-series regressions, matching on firm characteristics and Fama and MacBeth (1973) regressions) and implies that standard asset pricing models cannot explain the customer satisfaction premium. Thus, it must either be the case that the observed abnormal returns are a reflection of a source of risk not captured by the models, or that the abnormal returns are evidence of systematic mispricing.

Indeed, several previous papers (Edmans 2011, Edmans et al. 2020, Green et al. 2019 and Huang 2018) argue that the market may be slow to incorporate information about intangible assets in stock valuations, suggesting that the customer satisfaction premium may be a reflection of mispricing. However, in a series of tests we find no indication of systematic mispricing. Specifically, we document that there are few limits to arbitrage because the abnormal return of a customer-satisfaction-based long-short strategy is mainly due to the long leg of the strategy, the stocks in the customer-satisfaction portfolio are large and have low idiosyncratic volatility, and the turnover in the customer satisfaction portfolio is moderate. We further relate customer satisfaction scores to subsequent earnings announcements. If the scores contained information on future cash flows not yet incorporated into stock prices, one would expect that these scores are positively related to the information revealed by subsequent earnings surprises. We find no evidence of such a relation.

Customer satisfaction is an output-based measure of customer capital, which in turn is a component of a firm's organizational capital. We propose a theoretical foundation for the positive relation between customer satisfaction and returns based on the model in Eisfeldt and Papanikolaou (2013). Eisfeldt and Papanikolaou (2013) develop a model which predicts that investments in organizational capital are more risky than investments in tangible capital because they may be devalued by innovations (as part of "shocks to frontier efficiency") in other firms, which enables "key talent" to extract rents from shareholders. We suggest that innovativity should play a similar role in case of customers. To explore this link we analyze whether the customer satisfaction premium is higher among firms that are more exposed to such innovation risk. We find that the customer satisfaction premium is larger among firms with high equity duration and higher operating leverage, and is larger among firms which are more exposed to competitive threats as measured by the product market fluidity measure of Hoberg et al. (2014). We also document a time-series relation between the return of the customer satisfaction strategy and factors related to measures of innovative activity, such as venture capital financing, aggregate R&D spending, or patenting activity. Based on our findings, we conclude that the customer satisfaction premium is a compensation for risk not captured by standard risk factors.

# References

Aksoy, L., B. Cooil, C. Groening, T. L. Keiningham, and A. Yalcin. 2008. The Long-Term Stock Market Valuation of Customer Satisfaction. *Journal of Marketing* 72:105–122.

Anderson, E. W., C. Fornell, and S. K. Mazvancheryl. 2004. Customer Satisfaction and Shareholder Value. *Journal of Marketing* 68 (4): 172–185.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang. 2006. The Cross-Section of Volatility and Expected Returns. *Journal of Finance* 61 (1): 259–299.

Asness, C. S., A. Frazzini, and L. H. Pedersen. 2019. Quality Minus Junk. *Review of Accounting Studies* 24 (1): 34–112.

Asquith, P., P. A. Pathak, and J. R. Ritter. 2005. Short Interest, Institutional Ownership, and Stock Returns. *Journal of Financial Economics* 78 (2): 243–276.

Atkeson, A., and P. J. Kehoe. 2005. Modeling and Measuring Organization Capital. *Journal of Political Economy* 113 (5): 1026–1053.

Ball, R., J. Gerakos, J. T. Linnainmaa, and V. Nikolaev. 2016. Accruals, Cash Flows, and Operating Profitability in the Cross Section of Stock Returns. *Journal of Financial Economics* 121 (1): 28–45.

Barillas, F., and J. Shanken. 2018. Comparing Asset Pricing Models. *Journal of Finance* 73 (2): 715–754.

Barroso, P., and P. Santa-Clara. 2015. Momentum has its Moments. *Journal of Financial Economics* 116 (1): 111–120.

Belo, F., V. D. Gala, J. Salomao, and M. A. Vitorino. 2018. Decomposing Firm Value. *Working Paper.*

Belo, F., X. Lin, and M. A. Vitorino. 2014. Brand Capital and Firm Value. *Review of Economic Dynamics* 17 (1): 150–169.

Berkman, H., V. Dimitrov, P. C. Jain, P. D. Koch, and S. Tice. 2009. Sell on the News: Differences of Opinion, Short-Sales Constraints, and Returns around Earnings Announcements. *Journal of Financial Economics* 92 (3): 376–399.

Carhart, M. M. 1997. On Persistence in Mutual Fund Performance. *Journal of Finance* 52 (1): 57–82.

Chen, H., P. De, Y. J. Hu, and B.-H. Hwang. 2014. Wisdom of Crowds: The Value of Stock Opinions Transmitted Through Social Media. *Review of Financial Studies* 27 (5): 1367–1403.

Clausen, S., and S. Hirth. 2016. Measuring the Value of Intangibles. *Journal of Corporate Finance* 40:110–127.

Cohen, L., K. Diether, and C. Malloy. 2013. Misvaluing Innovation. *Review of Financial Studies* 26 (3): 635–666.

Corrado, C. A., and C. R. Hulten. 2010. How Do You Measure a "Technological Revolution"? *American Economic Review* 100 (2): 99–104.

Corrado, C. A., C. R. Hulten, and D. Sichel. 2009. Intangible Capital and U.S. Economic Growth. *Review of Income and Wealth* 55 (3): 661–685.

Daniel, K., D. Hirshleifer, and L. Sun. 2020. Short- and Long-Horizon Behavioral Factors. *Review of Financial Studies* 33 (4): 1673–1736.

Dou, W. W., Y. Ji, D. Reibstein, and W. Wu. 2020. Inalienable Customer Capital, Corporate Liquidity, and Stock Returns. *Journal of Finance.*

Edmans, A. 2011. Does the Stock Market Fully Value Intangibles? Employee Satisfaction and Equity Prices. *Journal of Financial Economics* 101 (3): 621–640.

Edmans, A., L. Li, and C. Zhang. 2020. Employee Satisfaction, Labor Market Flexibility, and Stock Returns Around the World. *Working Paper.*

Eisfeldt, A. L., and D. Papanikolaou. 2013. Organization Capital and the Cross-Section of Expected Returns. *Journal of Finance* 68 (4): 1365–1406.

— . 2014. The Value and Ownership of Intangible Capital. *American Economic Review: Papers & Proceedings* 104 (5): 189–194.

Engelberg, J., R. D. McLean, and J. Pontiff. 2018. Anomalies and News. *Journal of Finance* 73 (5): 1971–2001.

Ewens, M., R. H. Peters, and S. Wang. 2019. Acquisition Prices and the Measurement of Intangible Capital. *Working Paper*.

Fama, E. F., and K. R. French. 1992. The Cross-Section of Expected Stock Returns. *Journal of Finance* 47 (2): 427–465.

— . 1993. Common Risk Factors in the Returns of Stocks and Bonds. *Journal of Financial Economics* 33 (1): 3–56.

— . 1996. Multifactor Explanations of Asset Pricing Anomalies. *Journal of Finance* 51 (1): 55–84.

— . 2015. A Five-Factor Asset Pricing Model. *Journal of Financial Economics* 116 (1): 1–22.

— . 2018. Choosing Factors. *Journal of Financial Economics* 128 (2): 234–252.

Fama, E. F., and J. D. MacBeth. 1973. Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy* 81 (3): 607–636.

Fornell, C., M. D. Johnson, E. W. Anderson, J. Cha, and B. E. Bryant. 1996. The American Customer Satisfaction Index: Nature, Purpose, and Findings. *Journal of Marketing* 60 (4): 7–18.

Fornell, C., S. Mithas, F. V. Morgeson III, and M. Krishnan. 2006. Customer Satisfaction and Stock Prices: High Returns, Low Risk. *Journal of Marketing* 70 (1): 3–14.

Fornell, C., F. V. Morgeson III, and G. T. M. Hult. 2016a. Stock Returns on Customer Satisfaction Do Beat the Market: Gauging the Effect of a Marketing Intangible. *Journal of Marketing* 80 (5): 92–107.

Fornell, C., F. V. Morgeson, and G. T. M. Hult. 2016b. An Abnormally Abnormal Intangible: Stock Returns on Customer Satisfaction. *Journal of Marketing* 80 (5): 122–125.

Frazzini, A., and L. H. Pedersen. 2014. Betting Against Beta. *Journal of Financial Economics* 111 (1): 1–25.

Fung, W., and D. A. Hsieh. 2004. Hedge Fund Benchmarks: A Risk-Based Approach. *Financial Analysts Journal* 60 (5): 65–80.

Gormley, T. A., and D. A. Matsa. 2014. Common Errors: How to (and Not to) Control for Unobserved Heterogeneity. *Review of Financial Studies* 27 (2): 617–661.

Gourio, F., and L. Rudanko. 2014. Customer Capital. *Review of Economic Studies* 81 (3): 1102–1136.

Grammig, J., and S. Jank. 2016. Creative Destruction and Asset Prices. *Journal of Financial and Quantitative Analysis* 51 (6): 1739–1768.

Green, T. C., R. Huang, Q. Wen, and D. Zhou. 2019. Crowdsourced Employer Reviews and Stock Returns. *Journal of Financial Economics* 134 (1): 236–251.

Gruca, T. S., and L. L. Rego. 2005. Customer Satisfaction, Cash Flow, and Shareholder Value. *Journal of Marketing* 69 (3): 115–130.

Gu, L., D. Hackbarth, and T. Johnson. 2018. Inflexibility and Stock Returns. *The Review of Financial Studies* 31 (1): 278–321.

Harvey, C. R., Y. Liu, and H. Zhu. 2016. ... and the Cross-Section of Expected Returns. *Review of Financial Studies* 29 (1): 5–68.

Hirshleifer, D., P.-H. Hsu, and D. Li. 2013. Innovative Efficiency and Stock Returns. *Journal of Financial Economics* 107 (3): 632–654.

Hoberg, G., G. Phillips, and N. Prabhala. 2014. Product Market Threats, Payouts, and Financial Flexibility. *Journal of Finance* 69 (1): 293–324.

Hou, K., H. Mo, C. Xue, and L. Zhang. 2020. An Augmented q-Factor Model with Expected Growth. *Review of Finance*: 1–40.

Hou, K., C. Xue, and L. Zhang. 2015. Digesting Anomalies: An Investment Approach. *Review of Financial Studies* 28 (3): 650–705.

Huang, A. G. 2009. The Cross Section of Cashflow Volatility and Expected Stock Returns. *Journal of Empirical Finance* 16 (3): 409–429.

Huang, J. 2018. The Customer Knows Best: The Investment Value of Consumer Opinions. *Journal of Financial Economics* 128 (1): 164–182.

Jacobson, R., and N. Mizik. 2009. The Financial Markets and Customer Satisfaction: Reexamining Possible Financial Market Mispricing of Customer Satisfaction. *Marketing Science* 28 (5): 810–819.

Kelly, B., and H. Jiang. 2014. Tail Risk and Asset Prices. *Review of Financial Studies* 27 (10): 2841–2871.

Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman. 2018. Technological Innovation, Resource Allocation, and Growth. *Quarterly Journal of Economics* 17 (4): 1134–1141.

Lamont, O. A. 2001. Economic Tracking Portfolios. *Journal of Econometrics* 105 (1): 161–184.

Larkin, Y. 2013. Brand Perception, Cash Flow Stability, and Financial Policy. *Journal of Financial Economics* 110 (1): 232–253.

Lev, B., and S. Radhakrishnan. 2005. *The Valuation of Organization Capital*, 73–110. University of Chicago Press.

— . 2015. Organization Capital. *Working Paper*.

Li, K., B. Qiu, and R. Shen. 2017. Organization Capital and Mergers and Acquisitions. *Working Paper*.

Li, W. C. Y., and B. Hall. 2016. Depreciation of Business R&D Capital. *Working Paper*.

Lim, S. C., A. J. Macias, and T. Moeller. 2016. Intangible Assets and Capital Structure. *Working Paper*.

Loughran, T., and J. W. Wellman. 2011. New Evidence on the Relation between the Enterprise Multiple and Average Stock Returns. *Journal of Financial and Quantitative Analysis* 46 (6): 1629–1650.

Luo, X., C. Homburg, and J. Wieseke. 2010. Customer Satisfaction, Analyst Stock Recommendations, and Firm Value. *Journal of Marketing Research* 47 (6): 1041–1058.

Madden, T. J., F. Fehle, and S. Fournier. 2006. Brands Matter: An Empirical Demonstration of the Creation of Shareholder Value Through Branding. *Journal of the Academy of Marketing Science* 34 (2): 224–235.

Mandelker, G. N., and S. G. Rhee. 1984. The Impact of the Degrees of Operating and Financial Leverage on Systematic Risk of Common Stock. *Journal of Financial and Quantitative Analysis* 19 (1): 45–57.

Moreira, A., and T. Muir. 2017. Volatility-Managed Portfolios. *Journal of Finance* 72 (4): 1611–1644.

Nagel, S. 2005. Short Sales, Institutional Investors and the Cross-Section of Stock Returns. *Journal of Financial Economics* 78 (2): 277–309.

Newey, W., and K. West. 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55 (3): 703–708.

Novy-Marx, R. 2011. Operating Leverage. *Review of Finance* 15 (1): 103–134.

— . 2013. The Other Side of Value: The Gross Profitability Premium. *Journal of Financial Economics* 108 (1): 1–28.

O'Brien, T. J., and P. A. Vanderheiden. 1987. Empirical Measurement of Operating Leverage for Growing Firms. *Financial Management* 16 (2): 45–53.

O'Sullivan, D., M. C. Hutchinson, and V. O'Connell. 2009. Empirical Evidence of the Stock Market's (Mis)pricing of Customer Satisfaction. *International Journal of Research in Marketing* 26 (2): 154–161.

Ortiz-Molina, H., and G. M. Phillips. 2014. Real Asset Illiquidity and the Cost of Capital. *Journal of Financial and Quantitative Analysis* 49 (1): 1–32.

Pástor, L., and R. F. Stambaugh. 2003. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy* 111 (3): 642–685.

Peters, R. H., and L. A. Taylor. 2017. Intangible Capital and the Investment-q Relation. *Journal of Financial Economics* 123 (2): 251–272.

Prescott, E. C., and M. Visscher. 1980. Organization Capital. *Journal of Political Economy* 88 (3): 446–461.

Stambaugh, R. F., J. Yu, and Y. Yuan. 2015. Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle. *Journal of Finance* 70 (5): 1903–1948.

Stambaugh, R. F., and Y. Yuan. 2017. Mispricing Factors. *Review of Financial Studies* 30 (4): 1270–1315.

Tetlock, P. C., M. Saar-Tsechansky, and S. Macskassy. 2008. More Than Words: Quantifying Language to Measure Firms' Fundamentals. *Journal of Finance* 63 (3): 1437–1467.

Tuli, K. R., and S. G. Bharadwaj. 2009. Customer Satisfaction and Stock Returns Risk. *Journal of Marketing* 73 (6): 184–197.

Vassalou, M. 2003. News Related to Future GDP Growth as a Risk Factor in Equity Returns. *Journal of Financial Economics* 68 (1): 47–73.

Vitorino, M. A. 2013. Understanding the Effect of Advertising on Stock Returns and Firm Value: Theory and Evidence from a Structural Model. *Management Science* 60 (1): 227–245.

Vomberg, A., C. Homburg, and T. Bornemann. 2015. Talented People and Strong Brands: The Contribution of Human Capital and Brand Equity to Firm Value. *Strategic Management Journal* 36 (13): 2122–2131.

Wang, B. 2019. The Cash Conversion Cycle Spread. *Journal of Financial Economics* 133 (2): 472–497.

Weber, M. 2018. Cash Flow Duration and the Term Structure of Equity Returns. *Journal of Financial Economics* 128 (3): 486–503.

## Table 1: Summmary Statistics

Panel A reports summary statistics (mean, standard deviation and various percentiles) for customer satisfaction related variables based on ACSI data. The table includes the customer satisfaction (in the following: CS) level and the industry-adjusted CS level, which is the CS level demeaned by the cross-sectional industry mean (based on the ACSI industry classification). Moreover, first differences of CS and industry-adjusted CS are shown, defined as the change of the respective CS level from period t-1 to period t. Panel B reports mean, median and extreme percentile values for various firm characteristics. The panel shows figures for all firms in the ACSI sample and for all firms in the CRSP/Compustat universe. Only firms with common stocks that trade on either the NYSE, NASDAQ or AMEX are included. The sample period comprises January 2001 to December 2018. Definitions of variables are provided in appendix A.2.

Panel A: Customer Satisfaction Statistics

| | Mean | SD | P1 | P25 | Median | P75 | P99 |
|---|---|---|---|---|---|---|---|
| CS Level | 75.63 | 6.42 | 56 | 72 | 76 | 80 | 87 |
| Industry-Adjusted CS Level | -0.15 | 3.88 | -12 | -2 | -0.17 | 2 | 9.11 |
| CS Delta | 0.18 | 2.85 | -7.00 | -1.00 | 0 | 2 | 7 |
| Industry-Adjusted CS Delta | -0.04 | 2.33 | -5.44 | -1.33 | 0 | 1.25 | 5.75 |

Panel B: Firm Characteristics Statistics

| | ACSI sample firms | | | | CRSP/Compustat sample firms | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Median | P5 | P95 | Mean | Median | P5 | P95 |
| Market Equity (Bn$) | 25.34 | 15.18 | 0.88 | 86.85 | 3.06 | 0.34 | 0.01 | 14.40 |
| Market Beta | 0.89 | 0.76 | -0.04 | 2.31 | 1.22 | 1.06 | -0.12 | 3.25 |
| Total Q | 1.35 | 0.80 | 0.00 | 4.87 | 1.75 | 0.75 | -0.24 | 5.94 |
| Book-to-Market | 0.79 | 0.45 | 0.08 | 1.58 | 0.86 | 0.57 | 0.10 | 2.26 |
| Investment Rate | 0.12 | 0.09 | 0.04 | 0.32 | 0.16 | 0.10 | 0.01 | 0.52 |
| Gross Profitability | 0.32 | 0.28 | 0.03 | 0.78 | 0.27 | 0.25 | -0.07 | 0.80 |
| Market Leverage | 0.39 | 0.38 | 0.09 | 0.79 | 0.31 | 0.26 | 0.03 | 0.79 |
| Operating Leverage | 2.17 | 1.35 | -1.26 | 10.94 | 1.94 | 1.34 | -0.93 | 7.25 |
| Cash Holdings | 0.11 | 0.06 | 0.01 | 0.41 | 0.20 | 0.09 | 0.01 | 0.76 |
| Cash Flow | 0.28 | 0.15 | 0.00 | 1.06 | -0.76 | 0.13 | -4.62 | 1.44 |
| Free Cash Flow | 0.06 | 0.05 | -0.03 | 0.19 | -0.03 | 0.02 | -0.47 | 0.17 |
| Momentum | 0.13 | 0.11 | -0.43 | 0.71 | 0.12 | 0.06 | -0.68 | 1.10 |
| Turnover | 0.22 | 0.15 | 0.05 | 0.58 | 0.17 | 0.10 | 0.01 | 0.51 |
| Price | 59.67 | 39.44 | 7.43 | 137.58 | 57.20 | 14.65 | 1.02 | 71.29 |
| Idiosyncratic Volatility | 1.39 | 1.07 | 0.49 | 3.29 | 2.64 | 1.94 | 0.64 | 7.10 |
| Short Interest | 0.04 | 0.02 | 0.01 | 0.15 | 0.04 | 0.02 | 0.00 | 0.15 |
| Institutional Ownership | 0.68 | 0.70 | 0.35 | 0.96 | 0.51 | 0.53 | 0.01 | 0.99 |

# Table 2: Portfolio Mean Values

This table presents summary statistics of firm characteristics for quintile portfolios obtained from sorts based on the CS levels and the industry-adjusted CS levels. The columns show time-series averages of the quintile portfolio means of firm characteristics and of intangible capital proxies calculated based on capitalized expenses. Firms are sorted into five portfolios based on either their regular or industry-adjusted customer satisfaction levels. Until May 2010 portfolios are rebalanced quarterly, subsequent to an ACSI reporting month. From May 2010 rebalancing is done monthly. Definitions of variable are provided in appendix A.2. The definitions of the intangible capital proxies can be found in the main text. The proxies for capitalized intangible capital are all scaled by book value of total assets. In columns 6-10 all firm characteristics except the market value of equity are standardized by industry (using the ACSI industry classification) to assure consistency with the definition of the industry-adjusted CS levels. The sample period is January 2001 to December 2018.

| | CS Level Sorted Portfolios | | | | | Industry-Adjusted CS Level Sorted Portfolio | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio | Bottom | 2 | 3 | 4 | Top | Bottom | 2 | 3 | 4 | Top |
| CS Level | 66.34 | 73.23 | 76.35 | 79.33 | 83.39 | 69.42 | 75.25 | 76.96 | 77.99 | 78.91 |
| Industry-Adjusted CS Level | -3.38 | -1.11 | 0.55 | 1.54 | 1.76 | -5.35 | -1.63 | -0.10 | 1.55 | 4.97 |
| CS Delta | -0.56 | -0.20 | 0.29 | 0.60 | 0.79 | -0.70 | -0.26 | 0.23 | 0.82 | 0.81 |
| Industry-Adjusted CS Delta | -0.57 | -0.30 | -0.01 | 0.34 | 0.38 | -0.91 | -0.31 | 0.02 | 0.44 | 0.58 |
| Market Equity (Bn$) | 26.79 | 23.59 | 22.89 | 22.20 | 27.79 | 23.57 | 25.12 | 27.42 | 22.65 | 24.48 |
| Market Beta | 0.935 | 0.922 | 0.922 | 0.907 | 0.759 | 0.015 | 0.031 | 0.037 | -0.079 | -0.036 |
| Book-to-Market | 0.810 | 0.648 | 0.660 | 0.676 | 0.399 | 0.196 | 0.006 | 0.022 | -0.054 | -0.197 |
| Total q | 1.059 | 1.312 | 1.355 | 1.560 | 1.728 | -0.105 | -0.081 | -0.026 | 0.020 | 0.185 |
| Market Leverage | 0.500 | 0.417 | 0.397 | 0.356 | 0.294 | 0.164 | 0.068 | 0.030 | 0.002 | -0.247 |
| Operating Leverage | 2.995 | 2.031 | 2.078 | 2.173 | 1.688 | 0.064 | 0.005 | 0.006 | -0.023 | -0.062 |
| Investment Rate | 0.143 | 0.114 | 0.117 | 0.118 | 0.115 | -0.043 | -0.087 | 0.050 | -0.044 | 0.120 |
| Gross Profitability | 0.205 | 0.317 | 0.339 | 0.339 | 0.415 | -0.058 | -0.004 | -0.030 | 0.022 | 0.102 |
| Price | 45.50 | 51.50 | 59.31 | 52.43 | 69.61 | -0.147 | -0.106 | 0.035 | 0.073 | 0.153 |
| Cash Holdings | 0.067 | 0.076 | 0.068 | 0.072 | 0.084 | -0.024 | -0.038 | -0.064 | -0.014 | 0.120 |
| Cash Flow | 0.231 | 0.281 | 0.307 | 0.276 | 0.269 | -0.115 | 0.010 | 0.006 | 0.048 | 0.059 |
| Free Cash Flow | 0.041 | 0.056 | 0.061 | 0.072 | 0.087 | -0.196 | -0.047 | -0.024 | 0.061 | 0.223 |
| Idiosyncratic Volatility | 1.608 | 1.382 | 1.375 | 1.364 | 1.218 | 0.154 | -0.001 | -0.034 | -0.040 | -0.115 |
| Short Interest | 0.043 | 0.040 | 0.040 | 0.038 | 0.037 | 0.048 | -0.006 | -0.052 | 0.044 | -0.064 |
| Institutional Ownership | 0.691 | 0.657 | 0.685 | 0.695 | 0.671 | 0.029 | -0.018 | 0.030 | 0.064 | -0.100 |
| Turnover | 0.244 | 0.200 | 0.202 | 0.208 | 0.198 | 0.079 | -0.024 | -0.022 | -0.010 | -0.046 |
| Capitalized Expenses | | | | | | | | | | |
| Orga Capital (SGA - XRD) | 0.050 | 0.119 | 0.126 | 0.120 | 0.156 | 0.021 | 0.044 | 0.003 | -0.032 | -0.031 |
| Orga Capital (ADV) | 0.062 | 0.152 | 0.184 | 0.211 | 0.255 | -0.102 | 0.016 | -0.050 | 0.052 | 0.129 |
| Orga Capital (Staff) | 0.644 | 0.506 | 0.706 | 1.035 | 1.479 | -0.220 | -0.040 | -0.055 | 0.262 | 0.045 |
| Orga Capital (Pensions) | 0.019 | 0.020 | 0.017 | 0.022 | 0.030 | 0.054 | -0.005 | -0.101 | 0.128 | -0.078 |
| Knowledge Capital (R&D) | 0.009 | 0.015 | 0.015 | 0.020 | 0.053 | -0.222 | 0.025 | 0.097 | 0.031 | 0.052 |
| MV of Assets unexplained | 0.345 | 0.265 | 0.328 | 0.370 | 0.450 | -0.051 | -0.003 | 0.003 | 0.006 | 0.047 |

## Table 3: Return Statistics

This table describes the performance of value-weighted long-short portfolios based on customer satisfaction levels and compares it to the performance of other frequently employed factors, namely the book-to-market (HML), profitability (RMW) and investment factor (CMA) from Fama and French (2015), the momentum factor from Carhart (1997), the liquidity factor from Pástor and Stambaugh (2003), the betting-against-beta (BAB) factor from Frazzini and Pedersen (2014), the quality-minus-junk (QMJ) factor from Asness et al. (2019), the performance (PERF) factor from Stambaugh and Yuan (2017), the financing (FIN) factor from Daniel et al. (2020) and the expected investment growth (EG) factor from Hou et al. (2020). Only the most profitable factor of each of the corresponding factor models is included. The Fama and French factors and the momentum factor are from Kenneth French's website, the QMJ and BAB factors from the AQR website, the LIQ factor is from Lubos Pastor's website, the PERF factor from Robert Stambaugh's website, the FIN factor from Kent Daniel's website, and the EG factor from Lu Zhang's website. The table reports, for each factor, the annualized average excess return, the minimum and maximum monthly returns, the annualized standard deviation, the skewness, the kurtosis, and the annualized Sharpe ratio. The sample period covers January 2001 to December 2018.

| Return Statistics | | | | | | | |
|---|---|---|---|---|---|---|---|
| Strategy/Factor | Mean | Minimum | Maximum | Standard Deviaton | Skewness | Kurtosis | Sharpe Ratio |
| Industry-Adjusted CS Level | 12.04 | -13.54 | 15.23 | 15.71 | -0.17 | 5.05 | 0.77 |
| CS Level | 2.97 | -10.07 | 10.73 | 12.64 | 0.15 | 3.58 | 0.23 |
| Industry-Adjusted CS Delta | 1.20 | -9.56 | 12.67 | 10.93 | 0.24 | 4.28 | 0.11 |
| CS Delta | 2.81 | -14.12 | 10.29 | 7.74 | -0.25 | 4.92 | 0.36 |
| Book-to-Market (HML) | 0.89 | -11.10 | 12.90 | 9.02 | 0.30 | 6.45 | 0.10 |
| Profitability (RMW) | 3.89 | -9.14 | 9.00 | 9.51 | 0.14 | 5.97 | 0.41 |
| Investment (CMA) | 1.75 | -4.60 | 9.58 | 7.42 | 1.03 | 6.29 | 0.24 |
| Momentum (WML) | 2.33 | -34.39 | 12.54 | 17.69 | -1.95 | 15.61 | 0.13 |
| Liquidity (LIQ) | 5.00 | -12.66 | 10.19 | 13.59 | -0.40 | 4.20 | 0.37 |
| Betting-Against-Beta (BAB) | 10.91 | -14.26 | 15.39 | 16.76 | 0.16 | 6.69 | 0.65 |
| Quality-Minus-Junk (QMJ) | 4.80 | -9.10 | 8.64 | 12.32 | -0.02 | 4.44 | 0.39 |
| Performance (PERF) | 8.60 | -21.45 | 18.52 | 22.09 | -0.02 | 5.71 | 0.39 |
| Financing (FIN) | 5.38 | -9.99 | 20.42 | 15.01 | 1.13 | 7.38 | 0.36 |
| Exp. Inv. Growth (EG) | 5.24 | -5.40 | 6.75 | 8.40 | 0.46 | 4.06 | 0.62 |

# Table 4: Industry-Adjusted Customer Satisfaction Strategy

The table presents results of factor-spanning regressions. Firms are sorted into 5 portfolios based on their industry-adjusted customer satisfaction levels. Firm-level CS values are demeaned by the cross-sectional monthly industry mean (using the ACSI industry classification). Until May 2010 portfolios are rebalanced quarterly, subsequent to an ACSI reporting month, from May 2010 onwards monthly. The CS strategy return is the return of a self-financing portfolio that is long the high industry-adjusted CS portfolio and short the low industry-adjusted CS portfolio. Alpha is the intercept in a time-series regression of monthly CS strategy returns on various factor models. We show alphas and factor loadings for value-weighted portfolios. The benchmark models used are the CAPM, the Carhart (1997) 4 factor model, the Fama and French (2015) 5-factor model, the Fama and French (2018) 6-factor model, the Hou et al. (2015) q-factor model, the Hou et al. (2020) q5 model, the Stambaugh and Yuan (2017) mispricing factor model, the Barillas and Shanken (2018) 6-factor model and the Daniel et al. (2020) behavioral factor model. A further factor combination we employ consist of the Fama and French (1993) 3-factor model augmented by the Asness et al. (2019) quality-minus-junk and the Frazzini and Pedersen (2014) betting-against-beta factor. We obtain the SMB (size), HML (book-to-market), CMA (investment), RMW (profitability) and the momentum factor (UMD) from Kenneth French's website. QMJ (quality-minus-junk) and BAB (betting-against-beta) are from the AQR website, the mispricing factors MGMT (management) and PERF (performance) are from Robert Stambaugh's website, the factors FIN (financing) and PEAD (post-earnings announcement drift) are from Kent Daniel's website, and the factors from the q-factor model and the q5 model are from Lu Zhang's website. We replicate the cash-based operating profitability factor from the Fama-French 6-factor model. The sample period extends from January 2001 to December 2018, except for the liquidity and the mispricing model where the sample period ends in December 2017 and December 2016, respectively. Heteroscedasticity and autocorrelation robust Newey and West (1987) t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Model | CAPM | C4 | FF5 | FF6 | Q-Factor | Q5 | MISP | BS | FF3+ QMJ+BAB | BF |
|---|---|---|---|---|---|---|---|---|---|---|
| MKT | 0.083 | 0.139 | 0.208*** | 0.171** | 0.085 | 0.164* | 0.210** | 0.089 | 0.203** | -0.010 |
| | (1.233) | (1.613) | (3.024) | (2.010) | (0.728) | (1.717) | (2.102) | (0.792) | (2.197) | (-0.098) |
| Size | | -0.053 | 0.024 | 0.064 | -0.133 | -0.063 | -0.107 | -0.063 | -0.015 | |
| | | (-0.595) | (0.288) | (0.668) | (-1.194) | (-0.636) | (-0.935) | (-0.576) | (-0.172) | |
| HML | | -0.640*** | -0.666*** | -0.541*** | | | | -0.343** | -0.645*** | |
| | | (-3.874) | (-3.740) | (-2.947) | | | | (-1.983) | (-3.808) | |
| UMD | | 0.054 | | -0.014 | | | | -0.010 | | |
| | | (0.412) | | (-0.109) | | | | (-0.070) | | |
| Investment | | | -0.104 | -0.027 | -0.605*** | -0.653*** | | -0.336** | | |
| | | | (-0.583) | (-0.196) | (-3.344) | (-4.183) | | (-1.975) | | |
| Profitability | | | 0.399** | 0.551*** | 0.012 | -0.135 | | -0.226 | | |
| | | | (2.459) | (3.384) | (0.055) | (-0.684) | | (-1.157) | | |
| EG | | | | | | -0.590*** | | | | |
| | | | | | | (-4.326) | | | | |
| QMJ | | | | | | | | | 0.179 | |
| | | | | | | | | | (0.831) | |
| BAB | | | | | | | | | 0.075 | |
| | | | | | | | | | (0.786) | |
| MGMT | | | | | | | -0.562*** | | | |
| | | | | | | | (-4.586) | | | |
| PERF | | | | | | | 0.370*** | | | |
| | | | | | | | (4.141) | | | |
| FIN | | | | | | | | | | -0.250** |
| | | | | | | | | | | (-1.974) |
| PEAD | | | | | | | | | | 0.172 |
| | | | | | | | | | | (0.874) |
| *alpha* | 0.895*** | 0.955*** | 0.795*** | 0.717*** | 1.051*** | 0.741*** | 0.840** | 1.094*** | 0.779*** | 1.020*** |
| | (3.255) | (3.250) | (3.150) | (2.629) | (3.159) | (2.528) | (2.404) | (3.205) | (2.606) | (2.945) |

# Table 5: Alphas of Customer Satisfaction Based Strategies

The table presents intercepts of time-series regressions of monthly CS-based portfolio returns on the same factor models used in table 4. In Panel A the dependent variable is the return of an equal-weighted long/short-strategy obtained from sorts on the industry-adjusted CS level. In Panel B the dependent variable is the return of a CS factor constructed from a 2x3 sort as in Fama and French (1993). To construct the factor all firms in the ACSI universe are sorted into 3 portfolios based on their 20% and 80% breakpoints for the industry-adjusted CS level. Independently, all firms are sorted into two size groups based on the median market capitalization. In Panel C the dependent variable is the excess return over the risk-free rate of a portfolio that includes *all* firms for which an ACSI customer satisfaction value has been reported in the previous 12 month. Results for both value-weighted and equal-weighted returns are shown. The sample period extends from January 2001 to December 2018, except in case of the liquidity and mispricing models where the sample period ends in December 2017 and December 2016, respectively. Returns and alphas are given as monthly percentage values. Heteroscedasticity and autocorrelation-robust Newey and West (1987) t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Model | CAPM | C4 | FF5 | FF6 | Q-Factor | Q5 | MISP | BS | FF3+ QMJ+BAB | BF |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Panel A: Equal-Weighted Strategy | | | | | |
| *alpha* | 0.500** | 0.550** | 0.403** | 0.507** | 0.608** | 0.515** | 0.584** | 0.629** | 0.365 | 0.541** |
| | (2.260) | (2.192) | (2.086) | (2.062) | (2.426) | (2.121) | (1.982) | (2.530) | (1.231) | (2.055) |
| | | | | | Panel B: CS Return Factor (2x3) | | | | | |
| *alpha* | 0.566** | 0.643*** | 0.568** | 0.520** | 0.723*** | 0.640** | 0.696** | 0.758*** | 0.558** | 0.653** |
| | (2.460) | (2.666) | (2.361) | (2.350) | (2.750) | (2.192) | (2.331) | (2.880) | (2.225) | (2.554) |
| | | | | | Panel C: ACSI Index Firms Portfolio | | | | | |
| Value-Weighted | 0.150* | 0.159** | 0.071 | 0.100 | 0.098 | -0.002 | 0.062 | 0.101 | 0.020 | 0.001 |
| | (1.831) | (2.462) | (1.104) | (1.428) | (1.345) | (-0.038) | (0.879) | (1.389) | (0.383) | (0.020) |
| Equal-Weighted | 0.302** | 0.312*** | 0.149 | 0.322*** | 0.279** | 0.291 | 0.291** | 0.243** | 0.201 | 0.171 |
| | (2.325) | (3.029) | (1.333) | (2.769) | (2.448) | (1.077) | (2.379) | (2.140) | (1.537) | (1.412) |

# Table 6: Benchmarking the Customer Satisfaction Strategy

This table presents intercepts of time-series regressions of the monthly industry-adjusted long-short CS strategy returns on various factor combinations. Each benchmark model combines the market factor with the return of a long/short factor based on the firm characteristic indicated in the respective cell of the table. Details can be found in appendix A.2. The liquidity factor LIQ is from Lubos Pastor's website, and the short-term and long-term reversal factors STR and LTR are from Kenneth French's website. The sample period extends from January 2001 to December 2018. Alphas are reported as monthly percentage values. Heteroscedasticity and autocorrelation-robust Newey and West (1987) t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

| Industry-Adjusted CS Strategy and Benchmark Returns | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | OC | $OC^{Adv}$ | $OC^{Staff}$ | $OC^{Pension}$ | KC | $CAP^{Unex}$ | $OL^{NM}$ | $OL^{Reg}$ | FCF | $Vol^{CF}$ | GDP |
| *alpha* | 0.831*** | 0.669** | 0.845*** | 0.750*** | 0.843*** | 0.948*** | 0.698** | 0.939*** | 0.617* | 1.002*** | 0.907*** |
| | (2.903) | (2.486) | (3.060) | (2.609) | (3.141) | (3.366) | (2.587) | (3.478) | (1.964) | (3.337) | (3.173) |
| | Adv-Gr | Adv/M | R&D/M | $Ch/At^{Q}$ | $Ea^{Q}/P$ | $ATLQ^{Q}$ | CCC | Ivola | Tail | FF3+ LIQ | FF3+ STR+LTR |
| *alpha* | 0.999*** | 0.947*** | 0.811*** | 0.923*** | 1.092*** | 0.882*** | 0.939*** | 1.037*** | 0.861*** | 0.963*** | 0.909*** |
| | (3.563) | (3.477) | (3.100) | (3.496) | (3.537) | (3.406) | (3.269) | (3.536) | (2.858) | (3.847) | (2.933) |
| | Sales-Gr | Ability | ROA | NPY | Total Q | HHI | Turnover | Bid/Ask | DTD | Inflex | $EM^{Q}$ |
| *alpha* | 0.995*** | 0.811*** | 0.726** | 1.048*** | 0.948*** | 0.964*** | 1.072*** | 1.034*** | 0.786*** | 0.896*** | 0.945*** |
| | (3.687) | (3.112) | (2.432) | (3.321) | (3.335) | (3.510) | (3.652) | (3.925) | (2.746) | (3.304) | (3.528) |

# Table 7: Hedge Fund Alphas

This table presents factor loadings and monthly alphas of the "ACSI Long/Short Equity" hedge fund, a fund which follows a customer satisfaction based investment strategy. We obtain the hedge fund return data from Eurekahedge. Alpha is the intercept in a time-series regression of monthly hedge fund returns on various factor models. First, the same models as in table 4 are used. In addition, the Fung and Hsieh (2004) 7-factor hedge fund benchmark model is employed. The 7 hedge fund factors SP (Standard & Poor's 500 return), SCLC (Russell 2000 return - Standard & Poor's 500 return), 10Y (monthly change in the U.S. Fed 10-year yield), CredSpr (monthly change in the difference of Moody's Baa yield and the Fed's 10-year yield), BdOpt (return of portfolio of lookback straddles on bond futures), FXOpt (return of portfolio of lookback straddles on currency futures) and ComOpt (return of portfolio of lookback straddles on commodity futures) are from David Hsieh's website. The sample period runs from April 2000 to December 2016. Returns and alphas are in monthly percent, heteroscedasticity and autocorrelation robust Newey and West (1987) t-statistics are shown below the coefficient estimates. ***, **, and * refers to statistical significance at 1%, 5%, and 10% level, respectively.

| Model | CAPM | C4 | FF5 | FF6 | Q-Factor | Q5 | MISP | BS | FF3+ QMJ+BAB | BF | Fung and Hsieh 7F |
|---|---|---|---|---|---|---|---|---|---|---|---|
| MKT | 0.703*** | 0.643*** | 0.676*** | 0.622*** | 0.608*** | 0.633*** | 0.676*** | 0.620*** | 0.607*** | 0.703*** | |
| | (12.987) | (9.001) | (8.564) | (7.184) | (7.052) | (7.575) | (7.338) | (7.887) | (6.874) | (9.589) | |
| Size | | 0.180* | 0.180* | 0.244** | 0.167* | 0.189* | 0.111 | 0.137 | 0.143* | | |
| | | (1.929) | (1.944) | (2.252) | (1.659) | (1.942) | (1.340) | (1.361) | (1.968) | | |
| HML | | 0.043 | -0.016 | -0.010 | | | | 0.177 | 0.105* | | |
| | | (0.763) | (-0.158) | (-0.093) | | | | (1.319) | (1.781) | | |
| Investment | | | 0.079 | 0.106 | 0.042 | 0.004 | | -0.070 | | | |
| | | | (0.380) | (0.614) | (0.305) | (0.030) | | (-0.309) | | | |
| Profitability | | | 0.004 | 0.095 | -0.141 | -0.185 | | -0.104 | | | |
| | | | (0.027) | (0.802) | (-1.174) | (-1.514) | | (-0.960) | | | |
| UMD/EG | | -0.047 | | -0.032 | | 0.165* | | 0.073 | | | |
| | | (-0.745) | | (-0.609) | | (1.686) | | (1.014) | | | |
| MGMT/QMJ/PEAD | | | | | | | 0.008 | | -0.040 | 0.024 | |
| | | | | | | | (0.105) | | (-0.389) | (0.225) | |
| PERF/BAB/FIN | | | | | | | -0.013 | | -0.138** | -0.006 | |
| | | | | | | | (-0.195) | | (-2.548) | (-0.095) | |
| SP | | | | | | | | | | | 63.860*** |
| | | | | | | | | | | | (10.389) |
| SCLC | | | | | | | | | | | 28.143*** |
| | | | | | | | | | | | (5.077) |
| 10Y | | | | | | | | | | | -1.124 |
| | | | | | | | | | | | (-1.139) |
| CredSpr | | | | | | | | | | | 0.704 |
| | | | | | | | | | | | (0.870) |
| BdOpt | | | | | | | | | | | -2.811 |
| | | | | | | | | | | | (-1.624) |
| FXOpt | | | | | | | | | | | 1.065 |
| | | | | | | | | | | | (1.275) |
| ComOpt | | | | | | | | | | | 1.307 |
| | | | | | | | | | | | (1.004) |
| *alpha* | 0.629*** | 0.587*** | 0.545*** | 0.507*** | 0.614*** | 0.543*** | 0.591*** | 0.574*** | 0.742*** | 0.627*** | 0.511*** |
| | (4.081) | (4.043) | (3.045) | (3.208) | (3.685) | (3.028) | (3.189) | (3.632) | (3.574) | (3.119) | (4.027) |

# Table 8: Performance of Matched-Firm Portfolios

This table compares average monthly returns of the CS-based trading strategies with the returns of portfolios of matched firms. To each firm in the ACSI universe each month we match one firm from the remaining CRSP/Compustat universe. We use two sets of characteristics for the matching procedure. The first set consists of size, book-to-market, gross profitability, asset growth and prior return (momentum). The second set consists of size, Total q and idiosyncratic volatility. We match firms using one of two alternative matching procedures, matching based on the propensity score and covariates matching with the Mahalanobis distance. We apply nearest neighbor matching without replacement in both cases, and we require the matched firms to be in the same industry (defined by the first digit of the NAICS code) as the ACSI firm. This approach assigns, in each month, to each firm in the ACSI universe exactly one firm which is in the filtered CRSP/Compustat universe but not in the ACSI universe. We then identify for all four CS-based long-short strategies (those based on raw and industry-adjusted CS scores in both levels and first differences), in each month, the firms in the top and bottom CS quintile portfolios and construct mimicking portfolios of non-ACSI firms which are composed of the matched firms. For both the CS long-short portfolios and the mimicking portfolios we compute both equal-weighted and value-weighted returns. The average monthly returns of the CS portfolios and the corresponding mimicking portfolios are shown in Panel A. Panel B shows equal-weighted and value-weighted average returns of the portfolio of *all* firms of the ACSI universe and the corresponding mimicking portfolios. Heteroscedasticity- and autocorrelation-robust t-statistics for a test of the mean return against zero are reported in parentheses. The sample period extends from 2001 to 2018. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| | ACSI Firms | Matched Firms | | | |
|---|---|---|---|---|---|
| | | Propensity Score Matching | | Mahalanobis Distance Matching | |
| Matching Characteristics | | Size, BM, Gross Profitability, Asset Growth, Momentum | Size, Total q, Idiosyncratic Volatility | Size, BM, Gross Profitability, Asset Growth, Momentum | Size, Total q, Idiosyncratic Volatility |
| **Panel A: Long/Short Strategy Returns** | | | | | |
| Ind-Adj CS VW | 0.871*** | 0.062 | 0.057 | 0.017 | -0.194 |
| | (2.909) | (0.348) | (0.248) | (0.067) | (-0.944) |
| Ind-Adj CS EW | 0.486* | 0.181 | -0.100 | 0.059 | 0.020 |
| | (1.949) | (1.103) | (-0.704) | (0.357) | (0.127) |
| CS Level VW | 0.242 | 0.207 | 0.152 | -0.025 | -0.236 |
| | (1.019) | (0.770) | (0.899) | (-0.104) | (-1.000) |
| CS Level EW | 0.368 | 0.495* | 0.203 | 0.013 | -0.048 |
| | (1.211) | (1.947) | (1.458) | (0.060) | (-0.262) |
| Ind-Adj CS Delta VW | 0.118 | 0.062 | -0.064 | -0.001 | 0.032 |
| | (0.562) | (0.296) | (-0.439) | (-0.006) | (0.147) |
| Ind-Adj CS Delta EW | 0.064 | 0.003 | -0.242 | 0.045 | -0.173 |
| | (0.431) | (0.020) | (-1.259) | (0.237) | (-0.841) |
| CS Delta VW | 0.269* | 0.417* | -0.120 | -0.050 | 0.192 |
| | (1.797) | (1.766) | (-0.488) | (-0.209) | (0.904) |
| CS Delta EW | 0.289* | 0.373* | -0.149 | 0.098 | -0.245 |
| | (1.694) | (1.808) | (-0.899) | (0.397) | (-1.530) |
| **Panel B: Portfolio Excess Returns** | | | | | |
| ACSI firms VW | 0.548* | 0.346 | 0.421 | 0.390 | 0.480 |
| | (1.781) | (0.977) | (1.211) | (1.132) | (1.564) |
| ACSI firms EW | 0.757** | 0.639* | 0.673* | 0.778** | 0.748** |
| | (2.064) | (1.718) | (1.907) | (2.201) | (2.246) |

## Table 9: Fama and MacBeth Regressions

The table reports results from Fama and MacBeth (1973) regressions of returns on the trading signal for the industry-adjusted customer satisfaction level. Regressions include various controls. The variable definitions can be found in appendix A.2. The independent control variables are winsorized at the 1% and 99% levels. The sample covers January 2001 to December 2018. Test statistics are in parentheses. The time-series averages of the coefficient estimates and their associated time-series t-statistics are reported. ***, **, and * refers to statistical significance at the 1%, 5%, and 10% level, respectively.

| | Regressions of the form $r_{i,t+1} = \beta' x_{i,t} + \epsilon_{i,t}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Ind-Adj CS | 0.041** | 0.043*** | 0.048*** | 0.044*** | 0.042*** | 0.036** | 0.041*** | 0.029** | 0.033** |
| | (2.381) | (2.870) | (3.246) | (2.646) | (2.645) | (2.497) | (2.767) | (1.990) | (2.201) |
| Total q | | 0.036 | 0.026 | | | | | | |
| | | (0.814) | (0.647) | | | | | | |
| Beta | | 0.158 | 0.220 | 0.273 | 0.255 | -0.103 | 0.009 | -0.317 | -0.313 |
| | | (0.569) | (0.829) | (1.122) | (1.110) | (-0.434) | (0.038) | (-1.310) | (-1.362) |
| Operating Leverage (Reg) | | -0.075*** | | -0.026 | | -0.044** | | -0.040* | |
| | | (-2.605) | | (-1.368) | | (-2.215) | | (-1.963) | |
| Operating Leverage (NM) | | | -0.042 | | -0.016 | | -0.036 | | -0.039 |
| | | | (-0.296) | | (-0.124) | | (-0.283) | | (-0.295) |
| Market Leverage | | -1.054** | -1.164** | | | | | | |
| | | (-2.295) | (-2.166) | | | | | | |
| Free Cash Flow | | -0.228 | -1.003 | | | | | | |
| | | (-0.151) | (-0.693) | | | | | | |
| Log Size | | | | -0.109 | -0.148** | -0.088 | -0.086 | -0.049 | -0.042 |
| | | | | (-1.505) | (-2.180) | (-1.175) | (-1.181) | (-0.586) | (-0.524) |
| Book-to-Market | | | | 0.485*** | 0.203** | | | | |
| | | | | (3.569) | (2.201) | | | | |
| Profitability | | | | 0.991** | 0.802* | | | | |
| | | | | (2.578) | (1.971) | | | | |
| Asset Growth | | | | 0.275 | 0.384 | | | | |
| | | | | (0.666) | (0.997) | | | | |
| Turnover | | | | -1.705* | -0.913 | | | | |
| | | | | (-1.743) | (-1.027) | | | | |
| Idiosyncratic Volatility | | | | -0.243 | -0.307** | -0.283 | -0.136 | | |
| | | | | (-1.563) | (-2.134) | (-1.574) | (-0.844) | | |
| $\text{Mom}_{-12,-2}$ | | | | | | -0.013 | 0.239 | -0.029 | -0.002 |
| | | | | | | (-0.022) | (0.437) | (-0.053) | (-0.004) |
| $\text{Ret}_{-1,0}$ | | | | | | -0.001 | 0.004 | -0.004 | 0.001 |
| | | | | | | (-0.094) | (0.266) | (-0.267) | (0.108) |
| Orga. Capital (SGA-XRD) | | | | | | 0.698 | 0.802 | 0.332 | 0.357 |
| | | | | | | (0.793) | (0.738) | (0.376) | (0.357) |
| Orga. Capital (ADV) | | | | | | -0.085 | -0.225 | 0.012 | -0.191 |
| | | | | | | (-0.186) | (-0.425) | (0.027) | (-0.402) |
| Cash-to-Assets | | | | | | | | 1.042* | 0.867 |
| | | | | | | | | (1.644) | (1.423) |
| Short Interest | | | | | | | | 0.002 | 0.016 |
| | | | | | | | | (0.046) | (0.484) |
| Tail Risk | | | | | | | | 0.001 | 0.003 |
| | | | | | | | | (0.239) | (1.050) |

Table 10: Extreme Quintile Portfolios

This table shows the alphas of the extreme (i.e. the first and the fifth) quintile portfolios. The alphas constitute the intercepts of time-series regressions of the excess returns of the respective quintile portfolio on various factor combinations (see table 4 for details). The sample period extends from January 2001 to December 2018, except for the liquidity and mispricing models where the sample period ends in December 2017 and December 2016, respectively. Alphas are reported as monthly percentage values. Heteroscedasticity and autocorrelation robust Newey and West (1987) t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Model | CAPM | C4 | FF5 | FF6 | Q-Factor | Q5 | MISP | BS | FF3+ QMJ+BAB | BF |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Industry-Adjusted CS Level | | | | | |
| | | | | | Long Leg | | | | | |
| Value-Weighted | 0.632*** | 0.670*** | 0.527*** | 0.509** | 0.672*** | 0.393** | 0.569** | 0.697*** | 0.472*** | 0.562*** |
| | (3.998) | (3.638) | (3.384) | (2.599) | (3.389) | (2.342) | (2.571) | (3.333) | (2.602) | (3.002) |
| Equal-Weighted | 0.577*** | 0.622*** | 0.468*** | 0.688*** | 0.659*** | 0.601*** | 0.675*** | 0.637*** | 0.507*** | 0.513*** |
| | (4.589) | (4.982) | (3.480) | (4.608) | (4.564) | (3.881) | (4.203) | (4.627) | (3.059) | (3.216) |
| | | | | | Short Leg | | | | | |
| Value-Weighted | 0.264 | 0.285 | 0.268 | 0.207 | 0.379* | 0.347* | 0.271 | 0.396* | 0.307* | 0.458** |
| | (1.305) | (1.563) | (1.408) | (1.178) | (1.733) | (1.713) | (1.224) | (1.831) | (1.656) | (2.065) |
| Equal-Weighted | -0.077 | -0.072 | -0.065 | -0.181 | -0.051 | -0.086 | -0.090 | -0.008 | -0.143 | 0.029 |
| | (-0.350) | (-0.311) | (-0.303) | (-0.760) | (-0.222) | (-0.356) | (-0.371) | (-0.034) | (-0.503) | (0.118) |

# Table 11: Earnings Surprises and Customer Satisfaction

This table reports results of regressions of earnings surprises on the customer satisfaction (CS) scores. We use four versions of the CS scores, the raw and the industry-adjusted scores, both in levels and in first differences. The earnings surprises are defined as the difference between actual earnings and the median analyst earnings forecast from IBES, scaled by the closing stock price of the previous month. In panel A the earnings surprise of quarter t is regressed on the customer satisfaction score of quarter t and on control variables from quarter t-1. The definitions of the control variables can be found in appendix A.2. Standard errors are clustered by firm and quarter. In panel B, we follow Engelberg et al. (2018) and regress the earnings surprise on dummy variables indicating the portfolio affiliation of a stock. We sort firms into quintiles based on the CS score and set the dummy variable Long Portfolio (Short Portfolio) to 1 for all firms in the highest (lowest) CS quintile. We use as control variables the number of analyst estimates, a single forecast dummy equal to one if there is only one forecast for a firm, and forecast dispersion, defined as the standard deviation of the forecasts divided by the stock price. Dispersion is set to 0 if there is only one forecast. Standard errors are clustered by time. The sample period extends from 2001 to 2018. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Panel A: Determinants of Earnings Surprises | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| | Levels | | | | | | First Differences | | | | | |
| Industry-Adjusted CS | 0.210 | 0.073 | 0.007 | | | | 0.256 | 0.039 | 0.023 | | | |
| | (1.162) | (1.232) | (0.433) | | | | (1.095) | (0.776) | (0.697) | | | |
| Unadjusted CS | | | | 0.212 | 0.017 | 0.008 | | | | 0.074 | 0.037 | 0.030 |
| | | | | (1.035) | (0.781) | (0.612) | | | | (1.198) | (0.980) | (0.952) |
| Ln(Market Equity) | | -0.803 | -0.301 | | -0.810 | -0.299 | | -0.824 | -0.200 | | -0.831 | -0.200 |
| | | (-1.571) | (-1.576) | | (-1.555) | (-1.568) | | (-1.622) | (-1.101) | | (-1.617) | (-1.102) |
| Book-to-Market | | -0.598* | -0.643* | | -0.610* | -0.642* | | -0.635 | -0.629* | | -0.636 | -0.630* |
| | | (-1.735) | (-1.731) | | (-1.699) | (-1.729) | | (-1.589) | (-1.651) | | (-1.603) | (-1.653) |
| Gross Profitability | | -0.048 | -2.394 | | -0.039 | -2.392 | | 0.267 | -2.645* | | 0.295 | -2.650* |
| | | (-0.062) | (-1.592) | | (-0.050) | (-1.592) | | (0.335) | (-1.798) | | (0.363) | (-1.799) |
| Investment Rate | | 0.806 | -0.039 | | 0.792 | -0.042 | | 0.843 | 0.278 | | 0.827 | 0.279 |
| | | (1.015) | (-0.053) | | (1.013) | (-0.057) | | (1.072) | (0.397) | | (1.065) | (0.398) |
| Momentum-2,-12 | | 1.279 | 1.228 | | 1.303 | 1.224 | | 1.373 | 1.237 | | 1.375 | 1.234 |
| | | (1.250) | (1.440) | | (1.243) | (1.431) | | (1.278) | (1.540) | | (1.276) | (1.536) |
| Organizational Capital | | -0.011 | -0.005 | | -0.010 | -0.005 | | -0.013 | -0.003 | | -0.013 | -0.003 |
| (ADV) | | (-1.287) | (-0.967) | | (-1.256) | (-0.974) | | (-1.389) | (-0.574) | | (-1.397) | (-0.570) |
| Organizational Capital | | -0.021* | 0.014 | | -0.023* | 0.015 | | -0.025* | 0.025 | | -0.026* | 0.025 |
| (SGA - XRD) | | (-1.969) | (0.711) | | (-1.794) | (0.716) | | (-1.860) | (1.174) | | (-1.799) | (1.177) |
| Operating Leverage | | 0.015 | 0.078** | | 0.015 | 0.078** | | 0.018 | 0.073** | | 0.018 | 0.073** |
| | | (0.488) | (2.479) | | (0.489) | (2.486) | | (0.584) | (2.521) | | (0.598) | (2.504) |
| Market Leverage | | -4.216 | -4.048 | | -4.302 | -4.038 | | -4.111 | -3.734 | | -4.124 | -3.736 |
| | | (-1.217) | (-1.548) | | (-1.198) | (-1.535) | | (-1.120) | (-1.518) | | (-1.122) | (-1.518) |
| Idiosyncratic Volatility | | -0.412 | -0.544 | | -0.417 | -0.545 | | -0.458 | -0.543 | | -0.455 | -0.543 |
| | | (-0.691) | (-1.186) | | (-0.702) | (-1.181) | | (-0.741) | (-1.167) | | (-0.741) | (-1.166) |
| Time F.E. | Yes | Yes | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes | No |
| Firm F.E. | No | Yes | No | No | Yes | No | No | Yes | No | No | Yes | No |
| Industry x Time F.E. | No | No | Yes | No | No | Yes | No | No | Yes | No | No | Yes |
| N | 8596 | 7742 | 7742 | 8596 | 7742 | 7742 | 8270 | 7477 | 7477 | 8270 | 7477 | 7477 |

| Panel B: Portfolio Affiliation and Analysts' Earnings Forecast Errors | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Levels | | | | First Differences | | | |
| Long Portfolio Industry-Adjusted CS | 0.014 | 0.006 | | | 0.013 | 0.006 | | |
| | (1.490) | (0.601) | | | (1.321) | (0.588) | | |
| Short Portfolio Industry-Adjusted CS | -0.010 | -0.017* | | | -0.008 | -0.015 | | |
| | (-1.017) | (-1.811) | | | (-0.788) | (-1.593) | | |
| Long Portfolio Unadjusted CS | | | 0.012 | 0.004 | | | 0.010 | 0.003 |
| | | | (1.248) | (0.400) | | | (1.023) | (0.299) |
| Short Portfolio Unadjusted CS | | | -0.008 | -0.015 | | | 0.010 | 0.002 |
| | | | (-0.787) | (-1.597) | | | (1.013) | (0.237) |
| Number of Estimates | | 0.063*** | | 0.063*** | | 0.063*** | | 0.060*** |
| | | (4.302) | | (4.315) | | (4.311) | | (4.146) |
| Single Forecast | | -2.310*** | | -2.309*** | | -2.309*** | | -2.314*** |
| | | (-8.462) | | (-8.457) | | (-8.459) | | (-8.476) |
| Dispersion | | -0.157** | | -0.157** | | -0.157** | | -0.157** |
| | | (-2.144) | | (-2.144) | | (-2.144) | | (-2.144) |
| Time F.E. | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 218445 | 218442 | 218445 | 218442 | 218445 | 218442 | 218445 | 218442 |

# Table 12: CS Strategy Returns and Risk of Customer Capital Investment

This table reports monthly mean returns of portfolios obtained from double sorts on a variable expected to determine the rent extraction potential of customers, thus reflecting the risk of investment in customer capital, and the industry-adjusted CS level. The variables we use are equity duration as defined by Weber (2018), operating leverage as defined by O'Brien and Vanderheiden (1987), and text-based product market fluidity as introduced by Hoberg et al. (2014). We obtain product market fluidity from the Hoberg-Phillips data library. In Panel A, we first compute the cross-sectional mean value of the respective variable for each ACSI industry. Each month, we then split the industries in industries with high and low risk exposure based on the value of the median industry. In Panel B, we split the CRSP/Compustat universe in a high and low risk exposure group based on the median sample firm value. Subsequently, within the high and low groups we split the sample into terciles based on the industry-adjusted CS value. We show the difference in value-weighted mean returns between the top and bottom tercile CS portfolios within the low and high risk exposure groups and the respective difference in returns of the CS-based long/short strategy between the high and low characteristic groups. Moreover, we report the alpha of the difference portfolios with respect to the Fama and French (2018) 6-factor model and the Hou et al. (2020) q5 model. Newey and West (1987) t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * refers to statistical significance at 1%, 5%, and 10% level, respectively.

| | Industry-Adjusted Customer Satisfaction Level Premium | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Equity Duration | | | Operating Leverage | | | Product Market Fluidity | | |
| | Low | High | Diff | Low | High | Diff | Low | High | Diff |
| **Panel A: Industry-Level Sorts** | | | | | | | | | |
| Diff | 0.199 | 0.837*** | 0.637** | 0.360** | 0.679** | 0.319 | 0.486* | 0.690*** | 0.204 |
| | (0.876) | (3.165) | (2.011) | (2.179) | (2.555) | (1.032) | (1.741) | (3.201) | (0.575) |
| FF6 | 0.295 | 0.652** | 0.357 | 0.227 | 0.517* | 0.289 | 0.192 | 0.782*** | 0.590 |
| | (1.370) | (2.187) | (1.007) | (1.143) | (1.788) | (0.784) | (0.629) | (3.588) | (1.584) |
| Q5 | 0.364 | 0.711** | 0.347 | 0.397* | 0.645** | 0.248 | 0.124 | 0.875*** | 0.752** |
| | (1.558) | (2.240) | (0.881) | (1.793) | (2.180) | (0.640) | (0.485) | (3.783) | (2.162) |
| **Panel B: Firm-Level Sorts** | | | | | | | | | |
| Diff | -0.122 | 0.883*** | 1.004*** | 0.381* | 0.590** | 0.209 | 0.227 | 0.840*** | 0.613* |
| | (-0.472) | (4.338) | (3.682) | (1.837) | (2.049) | (0.613) | (0.954) | (3.402) | (1.779) |
| FF6 | 0.230 | 0.633*** | 0.403 | 0.170 | 0.551 | 0.381 | 0.101 | 0.794*** | 0.694* |
| | (0.720) | (3.088) | (1.180) | (0.744) | (1.588) | (0.936) | (0.413) | (2.995) | (1.921) |
| Q5 | 0.075 | 0.760*** | 0.685* | 0.294 | 0.519 | 0.225 | 0.073 | 0.903*** | 0.829** |
| | (0.268) | (3.405) | (1.947) | (1.390) | (1.476) | (0.534) | (0.334) | (3.175) | (2.238) |

## Table 13: CS Strategy Returns and Innovative Activity

This table shows results for tests of the relation between the customer satisfaction strategy and innovative activity. Data on venture capital financing (VC) are from Refinitiv EIKON. We aggregate the equity invested by funds across all deals within a month. Patent data are from the USPTO, accessible on www.patentsview.org. We use the total number of newly granted patents within a month (GP), the total number of reissued patents within a months (RP), and the monthly average number of patent applications over the last 12 months (PA). Moreover, we employ the average R&D expenditure-to-total assets ratio (R&D), where we use data from Compustat quarterly. Panel A presents results for time-series regressions of the industry-adjusted customer satisfaction strategy on measures of innovative activity with and without controlling for market returns. For all variables, we use first differences, similar to to Grammig and Jank (2016). Regressions are estimated via OLS employing robust standard errors. T-statistics are in parentheses. The last column reports results of an F-test whether the coefficients on the current and lagged measures of innovative activity are jointly zero. In Panel B, we regress the customer satisfaction strategy on an innovativity factor and on a model consisting of the market factor and an innovativity factor. The innovativity factors are represented by cross-sectional return factors in the manner of Hirshleifer et al. (2013). The factors are obtained from quintile sorts on the ratio of number of patents granted in the previous year to total assets and on the number of citations obtained in the previous year to market capitalisation. We report the factor coefficients and the alphas.

Panel A: Innovativity and Returns of Customer Satisfaction Strategy

Dependent Variable $R_t^{CS}$

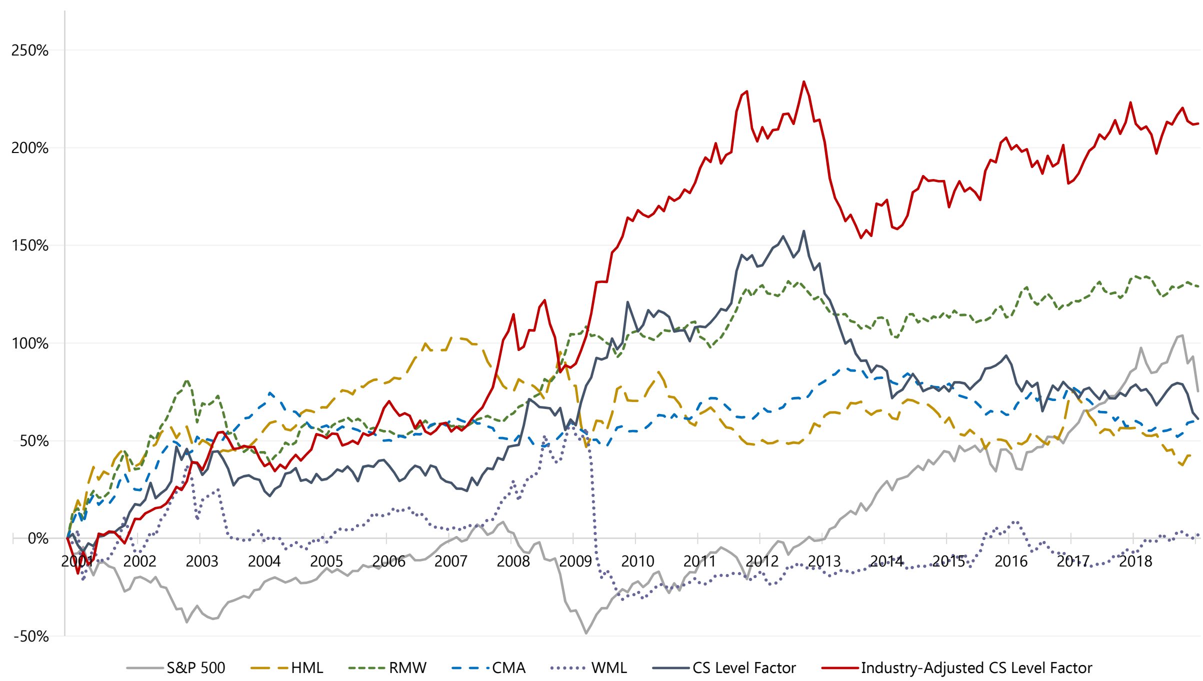
| Innovativity $I_t$ | $I_t$ | $I_{t-1}$ | $MKT_t$ | $R_{t-1}^{CS}$ | p(F) |
|---|---|---|---|---|---|
| Aggregate Venture Capital Financing | -0.089* | -0.058 | | | 0.012 |
| | (-1.716) | (-0.907) | | | |
| | -0.089* | -0.059 | 0.072 | 0.078 | 0.015 |
| | (-1.688) | (-0.949) | (0.828) | (0.941) | |
| Number of Newly Granted Patents | -0.098 | 0.014 | | | 0.292 |
| | (-1.430) | (0.251) | | | |
| | -0.090 | 0.013 | 0.062 | 0.076 | 0.345 |
| | (-1.315) | (0.223) | (0.664) | (0.904) | |
| Number of Reissued Patents | -18.808* | 7.270 | | | 0.122 |
| | (-1.915) | (0.809) | | | |
| | -18.097* | 7.646 | 0.072 | 0.064 | 0.143 |
| | (-1.782) | (0.850) | (0.806) | (0.743) | |
| Number of Patent Applications | -0.879** | -0.195 | | | 0.000 |
| | (-2.110) | (-0.462) | | | |
| | -0.867** | -0.152 | 0.074 | -0.152 | 0.000 |
| | (-2.084) | (-0.354) | (0.845) | (-0.354) | |
| Average R&D Expenditures scaled by | -0.243* | -0.001 | | | 0.084 |
| Total Assets | (-1.897) | (-0.004) | | | |
| | -0.233* | 0.011 | 0.057 | 0.038 | 0.107 |
| | (-1.750) | (0.086) | (0.675) | (0.479) | |

Panel B: Patent Factor Regressions

| | Innovativity Factor | | Innovativity and Market Factor | | |
|---|---|---|---|---|---|
| | $\beta_I$ | $\alpha$ | $\beta_I$ | $\beta_{MKT}$ | $\alpha$ |
| Patents | 0.438*** | 0.884*** | 0.470*** | -0.059 | 0.908*** |
| | (6.935) | (3.505) | (6.535) | (-0.932) | (3.659) |
| Citations | 0.422*** | 0.761*** | 0.449*** | -0.040 | 0.769*** |
| | (6.032) | (3.212) | (4.531) | (-0.489) | (3.285) |

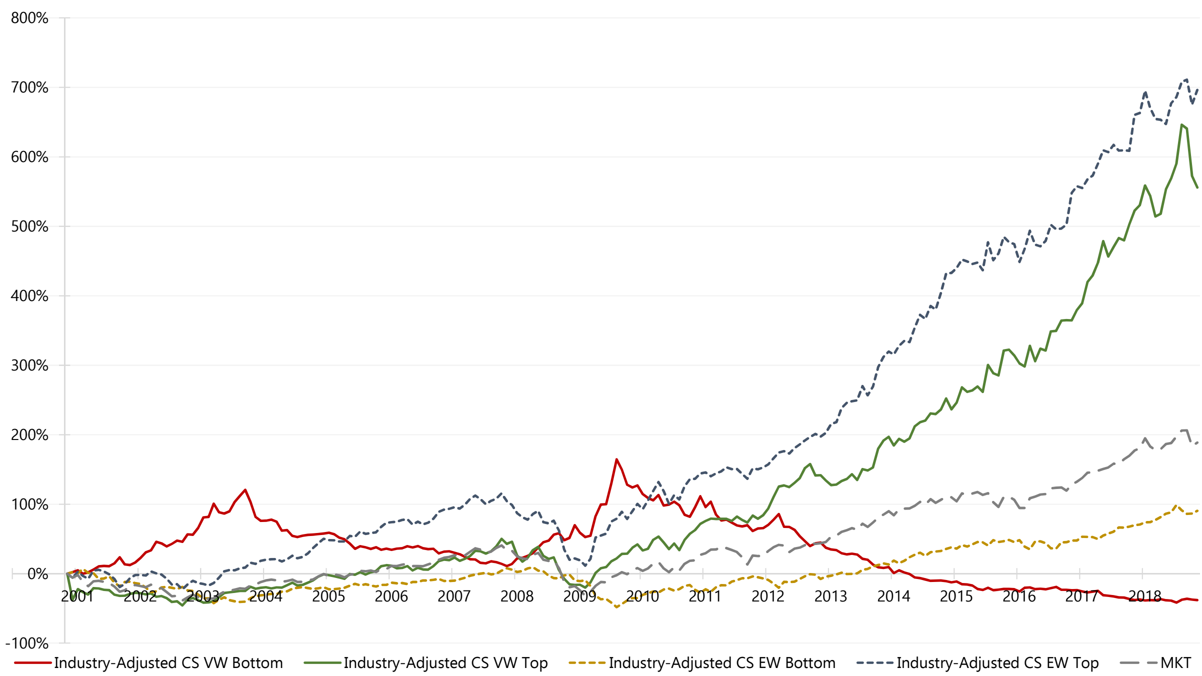
# Figure 1: Cumulative Returns of Customer Satisfaction Based Factors

This figure shows cumulative returns of two factors based on the raw and industry-adjusted customer satisfaction levels. Each month, all firms in the ACSI universe are sorted into 3 portfolios based on their 20% and 80% breakpoints according to their raw and industry-adjusted CS levels, respectively. Independently, all firms are sorted into two size groups (above (big) and below (small) the median market capitalization). The CS factor then is the difference between the equal-weighted average of the two (small and big) high CS portfolios and the equal-weighted average of the two low CS portfolios. The figure further displays the market factor (denoted S&P 500), the book-to-market (HML), profitability (RMW), and investment (CMA) factors from the Fama and French (2015) 5-factor model and the momentum (WML) factor from the Carhart (1997) 4-factor model. The factor data is from Kenneth French's website.



## Figure 2: Long and Short Leg Returns

The figure shows the cumulative excess returns over the risk-free rate of the long leg and the cumulative excess returns of the short leg over the risk-free rate for the industry-adjusted customer satisfaction level strategy. All firms in the ACSI universe are sorted into 5 portfolios based on their industry-adjusted customer satisfaction level. Industry definitions from the ACSI are used and firm-level values are demeaned by the cross-sectional monthly industry mean. Until May 2010 portfolios are rebalanced quarterly, subsequent to an ACSI reporting month. From May 2010 onward rebalancing is done monthly. The long leg represents the top portfolio and the short leg the bottom portfolio obtained from these sorts. We plot the results for both the value-weighted and equal-weighted portfolio excess returns. We also display the market excess return (MKT), defined as the return of the value-weighted CRSP index.



# A Appendix: Data and Variables

## A.1 ACSI Data

The American Customer Satisfaction Index (ACSI) relies on approximately 180,000 customer interviews per year in order to obtain the final customer satisfaction values. For this, customers are randomly asked questions about their purchase and use of specific products and service in the recent time via email.[28] Suited respondents are then asked from which company or which brand they have purchased the respective product. The surveys and interviews are mostly conducted in the quarter before the announcement of the ACSI values. The responses are then used as input to a proprietary multi-equation econometric model. It is a cause-and-effect model, which includes drivers for customer satisfaction on the left side, customer satisfaction itself in the center, and outcomes from customer satisfaction on the right side. Drivers are perceived quality, customer expectations and perceived value and outcomes are customer complaints and customer loyalty, which included customer retention and price tolerance. Each of these drivers and outcomes is measured from up to 10 elements, which consists of questions or assessments related to the respective industry products and services. The elements are weighted within the model with specific weights, such that for each driver and outcome a value between 0 and 100 is obtained, based on customer evaluations. The model subsequently quantifies the strength of the effect of the drivers on the outcomes. Eventually, customer satisfaction is obtained from this model, such that the customer satisfaction value maximizes the explanatory power of the model. The impact of the drivers is self-weighting, such that the explanatory power is maximized.

The customer satisfaction scores are reported on a 0 to 100 scale. Each firm in this index obtains a new customer satisfaction value one time per year. The point in time within a year is dependent on the industry a company belongs to. For all firms in a certain industry, the scores are reported on the same day in the same month. Until May 2010, the data was

[28] Information about the index and industry formation is from Fornell et al. (1996) and from the ACSI website: www.theacsi.org

published quarterly in February, May, August and November; in each of these months for a different set of industries. Since May 2010, the data is published monthly, such that each month for another set of industries information is released. There are a total of 42 industries, which again are ascribed to 10 different sectors. In the beginning, the industry definitions followed the SIC-codes and mainly were related to the two first digits of the SIC-codes, as described by Fornell et al. (1996). In 2004 there were slight differences in the definitions, as the industry basis changes from SIC-codes to NAICS-codes. This mainly affected the industries that were included in the time after this change, but also food service industries. In our sample period we can link ACSI data to stock market data for 230 firms with 248 stock classes. For most firms there is not a consistent ACSI time-series of 17 years, but only a fraction of the years is covered. Before filtering, each month in average there are 138 firms for which we can link customer satisfaction data to stock market data. We only keep firms with common stocks with share code 10 or 11 that trade on either the NYSE, NASDAQ or AMEX. Consequently, after filtering each month in average we are left with 132 firms.

## A.2 Construction of Relevant Variables

### Variables used in analyses

| | |
|---|---|
| Market Equity | Market equity describes the market capitalization, which is defined as shares outstanding (CSHO) times price (PRCC_F), both taken from Compustat. |
| Total Q | Total q is taken from Peters and Taylor (2017) and defined as firm value scaled by the sum of physical and intangible capital. Firm value is defined as market equity (from Compustat) plus book value of debt (DLTT+DLC) minus current assets (ACT). Physical capital is property plant and equipment (PPEGT). Intangible capital is balance sheet intangibles (INTAN) plus organizational and knowledge capital. We obtain the latter two types of capital by applying the perpetual inventory method to different types of expenses, as described in the main text. |
| Book-to-Market | Book-to-market is the book value of equity for the fiscal year ends in calendar year t-1, scaled by market equity from the end of December of year t-1. For the book equity definition we follow Fama and French (2015). |
| Gross Profitability | Gross profitability is sales (SALE) minus costs of goods sold (COGS) scaled by total assets (AT), following Novy-Marx (2013). |
| Cash-Based Operating Profitability | Cash-based operating profitability is used in Fama and French (2018) and defined as in Ball et al. (2016). It is revenues minus cost of goods sold (COGS) minus selling, general and administrative expenses before research and development expenditures (XSGA - XRD) minus the accrual component over total assets. The accrual component is the change in accounts receivable from fiscal year t-1 to fiscal year t plus the change in inventory plus the change in prepaid expenses minus the change in deferred revenue, minus the change in accounts payable, and minus the change in accrued expenses. |
| Market Leverage | Market leverage is long-term debt plus current liabilities (DLTT+DLC) scaled by the numerator plus market equity. |
| Book Leverage | Book leverage is total liabilities (LT) over total assets. |
| Operating Leverage ($\mathrm{OL}_{Reg}$) | Operating leverage is based on a regression and either the measure of Mandelker and Rhee (1984), or the detrended measure of O'Brien and Vanderheiden (1987). Depending on whether we study returns, where look-ahead bias might potentially exist, or whether we study the firm characteristic itself, we either use the Mandelker and Rhee (1984) measure in the first case, or the O'Brien and Vanderheiden (1987) measure in the second case. Mandelker and Rhee (1984) propose to regress the logarithm of earnings on the logarithm of sales in a rolling window time-series regression: $lnE_{it} = \alpha_{it} + ol_{it} lnS_{it} + \epsilon_{it}$ O'Brien and Vanderheiden (1987) claim that by this approach the growth trend of earnings relative to the growth trend of sales is primarily measured. They therefore propose to first linearly eliminate the growth trend from the logarithms before conducting the time-series regression: $\delta_{it}^{E} = \alpha_{it} + dol_{it}^{det} \delta_{it}^{S} + \epsilon_{it}$ |
| Cash Holdings | Cash holdings is cash (CH) over total assets (AT). |
| Cash Flow | Cash flow based on balance sheet data. The definition follows, among others, Peters and Taylor (2017) and is defined as the sum of income before extraordinary items (IB) and depreciation expense (DP), scaled by property, plant, and equipment (PPEGT). |
| Free Cash Flow (FCF) | Cash flow based on cash flow statement data. The proxy for free cash flow is based on the cash flow statement and defined as operating cash flow scaled by total assets. We calculate the operating cash flow as net cash flows from operating activities (OANCF) minus depreciation expense (DPC) and minus cash dividends on preferred stock (PDVC), where we set the latter to 0 if missing. |

| | |
|---|---|
| Market Beta | Market beta is computed from monthly stock return data from CRSP by regressing 36 month of firm-level excess returns on market excess returns, where we require that at least 24 months of data are available. |
| Investment Rate | The investment rate is capital expenditures (CAPX) scaled by one year lagged value of property, plant and equipment (PPEGT). |
| Momentum$_{-12,-2}$ | Month t momentum is defined as the cumulative return from month t-12 to month t-2. |
| Turnover | Turnover is trading volume (VOL) over shares outstanding (SHROUT), multiplied by 100. |
| Idiosyncratic Volatility (Ivola) | The definition of idiosyncratic volatility is following Ang et al. (2006). We compute idiosyncratic volatility as the standard deviation of the daily return residual relative to the Fama and French (1992) three-factor model in a certain month. |
| Short Interest | Short interest is shares held short from firm-level short interest data from Compustat divided by shares outstanding from CRSP. |
| Institutional Ownership | Institutional ownership is shares held by institutions from 13F filings divided by shares outstanding from CRSP. |
| MV of Assets Unexplained (CAP$^{Unex}$) | The market value of assets is defined as market capitalization (from CRSP) plus total liabilities (LT) and the explained amount of asset value is defined as organizational capital (based on 30% of SGA-XRD) plus knowledge capital (based on R&D) plus property, plant and equipment (PPEGT). The market value of assets unexplained is the market value minus the explained amount of assets, divided by the market value. |
| Fixed Assets | We define fixed assets as property, plant and equipment (PPEGT) scaled by total assets (AT). |
| Cash Flow Duration | Cash flow duration is based on the definition of Weber (2018). We compute cash flow duration as time-weighted discounted cash flows over price: $CFD_{it} = (\sum_{s=1}^{T} s{*}CF_{it-s}/(1+r)^s)/P_{it}$. Cash flows are predicted by assuming clean surplus accounting: $CF_{it+s} = E_{it+s} - (BV_{it+s} - BV_{it+s-1}) = BV_{it+s-1} * [E_{it+s}/BV_{it+s-1} - (BV_{it+s} - BV_{it+s-1})/BV_{it+s-1}]$. The growth in earnings and the growth in book equity are modeled as autoregressive process. As in Weber (2018) we use an AR(1) coefficient of 0.41 for $E_{it+s}/BV_{it+s-1}$ and 0.24 for $BV_{it+s}$. The discount-rate r is fixed at 0.12, the average cost of equity at 0.12, and the long-run nominal growth rate at 0.06. Return on equity and the growth in book equity converge to those values in the long run. We use a detailed forecasting period of 15 years and add a perpetuity for the cash flows occurring in the years thereafter. |

## Variables in long/short strategies and factors used as benchmarks

| | |
|---|---|
| OL$^{NM}$ | The operating leverage definition following Novy-Marx (2011). Operating leverage is defined as cost of goods sold (Compustat item COGS), plus selling, general and administrative expenses (item XSGA) divided by total assets (item AT), all items from the same fiscal year. |
| Vol$^{CF}$ | Cash flow volatility, where the definition is following Huang (2009). Cash flow volatility is the standard deviation of the operating cash flows-to-sales ratio. Quarterly operating cash flows are defined as income before extraordinary items (IBQ) plus depreciation and amortization (DPQ), and plus the change in working capital (WCAPQ) from the last quarter. |
| ROA | Return on assets, defined as net income (IB) scaled by total assets (AT). |

| | |
|---|---|
| Adv-Gr | Advertising Growth, defined as growth in advertising expenses, which is the growth rate of advertising expenses (XAD) from the fiscal year ending in calendar year t–2 to the fiscal year ending in calendar year t–1. |
| Adv/M | Advertising expenses-to-market, defined as advertising expenses (XAD) for the fiscal year ending in calendar year t–1 divided by market equity (from CRSP) at the end of December of year t–1. We keep only firms with positive advertising expenses. |
| R&D/M | R&D expenses-to-market, calculated as R&D expenses (XRD) from the fiscal year ending in calendar year t–1 divided by market equity (from CRSP) from the end of December of t–1. We keep only firms with positive R&D expenses. |
| Ch/At$^Q$ | Quarterly Cash-to-Assets, measured as quarterly cash holdings (CHEQ) scaled by quarterly total assets (ATQ). |
| Ea$^Q$/P | Quarterly earnings-to-price, defined as income before extraordinary items (IBQ) divided by market equity (from CRSP) from the end of month t–1. We use quarterly earnings from the most recent quarterly earnings announcement dates (RDQ). The difference between the end of the fiscal quarter and the earnings announcement date should not exceed six months. Moreover, the earnings announcement date should be after the corresponding fiscal quarter end. |
| ATLQ$^Q$ | Quarterly asset liquidity following Ortiz-Molina and Phillips (2014). They measure asset liquidity as cash holdings (CHEQ) + 0.75×non-cash current assets + 0.50×tangible fixed assets. Non-cash current assets are defined as current assets (ACTQ) minus cash. Tangible fixed assets are defined as total assets (ATQ) minus current assets (ACTQ), minus goodwill (GDWLQ), and minus intangibles (INTANQ). The term is scaled by one quarter lagged total assets. |
| CCC | The cash conversion cycle following Wang (2019). We compute the measure using quarterly data as 365*[(average inventories/cost of goods sold)+(average accounts receivable/sales)+(average accounts payable/cost of goods sold)]. The average of inventories (INVTQ), accounts receivable (RECTQ), and accounts payable(APQ) are calculated as the average of the beginning and end of quarter values. The cost of goods sold (COGSQ) and Sales (REVTQ) are the end of quarter values. |
| Tail | Tail risk, where we use the measure from Kelly and Jiang (2014). First, we estimate the common time-varying component of return tail, $\lambda_t$:<br>$\lambda_t = \frac{1}{K_t}\sum_{k=1}^{K_t} ln\frac{R_{k,t}}{u_t}$, where $R_{k,t}$ is the k$^{th}$ daily return that falls below the threshold value $u_t$, which in our case is the fifth percentile of all daily returns in month t, and $K_t$ is the total number of daily returns that are below $u_t$. Then, we estimate tail risk sensitivities of individual stocks as the slope of a regression of stock excess returns on one-month-lagged tail risk over the previous 120 months, where we require at least 36 observations. |
| Sales-Gr | Sales Growth, defined as growth in revenues, which is the growth rate of revenues (SALE) from the fiscal year ending in calendar year t–2 to the fiscal year ending in calendar year t–1. |
| Ability | Innovation ability, as discussed in Cohen et al. (2013). The measure determines how good a firm is able to turn R&D expenditures into firm value. Innovation ability is computed by running firm level rolling regressions of sales growth on the lagged logarithm of the R&D-to-Sales ratio:<br>$log(\frac{Sales_t}{Sales_{t-1}}) = ia_{itj}log(\frac{R\&D_{t-j}}{Sales_{t-j}})$<br>The regressions are run for j = [1,5]. The final measure is the average of the 5 $ia_{itj}$ coefficients obtained in the regressions. |
| Bid/Ask | The bid-ask spread based on data from CRSP. It is defined as the difference in the ask or high price and the bid or low price from CRSP. |

| | |
|---|---|
| NPY | Net payout yield, where net payout is defined as total payouts minus equity issuance. Total payouts are dividends on common stock (DVC) plus repurchases. Repurchases are the total expenditure on the purchase of common and preferred stocks (PRSTKC) plus any reduction (negative change over the previous year) in the value of the net number of preferred stocks outstanding (item PSTKRV). Equity issuance is the sale of common and preferred stock (SSTK) minus any increase (positive change over the previous year) in the value of the net number of preferred stocks outstanding (PSTKRV). The net payout yield is defined as net payout from the fiscal year ending in calendar year t–1 divided by market equity (from CRSP) from the end of December of t–1. |
| HHI | Herfindahl-Hirschman Index, measures the firm industry concentration and is defined as $\sum_{i=1}^{N_j} sales_{ij}^2$, where $\text{sales}_{ij}$ is the share of sales of a firm i in industry j, $\text{sales}_{ij} = \text{sales}_i/\text{sales}_j$, and $N_j$ is the number of firms in an industry. Industries are defined as the first three digits of the SIC-code. We exclude financial firms (SIC-code 6000 to 6999) and regulated industries, which are gas and electric utilities (4900 to 4939). |
| DTD | Distance-to-default, defined as the logarithm of book leverage over equity volatility. Book leverage is total liabilities (LT) over total assets (AT), equity volatility is the annualized standard deviation of monthly stock returns from the previous 36 months. The distance-to-default measure is based on Moody's KMV (Keaholfer, McQuown and Vasicek) model. |
| Inflex | Inflexibility, referring to a firm's scale flexibility to contract or expand its assets, employing the measurement approach of Gu et al. (2018). Inflexibility is based on quarterly data and defined as the historical range of a firm's operating costs over sales (SALEQ) ratio, scaled by the standard deviation of the logarithm of changes in sales (SALEQ) over assets (ATQ). Operating costs are the sum of costs of goods sold (COGSQ) and selling, general, and administrative expenses (XSGAQ). The historical range of the cost-to-sales ratio is the difference in its maximum and minimum value between firm quarter 0 and quarter t–1. The standard deviation of the log sales-to-assets ratio is computed over the same time period: $INFLEX_{it} = (max(\frac{OPC}{Sales})_{i0t} - min(\frac{OPC}{Sales})_{i0t})/std(\Delta log(\frac{Sales}{Assets}))_{i0t}$ |
| $\text{EM}^Q$ | The quarterly earnings multiple, as studied in Loughran and Wellman (2011). It is computed using quarterly data and defined as enterprise value scaled by earnings before interest, taxes, depreciation and amortization (EBITDAQ). Enterprise value is the market equity (from CRSP) plus total debt (DLCQ plus DLTTQ) plus preferred stock (PSTKQ) minus cash and short-term investments (CHEQ). |
| GDP/MFTRALL | Following Vassalou (2003) and Lamont (2001) we construct a factor mimicking GDP-tracking portfolio, MFTRALL, that is based on predictability of GDP growth. First, we run the following predictive regression: $\text{GDPGR}_{t,t+4} = \text{cB}_{t-1,t} + \text{kZ}_{t-2,t-1} + \epsilon_{t,t+4}$, where $\text{B}_{t-1,t}$ is a set of returns of base assets that are supposed to predict GDP-growth and $\text{Z}_{t-2,t-1}$ is a set of control variables that are supposed to predict the returns of the base assets. Our set $\text{B}_{t-1,t}$ consists of the 6 portfolios double sorted on size and book-to-market that are used to construct the HML and SMB factors, the momentum strategy return WML, the return on long-term government bonds minus the return on short-term government bonds TERM and the return on long-term corporate bonds minus the return on long-term government bonds DEF. Our set $\text{Z}_{t-2,t-1}$ of control variables consists of the risk-free rate RF, the yield spread of long-term Treasury bonds minus the T-bill rate TERMY, the yield spread of long-term corporate bonds minus the yield on long-term government bonds DEFY, the one-year inflation rate INF and the one-year growth in industrial production IPGR. The final factor is then computed with the base asset returns and the corresponding estimated sensitivities, employing monthly return data and quarterly GDP-data: $\text{GDP}_t = \text{MFTRALL}_t = \text{cB}_t$ |
| Organizational and Knowledge Capital | Intangible capital as defined in section 3. Expenses are capitalized with the perpetual inventory method. OC is based on 30% of selling, general and administrative expenses (excluding R&D expenses), $\text{OC}^{Adv}$ is based on advertising expenses, $\text{OC}^{Staff}$ is based on staff expenses, $\text{OC}^{Pension}$ is based on pension expenses and KC is based on R&D expenses. |

# Do Contented Customers Make Shareholders Wealthy? - Implications of Intangibles for Security Pricing

Internet Appendix

# A Additional Tables

Table A.1: Regular Portfolio Mean Values in Industry-Adjusted CS Portfolios

This table presents summary statistics of firm characteristics for portfolios obtained from sorts based on the industry-adjusted CS level. The columns show time-series averages of the cross-sectional portfolio means of firm characteristics and of intangible capital proxies calculated based on capitalized expenses. Firms are sorted into five portfolios based on their industry-adjusted customer satisfaction level, where the ACSI industry definitions are applied. Until May 2010 portfolios are rebalanced quarterly, subsequent to an ACSI reporting month. From May 2010 rebalancing is done monthly. Values shown for the customer satisfaction based variables, for the firm characteristics, and for the different intangible capital proxies are regular values. Variable definitions are in appendix A.2 and definitions for intangible capital proxies can be found in the main text. The proxies for capitalized intangible capital are all scaled by book value of total assets. The sample period comprises January 2001 to December 2018.

| Industry-Adjusted Customer Satisfaction Sorted Portfolios | | | | | |
|---|---|---|---|---|---|
| Portfolio | Bottom | 2 | 3 | 4 | Top |
| CS Level | 69.42 | 75.25 | 76.96 | 77.99 | 78.91 |
| Industry Demeaned CS Level | -5.35 | -1.63 | -0.10 | 1.55 | 4.97 |
| CS Delta | -0.70 | -0.26 | 0.23 | 0.82 | 0.81 |
| Industry Demeaned CS Delta | -0.91 | -0.31 | 0.02 | 0.44 | 0.58 |
| Market Equity | 23.57 | 25.12 | 27.42 | 22.65 | 24.48 |
| Market Beta | 0.899 | 0.920 | 0.913 | 0.840 | 0.876 |
| Book-to-Market | 0.764 | 0.618 | 0.624 | 0.611 | 0.564 |
| Total q | 1.071 | 1.210 | 1.319 | 1.225 | 2.206 |
| Market Leverage | 0.443 | 0.389 | 0.378 | 0.394 | 0.358 |
| Operating Leverage | 2.363 | 2.346 | 2.170 | 1.946 | 2.093 |
| Investment Rate | 0.128 | 0.107 | 0.117 | 0.105 | 0.148 |
| Gross Profitability | 0.288 | 0.358 | 0.331 | 0.334 | 0.301 |
| Price | 42.98 | 52.94 | 51.71 | 53.65 | 77.24 |
| Cash Holdings | 0.069 | 0.076 | 0.069 | 0.069 | 0.085 |
| Cash Flow | 0.222 | 0.333 | 0.314 | 0.254 | 0.243 |
| Free Cash Flow | 0.047 | 0.068 | 0.065 | 0.064 | 0.073 |
| Idiosyncratic Volatility | 1.573 | 1.399 | 1.324 | 1.319 | 1.333 |
| Short Interest | 0.044 | 0.041 | 0.035 | 0.040 | 0.036 |
| Institutional Ownership | 0.679 | 0.673 | 0.671 | 0.701 | 0.675 |
| Turnover | 0.237 | 0.204 | 0.190 | 0.203 | 0.217 |
| Capitalized Expenses | | | | | |
| Organizational Capital (SGA - XRD) | 0.101 | 0.142 | 0.124 | 0.120 | 0.084 |
| Organizational Capital (ADV) | 0.170 | 0.202 | 0.176 | 0.202 | 0.149 |
| Organizational Capital (Staff) | 0.623 | 0.517 | 0.578 | 1.069 | 1.322 |
| Organizational Capital (Pensions) | 0.018 | 0.022 | 0.020 | 0.025 | 0.022 |
| Knowledge Capital (R&D) | 0.013 | 0.024 | 0.027 | 0.022 | 0.026 |
| MV of Assets unexplained | 0.305 | 0.344 | 0.362 | 0.362 | 0.395 |

# Table A.2: Customer Satisfaction Level Strategy

The table presents results of factor-spanning regressions. All firms in the ACSI universe are sorted into 5 portfolios based on their level of customer satisfaction. Until May 2010 portfolios are rebalanced quarterly, subsequent to an ACSI reporting month. From May 2010 rebalancing is done monthly. The strategy return is the return of a self-financing portfolio that is long the high customer satisfaction portfolio and short the low customer satisfaction portfolio. Alpha is the intercept in a time-series regression of monthly strategy returns on various factor models and factor combinations. We show alphas and coefficients for value-weighted portfolios, and only alphas for equal-weighted portfolios. The benchmark models used are the same as in table 4. The sample period runs from January 2001 to December 2018, except in case of the liquidity and mispricing model, where the period only runs until December 2017 and December 2016, respectively. Returns and alphas are in monthly percent, heteroscedasticity and autocorrelation robust Newey and West (1987) t-statistics are shown below the coefficient estimates. ***, **, and * refers to statistical significance at the 1%, 5%, and 10% level, respectively.

| Model | CAPM | C4 | FF5 | FF6 | Q-Factor | Q5 | MISP | BS | FF3+ QMJ+BAB | BF |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Value-Weighted Strategy | | | | | |
| MKT | -0.052 | -0.076 | 0.051 | -0.061 | -0.025 | 0.164* | -0.078 | -0.037 | 0.045 | -0.113 |
| | (-0.646) | (-1.055) | (0.616) | (-0.690) | (-0.292) | (1.717) | (-0.858) | (-0.507) | (0.526) | (-1.131) |
| Size | | 0.031 | 0.094 | 0.030 | -0.038 | -0.063 | -0.116 | 0.151 | 0.070 | |
| | | (0.371) | (1.101) | (0.367) | (-0.460) | (-0.636) | (-1.000) | (1.571) | (0.734) | |
| HML | | -0.516*** | -0.492*** | -0.406*** | | | | -0.408*** | -0.467*** | |
| | | (-5.986) | (-3.957) | (-3.338) | | | | (-2.733) | (-5.220) | |
| UMD | | -0.067 | | -0.093* | | | | -0.357*** | | |
| | | (-1.554) | | (-1.733) | | | | (-2.872) | | |
| Investment | | | -0.221 | -0.175 | -0.517*** | -0.653** | | -0.158 | | |
| | | | (-1.252) | (-0.928) | (-3.963) | (-4.183) | | (-0.792) | | |
| Profitability | | | 0.408** | 0.253 | 0.137 | -0.135 | | 0.352** | | |
| | | | (2.549) | (1.011) | (1.034) | (-0.684) | | (2.342) | | |
| EG | | | | | | 0.590*** | | | | |
| | | | | | | (4.326) | | | | |
| QMJ | | | | | | | | | 0.246 | |
| | | | | | | | | | (1.375) | |
| BAB | | | | | | | | | -0.052 | |
| | | | | | | | | | (-0.838) | |
| MGMT | | | | | | | -0.374*** | | | |
| | | | | | | | (-3.597) | | | |
| PERF | | | | | | | 0.087 | | | |
| | | | | | | | (1.338) | | | |
| FIN | | | | | | | | | | -0.133 |
| | | | | | | | | | | (-1.249) |
| PEAD | | | | | | | | | | -0.006 |
| | | | | | | | | | | (-0.061) |
| *alpha* | 0.266 | 0.356 | 0.154 | 0.283 | 0.339 | 0.284 | 0.473 | 0.356 | 0.205 | 0.367 |
| | (1.089) | (1.541) | (0.656) | (1.044) | (1.184) | (0.942) | (1.605) | (1.400) | (0.773) | (1.233) |
| | | | | | Equal-Weighted Strategy | | | | | |
| *alpha* | 0.503* | 0.448 | 0.167 | 0.253 | 0.351 | 0.303 | 0.321 | 0.345 | 0.072 | 0.332 |
| | (1.802) | (1.526) | (0.793) | (0.918) | (1.318) | (1.358) | (1.086) | (1.295) | (0.264) | (1.241) |

# Table A.3: Alphas of Customer Satisfaction Based Strategies

The table presents time-series regression intercepts of monthly strategy returns on various factor models and factor combinations. In Panel A, the return of the value-weighted unadjusted customer satisfaction level strategy is the dependent variable. This strategy is regressed on a benchmark model that includes the market factor and a long/short factor based on the respective labelled firm characteristic. The same benchmark factors as in table 6 are employed. In Panel B strategy returns based on first differences in customer satisfaction are employed as dependent variable. The strategies are either based on the change in the CS level, compared to the last published value, or the industry-adjusted change in the CS level. Panel C uses factor returns from factor mimicking portfolios, as in table 5. The factors are based on the unadjusted CS level. In panel B and panel C the same models and factors are used as in table 4. The sample period runs from January 2001 to December 2018, except in case of the liquidity and mispricing model, where the period only runs until December 2017 and December 2016, respectively. Returns and alphas are in monthly percent, heteroscedasticity and autocorrelation robust Newey and West (1987) t-statistics are shown below the coefficient estimates. ***, **, and * refers to statistical significance at 1%, 5%, and 10% level, respectively.

Panel A: CS Level Strategy and Benchmark Returns

| | OC | OC$^{Adv}$ | OC$^{Staff}$ | OC$^{Pension}$ | KC | CAP$^{Unex}$ | OL$^{NM}$ | OL$^{Reg}$ | FCF | Vol$^{CF}$ | GDP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *alpha* | 0.168 | 0.093 | 0.214 | 0.180 | 0.210 | 0.305 | 0.160 | 0.276 | 0.114 | 0.330 | 0.321 |
| | (0.714) | (0.417) | (0.935) | (0.730) | (0.929) | (1.227) | (0.667) | (1.129) | (0.432) | (1.217) | (1.279) |
| | Adv-Gr | Adv/M | R&D/M | Ch/At$^{Q}$ | Ea$^{Q}$/P | ATLQ$^{Q}$ | CCC | Ivola | Tail | FF3+ LIQ | FF3+ STR+LTR |
| *alpha* | 0.350 | 0.296 | 0.178 | 0.295 | 0.359 | 0.256 | 0.335 | 0.313 | 0.226 | 0.390* | 0.241 |
| | (1.384) | (1.208) | (0.792) | (1.246) | (1.300) | (1.098) | (1.281) | (1.211) | (0.882) | (1.735) | (0.957) |
| | Sales-Gr | Ability | ROA | NPY | Total Q | HHI | Turnover | Bid/Ask | DTD | Inflex | EM$^{Q}$ |
| *alpha* | 0.405 | 0.277 | 0.177 | 0.364 | 0.313 | 0.312 | 0.337 | 0.391 | 0.178 | 0.266 | 0.272 |
| | (1.618) | (1.130) | (0.707) | (1.326) | (1.250) | (1.274) | (1.292) | (1.518) | (0.802) | (1.081) | (1.115) |

Panel B: Strategies Based on First Differences in CS

| Model | CAPM | C4 | FF5 | FF6 | Q-Factor | Q5 | MISP | BS | FF3+ QMJ+BAB | BF |
|---|---|---|---|---|---|---|---|---|---|---|
| Industry-Adjusted CS Delta | | | | | | | | | | |
| Value-Weighted | 0.073 | 0.155 | 0.199 | 0.200 | 0.161 | 0.330 | 0.246 | 0.144 | 0.162 | 0.188 |
| | (0.360) | (0.677) | (0.863) | (0.842) | (0.738) | (1.331) | (0.977) | (0.643) | (0.685) | (0.876) |
| Equal-Weighted | 0.107 | 0.076 | 0.093 | 0.090 | 0.081 | 0.090 | 0.031 | 0.063 | 0.068 | 0.107 |
| | (0.747) | (0.527) | (0.619) | (0.618) | (0.537) | (0.593) | (0.204) | (0.414) | (0.477) | (0.682) |
| CS Delta | | | | | | | | | | |
| Value-Weighted | 0.280* | 0.275* | 0.180 | 0.140 | 0.271 | 0.305 | 0.230 | 0.273 | 0.166 | 0.256 |
| | (1.772) | (1.741) | (1.064) | (0.720) | (1.549) | (1.524) | (1.275) | (1.503) | (0.976) | (1.262) |
| Equal-Weighted | 0.283 | 0.229 | 0.154 | 0.140 | 0.261 | 0.292 | 0.148 | 0.247 | 0.193 | 0.254 |
| | (1.626) | (1.341) | (0.717) | (0.588) | (1.419) | (1.449) | (0.714) | (1.344) | (1.052) | (1.339) |

Panel C: CS Return Factor (2x3)

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| CS Level | 0.344 | 0.393 | 0.166 | 0.200 | 0.334 | 0.291 | 0.423 | 0.335 | 0.212 | 0.312 |
| | (1.379) | (1.509) | (0.732) | (0.731) | (1.262) | (1.077) | (1.447) | (1.324) | (0.803) | (1.181) |

## Table A.4: Extreme Quintile Portfolios of Further Customer Satisfaction Strategies

This table shows the alphas of extreme quintile portfolios of further investment strategies based on customer satisfaction. The extreme quintile portfolios are the long and short leg portfolios of the various customer satisfaction based strategies. The alphas are the regression intercepts in time-series regressions of the excess returns of the long and short portfolio of the respective indicated strategy with respect to various factor models and factor combinations. The strategies are based on levels or first differences. For both cases we show the results for the unadjusted version, and for first differences we also show results for the industry-adjusted version. The factors and models employed are the same as in table 4. The sample period runs from January 2001 to December 2018, except in case of the liquidity and mispricing model, where the period only runs until December 2017 and December 2016, respectively. Returns and alphas are in monthly percent, heteroscedasticity and autocorrelation robust Newey and West (1987) t-statistics are shown below the coefficient estimates. ***, **, and * refers to statistical significance at 1%, 5%, and 10% level, respectively.

| Model | CAPM | C4 | FF5 | FF6 | Q-Factor | Q5 | MISP | BS | FF3+ QMJ+BAB | BF |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Long Leg | | | | | |
| CS Level | | | | | | | | | | |
| Value-Weighted | 0.400*** | 0.439*** | 0.222 | 0.434*** | 0.352** | 0.246 | 0.391** | 0.364** | 0.217 | 0.261* |
| | (2.874) | (3.205) | (1.647) | (2.638) | (2.185) | (1.466) | (2.447) | (2.317) | (1.379) | (1.669) |
| Equal-Weighted | 0.570*** | 0.563*** | 0.303** | 0.487*** | 0.485*** | 0.456*** | 0.523*** | 0.465*** | 0.363** | 0.389** |
| | (3.311) | (3.581) | (2.115) | (3.054) | (2.997) | (3.069) | (3.114) | (2.922) | (2.046) | (2.537) |
| Industry-Adjusted CS Delta | | | | | | | | | | |
| Value-Weighted | 0.250 | 0.288 | 0.180 | 0.236 | 0.211 | 0.073 | 0.245 | 0.202 | 0.133 | 0.104 |
| | (1.346) | (1.566) | (1.187) | (1.292) | (1.190) | (0.444) | (1.303) | (1.263) | (0.837) | (0.718) |
| Equal-Weighted | 0.365** | 0.343** | 0.213 | 0.382** | 0.319** | 0.267 | 0.324* | 0.267* | 0.232 | 0.241 |
| | (2.108) | (2.483) | (1.358) | (2.186) | (2.003) | (1.558) | (1.753) | (1.951) | (1.387) | (1.365) |
| CS Delta | | | | | | | | | | |
| Value-Weighted | 0.414*** | 0.405*** | 0.221* | 0.268* | 0.357*** | 0.187 | 0.252* | 0.360** | 0.186 | 0.246** |
| | (3.573) | (3.204) | (1.943) | (1.904) | (2.793) | (1.526) | (1.731) | (2.565) | (1.420) | (2.094) |
| Equal-Weighted | 0.458*** | 0.445*** | 0.245 | 0.408** | 0.451*** | 0.367** | 0.374* | 0.415*** | 0.339** | 0.344* |
| | (2.618) | (3.102) | (1.582) | (2.084) | (2.991) | (2.356) | (1.809) | (2.673) | (1.984) | (1.846) |
| | | | | | Short Leg | | | | | |
| CS Level | | | | | | | | | | |
| Value-Weighted | -0.134 | -0.083 | -0.069 | -0.151 | -0.013 | 0.038 | 0.082 | -0.008 | -0.012 | 0.106 |
| | (-0.818) | (-0.575) | (-0.420) | (-1.005) | (-0.070) | (0.192) | (0.396) | (-0.047) | (-0.073) | (0.530) |
| Equal-Weighted | -0.067 | -0.115 | -0.136 | -0.234 | -0.134 | -0.102 | -0.202 | -0.120 | -0.291 | -0.056 |
| | (-0.269) | (-0.479) | (-0.636) | (-1.032) | (-0.650) | (-0.467) | (-0.784) | (-0.568) | (-1.055) | (-0.218) |
| Industry-Adjusted CS Delta | | | | | | | | | | |
| Value-Weighted | 0.177 | 0.133 | -0.018 | 0.036 | 0.050 | -0.257 | -0.001 | 0.058 | -0.029 | -0.084 |
| | (1.103) | (0.719) | (-0.098) | (0.187) | (0.290) | (-1.422) | (-0.004) | (0.318) | (-0.154) | (-0.538) |
| Equal-Weighted | 0.258 | 0.266* | 0.120 | 0.292* | 0.238 | 0.176 | 0.293* | 0.203 | 0.164 | 0.135 |
| | (1.395) | (1.727) | (0.749) | (1.784) | (1.430) | (1.016) | (1.960) | (1.266) | (0.948) | (0.857) |
| CS Delta | | | | | | | | | | |
| Value-Weighted | 0.134 | 0.130 | 0.041 | 0.128 | 0.085 | -0.117 | 0.022 | 0.087 | 0.020 | -0.010 |
| | (0.901) | (0.938) | (0.298) | (0.821) | (0.653) | (-0.737) | (0.151) | (0.652) | (0.132) | (-0.075) |
| Equal-Weighted | 0.175 | 0.216 | 0.091 | 0.268 | 0.190 | 0.075 | -0.226 | -0.167 | -0.146 | -0.090 |
| | (0.905) | (1.196) | (0.443) | (1.372) | (1.102) | (0.413) | (-1.101) | (-0.952) | (-0.611) | (-0.471) |

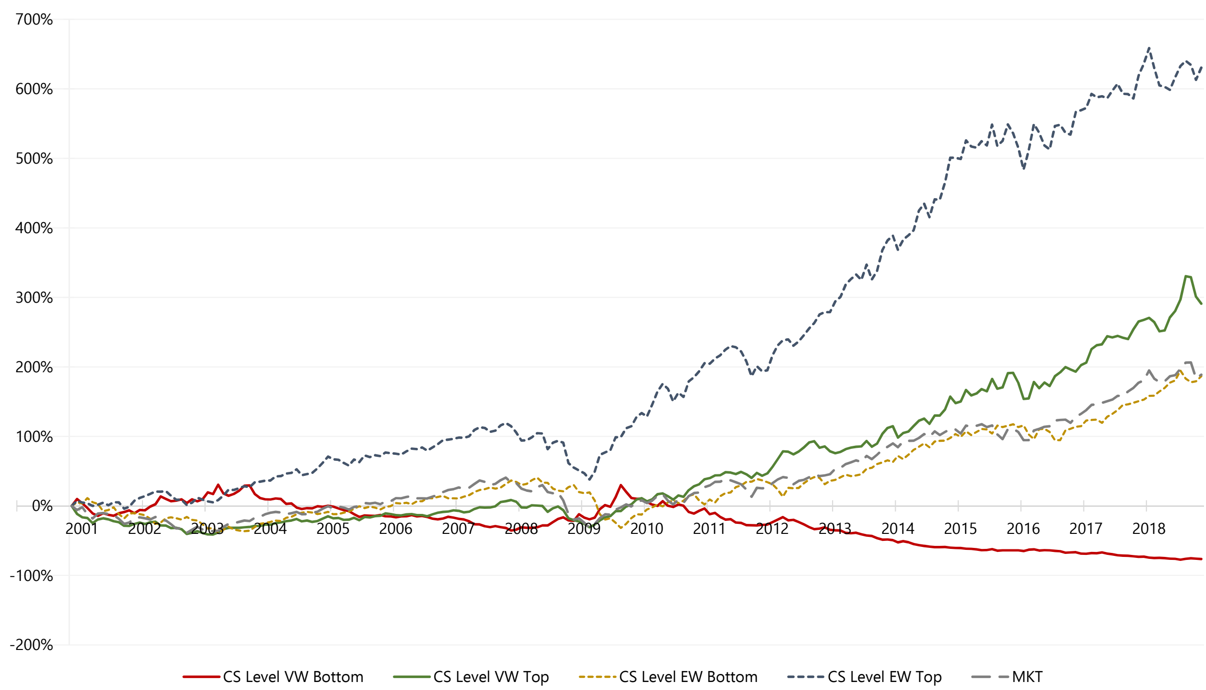
## Table A.5: Fama and MacBeth Regressions with Further Customer Satisfaction Variables

The table reports results from Fama and MacBeth (1973) regressions of returns on the trading signal for the unadjusted customer satisfaction level, or the first differences in the industry-adjusted or unadjusted customer satisfaction level. Regressions include various controls. The variable definitions can be found in appendix A.2. The independent control variables are winsorized at the 1% and 99% levels. The sample covers January 2001 to December 2018. Test statistics are in parentheses. The time-series averages of the coefficient estimates and their associated time-series t-statistics are reported. ***, **, and * refers to statistical significance at the 1%, 5%, and 10% level, respectively.

| | Regressions of the form $r_{i,t+1} = \beta' x_{i,t} + \epsilon_{i,t}$ | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | | | CS Level | | | | | Ind-Adj CS Delta | | | | | CS Delta | | |
| CS Variable | 0.029 | 0.014 | 0.021 | 0.013 | 0.023 | 0.010 | 0.002 | 0.002 | 0.008 | -0.007 | 0.033* | 0.043** | 0.022 | 0.022 | 0.014 |
| | (1.190) | (0.689) | (1.198) | (0.719) | (1.199) | (0.610) | (0.104) | (0.135) | (0.527) | (-0.468) | (1.802) | (2.539) | (1.407) | (1.457) | (0.832) |
| Total q | | 0.047 | | | | | 0.041 | | | | | 0.035 | | | |
| | | (1.053) | | | | | (0.929) | | | | | (0.778) | | | |
| Beta | | 0.153 | 0.251 | -0.121 | -0.341 | | 0.111 | 0.287 | -0.083 | -0.334 | | 0.115 | 0.297 | -0.091 | -0.337 |
| | | (0.545) | (1.099) | (-0.512) | (-1.478) | | (0.395) | (1.216) | (-0.334) | (-1.395) | | (0.410) | (1.259) | (-0.368) | (-1.392) |
| Operating Leverage (Reg) | | -0.070** | | -0.042** | | | -0.072** | | -0.043** | | | -0.068** | | -0.041** | |
| | | (-2.492) | | (-2.164) | | | (-2.454) | | (-2.174) | | | (-2.355) | | (-2.055) | |
| Operating Leverage (NM) | | | -0.003 | | -0.036 | | | -0.046 | | -0.036 | | | -0.053 | | -0.040 |
| | | | (-0.019) | | (-0.271) | | | (-0.352) | | (-0.279) | | | (-0.400) | | (-0.311) |
| Market Leverage | | -1.029** | | | | | -1.215*** | | | | | -1.166** | | | |
| | | (-2.182) | | | | | (-2.697) | | | | | (-2.581) | | | |
| Free Cash Flow | | -0.383 | | | | | -0.523 | | | | | -0.447 | | | |
| | | (-0.254) | | | | | (-0.346) | | | | | (-0.296) | | | |
| Log Size | | | -0.149** | -0.093 | -0.051 | | | -0.167** | -0.108 | -0.081 | | | -0.166** | -0.109 | -0.079 |
| | | | (-2.175) | (-1.207) | (-0.630) | | | (-2.451) | (-1.374) | (-0.935) | | | (-2.436) | (-1.400) | (-0.913) |
| Book-to-Market | | | 0.197** | | | | | 0.245** | | | | | 0.252** | | |
| | | | (2.255) | | | | | (2.125) | | | | | (2.156) | | |
| Profitability | | | 0.639 | | | | | 0.921** | | | | | 0.937** | | |
| | | | (1.625) | | | | | (2.205) | | | | | (2.264) | | |
| Asset Growth | | | 0.461 | | | | | 0.478 | | | | | 0.460 | | |
| | | | (1.189) | | | | | (1.230) | | | | | (1.173) | | |
| Turnover | | | -0.809 | | | | | -1.226 | | | | | -1.288 | | |
| | | | (-0.911) | | | | | (-1.288) | | | | | (-1.340) | | |
| Idiosyncratic Volatility | | | -0.304** | -0.276 | | | | -0.345** | -0.320* | | | | -0.337** | -0.312* | |
| | | | (-2.124) | (-1.540) | | | | (-2.197) | (-1.757) | | | | (-2.124) | (-1.707) | |
| Mom-12,-2 | | | | 0.007 | -0.019 | | | | 0.171 | 0.166 | | | | 0.152 | 0.139 |
| | | | | (0.012) | (-0.036) | | | | (0.281) | (0.303) | | | | (0.250) | (0.254) |
| Ret-1,0 | | | | -0.000 | 0.003 | | | | 0.001 | 0.003 | | | | 0.001 | 0.003 |
| | | | | (-0.022) | (0.231) | | | | (0.063) | (0.240) | | | | (0.085) | (0.194) |
| Orga. Capital (SGA-XRD) | | | | 0.500 | 0.142 | | | | 0.526 | 0.227 | | | | 0.591 | 0.341 |
| | | | | (0.578) | (0.144) | | | | (0.591) | (0.229) | | | | (0.662) | (0.346) |
| Orga. Capital (ADV) | | | | -0.124 | -0.324 | | | | -0.157 | -0.283 | | | | -0.219 | -0.317 |
| | | | | (-0.266) | (-0.672) | | | | (-0.347) | (-0.615) | | | | (-0.479) | (-0.681) |
| Cash-to-Assets | | | | | 1.086* | | | | | 1.081* | | | | | 1.035 |
| | | | | | (1.795) | | | | | (1.681) | | | | | (1.615) |
| Short Interest | | | | | 0.017 | | | | | -0.003 | | | | | -0.002 |
| | | | | | (0.500) | | | | | (-0.100) | | | | | (-0.070) |
| Tail Risk | | | | | 0.003 | | | | | 0.001 | | | | | 0.002 |
| | | | | | (1.042) | | | | | (0.445) | | | | | (0.469) |

Figure A.1: Long and Short Leg Returns of Unadjusted CS Level Strategy

This figure shows the cumulative excess returns over the risk-free rate of the long and the short leg of the unadjusted customer satisfaction level strategy. All firms in the ACSI universe are sorted into 5 portfolios based on their unadjusted customer satisfaction level. Until May 2010 portfolios are rebalanced quarterly, subsequent to an ACSI reporting month. From May 2010 rebalancing is done monthly. The long leg represents the top portfolio and the short leg the bottom portfolio obtained from these sorts. We plot the results for both the value-weighted and equal-weighted portfolio excess returns. We also display the market excess return (MKT), defined as the return of the value-weighted CRSP index.



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