Company Name Fluency, Investor Recognition, and Firm Value

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Abstract

We find companies with short, easy to pronounce names have higher breadth of ownership, greater share turnover, and lower transaction price impacts. The relation is stronger among small firms and is consistent with companies with more fluent names having higher levels of investor recognition. Fluent company names also translate into higher valuations. After controlling for size and proxies for growth, we find that firms with more fluent names have higher Tobin's Q and market-to-book ratios. Corporate name changes increase fluency on average, and fluency improving name changes are associated with increases in breadth of ownership, liquidity, and firm value.

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1. Introduction

Choosing from among the thousands of stocks to invest in is a difficult decision for most people. When making complicated choices, research from psychology suggests people simplify the task by relying on mental shortcuts (Tversky and Kahneman, 1973). One input shown to be influential in the decision making process is fluency, or the ease with which people process information. Research has established that fluency has an impact on judgment that is independent of the content of the information.[1] Specifically, fluent stimuli have been shown to appear more familiar and likeable than similar but less-fluent stimuli, resulting in higher judgments of preference (Alter and Oppenheimer, 2009 provide a review).

The observation that fluency gives rise to feelings of familiarity and affinity suggests it may influence investor behavior. A number of studies show that investors are drawn to familiar stocks. French and Poterba (1991) document that investors overweight domestic stocks in their portfolios, and Coval and Moskowitz (1999, 2001) and Huberman (2001) find that fund managers prefer investing in locally headquartered firms.[2] There is also evidence that affect influences investment decisions. For example, Statman, Fisher, and Anginer (2008) present a theory in which admired companies have higher valuations, and they find corresponding empirical evidence of lower returns among *Fortune's* most admired companies. Similarly, Hong and Kacperczyk (2009) find

[1] For example, Schwarz et al. (1991) ask participants to recall examples of assertive behavior and find those asked to recall six examples (an easy task) later rate themselves as being more assertive than those asked to recall twelve examples (a difficult task). Participants emphasize ease of recall over the information gathered by the exercise.

[2] Other work that suggest familiarity can influence investment decisions includes: Cooper and Kaplanis (1994), Benartzi (2001), Grinblatt and Keloharju (2001), Pagano et al. (2002), Sarkissian and Schill (2004), Seasholes and Zhu (2009), Massa and Siminov (2006), and Cohen (2009).

"sin" stocks (e.g. alcohol, tobacco, and gaming companies) have lower analyst coverage and higher expected returns than otherwise comparable stocks.[3]

In this article, we investigate a new channel by which familiarity and affinity may influence investor behavior. Specifically, we examine the effects of company name fluency on breadth of ownership, liquidity, and firm value. Marketing research has long emphasized the importance of product names. For example, Bao, Shao, and Rivers (2008) document that products with easy to pronounce names exhibit increased brand recognition. Cooper, Dimitrov, and Rau (2001) suggest the choice of company name may be important to investors as well. They find significant event period returns for firms with name changes to dotcom names during the internet boom. In related work, Cooper, Gulen, and Rau (2005) find mutual funds receive increased flows following name changes which incorporate recently successful styles. Our emphasis is not on the information signaled by a company name but rather the ease with which the information is processed by investors.

We hypothesize that companies with names that are easy to mentally process (i.e. fluent names) will experience higher levels of breadth of ownership, improved liquidity, and higher firm values. Practically speaking, when choosing from among drug manufacturers, people may instinctively feel more comfortable investing in a name like *Forest Laboratories* than the less fluent *Allergan Ligand Retinoid Therapeutics*. We operationalize this idea by developing a measure of company name fluency based on length and ease of pronunciation. Oppenheimer (2006) finds evidence that short, simple

[3] There is evidence consistent with affect influencing aggregate market returns as well. For example, Hirshleifer and Shumway (2003) find that stock market returns are higher on sunny days, and Edmans, Garcia, and Norli. (2007) find that losses in soccer matches have a significant negative effect on the losing country's stock market.

words are processed more fluently, which activates positive affective states and biases statement evaluation. Along these lines, we reason that shorter company names are easier to process than longer names (e.g. *Google* vs. *Albuquerque Western Solar Industries*), and we develop a length score based on the number of words in a company name.

Research in psychology suggests ease of pronunciation also has an impact on fluency and decision making. For example, Song and Schwarz (2009) ask participants to evaluate fictional food additives and amusement park rides and find that less fluent names (e.g. *Hnegripitrom* and *Vaiveahtoishi*) are considered to be riskier than more fluent choices (e.g. *Magnalroxate* and *Chunta*). In a financial setting, Alter and Oppenheimer (2006) find survey participants predict significantly higher future returns for fictional companies with more fluent names (e.g. *Barnings* vs. *Xagibdan*).

We examine two fluency proxies that correlate with ease of pronunciation. Our first measure is the "Englishness" algorithm of Travers and Olivier (1978) which evaluates an expression based on the frequency with which its letter clusters appear in the English language. Our second approach examines whether all the words in a company name comply with a spell-check filter, based on the idea that company names that contain dictionary words are on average easier to pronounce than proper nouns or coined expressions (e.g. *PharMerica* or *Genoptix*).

We first investigate whether company name fluency affects breadth of ownership and stock liquidity. We find companies with short, easy to pronounce names have higher levels of breath of ownership, greater share turnover, and lower levels of Amihud's (2002) illiquidity measure. The results are robust to firm controls and hold among both retail investors and mutual fund managers. The results are weaker among older and larger firms, which is consistent with the idea that less fluent names become familiar through repeated exposure (e.g. *Xerox*). Together, the evidence supports the view that companies with fluent names more easily attract investors.

We next investigate the relationship between fluency and firm value. We expect the familiarity and affinity associated with fluency to generate excess demand for companies with fluent names relative to companies with non-fluent names. If demand curves for stocks are downward sloping (e.g. Shleifer, 1986, and Kaul, Mehrotra, and Morck, 2000), then these differences in demand should translate into differences in valuation. Moreover, the effects of fluency on breadth of ownership and liquidity may also have important implications for firm value. For example, Merton's (1987) investor recognition hypothesis suggests breadth of ownership influences valuation. Specifically, Merton (1987) develops a model in which investors are only aware of a subset of available securities and trade within this subset. The resulting lack of diversification introduces risk, with firms with lower investor recognition receiving lower valuations and higher investment returns.[4] In other work, Amihud and Mendelson (1986) show that firms with higher levels of liquidity have lower required rates of returns and therefore higher firm values.

Consistent with this reasoning, we find that firms with more fluent names have significantly higher Tobin's Q and market-to-book ratios. After controlling for return on equity and other proxies for growth opportunities, we find that companies with the most fluent names trade at a 10.4% premium to those with the least fluent names. For the median size firm in our sample this translates into an additional $15.4 million in added

[4] Several papers find empirical support for Mertons's (1987) investor recognition hypothesis including Kadlec and McConnell (1994), Foerster and Karolyi (1999), Chen, Noronha, and Singal (2004), Hong, Kubik, and Stein (2008), and Bodnaruk and Ostberg (2009).

value. Similar to the results for breadth of ownership, we find the connection between company name fluency and valuation weakens among larger and older firms. Moreover, we find that after controlling for breadth of ownership and liquidity, the fluency premium is cut in half, which suggests that breadth of ownership and liquidity are channels through which company name fluency increases firm value.

We next investigate the effects of fluency altering name changes. Our sample consists of 2,410 firms that have variation in their fluency score over time. We document that name changes significantly increase fluency on average, which is consistent with an awareness on the part of firms of the importance of name fluency. Moreover, using fixed effect regressions we find that within-firm variation in fluency score is significantly related to breadth of ownership, liquidity, and firm value. For example, changing a company name from highly non-fluent to highly fluent is associated with a 21.88% increase in retail breadth of ownership, an 11.64% increase in total turnover, and a 4.52% increase in firm value.

The remainder of the paper is organized as follows. Section 2 describes the data and our method for measuring fluency and presents descriptive statistics; Sections 3 and 4 examine the effects of company name fluency on breadth of ownership and liquidity; Section 5 examines the value implications of name fluency for stocks; Section 6 presents additional analysis, and Section 7 concludes.

2. Data and methodology

2.1 Sample selection

Our initial sample includes all securities with sharecodes 10 or 11 (e.g. excluding ADR's, closed-end funds, REIT's) that are contained in the intersection of the CRSP monthly return file and the COMPUSTAT fundamentals annual file between 1982 and 2009.[5] We obtain historical company names from CRSP and begin by expanding CRSP abbreviations. For example, 'COMMONWEALTH TELE ENTRPS INC' is changed to "Commonwealth Telephone Enterprises Inc." If a CRSP abbreviation is ambiguous (e.g. "TELE" could stand for telephone, telecommunications, television, etc.), we check the SEC Edgar system to obtain the company legal name (i.e. the official company name as reported on its SEC filings). After satisfying the data requirements, our final sample consists of 14,926 companies, 18,585 unique company-names, and 133,400 firm-year observations.

2.2 Measures of company name fluency

Alter and Oppenheimer (2009) define fluency as "the subjective experience of ease with which people process information." We are specifically interested in linguistic fluency, which concerns phonological and lexical simplicity as opposed to other forms of fluency such as visual clarity, etc. For example, McGlone and Tofighbakhsh (2000) find rhyming aphorisms are considered to be more true than similar non-rhyming versions (e.g. *Woes unite foes* vs. *Woes unite enemies*). Oppenheimer (2006) finds substituting simpler alternatives for more complex words into college admission essays (e.g. *use* vs. *utilize*) improves assessments of the writer's intelligence. In other work, Shah and Oppenheimer (2007) find survey participants place more emphasize on stock recommendations from (hypothetical Turkish) brokerage firms with easier to pronounce names (e.g. *Artan* vs. *Lasiea*).

[5] Prior to 1982, volume data was unavailable for NASDAQ firms. We repeat our analysis for all NYSE and AMEX firms from 1963-2008 and find similar results.

In a similar way, we hypothesize that investors may instinctively prefer stocks with fluent company names. We measure name fluency along three dimensions. First, we reason that shorter company names are likely to be easier to mentally process. In order to measure company name length, we first remove expressions that are part of the legal name but are often omitted when referring to the company. Specifically, we exclude expressions like Co., Corp., Inc., Ltd., LLC, and FSB if they are the last expression in the company name. We also exclude conjunctions (e.g. *and*, *or*, and *the*) and drop the state of incorporation, which is frequently reported in bank names. Thus, "Home & City Savings Bank/NY" is modified to "Home City Savings Bank." After these adjustments, we count the number of words in a company name. Company names containing one word (e.g. *Google* or *Microsoft*) are given a *length score* of 3, two words (e.g. *Sun Microsystems*) are given a *length score* of 2, and greater than two words (e.g. *Albuquerque Western Solar Industries*) are given a *length score* of 1.[6]

We also examine two measures of name fluency related to ease of pronunciation. Our first approach is the linguistic algorithm developed by Travers and Olivier (1978) to assess the "Englishness" of a given word. The Englishness (E) of an n-letter string $\#L_1,L_2,\ldots,L_n\#$ (where # denotes "space" and L_i denotes the letter in the ith position in the string) is defined as the probability that the string will be generated by the rule:

$$\begin{aligned} E &= P\left(\# L_1 L_2 \ldots L_{n-1} L_n \#\right) \\ &= P(\#)\cdot P\left(L_1 \mid \#\right)\cdot P\left(L_2 \mid \# L_1\right)\cdot P\left(L_3 \mid L_1 L_2\right),\ldots,P\left(L_n \mid L_{n-2} L_{n-1}\right)\cdot P\left(\# \mid L_{n-1} L_n\right) \end{aligned} \tag{1}$$

where each conditional probability $P\left(L_k \mid L_{k-2} L_{k-1}\right)$ is the probability that letter L_k follows letters L_{k-2} and L_{k-1} in printed English. Intuitively, the trigam "THE" appears in printed

[6] The results are very similar when using 1/ the number of words in the company name to measure length.

English roughly 500 times more often than the trigram "THL" (i.e. $P(E|TH) > P(L|TH)$). Thus, words that contain the trigram "THE" will be viewed as more English than words that contain the trigam "THL."

The probability expression in Equation (1) is estimated by substituting relative bigram and trigram frequencies $F(L_{k-2}L_{k-1}L_k)/F(L_{k-2}L_{k-1})$ in for $P(L_k | L_{k-2}L_{k-1})$. Negative logs are also taken to create a positive Englishness score that generally ranges between 1 and 20. Specifically, E is estimated as:

$$E' = -\left[\log F(\#L_1L_2) + \log\frac{F(L_1L_2L_3)}{F(L_1L_2)} + \cdots + \log\frac{F(L_{n-1}L_nL_\#)}{F(L_{n-1}L_n)}\right]. \qquad (2)$$

We estimate $F(L_{k-2}L_{k-1}L_k)$ using data from *The Corpus of Contemporary American English* which provides detailed estimates on the frequency of English words from over 160,000 texts from 1990 to 2010.[7] Travers and Olivier (1978) show that statistical Englishness (E') is correlated with other measures of pronounceability and facilitates recall in tests of word recognition. In practice Englishness is correlated with word length, and we control for this tendency by regressing Englishness on word length and using the residuals as our measure of Englishness.

Since one highly non-English word can considerably reduce the fluency of a company name, we focus on the word with the lowest Englsishness score within the company name. We then rank companies based on their minimum Englishness score. Companies in the bottom quintile of Englishness are given an *Englishness* score of 0, and all other companies are given an *Englishness* score of 1.

[7] The dataset is maintained by Mark Davies, Professor of Corpus Linguistics at Bringham Young University and is available at: http://corpus.byu.edu/coca. Our sample consists of the top 60,000 English words with frequency of appearance in the corpus.

Our final measure of fluency is based on word familiarity which is also related to ease of pronunciation. We propose that words that appear in the English dictionary are likely to be more familiar and recognizable on average than proper nouns or created expressions (e.g. *PharMerica* or *Genoptix*). To operationalize this idea, we examine whether each word within the (adjusted) company name passes through Microsoft spell check in all lower-case letters. If all words in the company name pass through the spell check filter then the company is given a *dictionary* score of 1. All other company names are given a *dictionary score* of 0. Our primarily measure of company name fluency is an aggregate score which is the sum of the *length*, *Englishness*, and *dictionary* scores.

2.3 Other variable construction

For each firm, we collect data on share price, shares outstanding, stock returns, volume, exchange membership, and SIC codes from CRSP. We obtain data on book value of equity, book value of debt, book value of assets, S&P 500 membership, the number of industry segments in which the firm operates, advertising expenditures, research and development expenditures (R&D), net income, earnings before interest taxes depreciation and amortization (EBITDA), and sales from COMPUSTAT. For each firm-year we compute the following variables:

- *Size* – market capitalization computed as share price times total shares outstanding at the end of the year.
- *Age* – the number of months since a firm's first return appeared in CRSP.
- *BM* – book-to-market ratio computed as the book value of equity for the fiscal year ended before the most recent June 30th, divided by the market capitalization on December 31st of the same fiscal year.
- *Volatility* – the standard deviation of monthly returns during a given year.
- *Turnover* – average monthly turnover (i.e. share volume scaled by shares outstanding) over the 12 months in the year.

- *Momentum* – the return on the stock over the past two to twelve months, measured at the end of the year.
- *NYSE*– a dummy variable which equals one if the firms trades on the NYSE and zero otherwise.
- *S&P 500* – a dummy variable which equals one if the firm belongs to the S&P 500 and zero otherwise.
- *Illiquidity* – the Amihud (2002) measure computed using all daily data available for a given year.
- *Adv/Sales (R&D/Sales)* – total advertising expenditures (research and development expenditures) scaled by total sales. Following Himmelberg, Hubbard, and Palia (1999) we set missing values of *Adv*/Sales, and *RD/Sales* to 0 and include an indicator variable that equals one when there is a missing value, and zero otherwise.
- *Profitability* – EBITDA scaled by book value of assets. We set negative values of profitability to zero and include an indicator variable that equals one when there is a negative value and zero otherwise.
- *Growth* –sales growth measures over the past three years. If less than three years of sales data is available, sales growth is estimated using all available data. If no information on prior sales is available, we set sales growth to zero and including an indicator variable that equals one when there is a missing value, and zero otherwise.
- *Leverage* – book value of debt scaled by book value of assets.
- *Asset Turnover* – sales divided by book value of assets.
- *Payout* – the sum of dividends and repurchases divided by net income.
- *Tobin's Q* – Enterprise Value (debt plus market equity) scaled by book value (debt plus book equity).
- *MF Breadth* – the number of unique mutual funds holding the firms' stock at the end of the given year. The number of mutual fund shareholders is computed from the Thomson Financial *S12 files.*
- *Retail Breadth* – the number of retail investors holding the firm's stock at the end of the given year. The number of retail shareholders is taken from a large discount brokerage that contains the holdings of 78,000 households from January 1991 to November 1996.[8]
- *Retail Turnover* – is the average monthly retail turnover over the 12 months in the year and is also computed using the discount brokerage dataset.

[8] Other papers that use this data include Barber and Odean (2000, 2001) and Kumar (2009).

With the exception of *Ret Breadth and Ret Turn* which span from 1991-1996, all other variables are computed each year from 1982-2009.

2.4 Descriptive Statistics

Table 1 presents the time-series average of annual cross-sectional summary statistics computed from 1982-2009. In an average year, our cross section includes 4600 firms. The average firm has a market capitalization of $1.6 billion, annual turnover of a 101%, and a book-to-market ratio of 0.69. We can also see the means of most of our variables are significantly larger than the medians. In order to reduce the effects of outliers on the analysis, we use log-transformations for most of our regression analysis.

We also present summary statistics for stocks sorted on their aggregate fluency score. We see that the distribution is bell-shaped; with relatively few firms being either highly fluent (i.e. fluency score =5) or highly non-fluent (i.e. fluency score = 1).[9] In unreported results, we find that roughly 23% of firms have a length score of 3, 49% of firms have a length score of 2, and 28% have a length score of 1. Roughly 34% have a dictionary score of 1, and by construction, 80% of firms each year have an Englishness score of 1. Englishness score and dictionary score are positively correlated (ρ = 0.25), and both are negatively correlated with length score (ρ = -0.07, and -0.26, respectively).

Table 1 reveals that fluency scores also appear correlated with certain firm characteristics. Fluent companies (i.e. those with a fluency score of 4 or more) tend to be larger, as measured by both market capitalization and sales, and older than non-fluent

[9]Examples of company names with fluency scores equal to 1 include: Knape & Vogt Manufacturing Co., Aehr Test Systems, John F. Lawhon Furniture Co., Teknekron Communications Systems Inc., American Xtal Technology Inc., Mehl-Biophile International Corp., and Hilb Rogal & Hobbs Co. Examples with fluency score equal to 5 include: Move Inc., Post Inc., Ball Corp., Dial Corp., Sage Inc., Dice Inc., Unit Corp., and Case Corp.

companies (i.e. those with a fluency score of 2 or less). They also tend to have higher turnover ratios, lower book-to-market ratios, and greater stock price volatility. Lastly, we see that the median fluent company tends to be more profitable than the median non-fluent company. Although the correlations are relatively modest (i.e. $\rho < 0.10$), it will be important to control for firm characteristics in our tests.

3. The effects of fluency on breadth of ownership

In this section we investigate whether investors are more likely to hold stock in companies with fluent names. Specifically, we examine whether company name fluency is related to the number of retail investors and mutual funds who own the stock. We examine this relation by estimating regressions in which the dependent variable is the natural log of the number of retail or mutual fund shareholders and our independent variables include the company name fluency score and other firm characteristics.[10]

Specifically, we estimate the following regression specification:

$$Ownership_{i,t} = a_0 + a_1 Fluency_{it-1} + \mathbf{a_2 X_{it-1}} + \varepsilon_{it}, \quad \text{i=1,...,N} \quad \text{t=1,...,T} \tag{3}$$

where fluency is the company's aggregate fluency score, $\mathbf{X_{it-1}}$ is a vector of firm characteristics, and ε_{it} is measurement error. Our hypothesis is a_1 is greater than zero. $\mathbf{X_{it-1}}$ includes a variety of firm characteristics that can help explain cross-sectional variation in breadth of ownership. For example, since breadth of ownership is likely to be strongly related to firm size, we include log(*size*) and $[\log(size)]^2$. Transaction costs and

[10] We examine retail and mutual fund ownership samples to investigate the effects of fluency on different investor types. An alternative approach is to examine the total number of shareholders from COMPUSTAT. However, COMPUSTAT ownership data are frequently missing particularly for smaller firms where the effects of name fluency are likely to be stronger. For example, in the smallest (largest) NYSE size quintiles the percentage of missing observations is 13.45% (1.83%). If we repeat the analysis using COMPUSTAT shareholder data and assume missing values are equal to 500 (the minimum listing requirement), we find a highly significant relation between breadth of ownership and fluency score. Excluding observations with missing data produces similar but statistically weaker results.

stock liquidity also influence the holdings of investors (e.g. Falkenstein, 1996), and we therefore include the reciprocal of share price (1/*Price*) and log (*turnover*). Investors may also tilt their holdings towards more profitable stocks, value stocks, momentum stocks, older stocks, and more volatile stocks (e.g. Gompers and Metrick, 2001). Thus, we include profitability (Winsorized at the 99^{th} percentile), log (*book-to-market ratio*), *momentum*, log (*age*), and log (*volatility*).

Grullon, Kanatas, and Weston (2004) show that advertising influences breadth of ownership, Kadlec and McConnell (1994) show that switching to the NYSE increases a firms' investor base, and Chen, Noronha, and Singal (2004) show that being added to the S&P 500 results in a larger investor base. To control for these effects we include log (*advertising*), *NYSE,* and *S&P 500.* Since certain industries may be more visible than others, we also include dummies based on the Fama and French (1997) 49 industry classification (using two or three digit SIC codes produces similar results). Lastly, to control for time trends, we include year dummy variables. All variables are defined as in section 2.2, and the independent variables are lagged one year relative to the dependent variable.

Table 2 presents the results of the panel regression, where t-statistics based on standard errors clustered by firm are reported in parentheses.[11] The first column indicates a positive and significant relation between the aggregate fluency score of a company name and retail shareholders. Specifically, a one unit increase in aggregate fluency score, results in a 3.92% increase in the number of retail shareholders. Alternatively, a company

[11] Petersen (2009) shows that in the presence of a firm effect standard errors clustered by firm produce unbiased standard errors regardless of whether the firm effect is permanent or temporary. In contrast, other methods, such as Fama-MacBeth (1973) or regressions with a Newey-West (1987) adjustment for serial correlation tend to understate the true standard errors.

with an aggregate fluency score of 5 is expected to have roughly 15.68% more retail shareholders than a company with an aggregate fluency score of 1. Column 2 decomposes the aggregate fluency score into the length score, Englishness score, and dictionary score. Although the coefficient on Englishness is not statistically significant, both length score and dictionary score are positively and significantly related to retail breadth of ownership. Moreover, the economic magnitudes of these effects are sizable. Reducing the length of the company by one word is associated with an increase of 4.44% in retail breadth of ownership, while company names that contain all dictionary words tend to have 6.11% more shareholders than company names that contain non-dictionary words.

Columns 3 and 4 repeat the analysis for mutual fund shareholders. One might expect mutual fund managers as sophisticated investors to be less prone to making investment decisions based on non-financial considerations. However, Coval and Moskowitz (1999) find that institutional investors prefer investing in locally headquartered firms, and Grullon, Kanatas and Weston (2004) find that institutional investors are more likely to hold firms that advertise heavily, suggesting that sophisticated investors may also have a preference for the familiar.[12] Consistent with our retail investor results, we find that fluent companies tend to be held by more mutual fund managers. Specifically, a one unit increase in fluency score is associated with 2.04% increase in mutual fund breadth of ownership. The estimate is roughly half the coefficient reported for retail shareholders, which is consistent with individual investors relying more heavily on non-financial criteria, such as the fluency of a company name, when

[12] Coval and Moskowitz (1999) argue institutional investors preference for locally headquartered firms may be rational. For example, geographic proximity may reduce information asymmetries.

making investment decisions. In column 4 we find that both length score and dictionary score are also significantly related to mutual fund breadth of ownership.

4. The effects of fluency on firm liquidity

In the previous section we show that companies with fluent names attract a larger number of retail and mutual fund shareholders. This larger investor base may result in increased trading volume and improved liquidity. We test this hypothesis by estimating panel regressions of the natural log of either retail or total turnover on fluency scores and other firm characteristics as in Equation (3). Since the decision to hold a stock and trade a stock are closely related, we use the same set of control variables as in Section 3.

The results are presented in Table 3. The first column reveals that retail turnover is significantly related to fluency scores. Specifically, a one unit increase in fluency is associated with a 5.26% increase in retail turnover. The second column reveals that both length score and dictionary score are positive and significantly related to retail turnover. Columns 3 and 4 present the results for total turnover. Total turnover is also significantly positively related to the aggregate fluency score as well as all three components of fluency. A one unit increase in the length score, Englishness score and dictionary score are associated with a 3.38%, 5.20%, and 4.30% increase in total turnover.

The results suggest that companies with more fluent names not only attract more shareholders but also generate greater amounts of trading. If much of this trading is unrelated to private information, then fluency may also reduce adverse selection costs which could result in fluent stocks having smaller price impacts. To test this idea, we use the Amihud (2002) illiquidity measure as a proxy for impact of order flow on prices. Columns 5-6 report the relationship between the natural log of the Amihud (2002) illiquidity measures and our fluency score. The results indicate that fluent firms are significantly more liquid (i.e. have smaller price impacts). Specifically, a one unit increase in fluency reduces illiquidity by 4.56%. The illiquidity measure is also significantly negative related to the length score, Englishness score, and dictionary score. Taken together, our findings suggest that stocks with fluent names are more widely held and have greater levels of liquidity than similar but less fluent companies.

5. Fluency and firm value

5.1 Baseline Specification

We investigate the effects of fluency on firm valuation by estimating regressions in which the dependent variable is a relative measure of firm value. The independent variables include the company name fluency score and a number of firm controls. Specifically, we estimate the following panel regression:

$$Value_{i,t} = a_0 + a_1 Fluency_{it-1} + \mathbf{a_2 X_{it\text{-}1}} + \varepsilon_{it}, \quad \text{i=1,...,N} \quad \text{t=1,...,T} \tag{4}$$

where fluency is the companies aggregate fluency score, $\mathbf{X_{it\text{-}1}}$ is a vector of firm characteristics, and ε_{it} is measurement error. Our hypothesis is that a_1 is greater than zero, which is consistent with several related hypotheses:

H1: The joint hypothesis that fluency influences demand and demand curves for stocks are downward sloping (e.g. Shleifer, 1986).

H2: The joint hypothesis that fluency is associated with higher breadth of ownership (as shown in section 3) and greater breadth of ownership leads to higher valuations (e.g Merton, 1987).

H3: The joint hypothesis that fluency is associated with improved liquidity (as shown as section 4) and higher liquidity results in elevated firm valuations (e.g. Amihud and Mendelson, 1986).

Our two primary measures of firm value are market-to-book value of equity and Tobin's Q, the ratio of enterprise value (debt plus market equity) to book value (debt plus book equity). We exclude observations with negative book values of equity. We take the natural log of both variables in order to reduce the impact of outliers.[13]

Our vector of firm characteristics, $\mathbf{X_{it-1}}$ include several variables to control for differences in growth opportunities, non-tangible assets, and agency problems.[14] To control for growth opportunities we include *Growth,* defined as sales growth over the past three years, log (*age)*, and log (*sales*)*.* We also include a firm's *profitability* (EBITDA/Assets). We set negative values of *profitability* to zero and include a corresponding negative *profitability* indicator variable. We also Winsorize profitability at the 99th percentiles. Firms with high R&D may also have better growth options. Moreover, R&D is an intangible asset that is often not captured in the book value. Similarly, advertising may increase firm value through improved brand recognition but does not have a direct effect on book value. Lastly, firms with high asset turnovers likely have a large amount of intangible assets, which is likely to be associated with a low book value and a high Tobin's Q. To control for these effects, we include *R&D/Sales*, *Adv/Sales* (both Winsorized at the 99%)., and *Asset Turnover* (Winsorized at the 1st and 99th percentile).

To control for agency problems, we include *Leverage* and *Payout.* Both reduce free cash flows available to the manager and therefore limit the manager's ability to implement value destroying investment decisions. *Leverage,* and *Payout* are both

[13] Hirsh and Seaks (1993) highlight that "firm and industry characteristics have multiplicative rather than additive effects on the market valuations of company assets, and provide a strong presumption for employing ln(Q) rather than Q." We show in Table 5 the results are not sensitive to taking logs.

[14] Our list of valuation controls is based on Edmans, Goldstein, and Jiang (2010) who also provide more detailed justifications.

Winsorized at the 1st and 99th percentile. We control for the diversification discount (e.g. Lang and Stulz (1994)) by including the log of the total number of industry segments in which the firm operates. We also include *NYSE,* and *S&P 500* since exchange membership and index membership may affect a firm's investor base and liquidity. Lastly, we include year dummies and industry dummies based on the Fama and French (1997) 49 industry classification. All independent variables are lagged one year relative to the dependent variable.

Table 4 presents the results of the panel regression where t-statistics based on standard errors clustered by firm are reported in parentheses. The first column indicates that Tobin's Q is positive and significantly related to fluency scores. A company name with a fluency score of 5 is expected to have a 7.64% higher valuation than a company with a fluency score of 1. Moreover, all three components of the fluency score are significantly and positively related to Tobin's Q. Not surprisingly, columns 3 and 4 reveal a similar relationship between fluency score and market-to-book ratio. A company name with a fluency score of 5 is expected to have a 10.4% higher valuation than a company with a fluency score of 1. For the median size company in our sample this difference translates into an additional $15.4 million in added market capitalization.

5.2 Alternative Specifications

In Table 5, we examine the robustness of the relationship between fluency score and firm value. For the sake of brevity, in each row we now report only the coefficient estimate on fluency score and any new variables added to the specification. We report results for Tobin's Q; the results for market-to-book are very similar.[15] For reference, the first row of Table 5 reports the coefficient and t-statistic on fluency score in our baseline specification.

In Row 2, we repeat the analysis using the Fama-Macbeth (1973) methodology. The estimate from the Fama-Macbeth regression is similar in magnitude to the panel regression result and is highly significant. We also note that the standard error from the Fama-MacBeth estimate is significantly smaller than the standard error from the panel regression clustered by firm which highlights the importance of computing standard errors clustered by firm.[16]

Since the meaning of certain variables are often different for financial companies (e.g. leverage), in Row 3 we repeat our analysis excluding all financial companies (SIC code 6000-6999). The fluency score coefficient increases slightly, indicating that our results are not driven by financial firms. To verify that our results are not driven by outliers, in Row 4 we Winsorize the log of Tobin's Q at the 1% and 99% percentile. The coefficient on fluency score remain very similar suggesting that our results are not driven by outliers. Row 5 repeats the analysis using the raw value (i.e the non-logged value) of Tobin's Q. We see that a one unit increase in fluency score is associated with a 0.05 increase in Tobin's Q. The average (median) firm has a Tobin's Q of 2.06 (1.30). Thus, a 0.05 corresponds to a 2.43% (3.85%) increase, both of which are larger than the 1.94% predicted increase in our baseline specification (using a Winsorized value of Q leads to similar conclusions).

[15] We also repeat this type of analysis for breadth of ownership and liquidity. The results in Tables 2 and 3 are robust to various specifications.

[16] We also implement Fama-MacBeth (1973) regressions with a Newey-West (1987) adjustment for serial correlation. This approach still typically yields smaller standard errors than our panel regression approach with standard errors clustered by firm.

In Row 6 we add 4 digit SIC dummies. Adding a finer industry partition does reduce the coefficient on fluency, although this effect is not surprising. Using 4 digit SIC codes results in 641 different industry dummies with the average (median) industry containing 5.5 (2) different firms per year. If the median industry contains only two firms, then much of the variation in fluency scores is likely to occur at the industry level, which would be captured by our industry dummies. Nevertheless, the coefficient on fluency score remains highly significant suggesting that even within finely partitioned industries, there is a relationship between company name fluency and firm value.

In row 7 we include turnover. *H3,* the joint hypothesis that liquid firms have higher valuations and that fluency is related to higher liquidity, suggests that the coefficient on turnover should be positive and that the coefficient on fluency should decline in magnitude. Consistent with these predictions, we find that turnover is strongly related to firm value, and the coefficient on fluency score falls from 1.94 to 1.45. In row 8 we include mutual fund breadth of ownership. *H2,* the joint hypothesis that breadth of ownership is positively related to firm value and that fluency is related to breadth of ownership, predicts that the coefficient on breadth of ownership should be positive and the coefficient on fluency should be reduced. The findings from row 8 are consistent with these predictions. Lastly, in row 9 we include both turnover and breadth of ownership together. Both turnover and breadth of ownership remain highly significant and the coefficient on fluency drops to 1.16. This indicates that breadth of ownership and liquidity are two channels through which the fluency of a company name influences firm value. However, the coefficient on fluency score is still economically and statistically significant, which suggests company name fluency may affect firm value over and above its influence on breadth of ownership and liquidity.[17]

5.3 Implications for Expected Returns

The impact of name fluency on firm valuation raises the question of whether it influences stock returns as well. Consider a company with a fluency score of 1 that generates earnings of $1 a year in perpetuity and is priced at $20. This corresponds to a discount rate of 5%. Now consider a company with a fluency score of 5 that also generates earnings of $1 a year in perpetuity. Our market-to-book estimates suggest that the fluent company should trade at a 10.48% premium (2.62 × 4), implying a price of $22.10 and a corresponding discount rate of 4.52%. The difference in returns of 48 basis points per year (or 1 basis point per month per unit change in fluency score) is unfortunately too small to easily detect statistically given the observed variation in returns. Nevertheless, we investigate the relation between company name fluency and returns empirically with Fama-MacBeth (1973) regressions each year from 1982-2009 of monthly returns on fluency score and find no significant relation between fluency and returns. In the next section we explore the effects of fluency altering name changes on firm valuation, which provides a more concentrated test of the fluency-return relation.

6. Additional Analysis

6.1 The Interaction of Fluency and Firm Visibility

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[17] Grullon, Kanatas, and Weston (2004) examine the effect of advertising on breadth of ownership and stress the importance of controlling for nonlinear relations between controls and the dependent variables. We also employ a similar matching approach based on 125 Size, Age, and Profitability portfolios and regress abnormal (i.e. SAP-adjusted) measures of the dependent variables on name fluency and the list of controls. The fluency score coefficients are very similar in magnitude and significance to the coefficients reported in Tables 2, 3, and 4.

Research from psychology demonstrates that previous exposure to concepts increases their fluency. For example, Labroo, Dhar, and Schwarz (2008) find priming survey participants with the concept of a frog led to them to process a wine bottle with a frog on its label more favorably. Thus, we might expect that the fluency of a company name to have a stronger effect on investment decisions for less visible firms, since frequent exposure may improve the fluency of initially hard to process names.

Two of the largest companies with non-fluent names (a fluency score of less than two) in 2008 were *Wal-Mart Stores* and *Goldman Sachs*, while the 3 smallest companies with non-fluent names as measured by sales were: *Ambac Financial Group*, *Achillion Pharmaceuticals Inc.,* and *Opexa Therapeutics Inc.* Intuitively, *Achillion Pharmaceuticals Inc.* seems more difficult to process than *Wal-Mart Stores* or *Goldman Sachs*, presumably because frequent exposure has made these names more familiar.

We operationalize this idea by forming two measures of visibility: *Large* and *Old*. *Large* is a dummy variable which equals one if the firm's total sales exceeded the sales of the median NYSE firm and zero otherwise. Similarly, *Old* is a dummy variable that equals one if the firm is above the median age of all NYSE firms and zero otherwise.[18] We also include a *Large* + *Old* composite measure, which is simply the sum of *Large* and *Old.* We reason that investors are more likely to be familiar with larger and older firms. Moreover, younger firms have short earnings history and little other "hard" financial data, in which case investors may be more inclined to be influenced by non-financial criteria such as the name of the company.

We examine how fluency effects breadth of ownership, liquidity, and firm value across companies with different levels of visibility by repeating the regressions of Tables

[18] Using the natural log of sales and age generates similar results.

2, 3, and 4 with two additional terms: a visibility dummy and the interaction of this dummy with fluency scores. The results of the analysis are reported in Table 6. We can see that a one unit increase in fluency score is associated with a statistically significant 5.23% increase in retail shareholders for small firms. In contrast, a one unit increase in fluency score is associated with a statistically insignificant 0.99% decline (5.23% - 6.22%) in retail shareholders for larger firms. This pattern is consistent across all 7 dependent variables. Specifically, the relationship between fluency score and retail breadth of ownership, mutual fund breadth of ownership, retail turnover, total turnover, the Amihud (2002) illiquidity measure, Tobin's Q, and the market-to-book ratio is highly significant for small firms, but statistically insignificant for large firms. Moreover, the coefficient estimates for small and large firms are significantly different at a 10% level in all seven cases, and significantly different at a 5% level in 5 of the 7 cases. Using firm age as a proxy for visibility results in similar, albeit weaker results. The interaction term between fluency and *Old* is negative in all 7 cases and is statistically significant (either at the 10% or 5% level) in 3 of the 7 cases.[19]

6.2 Name Changes

An alternative approach to examine the impact of fluency on breadth of ownership, liquidity, and firm value is to examine companies that have changed their name. By focusing exclusively on within-firm variation, we can address the concern that companies with fluent names are systematically different from companies with non-fluent

[19] The fact that fluency has a larger effect on valuation for younger firms is consistent with the findings of Alter and Oppenheimer (2006), who find larger first day returns for fluently named IPOs. They examine a relatively small sample (89 observations) and rely on surveys to gauge name fluency. However, name recognition may be influenced by firm performance, and their methodology does not include controls common in the IPO literature. We examine the relation between first-day returns and name fluency following the methodology of Green and Hwang (2011). We find a positive, but statistically insignificant relationship between IPO first-day returns and aggregate fluency score.

names. Unfortunately, despite its conceptual, appeal there are significant limitations to studying name changes. First, name changes are rarely exogenous. They are frequently related to mergers (e.g. from *AOL* to *AOL Time Warner*), the desire to emphasize a particular brand (e.g. from *Consolidate Foods* to *Sarah Lee*), broaden a business line (e.g. from *Apple Computer* to *Apple*), narrow a business focus (e.g. from *Morrison Inc.* to *Morrison Restaurants Inc.*) or change perceptions after a reputation has deteriorated (e.g. from *Andersen Consulting* to *Accenture* or from *Phillip Morris* to *Altria*). In some cases, companies do change relatively cumbersome longer names to abbreviations, presumably to increase in fluency. For example, in 2002, *Minnesota Mining & Manufacturing Co.* changed its name to *3M Co.*, increasing its fluency score from 2 to 4. However, *Minnesota Mining & Manufacturing* had been colloquially known as "3M" for years prior to the name change, so it's not clear that the official name change actually altered the perceived fluency of the company name.

Despite these limitations, we examine the impact of name changes on breadth of ownership, liquidity, and firm value. Our sample includes 2,410 firms that have variation in their fluency score over time. Of these 2,410 firms, 1,343 (56%) increased the fluency of their name, whereas 44% reduced name fluency. The average fluency score prior to the name change is 2.94, while the average fluency score after the name change is 3.10. The increase of 0.16 is highly significant (t-stat = 5.51), which suggests that when companies change their name, they do tend to choose a more fluent name.

To examine how within-firm variation in fluency score effects breadth of ownership, liquidity, and valuation, we repeat the analysis in Tables 2, 3, and 4 but also include firm fixed effects. Unlike Tables 2, 3, and 4, in which the independent variables are lagged one year, in Table 7 all the independent variables are contemporaneous to the dependent variables. This change is made to ensure that our results capture any effects that occur in the year in which the name change took place.

Table 7 reports the results of this analysis. For brevity, the table only reports the coefficient of *fluency score* and two other variables known to improve investor recognition and firm value: *NYSE* and *S&P 500.* The central finding from Table 7 is that changes in fluency score are positively and significantly related to changes in breadth of ownership, liquidity, and firm value. In all 7 cases, the coefficient has the correct sign and is reliably different from zero at a 10% significance level. 6 (5) of the 7 coefficients are reliably different from zero at a 5% (1%) significance level. Moreover, the fixed effect coefficients are generally similar to the estimates from the panel regressions. The fixed effect results for Tobin's Q and market-to-book are roughly half the magnitude of the panel estimates but are still economically meaningful. For example, a company that changed its name from a fluency score of 1 to a fluency score of 5 would have a predicted increase in Tobin's Q of 4.52%. This effect is larger than the predicted increase in firm value associated with being added to the NYSE.

Conclusion

There is growing evidence that investors have a preference for familiar and likeable stocks. For example, investors tend to tilt their portfolio towards locally headquartered stocks and towards companies with large levels of advertising. Investors also gravitate towards Fortune's most admired stocks and shun tobacco stocks. This paper examines whether the fluency of a company name is another important source of familiarity and affinity that influences investment decisions. Building on the literature in psychology which finds that fluent stimuli appear more positive and familiar than disfluent stimuli, and marketing literature which emphasizes the importance of product names, we hypothesize that investor's will have a preference for companies with fluent names.

Consistent with this conjecture, we find companies with fluent names have higher levels of both retail and mutual fund shareholders as well as greater turnover and smaller transaction price impacts. Moreover, we show that this larger investor base and improved liquidity have important implications for firm value. Specifically, companies with fluent names trade at significant premiums relative to companies with less-fluent names. Our results suggest a new channel through which companies can take advantage of investors' preference for the familiar. Unlike the location of a firm's headquarters, which is likely influenced by economic considerations, or advertising which is costly, selecting a fluent company name appears to be a relatively low cost method for improving liquidity and firm value. Consistent with this observation, we find corporate name changes improve fluency on average, and fluency improving name changes are associated with significant improvements in breadth of ownership, liquidity, and firm value.

References

Alter, Adam and Daniel Oppenheimer, 2009, "Uniting the Tribes of Fluency to Form a Metacognitive Nation," *Personal Social Psychological Review* 13, 219-235.

Alter, Adam and Daniel Oppenheimer, 2006, "Predicting short-term stock fluctuations by using processing fluency," *Proceedings of the National Academy of Sciences,* 103, 9369-9372.

Amihud, Yakov, 2002. "Illiquidity and stock returns: cross-section and time-series effects," *Journal of Financial Markets,* 5, 31–56.

Amihud, Yakov and Haim Mendelson, 1986. "Asset pricing and the bid-ask spread," *Journal of Financial Economics,* 17, 223–249.

Bao, Yexing, Alan Shao, and Drew Rivers, 2008, "Creating new brand names: Effects of relevance, connotation, and pronounciation," Journal of Advertising Research, 48, 148-162.

Barber, Brad and Terrance Odean, 2000, "Trading is Hazzardous to Your Wealth: The Common Stock Investment Performance of Individual Investors," *Journal of Finance,* 55, 773-806.

Barber, Brad and Terrance Odean, 2001, "Boys Will Be Boys: Gender, Overconfidence, and Common Stock Investment," *Quarterly Journal of Economics,* 116, 261-292.

Benartzi, Shlomo, 2001, "Excessive extrapolation and the allocation of 401(k) accounts to company stock," *Journal of Finance*, 56, 1647-1764.

Bodnaruk, Andriy and Per Ostberg, 2009, "Does Investor Recognition Predict Returns," *Journal of Financial Economics*, 91, 208-226.

Chen, Honghui., Gregory Noronha, and Vijay Singal, 2004, "The price response to S&P 500 index additions and deletions: Evidence of asymmetry and a new explanation" *Journal of Finance,* 59, 1901-1929.

Cohen, Lauren, 2009, "Loyalty-Based Portfolio Choice," *Review of Financial Studies*, 22, 1213-1245.

Cooper, Ian and Evi Kaplanis, 1994, "Home bias in equity portfolios, inflation hedging and international capital market equilibrium," *Review of Financial Studies*, 7, 45-60.

Cooper, Michael, Hussein Gulen, and Raghavendra Rau, 2005, "Changing names with style: Mutual fund name changes and their effects on fund flows," *Journal of Finance,* 60, 2825-2858.

Cooper, Michael, Orlin Dimitrov, and Raghavendra Rau, 2001, "A rose.com by any other name," *Journal of Finance,* 56, 2371-2388.

Coval, Joshua and Tobias Moskowitz, 1999, "Home Bias at home: Local equity preference in domestic portfolios," *Journal of Finance,* 54, 2045-2073.

Coval, Joshua and Tobias Moskowitz, 2001, "The geography of investment: Informed trading and asset prices, *Journal of Political Economy,* 109, 811-841.

Edmans, Alex and Diego Garcio, and Oyvind Norli, "Sports Sentiment and Stock Returns," *Journal of Finance,* 55, 389-406.

Edmans, Alex, Itay Goldstein, and Wei Jiang, 2010, "The real effects of financial markets: The impact of prices on takeovers," Working Paper, University of Pennsylvania.

Falkenstein, Eric, 1996, "Preferences for stock characteristics as revealed by mutual fund portfolio holdings," *Journal of Finance*, 51, 111-135.

Fama, Eugene and James MacBeth, 1973, "Risk, return, and equilibrium: Empirical tests," *Journal of Political Economy* 81, 607-636.

Fama, Eugene and Kenneth French, 1997, "Industry Costs of Equity," *Journal of Financial Economics*, 43, 153-193

Foerster, Stephen and Andrew Karolyi, 1999, "The effects of market segmentation and investor recognition on asset prices: Evidence from foreign stock listings in the United States," *Journal of Finance,* 54, 981-1013.

French, Kenneth and James Poterba, 1991, "Investor diversification and international equity markets," *American Economic Review,* 81, 222-226.

Gompers, Paul and Andrew Metrick, 2001, "Institutional Investors and Equity Prices," *Quarterly Journal of Economics*, 116, 229-259.

Green, Clifton and Byoung Hwang, 2011, "IPOs as Lotteries: Skewness Preference and First-Day Returns, working paper, Emory University.

Grinblatt, Mark, and Matti Keloharju, 2001, "How Distance, language, and culture influence stockholdings and trades," *Journal of Financ*e, 56, 1053-1073.

Grullon, Gustavo, George Kanatas, and James Weston, 2004, "Advertising, breadth of ownership, and liquidity," *Review of Financial Studies,* 17, 439-461.

Himmelberg, Charles, Glenn Hubbard, and Darius Palia, 1999, ‘Understanding the determinants of managerial ownership and the link between ownership and performance,” *Journal of Financial Economics,* 53, 353-384.

Hirsh, Barry and Terry Seaks, 1993, “Functional Form in Regression Models of Tobin’s Q,” *Review of Economics and Statistics,*75, 381-385.

Hirshleifer, David and Tyler Shumway, 2003, “Good Day Sunshine: Stock Returns and the Weather,” *Journal of Finance,* 58, 1009-1032.

Hong, Harrison and Marcin Kacperczyk, 2009, “The Price of Sin: The Effect of Social Norms on Stock Markets,” *Journal of Financial Economics,* 93, 15-36.

Hong, Harrison, Jeffrey Kubik, and Jeremy Stein, 2008, “The only game in town: The stock price consequences of local bias,” *Journal of Financial Economics*, 90, 20-37.

Huberman, Gur, 2001, “Familiarity breeds investment,” *Review of Financial Studies,* 14, 659-680.

Kadlec, Gregory, and John McConnell, 1994, "The effect of market segmentation and liquidity on asset prices: Evidence from exchange listings," *Journal of Finance,* 49, 611 -636.

Kaul, Aditya, Vikas. Mehrotra, and Randall Morck, 2000, “Demand Curves for Stocks Do Slope Down: New Evidence from an Index Weights Adjustment,” *Journal of Finance*, 55, 893-912.

Kumar, Alok, 2009. “Who gambles in the stock market?” *Journal of Finance,* 64, 1889-1933.

Labroo, A. A., Dhar, R., & Schwarz, Norbert, 2008, “Of frowning watches and frog wines: Semantic priming, perceptual fluency, and brand evaluation,” *Journal of Consumer Research* 34, 819-831.

Lang, Larry and Rene Stulz, 1994, “Tobin’s Q, Diversification, and Firm Performance,” *Journal of Political Economy*, 102, 1248-1280.

Massa, Massimo and Andrei Simonov, 2006, “Hedging, Familiarity, and Portfolio Choices,” *Review of Financial Studies*, 19, 633-685.

McGlone, Matthew and Jessica Tofighbakhsh, 2000, “Birds of a Feather Flock Cojointly? Rhyme as Reason in Aphorisms,” *Psychological Science,* 11, 424-428.

Merton, R.C., 1987, "Presidential Address: A Simple Model of Capital Market Equilibrium with Incomplete Information," *Journal of Finance,* 42, 483-510.

Newey, Whitney and Kenneth West, 1987, "A simple positive definite hetereskedasticity and autocorrelation consistent covariance matrix," *Econometrica* 55, 703-708.

Oppenheimer, Daniel M., 2006, "Consequences of erudite vernacular utilized irrespective of necessity: Problems with using long words needlessly," *Applied Cognitive Psychology* 20, 139-156.

Pagano, Marco, Alisa Roell, and Josef Zechner, 2002, "The Geography of Equity Listing: Why Do Companies List Abroad?" *Journal of Finance*, 57, 2651-2694.

Petersen, Mitchell, 2009, "Estimating standard errors in panel data sets: Comparing approachs," *Review of Financial Studies,* 22, 435-480.

Sarkissian, Sergei and Michael Schill, 2004, "The Overseas Listing Decision: New Evidence of Proximity Preference," *Review of Financial Studies,* 17, 769-809.

Schwarz, Norbert, Herbert Bless, Fritz Strack, Gisela Klump, Helga Rittenauer-Schatka, and Annette Simmons, 1991, "Ease of retrieval as information: Another look at the availability heuristic," *Journal of Personality and Social Psychology*, 61, 195-202.

Seasholes, Mark and Ning Zhu, 2009,"Individual Investors and Local Bias," *Journal of Finance,* forthcoming.

Shah, Anuj and Daniel Oppenheimer, 2007, "Easy Does It: The Role of Fluency in Cue Weighting," *Judgment and Decision Making*, 2, 371-379.

Shleifer, Andrei., 1986, "Do Demand Curves for Stocks Slope Down?" *Journal of Finance,* 41, 579–590.

Song, H. & Schwarz, Norbert, 2009. "If it's difficult to pronounce, it must be risky: Fluency, familiarity, and risk perception." *Psychological Science* 20(2), 135–138.

Statman, Meir, Kenneth Fisher, and Deniz Anginer, 2008, "Affect in a Behavioral Asset Pricing Model," *Financial Analyst Journal,* 64, 20-29.

Travers, Jeffrey and Donald Olivier, 1978, "Pronounceability and Statistical 'Englishness' as Determinants of Letter Indentification," *American Journal of Psychology,* 91, 523-538.

Tversky, Amos and Daniel Kahneman, 1973, "Availability: A heuristic for judging frequency and probability," *Cognitive Psychology,* 5, 207-232.

Table 1: Summary Statistics

This table reports the time-series average of annual cross-sectional summary statistics. The sample includes all common stocks with available financial data in CRSP and COMPUSTAT, and spans from 1982-2009. Stocks are placed into one of 5 groups based on their company name fluency score. Fluency scores are the sum of a length score, Englishness score, and dictionary score. Company names consisting of one, two, and more than two words receive a length score of 3, 2, and 1, respectively. Stocks in the bottom quintile of Englishness, as measured using a linguistic algorithm, receive an Englishness score of 0; all other stocks receive an Englishness score of 1. Company names in which all words satisfy the spell-check filter receive dictionary scores of 1; all other stocks receive a dictionary score of 0. Share price, total shares outstanding, returns, trading volume, and exchange membership are obtained from CRSP; sales, book value of equity, EBITDA, and total assets are obtained from COMPUSTAT. Size is market capitalization. Age is the number of months since a firms' first return appeared in the CRSP database. Price is share price. Volatility is the standard deviation of monthly stock returns over the prior year. Turnover is monthly volume divided by shares outstanding averaged over the prior year. Book to Market is the book value of equity divided by market capitalization. Momentum (2-12) is the firms' equity return over the past 2 to 12 months. Profitability is EBITDA scaled by book value of assets.

	N	Size	Sales	Age	Price	Volatility	Turnover	BM	Mom (2-12)	Profitability
ALL Stocks										
Mean	4600	1603	1439	153	27.91	14.11%	101.00%	0.69	13.30%	5.12%
Median		148	143	121	12.53	11.79	63.10	0.55	4.45	9.09
Std Dev		7962	6525	112	643.00	9.93	159.43	1.31	63.26	27.38
Highly Fluent (Score =5)										
Mean	134	2480	2177	195	22.80	14.09	117.61	0.67	13.99	7.85
Median		254	277	182	15.36	11.89	75.36	0.53	5.18	11.44
Std Dev		7467	6641	124	43.37	9.44	155.90	0.80	58.93	24.36
Fluent (Score =4)										
Mean	1590	1742	1577	157	17.20	14.93	114.31	0.66	13.28	4.59
Median		164	145	164	11.49	12.68	71.40	0.51	3.00	9.64
Std Dev		9028	7252	113	19.49	9.87	184.34	1.40	66.60	27.21
Neutral (Score =3)										
Mean	1826	1556	1366	152	43.33	14.09	97.70	0.70	12.69	5.17
Median		143	146	120	12.34	11.74	61.54	0.56	4.37	9.09
Std Dev		7480	5562	113	1027	9.86	149.61	1.09	61.08	27.23
Non-fluent (Score =2)										
Mean	898	1380	1273	145	18.44	13.14	86.34	0.73	14.59	5.22
Median		125	126	114	13.8	10.75	53.56	0.59	6.50	7.41
Std Dev		6869	6480	107	18.67	9.83	119.61	1.25	61.64	25.21
Highly Non-fluent (Score =1)										
Mean	151	1419	1283	130	20.51	11.81	76.58	0.75	13.02	7.12
Median		148	178	105	15.79	9.62	44.33	0.62	6.69	7.73
Std Dev		5742	3989	108	24.52	8.72	108.85	0.82	54.91	17.74

Table 2: Company Name Fluency and Breadth of Ownership

The table reports the estimates from panel regressions of the natural log of the number of retail or mutual fund shareholders on fluency and other characteristics. Retail shareholder data are obtained from a large discount brokerage dataset that spans from1991-1996. Mutual fund shareholder data are obtained from the CDA/Spectrum S12 database from 1982-2009. Fluency scores are the sum of length, Englishness, and dictionary scores. Company names consisting of one, two, and more than two words receive a length score of 3, 2, and 1, respectively. Stocks in the bottom quintile of Englishness, as measured using a linguistic algorithm, receive an Englishness score of 0; all other stocks receive an Englishness score of 1. Company names in which all words satisfy the spell-check filter receive dictionary scores of 1; all other stocks receive a dictionary score of 0. Detailed definitions for other control variables are presented in section 2.3. The regressions also include year dummies, an S&P 500 Index dummy, a NYSE exchange dummy, and industry dummies based on the Fama-French (1997) 49 industry classification. All independent variables are computed in December of the previous year. Standard errors are clustered by firm, and t-statistics are reported below each estimate.

	Log (Retail Shareholders)		**Log (Mutual Fund Shareholders)**	
	(1)	(2)	(3)	(4)
Fluency Score	3.92		2.04	
	(2.95)		(3.88)	
Length Score		4.44		1.96
		(2.55)		(3.16)
Englishness		0.54		0.94
		(0.18)		(0.68)
Dictionary		6.11		2.94
		(2.35)		(3.28)
Log(Size)	-43.99	-43.83	103.00	103.01
	(-6.78)	(-6.75)	(44.46)	(44.46)
$Log(Size)^2$	3.67	3.66	-1.31	-1.31
	(12.83)	(12.80)	(-14.19)	(-14.19)
Profitability	-10.82	-10.86	39.30	39.26
	(-3.64)	(-2.65)	(8.89)	(8.88)
Log(Turnover)	41.54	41.52	30.21	30.20
	(31.90)	(31.90)	(48.97)	(48.98)
Log(Book to Market)	7.56	7.54	19.17	19.17
	(5.49)	(5.48)	(33.73)	(33.72)
$Mom_{t-2,t-12}$	-3.77	-3.80	11.49	11.48
	(-4.40)	(-4.44)	(17.90)	(17.90)
Log(Advertising)	4.80	4.79	-1.15	-1.15
	(3.40)	(3.40)	(-2.68)	(-2.68)
Log(Age)	24.66	24.71	2.36	2.38
	(16.62)	(16.59)	(4.61)	(4.65)
1/Price	6.11	6.09	-6.55	-6.56
	(5.94)	(5.93)	(-3.10)	(-3.10)
Log(Volatility)	39.99	39.99	-8.10	-8.11
	(18.01)	(18.01)	(-8.61)	(-8.61)
NYSE	36.50	36.40	14.80	14.81
	(10.73)	(10.72)	(13.36)	(13.36)
S&P 500	3.23	3.23	2.04	6.61
	(0.58)	(0.58)	(3.88)	(4.26)
Industry Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
R^2	62.49%	62.49%	88.18%	88.18%
Clusters	6337	6337	11838	11838
Obs.	24352	24352	94549	94549

Table 3: Company Name Fluency and Liquidity

This table reports the estimates from panel regressions of the natural log of retail turnover, total turnover or the Amihud (2002) illiquidity measure on fluency and other characteristics. Retail turnover is computed as retail share volume / shares outstanding * 1000, where volume is computed from a large discount brokerage dataset that spans from 1991-1996. Total turnover is total CRSP share volume / shares outstanding. The Amihud (2002) illiquidity measure is the absolute daily return of a stock scaled by its daily total dollar volume traded, averaged across all trading days in the year. The total turnover and Amihud measure span from 1982-2009. Fluency scores are the sum of length, Englishness, and dictionary scores. Company names consisting of one, two, and more than two words receive a length score of 3, 2, and 1, respectively. Stocks in the bottom quintile of Englishness, as measured using a linguistic algorithm, receive an Englishness score of 0; all other stocks receive an Englishness score of 1. Company names in which all words satisfy the spell-check filter receive dictionary scores of 1; all other stocks receive a dictionary score of 0. Detailed definitions for other control variables are presented in Section 2.3. The regressions also include year dummies, an S&P 500 Index dummy, a NYSE exchange dummies, and industry dummies based on the Fama-French (1997) 49 industry classification. All independent variables are computed in December of the previous year. Standard errors are clustered by firm, and t-statistics are reported below each estimate.

	Log (Retail Turnover)		**Log (Total Turnover)**		**Log (Amihud)**	
	(1)	(2)	(3)	(4)	(5)	(6)
Fluency Score	5.26		3.91		-4.56	
	(4.01)		(4.92)		(-4.33)	
Length Score		5.89		3.38		-3.49
		(3.40)		(3.56)		(-2.75)
Englishness		1.99		5.20		-10.10
		(0.68)		(2.42)		(-3.52)
Dictionary		7.15		4.30		-3.41
		(2.72)		(3.06)		(-1.80)
Log(Size)	96.93	97.00	45.71	45.75	-98.76	-98.84
	(17.36)	(17.36)	(13.99)	(14.00)	(-16.41)	(-16.41)
Log(Size)^2	-3.88	-3.88	-0.84	-0.84	-1.89	-1.89
	(-16.01)	(-16.01)	(-5.88)	(-5.88)	(-7.17)	(-7.16)
Profitability	0.12	0.10	-2.29	-2.33	-20.49	-20.45
	(0.03)	(0.02)	(-1.23)	(-1.25)	(-6.78)	(-6.77)
Log(Book to Market)	-0.81	-0.83	-1.96	-1.93	-1.93	-1.97
	(-0.60)	(-0.61)	(-2.63)	(2.61)	(-1.92)	(-1.95)
$\text{Momentum}_{t-2,t-12}$	5.33	5.29	8.69	8.70	-48.34	-48.36
	(4.93)	(4.90)	(17.34)	(17.35)	(-32.59)	(-32.59)
Log(Advertising)	4.50	4.50	1.85	1.84	-0.22	-0.21
	(3.22)	(3.22)	(2.57)	(2.56)	(-0.21)	(-0.20)
Log(Age)	2.98	3.02	-11.95	-11.92	2.07	2.02
	(2.14)	(2.17)	(-15.46)	(-15.43)	(1.99)	(1.95)
1/Price	-5.64	-5.66	-4.00	-4.01	5.59	5.59
	(-7.42)	(-7.47)	(-8.87)	(-8.87)	(5.65)	(5.64)
Log(Volatility)	79.68	79.65	66.20	66.18	-18.11	-18.10
	(37.41)	(37.38)	(65.52)	(65.47)	(-12.13)	(-12.12)
NYSE	22.01	21,96	-3.17	-3.17	-32.44	-32.44
	(6.64)	(6,62)	(-1.73)	(-1.73)	(-13.53)	(-13.54)
S&P 500	-1.24	-1.28	3.91	-2.59	32.91	32.78
	(-0.26)	(-0.27)	(4.92)	(-0.93)	(8.31)	(8.28)
Industry Dummies	YES	Yes	Yes	Yes	Yes	Yes
Year Dummies	YES	Yes	Yes	Yes	Yes	Yes
R^2	26.70%	26.71%	43.33%	43.34%	84.93%	84.94%
Clusters	6870	6870	14044	14044	14037	14037
Obs.	26475	26475	115341	115341	115269	115269

Table 4: Company Name Fluency and Firm Value

The table reports the estimates of panel regressions of the natural log of Tobin's Q or Market to Book on fluency and other characteristics. Tobin's Q is the ratio of the enterprise value (market value of equity plus debt) to book value (debt plus book equity). Market to Book is the market value of equity divided by book value of equity. Fluency scores are the sum of length, Englishness, and dictionary scores. Company names consisting of one, two, and more than two words receive a length score of 3, 2, and 1, respectively. Stocks in the bottom quintile of Englishness, as measured using a linguistic algorithm, receive an Englishness score of 0; all other stocks receive an Englishness score of 1. Company names in which all words satisfy the spell-check filter receive dictionary scores of 1; all other stocks receive a dictionary score of 0. Detailed definitions for other control variables are presented in Section 2.3.The regressions also include year dummies, an S&P 500 Index dummy, a NYSE exchange dummy, and industry dummies based on the Fama-French (1997) 49 industry classification. All independent variables are computed in December of the previous year. Standard errors are clustered by firm, and t-statistics are reported below each estimate.

	Log (Tobin's Q)		Log (Market to Book)	
	(1)	(2)	(4)	(5)
Fluency Score	1.94		2.62	
	(5.30)		(4.25)	
Length Score		2.15		2.69
		(4.50)		(3.39)
Englishness		1.78		3.29
		(2.12)		(2.47)
Dictionary		1.69		1.80
		(2.32)		(1.49)
Log(Sales)	-4.96	-4.97	-9.05	-9.06
	(-18.53)	(-18.56)	(-21.14)	(-21.13)
Profitability	3.03	3.03	4.74	4.74
	(61.64)	(61.64)	(66.07)	(66.06)
Log (Age)	-4.51	-4.52	-6.75	-6.77
	(-9.72)	(-9.75)	(-8.78)	(-8.79)
Sales Growth	1.23	1.23	3.22	3.22
	(2.70)	(2.69)	(2.39)	(2.39)
Asset Turnover	-2.00	-2.00	-1.28	-1.28
	(-3.84)	(-3.83)	(-1.43)	(-1.42)
Rd/Sales	2.38	2.38	2.37	2.37
	(4.25)	(4.23)	(3.53)	(3.52)
Adv/Sales	0.60	0.60	1.07	1.07
	(3.89)	(3.89)	(4.54)	(4.73)
Log (Segments)	-1.28	-1.30	-2.82	-2.83
	(-2.93)	(2.97)	(-3.60)	(-3.62)
Leverage	5.63	5.64	106.17	106.21
	(3.27)	(3.27)	(36.52)	(36.55)
Payout	-1.07	-1.07	-0.17	-0.18
	(-2.45)	(-2.45)	(-0.20)	(-0.20)
NYSE	4.83	4.83	11.65	11.65
	(5.84)	(5.83)	(7.89)	(7.89)
S&P 500	21.56	21.55	39.49	39.49
	(20.64)	(20.63)	(21.35)	(21.36)
Industy Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
R^2	34.22%	34.22%	28.51%	28.51%
Clusters	13422	13422	13422	13422
Obs.	110491	110491	110491	110491

Table 5: Company Name Fluency and Firm Value: Robustness Checks

This table presents the results of variations on the pooled regression in Table 4. The dependent variable is the natural log of Tobin's Q (unless stated otherwise). Row 1 reports the results from the main specification reported in Table 4. Row 2 reports the coefficients using the Fama-MacBeth (1973) methodology. Row 3 repeats the baseline specification but excludes financials (SIC of 6000-6999). Row 4 Winsorizes the dependent variable at the 1st and 99th percentile. Row 5 using Tobin's Q (not in logs) as the dependent variable. Row 7 employs a finer industry control partition (dummy variables based on 4 digit SIC codes). Rows 7 through 9 add log of turnover and log of mutual fund shareholders. With the exception of Row 2, t-statistics, based on standard errors clustered by firm are reported in parentheses. In Row 2, t-statistics are computed from the time-series standard deviation of annual coefficient estimates.

	Fluency Score	Turnover	MF Shareholders
1. Baseline Specification	1.94		
	(5.30)		
2. Fama-MacBeth Estimates	1.67		
	(7.63)		
3. Remove Financials	2.10		
	(4.92)		
4. Winsorize Q	1.86		
	(5.22)		
5. Raw Q (Not in logs) *100	5.00		
	(3.57)		
6. Add 4 Digit SIC Dummies	1.18		
	(3.62)		
7. Add Turnover	1.45	9.95	
	(4.12)	(30.59)	
8. Add MF Breadth	1.35		13.86
	(3.94)		(35.44)
9. Add Turnover and MF Breadth	1.16	5.81	11.55
	(3.42)	(17.32)	(28.58)

Table 6: The Interaction of Fluency with Measures of Visibility

The table reports the estimates of panel regression of breadth of ownership (Panel A), liquidity (Panel B), and valuation (Panel C) on fluency, the interaction of fluency and visibility measures, and other firm characteristics. The breadth of ownership, liquidity, and firm valuation regression are as specified in Tables 2, 3, and 4, respectively, with the addition of interaction terms related to firm visibility. Specifically, Large is a dummy variable that equals one if the firm's total sales exceed that of the median NYSE firm. Old is a dummy variable that equals one if the firm is above the median age of all NYSE firms and zero otherwise. Large + Old is the sum of Large plus Old. Standard errors are clustered by firm, and t-statistics are reported below each estimate.

Panel A: Breadth Of Ownership

	Retail Shareholders			Mutual Fund Shareholders		
Fluency Score	5.23	5.74	6.21	2.48	2.19	2.47
	(3.65)	(3.92)	(4.13)	(4.11)	(3.55)	(3.84)
Fluency * Large	-6.22			-1.72		
	(-1.90)			(-1.70)		
Fluency * Old		-6.40			-0.47	
		(-2.24)			(-0.45)	
Fluency * (Large + Old)			-4.60			-0.72
			(-2.53)			(-1.18)

Panel B: Liquidity

	Retail Turnover			Turnover			Amihud		
Fluency Score	6.29	6.19	6.77	4.81	4.37	4.98	-5.44	-4.92	-5.56
	(4.23)	(4.13)	(4.33)	(5.49)	(5.26)	(5.69)	(-4.69)	(-4.26)	(-4.62)
Fluency * Large	-5.78			-4.74			4.74		
	(-2.05)			(-2.71)			(1.96)		
Fluency * Old		-3.88			-1.70			1.26	
		(-1.44)			(-1.01)			(0.56)	
Fluency * (Large + Old)			-3.42			-2.23			2.18
			(-2.11)			(-2.28)			(1.52)

Panel C: Valuation Ratios

	Tobin's Q			Market-to-Book		
Fluency Score	2.28	2.41	2.55	3.35	3.19	3.60
	(5.47)	(5.78)	(5.82)	(4.87)	(4.70)	(5.09)
Fluency * Large	-1.85			-3.96		
	(-2.52)			(-2.97)		
Fluency * Old		-1.82			-2.27	
		(-2.82)			(-1.95)	
Fluency * (Large + Old)			-1.38			-2.27
			(-3.36)			(-3.19)

Table 7: The Effects of Company Name Changes on Breadth of Ownership, Liquidity, and Firm Value

The table reports the estimates of fixed effect panel regressions of breadth of ownership, liquidity, and valuation on fluency and other firm characteristics. The breadth of ownership, liquidity, and valuation regressions are as specified in 2, 3, and 4, respectively, with the addition of dummy variables for each firm. The fluency score coefficients thus measure the effects of fluency altering name changes. The table presents the coefficient and t-statistics for fluency score and for comparison purposes two other variables known to influence investor recognition: NYSE, and S&P 500 which denote membership on the NYSE stock exchange and the S&P 500 Index. For brevity, coefficients on all other control variables are not reported. All independent variables are computed in December of the current year.

	Retail Shareholders	MF Shareholders	Retail Turnover	Total Turnover	Amihud	Tobin's Q	Market to Book
Fluency Score	5.47	1.67	5.01	2.91	-3.65	1.13	1.16
	(2.96)	(2.99)	(1.92)	(4.84)	(-4.08)	(3.06)	(2.01)
NYSE	37.64	7.46	0.75	-10.96	-23.00	4.06	4.67
	(11.98)	(7.84)	(0.16)	(-10.10)	(-14.30)	(4.47)	(3.30)
S&P 500	24.70	8.25	17.55	-2.88	18.19	7.12	12.42
	(4.70)	(7.24)	(2.15)	(-2.12)	(9.05)	(8.36)	(9.37)
R^2	93.03%	94.96%	74.94%	80.50%	95.08%	68.35%	66.89%
Clusters	6516	11928	7051	13834	13823	14718	14718
Obs	25204	94902	27732	112100	112042	121476	121476