Trust and Lottery-Related Anomalies

Reza Bradrania [a], Ya Gao [b]

[a,b] *University of South Australia*

Abstract

We hypothesize that social trust affects the demand for lottery-like stocks which results in overpricing and lower expected return for these stocks. We show that the MAX effect only exists when firms are located in high social trust regions, supporting the positive relation between trust and investors' tendency to invest in risky assets. The effect of trust on the MAX effect is more pronounced when the region's education or income levels are lower, indicating that less educated or wealthy people possess less reliable information and rely more on trust in making economic or financial decisions. Our results are robust to using other proxies for lottery stocks and several robustness tests. Our findings provide a better understanding of the impact of trust on speculative behavior that can guide initiatives to promote more stable investment environments and avoid potential market distortions.

JEL classification: G11, G12, G14, G41

Keywords: MAX; Lottery; Trust; Skewness; Behavioral bias; Expected returns.

1. Introduction

Lottery-related anomalies are widely documented in the literature.[1] That is, stocks with lottery-like payoffs (i.e., stocks with skewed distributions that have a small probability of large payoffs) tend to significantly underperform compared to stocks with non-lottery-like payoffs. Using the maximum daily return (MAX) over a month as the proxy for lottery-like stocks[2], Bali et al. (2011) find that in the US stock market, stocks with high MAX in the previous month generate low returns in the subsequent month, suggesting that lottery-like stocks underperform compared to non-lottery-like stocks. This negative relation is usually referred to as the MAX effect or MAX anomaly. Following Bali et al. (2011), a growing body of studies has explored the existence of this effect in other stock markets[3], as well as the plausible driving factors of the MAX effect; these include investor sentiment (Fong and Toh, 2014), levels of mispricing (Zhong and Gray, 2016; Seif, Docherty, and Shamsuddin, 2018), reference-dependent preference (An, Wang, Wang, and Yu, 2020), an upper bound for price named the 52-week high (Byun, Goh, and Kim, 2020), individualism related to overconfidence and overoptimism (Cheon and Lee, 2018), individual investors' stock preference (Lin and Liu, 2018), earnings announcements (Nguyen and Truong, 2018; Baars and Mohrschladt, 2021), attention and social interaction (Bali, Hirshleifer, Peng, and Tang, 2019), property crime (Gao and Bradrania, 2024), and investors' weather-induced mood (Bradrania and Gao, 2024).

In this paper, we add to this strand of literature by examining the impact of social trust on lottery demand. Specifically, we study the role of social trust on the gambling behavior of investors and on the resulting underperformance of lottery-type stocks. Social trust or generalized trust is defined as the trust in anonymous others or the probability individuals attribute to the possibility of being cheated (Guiso, Sapienza, and Zingales, 2004, 2008; Pevzner, Xie, and Xin, 2015; Wei and Zhang, 2020; Limbach, Rau and Schürmann, 2021; Drobetz, Mönkemeyer, Requejo, and Schröder, 2023).[4] More formally, it is considered as the subjective probability that another individual will perform an action that is beneficial, or at least not harmful, to an individual, and the probability is high enough for that individual to consider cooperating with another individual in a society (Gambetta, 1988).

Prior research shows that trust enhances investment in trust-intensive activities (Guiso et al., 2004, 2008; El-Attar and Poschke, 2011; Barbi, Febo, and Giudici, 2023). For example, Guiso et al. (2004) find that high trust individuals are more likely to invest more in stocks (the most trust-intensive form of investment) and less in cash (the least trust-intensive form of investment). Guiso et al. (2008) show that individuals with high trust are more likely to buy risky assets and invest more in such assets. This suggests that investment in more risky assets constitutes a trust-intensive form of investment and that

[1] For example, see Kumar (2009), Boyer, Mitton, and Vorkink (2010), Bali, Cakici, and Whitelaw (2011), and Conrad, Kapadia, and Xing (2014).
[2] Lottery-like stocks, or equivalently, lottery-type stocks refer to stocks with lottery-like payoffs. We use lottery-like stocks and lottery-type stocks interchangeably hereafter.
[3] See, for example, the European market (Annaert, De Ceuster, and Verstegen, 2013; Walkshäusl, 2014), the South Korean market (Nartea, Wu, and Liu, 2014), the Australian market (Zhong and Gray, 2016), the Canadian market (Aboulamer and Kryzanowski, 2016), the Chinese market (Nartea, Kong, and Wu, 2017), the Taiwanese market (Hung and Yang, 2018), the Brazilian market (Berggrun, Cardona, and Lizarzaburu, 2019), the global market (Cheon and Lee, 2018), and nine advanced emerging markets (Seif., Docherty, and Shamsuddin, 2018).
[4] We use trust, generalized trust and social trust interchangeably hereafter.

high trust individuals believe the likelihood of being cheated in investing on these assets is low.

Consistent with the notion that trust fosters investment in more risky assets, we conjecture that social trust affects the demand for lottery-type stocks that ultimately results in underperformance of these stocks. Since lottery-like stocks are riskier than non-lottery-like stocks, we predict that investors residing in high-trust regions are more likely to buy more lottery-type stocks. This leads to a high demand for these stocks, which results in overpricing, in turn generating lower expected returns for these stocks. Consequently, we hypothesize that the negative lottery premium is stronger in high-trust regions. To our knowledge, this study is the first to investigate the role of social trust in lottery demand and the performance of lottery-like stocks. Our study relates trust to gambling preference through individuals' perception of the likelihood of being cheated in social interactions and provides guidance on investment decisions associated with trust-induced heterogeneity in gambling preferences.

The importance of trust in economic settings has been widely documented in the literature. For example, trust enhances investment and economic growth (e.g., Knack and Keefer, 1997; Zak and Knack, 2001; Algan and Cahuc, 2010), improves the performance of large organizations (e.g., La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1997; Fukuyama, 1995), promotes economic efficiency and financial development (Guiso et al., 2004) and encourages stock market participation (e.g., Guiso et al., 2008; El-Attar and Poschke, 2011). Trust also influences local bias or foreign bias (Shao and Wang, 2021; Wei and Zhang, 2020; Drobetz et al., 2023), government regulation (Aghion, Algan, Cahuc, and Shleifer, 2010), the size and organizational structure of firms (Bloom, Sadun, and Van Reenen, 2012), cross-border mergers and acquisitions (Ahern, Daminelli, and Fracassi, 2015), investors' reactions to corporate earnings announcements (Pevzner et al., 2015), the firm's cost of equity (Gupta, Raman, and Shang, 2018), and the cost of debt (Meng and Ying, 2019) and debt contracting (Brockman, El Ghoul, Guedhami, and Zheng, 2020). This study adds to this growing literature by showing the relation between social trust and lottery demand and its impact on investors' financial decisions.

To examine our hypothesis, we focus on all common stocks traded on Nasdaq and headquartered in the US from January 1996 to December 2018, because previous study suggests that trading in Nasdaq is localized (Loughran and Schultz, 2004; Schultz, 2003; Anand et al., 2011). Following Bali et al. (2011), we measure lottery-like stocks by using the maximum daily return (MAX) over the previous month in our main analysis.[5] We measure social trust based on the responses to the Word Value Survey (WVS) question, "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?", which is widely used to measure trust in the prior studies on trust (e.g., La Porta et al., 1997; Guiso et al., 2008; Aghion et al., 2010; Pevzner et al., 2015; Wei and Zhang, 2020). We follow Wei and Zhang (2020) and Pevzner et al. (2015) to measure our social trust index (TRUST) across different regions of the US. This is different from other studies that use the WVS to measure differences in trust across countries (e.g., La Porta et al., 1997; Guiso et al., 2008; Aghion et al., 2010; Pevzner et al., 2015). There are at least two benefits of the US setting. First, there

[5] In the robustness tests, we also use a set of alternative proxies for lottery demand such as alternative MAX measures and idiosyncratic skewness to examine the hypothesis.

are significant cross-sectional and time-series variations in social trust across different regions in the US, which allows us to examine the relation between social trust and lottery demand. Second, the identical regulatory and accounting standards faced by firms in our sample enable us to focus on the economic channel of social trust, since the differences in firms that arise from the international context, such as insider trading regulations, accounting rules, languages, and disclosure requirements, have been ruled out. In total, there are 10 US geographical regions and 8,875 firms in our sample.

We investigate our hypothesis in several ways. First, we show that there is a MAX effect in our sample by sorting the sample stocks into deciles based on MAX over the previous month. Then, we conduct a univariate portfolio analysis to test whether social trust relates to the MAX effect. Through dividing the sample into two groups, high-trust and low-trust, we find that social trust has an impact on the MAX effect and lottery demand, and that the MAX effect tends to be stronger in high-trust regions than in low-trust regions. The results support our hypothesis that high trust increases the propensity to invest in more risky assets and makes the MAX effect stronger. Second, we run Fama and MacBeth (1973) cross-sectional regressions under regions with high and low levels of trust, respectively. Consistent with the univariate portfolio analysis, we show that the MAX anomaly is affected by social trust through the positive association between trust and investors' tendency to invest in risky assets. More specifically, the coefficients on MAX are more negative and statistically significant for stocks headquartered in high-trust regions than those in low-trust regions. Additionally, we re-run the Fama and MacBeth (1973) cross-sectional regressions after controlling for trust and an interaction term between MAX and trust. We find that the MAX effect or the underperformance of lottery-type stocks only exists in high-trust regions, which supports our prior findings and provides additional evidence for our hypothesis. The findings are robust when we control for regional factors such as religion, and education and income levels that may impact investor preference for lottery stocks (Kumar, 2009) and are correlated with social trust (Guiso, Sapienza, and Zingales, 2003, 2004, 2008). We also find that the coefficient on TRUST is positive, indicating that trust increases the expected return on the stock investment, encouraging risky investments (e.g., Guiso et al., 2008; El-Attar and Poschke, 2011).

Trust is formed based on qualities of the financial system that determine the chance of frauds in the market. However, it is also a manifestation of the individual's subjective qualities based on their priors that can create significant variations in levels of trust among individuals (Guiso et al., 2004, 2008). If trust reflects the latter, we expect more educated or wealthier individuals to be less influenced by these priors because it is very likely that they have more reliable information about financial markets and a better understanding of how these markets work (Guiso et al., 2004, 2008; El-Attar and Poschke, 2011). Therefore, we conjecture that the effect of trust on lottery demand is weaker in regions with higher level of education (income), suggesting that more educated or wealthier individuals rely less on trust in making financial decisions.

To test this postulation, we split our sample into two groups by the level of education or income, and then run the Fama and MacBeth (1973) cross-sectional regressions. Consistent with our conjecture, we find that the effect of trust on the MAX effect is more pronounced when a region's education (or income) level is lower. The findings support prior research that shows the effect of trust can vary with the level of education or wealth, since less educated or wealthy people possess less reliable information and rely more on trust in making economic or financial decisions (e.g., Guiso et al., 2004, 2008; El-Attar and Poschke, 2011; Pevzner et al., 2015). We also find that among firms' regions with a high level of trust, the MAX effect is stronger for the low education or income level regions compared to the high education or income level regions. The results are consistent with Kumar (2009) who finds that less educated or wealthier investors exhibit a greater propensity to invest in stocks with lottery features. However, we show that these investors invest disproportionately more in lottery-type stocks only in high trust regions.

We conduct several robustness tests to support our main findings. When we use the orthogonalized MAX (i.e., the component of MAX that is orthogonal to the social trust index proxy TRUST) in the previous month as the sort variable in the univariate portfolio analysis, we do not find the MAX effect in our sample. The results provide additional evidence that the level of trust can impact the underperformance of lottery-type stocks. Then, we replace MAX with other lottery measures such as alternative constructions of MAX and idiosyncratic skewness, we find that our results remain robust. Finally, we use an alternative measure of income and find our results that relate income to trust and lottery demand relation are qualitatively unchanged. These robustness tests are discussed in detail in the Internet Appendix.

Our study contributes to the literature in several ways. Firstly, it adds to the studies on the lottery-related anomalies. We identify that social trust, as a new driving factor, plays an important role in the MAX anomaly and lottery-related anomalies. This complements existing research that studies the underlying drivers of anomalies related to lottery-type stocks, especially the MAX effect. Secondly, it extends the literature on the impact of social trust on economic outcomes and financial decisions by showing that social trust impacts the demand for lottery-type stocks. We also provide further evidence that this impact is related to education and income levels. Thirdly, we show that only in high trust regions, investors with lower levels of education and wealth are more inclined to invest in lottery-type stocks. These results suggest that more educated (wealthy) investors rely less on trust in making financial decisions. Finally and more broadly, since trust is a key dimension of social capital and culture (Putnam, 1993; Fukuyama, 1995; Knack and Keefer, 1997; Guiso, Sapienza, and Zingales, 2004, 2006, 2011; Bloom et al., 2012; Ahern et al., 2015; Wei and Zhang, 2020), our study further contributes to the literature on the role of social capital and culture in finance.

Our findings suggest that investors need to incorporate trust in their risk models to account for its impact on speculative behavior, ensuring they make more informed decisions and avoid potential market distortions. Our paper provides a better understanding of the impact of trust on making economic and financial decisions which can guide initiatives designed by policy makers to promote more stable investment environments. For example, our results that relate education to the impact of trust on speculative behavior indicate the importance of improving financial literacy and education, particularly in areas where investors rely more on trust due to lower educational and income levels.

The remainder of the paper is organized as follows. Section 2 provides the relevant data and variable definition. In Section 3, we show the underperformance of lottery-type stocks. In Section 4, we present our empirical results on the relationship between MAX and trust, as well as how the level of education or income can impact the effect of trust on the MAX effect. Section 5 provides further robustness checks. Section 6 concludes.

2. Data and main variables

In the present study, our measure of trust is calculated based on the responses to the Word Value Survey (WVS) 1981–2020 Integrated Questionnaire[6] (Inglehart et al., 2020), which is widely used in the prior research on social trust. Since we focus on social trust across different regions of the US, we collect our region-level social trust data from five waves (waves 3, 4, 5, 6, and 7) of the WVS from 1995 to 2020. These five waves of surveys were conducted approximately once every five years by WVS in the US, in 1995, 1999, 2006, 2011 and 2017. Therefore, our sample period is from January 1996 to December 2018.

The surveys report the location (state) of survey respondents and group them into 10 US geographical regions[7], which comprise New England, Middle Atlantic, South Atlantic, East South Central, West South Central, East North Central, West North Central, Rocky Mountain, Northwest, and California. In total, there are approximately 8,479 survey respondents in the five waves of the WVS.

Following prior studies on trust (e.g., La Porta et al., 1997; Guiso et al., 2008; Aghion et al., 2010; Pevzner et al., 2015; Wei and Zhang, 2020), we measure social trust based on the respondents' answers to the following WVS question: "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?" Similar to Pevzner et al. (2015), in each region for each survey year, we recode the response to this question to 1 if a respondent answers that most people can be trusted and 0 otherwise, and then we calculate the mean of the responses as our measure of social trust index (labeled as TRUST) in the year. Since TRUST is calculated for each survey year, we use linear interpolation to estimate the value of TRUST in the years between two consecutive surveys for each region.

In this study, we include all common stocks traded on the Nasdaq from January 1996 to December 2018. We focus on Nasdaq stocks since previous research suggests that trading in Nasdaq stocks is localized (Loughran and Schultz, 2004; Schultz, 2003; Anand et al., 2011). We follow Gupta et al. (2018) and Wei and Zhang (2020) and define a firm's location as the location of its headquarters. We collect firms' annual headquarters location (state) data in the US from Compustat and merge firm locations and regional TRUST data to construct our sample of stocks.

Table 1, Panel A, presents the details of the 10 US geographical regions in our study, the values of trust index (TRUST) for each region during the five survey years, the number of firms headquartered

[6] http://www.worldvaluessurvey.org/WVSDocumentationWVL.jsp.

[7] We follow Wei and Zhang (2020) and identify these geographical regions from the WVS. The states in each region are as follows. New England (Maine, New Hampshire, Vermont, Massachusetts, Rhode Island and Connecticut), Middle Atlantic (New York, Pennsylvania and New Jersey), South Atlantic (Delaware, Maryland, Washington D.C., Virginia, West Virginia, North Carolina, South Carolina, Georgia and Florida), East South Central (Kentucky, Tennessee, Mississippi and Alabama), West South Central (Oklahoma, Texas, Arkansas and Louisiana), East North Central (Wisconsin, Michigan, Illinois, Indiana and Ohio), West North Central (Missouri, North Dakota, South Dakota, Nebraska, Kansas, Minnesota and Iowa), Rocky Mountain (Montana, Wyoming, Nevada, Utah, Colorado, Arizona, New Mexico and Idaho), Northwest (Oregon, Washington), and California.

in each region during our sample period, as well as the total number of firms in our sample.

<Insert Table 1 about here>

In total, there are 49 US states and 8,875 firms during our sample period. Table 1 shows that the related rankings of social trust index (TRUST) in each region are relatively stable for each of the five survey waves (1995, 1999, 2006, 2011 and 2017). Higher index (TRUST) values correspond to higher trust; the Northwest region has the highest average TRUST, with values from 0.429 to 0.573, whereas the East South Central region has the lowest average TRUST, with values from 0.214 to 0.291.

TRUST also varies over time across these 10 different US geographical regions. For example, TRUST in the New England region increases from 0.331 in 1995 to 0.433 in 1999, then decreases slightly and remains stable between 0.425 and 0.415 from 2006 to 2011, but increases to 0.487 in 2017. However, the index in the Rocky Mountain region first increases from 0.275 in 1995 to 0.367 in 1999 and continues to increase to 0.434 in 2006, but its value decreases to 0.394 in 2011 and then to 0.382 in 2017.

We further collect regional demographic variables, such as the religious belief (CATH) at the state level from the Association of Religion Data Archives, the education level (EDU) in each state from the Economic Research Service in the US Department of Agriculture, and the state-level median household income (MHI) and the state-level per capita personal income (PCI) from the US Census Bureau. CATH is the percentage of Catholic adherents in each state. The state-level CATH data is available for 1990, 2000, 2010 and 2020. We obtain CATH for each survey year and linearly interpolate CATH for interim years. EDU is the percentage of the population over 25 years old in each state that holds a bachelor's degree or higher. The data for EDU at the state level is available for 1990, 2000, 2010 and 2019; therefore, we linearly interpolate EDU for interim years. Similarly, data for state-level median household income (MHI) and per capita personal income (PCI) are available for 1990, 2000 and 2010. We linearly interpolate MHI and PCI for intermediate years and then apply their values in 2010 to the period after 2010 (the period 2010–2018)[8]. Since both median household income and per capita personal income have been used as the state income in prior studies (see, e.g., Wei and Zhang, 2020; Shu et al., 2012), we use MHI as the proxy for income in our main analysis, and PCI as an alternative proxy for income in the robustness analysis.

Panel B of Table 1 shows the summary statistics of regional variables in our sample. These include the mean, standard deviation, 25th percentile, median, and 75th percentile of TRUST, CATH, EDU, MHI and PCI. For the entire sample, the mean (median) value of TRUST is 0.38 (0.38), the mean (median) value of CATH is 23.93% (26.38%), the mean (median) value of EDU is 27.59% (27.17%), the mean (median) value for MHI is 48726.19 (47517.00) dollars, and the mean (median) of PCI is 24741.23 (24260.50) dollars.

[8] We follow Hasan, Hoi, Wu, and Zhang (2017) as well as Shu et al. (2012) to backfill the data for the missing years using the available data from the most recent preceding year.

We obtain the firm-level transaction data (price, returns, volume and number of shares outstanding) from the Center for Research in Security Prices (CRSP). We use daily stock returns to compute the maximum daily stock returns (MAX) for each stock in each month and other variables of interest including the market beta (BETA) and idiosyncratic skewness (ISKEW). We also use daily stock returns and volume data to calculate a measure of illiquidity (ILLIQ) following Amihud (2002). The CRSP daily value-weighted index is used as the proxy for market return. We use monthly returns to compute proxies for intermediate-term momentum (MOM) and short-term reversals (REV). Monthly share prices and shares outstanding are used to calculate market capitalization (MKTCAP). Additionally, we use Compustat to obtain equity book value of firms to calculate the book-to-market ratios (BTM) for each firm.

Panel C of Table 1 presents the summary statistics for stock variables of interest in our sample. These include the mean, standard deviation, 25^{th} percentile, median, and 75^{th} percentile of the stock variables. SIZE is market capitalization in millions of dollars (MKTCAP) after taking the natural logarithm. Detailed information of all variables constructed in this section are provided in the Appendix.

3. Lottery demand and the cross-section of expected stock returns

In this section, we investigate the negative relation between extreme positive daily return (MAX) in the previous month and the expected stock returns, namely the MAX effect, in our sample. Every month from January 1996 to December 2018 we sort all sample stocks into 10 decile portfolios based on the maximum daily return (MAX) within the previous month. Table 2 reports both value-weighted and equal-weighted average monthly raw returns, and alphas relative to the CAPM, Fama and French (1993) three-factor model (FF3) and Fama and French (1993) and Carhart (1997) four-factor model (FFC4)[9], for the decile portfolios and the zero-cost portfolio[10] that is long the high MAX (decile 10) portfolio and short the low MAX (decile 1) portfolio. The *t*-statistics, adjusted following Newey-West (1987) using six lags, are presented in parentheses.

<Insert Table 2 about here>

Consistent with the negative MAX premium between the high MAX (decile 10) portfolio and the low MAX (decile 1) portfolio in Bali et al. (2011), the results in Table 2 show that there is a negative relation between MAX and the cross-section of expected returns in our sample. The value-weighted average raw return for the zero-cost portfolio is −1.03% per month and marginally significant at the 10% level (*t*-statistic = −1.88). This high-low MAX spread becomes stronger, and both economically and

[9] Following Fama and French (1993) and Carhart (1997), the FFC4 alpha is the estimated intercept from the regression of the excess portfolio return on excess return of the market portfolio (MKTRF), the size factor (SMB), the book-to-market factor (HML) and the momentum factor (UMD). We follow the same approach to calculate FF3 and CAPM alphas by using three factors (MKTRF, SMB and HML) and the market factor (MKTRF) as risk factors in regressions, respectively. MKTRF, SMB (small minus big), HML (high minus low), and UMD (winner minus loser) are described in and obtained from Kenneth French's data library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/).

[10] In other words, the zero-cost portfolio is the difference between high MAX (decile 10) and low MAX (decile 1) portfolio, also called the 'high-low MAX' portfolio.

statistically significant, at all conventional levels after adjusting for risk factors. The alphas with respect to CAPM, FF3, and FFC4 models are −1.57% (*t*-statistic = −3.34), −1.42% (*t*-statistic = −4.70), and −1.16% (*t*-statistic = −3.87) per month, respectively. Taking a closer look, the value-weighted average raw returns of the MAX-sorted decile portfolios tend to decrease, albeit not monotonically, from 1.28% per month for the low MAX (decile 1) portfolio to 0.25% per month for the high MAX (decile 10) portfolio. The corresponding alphas for CAPM, FF3, and FFC4 models exhibit a similar pattern across the decile portfolios of MAX.

The raw returns and alphas of equal-weighted portfolios show a similar pattern to those of value-weighted portfolios, though they are less significant. For instance, we find that the equal-weighted average raw return of the zero-cost portfolio is −0.59% per month (*t*-statistic = −1.05). This is consistent with the results of Bali et al. (2011), who demonstrate that the negative MAX premium is stronger for value-weighted compared to equal-weighted portfolios. Similar to the value-weighted portfolios, the difference in returns between high-low MAX portfolios becomes stronger after adjusting for risk factors. The CAPM, FF3 and FFC4 alphas are −1.11% (*t*-statistic = −2.30), −0.97% (*t*-statistic = −2.79) and −0.64% (*t*-statistic = −1.81) per month, respectively.

In summary, the results in Table 2 show that the lottery-like portfolio of stocks (decile 10 with high MAX) significantly underperforms the non-lottery-like portfolio (decile 1 with low MAX), which confirm that there is a MAX effect in our sample of stocks.

4. Trust and the lottery demand

4.1. Univariate portfolio analysis

In this section, we examine whether social trust can influence the MAX anomaly. We begin our analysis by using univariate portfolio analysis to test if social trust has an impact on the MAX effect.

We first create a ranking (or threshold) of TRUST over time for each region where firms are headquartered, and assign each firm-month to the high-TRUST or low-TRUST group depending on whether the one-month lagged value of TRUST for the firm's region is above or below the threshold of TRUST, respectively. [11] We consider the median as well as mean of TRUST as alternative thresholds for TRUST. Then, for each group in each month, we sort our stocks into deciles based on MAX and calculate the average monthly raw returns and several risk-adjusted returns for decile portfolios and for the difference between high (decile 10) and low (decile 1) MAX portfolio for the high-TRUST and low-TRUST groups. The results are presented in Table 3. Panel A and Panel B of Table 3 report the results of value-weighted returns and equal-weighted returns for the high-TRUST and low-TRUST groups, respectively.[12] The Newey-West (1987) adjusted *t*-statistics are presented in parentheses using six lags.

[11] We use time-series variation in the trust index (TRUST) for each region because TRUST varies over time across the 10 different US geographical regions. Both the cross-sectional and time-series variation in TRUST across regions could be used to identify the link between social trust and lottery demand that includes the MAX effect. In the Internet Appendix (Table IA2), we also create a ranking of TRUST using either region-level TRUST in each month or the time-series mean of TRUST in each region to group our sample stocks into subsamples based on the highest and lowest TRUST; the results follow a similar pattern.
[12] For brevity, we do not report the results of the risk-adjusted returns for decile portfolios of MAX in Table 3.

<Insert Table 3 about here>

The results in Panel A of Table 3 show that for the value-weighted portfolios, the MAX effect is stronger, and both economically and statistically significant, for the high-TRUST group (regions with high trust) compared to the low-TRUST group (regions with low trust). When we use the median of TRUST as the threshold, the raw return of the high-low MAX portfolio in the low-TRUST group is −0.87% per month with a *t*-statistic of −1.54. However, the corresponding raw return in the high-TRUST group is −1.34% per month with a *t*-statistic of −2.49. The magnitude of the high-low MAX spread is approximately 1.3 times larger than that generated by the unconditional portfolio analysis in Table 2 (−1.03% per month with a *t*-statistic of −1.88). We find a similar pattern for the risk-adjusted returns. For example, the CAPM alpha of the high-low MAX portfolio in the high-TRUST group is −1.85% per month with a *t*-statistic of −3.91, which is statistically significantly more negative compared with the corresponding return of −1.40% per month with a *t*-statistic of −2.82 in the low-TRUST group. The results are qualitatively similar when we use the mean of TRUST as the threshold.

We repeat the portfolio analysis in Panel A of Table 3 with the equal-weighted portfolios and report the results in Panel B of Table 3. The results for equal-weighted portfolios in Panel B show a similar pattern of raw returns and risk-adjusted returns to those for value-weighted portfolios in Panel A, albeit less economically and statistically significant. For instance, for the median of TRUST as the threshold, the FFC4 alpha of the high-low MAX portfolio in the high-TRUST group is −0.97% per month (*t*-statistic = −2.53), which is statistically significantly more negative compared with the corresponding return of −0.45% per month (*t*-statistic = −1.21) in the low-TRUST group. It again provides evidence that the MAX effect is stronger in regions with high trust than in regions with low trust.

Overall, the results in Table 3 support our hypothesis that social trust plays a significant role in the MAX effect and lottery demand. They also support the view that there is a positive relation between trust and investors' willingness to invest on risky assets (e.g., Guiso et al., 2004, 2008; El-Attar and Poschke, 2011; Barbi et al., 2023).

4.2. Cross-sectional regression analysis

To investigate the impact of social trust on the MAX anomaly while controlling for other variables that have asset-pricing implications in the cross-section, we continue our analysis by conducting Fama-MacBeth (1973) cross-sectional regressions across firms headquartered in different regions. Consistent with the previous portfolio-level analysis, to differentiate the effect of different levels of social trust on the MAX anomaly, we run the cross-sectional regressions under regions with high and low trust, respectively.

Similarly, we first divide our sample into two groups (high-TRUST and low-TRUST) based on the ranking of TRUST over time for each region where firms are headquartered. If the firm's region's one-month lagged value of TRUST is above or below the thresholds of TRUST of the region over time, then the firm-month is placed into the high-TRUST or low-TRUST group, respectively. The thresholds are median and mean of TRUST of the region of the firm's headquarters over time. Then, we run the monthly cross-sectional regressions for each high-TRUST and low-TRUST group. The full regression specification is as follows:

$$R_{i,t} = \lambda_{0,t-1} + \lambda_{1,t-1} MAX_{i,t-1} + \Lambda_{t-1} Z_{i,t-1} + \mathcal{E}_{i,t} \quad (1)$$

where $R_{i,t}$ is the realized return (in percent) on stock i in month t, $MAX_{i,t-1}$ is the maximum daily return for stock i in month $t-1$ and $\boldsymbol{Z}_{i,t-1}$ is a vector containing the control variables, which include market beta (BETA), natural log of market capitalization (SIZE), natural log of book-to-market ratio (BM), momentum (MOM), short-term reversal (REV) and illiquidity (ILLIQ). All the control variables are widely considered as determinants of stock returns in the cross-section, and their detailed definitions and constructions can be found in the Appendix. All independent variables are winsorized on a monthly basis at the 1% and 99% percentiles to alleviate concerns with outliers.

Table 4 reports the time-series averages of the slope coefficients, along with the Newey-West (1987) adjusted t-statistics using six lags (in parentheses) from the monthly cross-sectional regressions separately for the high-TRUST and low-TRUST groups.

<Insert Table 4 about here>

We find that the underperformance of lottery stocks that is proxied by MAX is more pronounced among the regions with high levels of trust than among the regions with low levels of trust. More specifically, for both median and mean thresholds, when the regression specification does not include control variables, the average coefficients on MAX in the high-TRUST group are more negative, and both economically and statistically significant, with values of −0.054 (t-statistic = −2.87) and −0.051 (t-statistic = −2.78), respectively. Conversely, the average coefficients on MAX in the low-TRUST group are insignificant, with values of −0.028 (t-statistic = −1.41) and −0.025 (t-statistic = −1.12), respectively, which are approximately half the values of those coefficients in the high-TRUST group. These results indicate that the MAX effect is roughly doubled across the regions with high trust.

When we add control variables to the regression specification, the results follow a similar pattern to the previous regression specification. For both median and mean thresholds, the average coefficients on MAX in the high-TRUST group decrease slightly in absolute magnitude, with values of −0.050 (t-statistic = −3.00) and −0.045 (t-statistic = −2.76), respectively, but these remain negative and statistically significant. However, the coefficients on MAX in the low-TRUST group become statistically insignificant, with values of −0.019 (t-statistic = −1.10) and −0.020 (t-statistic = −0.97), respectively. Similarly, we find that the coefficients on MAX for the high-TRUST group are approximately 2.3 to 2.6 times larger in absolute magnitude than those for the low-TRUST group.

In summary, the results in Table 4 provide direct evidence to support our hypothesis that social trust has an impact on the MAX effect and lottery demand. It shows that the MAX effect is strong, and both economically and statistically significant, in high-trust regions, however, it tends to be insignificant in low-trust regions, indicating that lottery demand is influenced by social trust through the positive association between trust and investors' tendency to invest on risky assets (e.g., Guiso et al., 2004, 2008; El-Attar and Poschke, 2011; Barbi et al., 2023).

4.3. Cross-sectional regression analysis with an interaction term

To examine whether our results of the cross-sectional regression across the full sample are robust and further examine the impact of social trust on the MAX effect, we re-run the Fama-MacBeth (1973) cross-sectional regressions after controlling for TRUST and an interaction term between MAX and a corresponding dummy variable that differentiates between firms that are headquartered in different regions with low and high TRUST values, without and with control variables. With this method, we can investigate how the MAX effect varies across firms' regions with different levels of social trust. We run the following monthly cross-sectional regression:

$$R_{i,t} = \lambda_{0,t-1} + \lambda_{1,t-1}MAX_{i,t-1} + \lambda_{2,t-1}TRUST_{i,t-1} + \lambda_{3,t-1}MAX_{i,t-1} \times DTRUST_{i,t-1} + \boldsymbol{\Lambda}_{t-1}\boldsymbol{Z}_{i,t-1} + \mathcal{E}_{i,t} \quad (2)$$

where $R_{i,t}$ is the realized return (in percent) on stock i in month t, $MAX_{i,t-1}$ is the maximum daily return for stock i in month $t-1$, and $TRUST_{i,t-1}$ is the social trust index in month $t-1$ for the region where firm i (i.e., stock i's firm) is headquartered. $DTRUST_{i,t-1}$ is a dummy variable with value that equals to one or zero, which is defined based on TRUST of the region where firm i is headquartered. If the firm's region's TRUST in month $t-1$ is above the median of TRUST of the firm's headquarter region over time (high level of trust), then $DTRUST_{i,t-1}$ is one and zero otherwise. [13] $\boldsymbol{Z}_{i,t-1}$ is a vector containing the control variables. Detailed information of the variables is provided in the Appendix. All independent variables are winsorized on monthly basis at the 1% and 99% percentiles to eliminate the potential impact of the outliers.

Table 5 presents the time-series averages of the slope coefficients for our full sample stocks from the outlined monthly cross-sectional regressions. The Newey-West (1987) adjusted t-statistics using six lags are presented in parentheses.

<Insert Table 5 about here>

Models (1) and (2) indicate that there is a significantly negative relation between the maximum daily return (MAX) over the previous month and the cross-sectional expected stock returns, which is consistent with the previous findings of the MAX effect in the US (e.g., Bali et al., 2011, among others). We find that the average coefficients on MAX are negative, and both economically and statistically significant, in the univariate model (1) and the multivariate model (2) that includes all control variables, with values of −0.038 (*t*-statistic = −2.08) and −0.030 (*t*-statistic = −1.93), respectively.

[13] In Table IA3 of the Internet Appendix, we also use mean of TRUST as the threshold to define the dummy variable for TRUST (DTRUST). The results are robust.

We then only include MAX and TRUST, without and with the control variables in the regression specification. The results are shown in models (3) and (4). In both models, the slope coefficients on MAX are statistically significant and they remain similar in absolute magnitude compared to those in models (1) and (2). This implies that MAX has information beyond social trust in explaining the cross-section of stock returns.

To explore the relation between the MAX effect and social trust, we consider the interaction term between MAX and the dummy variable for TRUST ($MAX \times DTRUST$). In models (5) and (6), we include MAX, TRUST, and $MAX \times DTRUST$ before and after considering control variables. The coefficient estimate on the interaction term can provide the economic difference of the MAX effect between firms headquartered in regions with low and high levels of social trust.

The results from model (5) show that the estimated coefficient on MAX becomes insignificant, with a value of −0.030 (t-statistic = −1.51), compared to the coefficients on MAX in models (1) and (3), whereas the estimated coefficient for interaction term ($MAX \times DTRUST$) is significantly negative at the 5% significance level, with a value of −0.022 (t-statistic = −2.22). The results indicate that the MAX effect is weaker and statistically insignificant (coefficient estimate = −0.030) among firms' regions with low trust; however, it becomes stronger among firms' regions with high trust, with the estimated coefficient of −0.022 (formally, (−0.022) × 1, t-statistic = −2.22).

When we include all control variables in model (6), the results are consistent with those shown in model (5). The estimated coefficient on MAX tends to be less significant with value of −0.022 (t-statistic = −1.32). However, the estimated coefficient on the interaction term ($MAX \times DTRUST$) is −0.025 (t-statistic = −2.71), which is significantly negative at the 1% significance level. Similarly, the results imply that MAX effect tends to be weaker and statistically insignificant (coefficient estimate = −0.022) among firms' regions with low trust, whereas it is stronger among firms' regions with high trust, with the estimated coefficient of −0.025 (t-statistic = −2.71). Thus, the results in models (5) and (6) show that the MAX effect among firms headquartered in high-trust regions is stronger than for firms headquartered in low-trust regions. Additionally, the slope coefficients on TRUST in both models (5) and (6) are marginally significant, with values of 1.321 (t-statistic = 1.87) and 1.070 (t-statistic = 1.70), respectively. The positive coefficients on TRUST suggest that there seems to be a positive relation between trust and expected stock returns, which is consistent with the finding of previous literature that lack of trust (the perceived risk of being cheated) decreases the expected return on the stock investment, making participation less attractive (e.g., Guiso et al., 2008; El-Attar and Poschke, 2011).

One potential concern regarding our findings of the effect of social trust on the MAX effect is that our social trust measure may be correlated with the regional demographic factors such as religion, education and income, which can also impact investor preference for lottery stocks. Kumar (2009) finds that Catholics and investors with lower levels of education and income have a stronger propensity to invest in lottery-like stocks. Guiso et al. (2003) show that Catholics are also more trusting. Also, the effect of trust can vary with the level of education or wealth, because less educated or wealthy people possess less reliable information and rely more on trust in making economic or financial decisions (e.g., Guiso et al., 2004, 2008; El-Attar and Poschke, 2011; Pevzner et al., 2015).

To address this concern and ensure that the impact of trust on the lottery demand is not due to these demographic characteristics such as religion, education and income, we follow Bali et al. (2019) and control for a firm's headquarters characteristics at the state level. The regional factors include the percent of Catholic population (CATH), the percent of the population aged 25 and older who attained a bachelor's degree or higher (EDU), and the median household income (MHI) measured in thousands of dollars in each state.[14] The detailed information of the variables can be found in the Appendix. We run monthly cross-sectional regressions for the following specification:

$$R_{i,t} = \lambda_{0,t-1} + \lambda_{1,t-1}MAX_{i,t-1} + \lambda_{2,t-1}TRUST_{i,t-1} + \lambda_{3,t-1}MAX_{i,t-1} \times DTRUST_{i,t-1} + \boldsymbol{\Lambda}_{t-1}\boldsymbol{Z}_{i,t-1} + \gamma_{1,t-1}CATH_{i,t-1} + \gamma_{2,t-1}EDU_{i,t-1} + \gamma_{3,t-1}MHI_{i,t-1} + \mathcal{E}_{i,t} \quad (3)$$

The results are reported in Table 6. The Newey-West (1987) adjusted t-statistics using six lags are presented in parentheses.

<Insert Table 6 about here>

Models (2) to (5) of Table 6 show that after controlling for regional factors such as CATH, EDU, and MHI, the results for the estimated coefficients on MAX and the interaction term are qualitatively similar to those in model (6) of Table 5.[15] For example, in model (5) of Table 6, consistent with the pattern in model (6) of Table 5, the estimated coefficient on MAX becomes less significant with value of −0.023 (t-statistic = −1.41), whereas the estimated coefficient on the interaction term ($MAX \times DTRUST$) is significantly negative at conventional levels, with the value of −0.025 (t-statistic = −2.41). The results suggests that MAX effect tends to be weaker and statistically insignificant (coefficient estimate = −0.023) among firms' regions with low trust, whereas it becomes stronger among firms' regions with high trust, with the estimated coefficient of −0.025 (t-statistic = −2.41). Thus, the results in Table 6 indicate that the impact of social trust on the MAX effect is not driven by religion, education, and income.

Overall, the results reported in Tables 5 and 6 provide further support to our findings in Table 4 and present how the MAX effect varies between firms headquartered in different regions with different (low or high) levels of social trust. More specifically, the MAX effect tends to be more pronounced among firms headquartered in regions with a high level of social trust rather than among firms headquartered in regions with a low level of social trust. In other words, lottery-like stocks in high social trust regions have lower expected returns compared to those in low social trust regions, indicating that the high level of social trust plays an important role in the MAX effect. Furthermore, the positive coefficients on TRUST support prior literature that suggests lack of trust reduces the expected return on the stock

[14] The results are qualitatively similar when we replace MHI (median household income) with PCI (per capita personal income) as an alternative measure of income in the unreported analyses.
[15] In unreported analyses, we also use mean of TRUST as the alternative threshold to define DTRUST and repeat the Fama-MacBeth (1973) cross-sectional regressions analysis in Table 6. Our main findings in Table 6 remain robust.

investment (e.g., Guiso et al., 2008; El-Attar and Poschke, 2011). Finally, the results in Table 6 show that the effect of social trust on the MAX effect is not driven by regional factors such as religion, education, and income.

4.4. Education, Wealth, and the effect of trust

Trust reflects either the characteristics of the financial system that indicate the chance of frauds in the market, or the individual's subjective characteristics based on their priors that can create significant variations in levels of trust among individuals (Guiso et al., 2004, 2008). If trust is formed based on personal characteristics of individuals, we should expect more educated individuals to be less influenced by these priors because they have more knowledge about markets (Guiso et al., 2004, 2008; El-Attar and Poschke, 2011; Pevzner et al., 2015). Furthermore, El-Attar and Poschke (2011) show that the effect of trust on households' portfolio choice is smaller for wealthier households, since wealthier households have more reliable information about financial markets and a better understanding of how these markets work. Consequently, they are less affected by their priors reflected in trust when making financial decisions. Therefore, we predict that the effect of trust on lottery demand is weaker in regions with higher education (income) level, indicating that more educated (wealthy) investors rely less on trust in making financial decisions. To shed light on the channels that trust impacts lottery demand, we now explore the effect of education and income levels on the relation between trust and the MAX effect.

First, we test whether less educated investors rely more on trust in investing disproportionately more in the lottery-type stocks, and thus the effect of trust on the MAX effect varies across regions with different education levels. We predict trust to be a more important driving factor of the MAX effect when the region's education level is lower. To test our prediction, we follow Kumar (2009) and assume that investors who live in regions with a higher (lower) education level are more likely to have a higher (lower) education level. We use the variable EDU as the proxy for the education level of each state. EDU is the fraction of the population over 25 years old in each state with a bachelor's degree or higher. We split our sample into two groups (low-EDU and high-EDU) by the level of education. In each month, we create a ranking of EDU across the states where firms are headquartered[16] and classify firms in a state that has a one-month lagged value of EDU below or above the median of EDU of the month as low-EDU or high-EDU, respectively. Then, we run the monthly cross-sectional regression Eq. (2) for each group. We use the median of TRUST of the region where firms are headquartered over time to define the dummy variable for TRUST (DTRUST). [17] All independent variables are winsorized on monthly basis at the 1% and 99% percentiles to avoid issues with the outliers.

Based on our conjecture, we expect a stronger (weaker) negative estimate on the interaction term between MAX and DTURST for the low (high) EDU group. Thus, the MAX effect should be stronger in high trust and low educated regions. The results are presented in Table 7. The *t*-statistics, adjusted

---

[16] We use cross-sectional variation in education level (EDU) across states in the analysis because EDU varies across the 49 different US states at the same time. However, EDU does not vary too much for each state over time.

[17] In Table IA7 of the Internet Appendix, we also use mean of EDU as the threshold to split our sample by education level and mean of TRUST to define the dummy variable for TRUST (DTRUST). The results are qualitatively similar.

following Newey-West (1987) using six lags, are presented in parentheses. For brevity, we only report analysis for the main specifications for each group.

<Insert Table 7 about here>

The results in models (1) and (2) show that the MAX effect is more pronounced in regions with a lower education level than in regions with a higher education level, which is consistent with the findings of Kumar (2009) that less educated investors invest disproportionately more in lottery-type stocks. For instance, when we only introduce MAX with the control variables to the regression specification in model (1), the average coefficient on MAX for the low-EDU group is −0.039 (t-statistic = −2.03), which is approximately 1.4 times larger in absolute magnitude than that for the high-EDU group (−0.028, t-statistic = −1.79). This finding is robust when we include MAX and TRUST with the control variables to the regression specification. In particular, in model (2) for the low-EDU group, the slope coefficient on MAX remains significant, with value of −0.039 (t-statistic = −2.06), implying that MAX has explanatory power in the cross-section of returns beyond the social trust, which is consistent with the results in models (3) and (4) of Table 5.

In model (3), the signs on the interaction terms for both low- and high-EDU groups are consistent with our predictions. The interaction term ($MAX \times DTRUST$) among low education regions is significantly negative, whereas it is indistinguishable from zero at conventical statistical levels among high education regions. When we introduce the interaction term in model (3), for the low-EDU group, the estimated coefficient on MAX decreases to approximately half of those in absolute magnitude in models (1) and (2) and becomes insignificant (−0.021, t-statistic = −0.95), whereas the coefficient on the interaction term is significantly negative (−0.046, t-statistic = −2.92). The results indicate that within the low-EDU group, the MAX effect is weaker (coefficient estimate = −0.021) and statistically insignificant among firms' regions with a low level of trust. However, it becomes stronger and significant among firms' regions with high level of trust with the estimated coefficient of −0.046 (t-statistic = −2.92).

The results in model (3) for the high-EDU group show a similar pattern to those for the low-EDU group. We find that the estimated coefficient on MAX decreases slightly to −0.025 and is insignificant (t-statistic = −1.50), while the coefficient on the interaction term is −0.017 (t-statistic = −1.68). This suggests that within the high-EDU group, the MAX effect becomes weaker and statistically insignificant (coefficient estimate = −0.025) among firms' regions with a low level of trust, whereas it is stronger, though insignificant at conventional levels, among firms' regions with a high level of trust. The results for the high-EDU group show that the MAX effect among firms' regions with a high level of trust is indistinguishable from zero.

Comparing the results in model (3) for the low-EDU group with those for the high-EDU group, we observe that among firms' regions with a high level of trust, the MAX effect is stronger for the low-EDU group with the estimated coefficient of −0.046 (t-statistic = −2.92) than that for the high-EDU group, for which the estimated coefficients of the interaction term and MAX are statistically indistinguishable from zero. These results suggest that the effect of social trust on the MAX effect is stronger among regions with a low education level than among regions with a high education level, indicating that less educated investors rely more on trust in investing more in the lottery-type stocks. The results in Table 7 show that less educated investors exhibit a greater propensity to invest in stocks with lottery features. However, less educated investors invest disproportionately more in lottery-type stocks only in high trust regions.

In summary, Table 7 provides further evidence to support our findings in Table 5, that a high level of social trust contributes to the MAX effect, however, the effect depends on the education level of investors. When we differentiate education level, the results show that the effect of trust on the MAX effect is more pronounced when the region's education level is lower, indicating that education can be the channel through which trust impacts the MAX effect. Our finding is consistent with the existing literature on trust that the effect of trust is stronger for people with less education, since less educated people have less reliable information and rely more on trust in making economic or financial decisions (e.g., Guiso et al., 2004, 2008; El-Attar and Poschke, 2011; Pevzner et al., 2015). Additionally, the results in Table 7 show that the MAX effect is stronger among regions with a low education level than regions with a high education level, which confirms that less educated investors invest disproportionately more in lottery-type stocks (Kumar, 2009). However, we provide evidence that the impact of education level on lottery demand exists only among high trust investors.

We now shift our focus to the impact of wealth on the relation between trust and MAX effect. Specifically, we examine whether low-income investors rely more on trust in investing disproportionately more in the lottery-type stocks, and therefore the impact of trust on the MAX effect varies across regions with different income levels. We expect trust to be a more important determinant of the MAX effect when the region's income level is lower. Similar to the education level, we assume that investors who live in high-income (low-income) regions tend to have higher (lower) income levels. We define MHI, the median household income in each state, as the proxy for the income level of each state. We repeat the analysis in Table 7, using MHI instead of the EDU variable. Specifically, in each month, we create a ranking of MHI across the states where firms are headquartered[18]. If a firm's state's one-month lagged MHI is below or above the median of MHI of the month, then the firm-month is categorized into the low-MHI or high-MHI group, respectively. We use the median of TRUST of the region where firms are headquartered over time to define the dummy variable for TRUST (DTRUST).[19] We predict a stronger (weaker) negative estimate on the interaction term between MAX and DTURST for the low (high) MHI group. Thus, the MAX effect is stronger in high trust and low-income regions. Table 8 presents the results.

<Insert Table 8 about here>

[18] Similar to EDU, there is obvious variation in MHI across the 49 different US states at the same time, whereas MHI does not change too much for each state over time. Thus, we use cross-sectional variation in income level (MHI) across states in each month in the analysis.

[19] In Table IA8 of the Internet Appendix, the results remain robust when we use mean of MHI as the threshold to split our sample by the level of income and mean of TRUST to define the dummy variable for TRUST (DTRUST).

In models (1) and (2), for both low-MHI and high-MHI groups, the slope coefficients on MAX remain significant before and after controlling for TRUST, indicating that MAX has information beyond the social trust in the cross-section of returns. When we compare the results in models (1) and (2) for the low-MHI group with those for the high-MHI group, the MAX effect is stronger for the regions of firms with a low level of income than the regions of firms with high level of income. For example, when we only include MAX with the control variable in model (1), the average coefficient on MAX for the low-MHI group (−0.045, t-statistic = −2.20) is approximately 1.7 times larger in absolute magnitude, and more significantly negative than that for the high-MHI group (−0.026, t-statistic = −1.67). This provides additional evidence to support Kumar (2009) that low-income investors invest disproportionately more in lottery-type stocks.

In model (3), we include the interaction term $(MAX \times DTRUST)$. We find that the coefficients on MAX reduce and tend to be insignificant for both low-MHI and high-MHI groups, with values of −0.018 (t-statistic = −0.77) and −0.021 (t-statistic = −1.24), respectively, compared to those coefficients in models (1) and (2). In particular, the estimated coefficient on MAX for the low-MHI group reduced more significantly, both economically and statistically, than that for the high-MHI group. By contrast, the coefficient on the interaction term for the low-MHI group is more significantly negative (−0.061, t-statistic = −3.95) and approximately 3.6 times larger in absolute magnitude than that for the high-MHI group (−0.017, t-statistic = −1.67). Consistent with our prediction, the interaction term among low-income regions is significantly negative, whereas it is insignificant at conventional levels among high-income regions.

The results show that within the low-MHI group, the MAX effect is significant (t-statistic = −3.95) among firms' regions with a high level of trust with the estimated coefficient of −0.061 (formally, (−0.061) × 1). However, it is weaker (coefficient estimate = −0.018) and statistically insignificant among firms' regions with a low level of trust. Similarly, we find that for the high-MHI group, the MAX effect becomes weaker and statistically insignificant among firms' regions with a low level of trust, whereas it is stronger (t-statistic = −1.67) among firms' regions with a high level of trust, with the estimated coefficient of −0.017 (formally, (−0.017) × 1).

Our results show that the MAX effect tends to be stronger among firms' regions with a high level of trust than among firms' regions with a low level of trust, depending on the level of income. We find that the effect of social trust on the MAX effect is more pronounced in low-income regions than in high-income regions. For example, among firms' regions with a high level of trust, the MAX effect is stronger for the low-MHI group with the estimated coefficient of −0.061 (t-statistic = = −3.95) than for the high-MHI group with the estimated coefficient of −0.017 (t-statistic = −1.67).

The results in Table 8 show that a high level of social trust plays a significant role in lottery demand and the MAX effect. When we consider the different levels of income, the results show that the effect of trust on the MAX effect is stronger in regions with lower income than in regions with higher income. Our finding of the relation between income level and the effect of trust on the MAX effect indicates that low-income investors rely more on trust in investing more in the lottery-type stocks. This supports the findings of El-Attar and Poschke (2011) that the effect of trust is smaller for wealthier households in making financial decisions, because trust matters more for less wealthy individuals who have less reliable information about financial markets. Our finding is consistent with that of Kumar (2009) that investors with low income invest disproportionately more in lottery-type stocks. However, we provide evidence that the impact of income level on lottery demand is limited to high-trust regions.

5. Robustness tests

We further conduct several additional analyses to test the robustness of our main results. More specifically, these additional tests are conducted to examine whether our main finding of the relation between social trust and the underperformance of lottery-type stocks is robust. In this section, we summarize these additional tests and discuss the tests in detail in the Internet Appendix. The relevant sections and tables of the Internet Appendix are presented in parentheses.

First, we demonstrate that the MAX effect is not revealed when using the component of MAX that is orthogonal to the social trust index proxy TRUST as the sort variable in the univariate portfolio analysis (Table IA1 of Section IA-1).

In our main tests, we conduct the univariate portfolio analysis that examines the relation between trust and lottery demand by creating a ranking (or threshold) of TRUST over time for each region to define high and low trust subsamples. We further show that our main results are robust when separately using the cross-sectional variation and time-series mean in trust index (TRUST) across regions as two alternative approaches to create the ranking of TRUST and define the highest and lowest trust regions (Table IA2 of Section IA-2).

In our main tests of Fama-MacBeth (1973) cross-sectional regressions with an interaction term, we use the median of TRUST as the threshold to define the dummy variable for TRUST (DTRUST). As a robustness test, we use mean of TRUST as the alternative threshold to define the dummy variable for TRUST and show that our previous findings are robust (Table IA3 of Section IA-3).

Then, we show that our main results continue to hold when using MAX(N), which is the average of N (N = 2, 3, 4, 5) highest daily returns over the past one month, as the alternative measures of lottery demand instead of MAX in the cross-sectional regressions (Tables IA4 and IA5 of Section IA-4). We also demonstrate that the main results are robust when replacing MAX with idiosyncratic skewness as the alternative proxy for lottery demand in the cross-sectional regressions (Table IA6 of Section IA-5).

In the main cross-sectional regressions that examine whether and how the effect of trust on the MAX effect varies across regions with different education (income) levels, we split our sample by education (income) level based on the median of EDU (MHI) across the states where firms are headquartered in each month and use the median of TRUST of the region where firms are headquartered over time to define the dummy variable for TRUST (DTRUST). We show that our results are robust when separately using mean of EDU (Table IA7 of Section IA-6) and mean of MHI (Table IA8 of Section IA-7) as the alternative threshold to split our sample by the education level and income level, respectively, with the mean of TRUST used as the alternative threshold to define DTRUST. Finally, we provide evidence that our main findings are qualitatively similar when MHI (median household income) is replaced with PCI (per capita personal income) as an alternative measure of income (Table IA9 of Section IA-8).

6. Conclusion

We explore whether the level of trust, as a driving factor, can play a role in the underperformance of lottery-type stocks. Since social trust is positively related to the tendency of investors to invest in risky assets (e.g., Guiso et al., 2004, 2008; El-Attar and Poschke, 2011; Barbi et al., 2023), and lottery-like stocks are riskier than non-lottery-like stocks, we conjecture that investors in high-trust regions tend to buy more lottery-type stocks. This leads to overpricing and consequently lower expected returns for these stocks. Therefore, we hypothesize that the underperformance of the lottery stocks or the negative lottery premium is stronger in high-trust regions than it is in low-trust regions.

We use MAX (maximum daily return) over the previous month as a proxy for lottery-type stocks, and find that trust, as a novel factor, plays a significant role in the underperformance of the lottery stocks. That is, there is a MAX anomaly in high-trust regions; however, the MAX effect does not exist in low-trust regions, supporting the proposition that trust fosters investing in risky assets (e.g., Guiso et al., 2004, 2008; El-Attar and Poschke, 2011; Barbi et al., 2023). We also find that the relationship between social trust and the lottery demand is not due to regional factors such as religion, education and income. We further show that the effect of trust on the MAX effect is more pronounced when the region's education or income level is lower, supporting previous studies on trust that argue the effect of trust on making economic decisions varies with education or wealth levels (e.g., Guiso et al., 2004, 2008; El-Attar and Poschke, 2011; Pevzner et al., 2015). Our results remain robust to a set of robustness tests reported in the Internet Appendix.

Our paper extends prior studies on lottery-related anomalies by showing social trust is an important factor in the underperformance of lottery-like stocks. It also provides insights into how trust as a key dimension of social capital and culture (Putnam, 1993; Fukuyama, 1995; Knack and Keefer, 1997; Guiso et al., 2004, 2006, 2011; Bloom et al., 2012; Ahern et al., 2015; Wei and Zhang, 2020) affects investors' financial decisions and ultimately financial market outcomes.

Appendix: Variable Definitions

MAX: The maximum daily return within a month as in Bali et al. (2011), which is calculated as the following equation:

$$\mathrm{MAX}_{\mathrm{i,t}} = \max\left(R_{i,d}\right), \quad \mathrm{d} = \{1,2, \ldots D_t\}, \tag{A1}$$

where $R_{i,d}$ is the return of stock i on day d and D_t is the number of trading days in month t.

MAX(N): the average of N (N = 2, 3, 4, 5) highest daily returns within a month.

BETA: The market beta over the month. Following Scholes and Williams (1977) and Dimson (1979), we consider nonsynchronous trading and use the lag, current and lead market return when estimating beta. We estimate beta using daily returns within each month for each stock:

$$\mathrm{R}_{\mathrm{i,d}} - \mathrm{r}_{\mathrm{f,d}} = \alpha_{\mathrm{i}} + \beta_{1,\mathrm{i}}\left(R_{m,d-1} - r_{f,d-1}\right) + \beta_{2,\mathrm{i}}\left(R_{m,d} - r_{f,d}\right) + \beta_{3,\mathrm{i}}\left(R_{m,d+1} - r_{f,d+1}\right) + \varepsilon_{i,d}, \tag{A2}$$

where $R_{i,d}$ is the return of stock i on day d and $R_{m,d}$ is the market return on day d, which is measured by the CRSP daily value-weighted index, and $r_{f,d}$ is the risk-free rate on day d, which is the one-month T-bill return obtained from Kenneth French's online data library. The market beta of stock i in month t is computed as $\widehat{\beta_{i,t}} = \widehat{\beta_{1,i}} + \widehat{\beta_{2,i}} + \widehat{\beta_{3,i}}$.

MKTCAP: The market value of equity, which is measured by a stock's price multiplied by shares outstanding in millions of dollars at the end of month $t-1$ for each stock.

SIZE: The natural log of market capitalization (MKTCAP).

BTM: Following Fama and French (1992), a firm's book-to-market ratio in month t is calculated by using the market value of equity at the end of December of the previous year and the book value at the end of the previous fiscal year. The book value of equity is calculated from the balance sheet data from Compustat, which is defined as stockholder's equity adding deferred taxes and investment tax credit then subtracting the book value of preferred stock. The book value of preferred stock is taken to be the redemption value, the liquidating value or the par value, taken as available in the given order.

BM: The natural log of book-to-market ratio (BTM).

MOM: Following Jegadeesh and Titman (1993), momentum for each stock in month t is defined as the cumulative return on the stock over the previous 11 months, starting two months earlier; that is, the cumulative return from month $t-12$ to month $t-2$, inclusive.

REV: The short-term reversal for each stock in month *t*, which is defined as the return on the stock over the past one month based on Jegadeesh (1990); that is, the return in month $t-1$.

ILLIQ: Following Amihud (2002), the illiquidity for each stock in month t is measured by using the monthly average of the absolute daily stock return divided by its dollar trading volume:

$$\mathrm{ILLIQ}_{\mathrm{i,t}} = \frac{1}{D}\sum_{d=1}^{D}\frac{|R_{i,d}|}{VOLD_{i,d}}, \tag{A3}$$

where $R_{i,d}$ is the return of stock i on day d and $VOLD_{i,d}$ is the daily trading volume in dollars for each stock, measured by volume times the stock price in millions of dollars. Following Lin and Liu (2018), we also require a minimum of ten non-missing daily trading volumes within a given month to compute the illiquidity.

ISKEW: Following Bali et al. (2011) and Harvey and Siddique (2000), the idiosyncratic skewness is estimated from the following regression for each stock:

$$\mathrm{R}_{\mathrm{i,d}} - \mathrm{r}_{\mathrm{f,d}} = \alpha_{\mathrm{i}} + \beta_{\mathrm{i}}\left(R_{m,d} - r_{f,d}\right) + \gamma_{\mathrm{i}}\left(R_{m,d} - r_{f,d}\right)^2 + \varepsilon_{i,d}, \tag{A4}$$

where $R_{i,d}$ is the return of stock i on day d, $R_{m,d}$ is the market return on day d, which is measured by the CRSP daily value-weighted index, $r_{f,d}$ is the risk-free rate on day d, which is the one-month T-bill return obtained from Kenneth French's online data library, and $\varepsilon_{i,d}$ is the idiosyncratic return on day d. The idiosyncratic skewness (ISKEW) of stock i in month t is computed as the skewness (or third moment) of daily residuals $\varepsilon_{i,d}$ in month t.

TRUST: Social trust index, which is commonly measured based on the responses to the following World Value Survey (WVS) question, "*Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?*", following prior studies (Guiso et al, 2008; Aghion et al., 2010; Pevzner et al., 2015; Wei and Zhang, 2020). In this study, the region-level trust data is available and collected from the WVS from 1995 to 2020. There are five waves of the WVS surveys (waves 3, 4, 5, 6, 7) conducted in the United States in 1995, 1999, 2006, 2011, 2017. In line with Wei and Zhang (2020), the surveys report the locations of survey respondents by 10 US geographical regions: New England (Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, and Connecticut), Middle Atlantic (New York, Pennsylvania, and New Jersey), South Atlantic (Delaware, Maryland, Washington, D.C., Virginia, West Virginia, North Carolina, South Carolina, Georgia, and Florida), East South Central (Kentucky, Tennessee, Mississippi, and Alabama), West South Central (Oklahoma, Texas, Arkansas, and Louisiana), East North Central (Wisconsin, Michigan, Illinois, Indiana, and Ohio), West North Central (Missouri, North Dakota, South Dakota, Nebraska, Kansas, Minnesota, and Iowa), Rocky Mountain (Montana, Wyoming, Nevada, Utah, Colorado, Arizona, New Mexico and Idaho), Northwest (Oregon, Washington), and California. In total, there are approximately 8,479 survey respondents in the five waves of the WVS. Similar to Pevzner et al. (2015), in each region for each year, we recode the response to this question to 1 if a respondent answers that most people can be trusted and 0 otherwise, and then we calculate the mean of the response as TRUST. Given that the index we calculated (TRUST) is available for the survey years, we use linear interpolation to estimate the value of TRUST in the years between two consecutive surveys for each region.[20] Thus, TRUST of month t for each region is the value of TRUST at the corresponding year (in year t). Higher index values correspond to higher trust.

DTRUST: A dummy variable based on TRUST within each region where firms are headquartered. If a firm's region's monthly TRUST value is above (high trust) the thresholds (median and mean, respectively) of TRUST of the region over time, then DTRUST is one and zero otherwise.

$\boldsymbol{MAX \perp TRUST}$**:** the portion of MAX of stock i in month t ($\mathrm{MAX_{i,t}}$) that is orthogonal to (or that cannot be explained by) the trust index in month t ($\mathrm{TRUST_{i,t}}$), which can be estimated from the following regression of MAX on TRUST for each stock i over the time:

$$\mathrm{MAX_{i,t}} = \alpha_\mathrm{i} + \beta_\mathrm{i}\mathrm{TRUST_{i,t}} + \varepsilon_\mathrm{i,t}, \tag{A5}$$

where $\mathrm{MAX_{i,t}}$ is the maximum daily return of stock i in month t, $\mathrm{TRUST_{i,t}}$ is the social trust for the region where firm of stock i is headquartered in month t, and $\varepsilon_{i,t}$ is the $MAX \perp TRUST$ of stock i in month t.

CATH: the proportion of Catholic adherents in each state. We obtain the state level state-level CATH data from the Association of Religion Data Archives (ADRA). The CATH data is available for 1990, 2000, 2010 and 2020, we therefore linearly interpolate CATH for interim years following the same procedure as TRUST described above. Then, CATH for each state in month t is the value of CATH at the corresponding year (in year t). Higher values correspond to higher level of Catholic adherents.

EDU: The fraction of population holding a bachelor's degree or higher in the population over 25 years old in each state. In our study, the state education level data is obtained from Economic Research Service in the US Department of Agriculture and expressed in percent. Since data for EDU at the state level is available for 1990, 2000, 2010 and 2019, we follow the same procedure as TRUST described above to linearly extrapolate EDU for interim years. Thus, EDU for each state in month t is the value of EDU at the corresponding year (in year t). Higher values correspond to higher education level.

MHI: Median household income in each state. In our study, the state-level median household income data is obtained from the US Census Bureau and expressed in dollars. Since data for MHI at the state level is available for 1990, 2000 and 2010, we follow the same procedure as EDU to linearly extrapolate MHI for interim years and apply its value in 2010 to the periods after 2010 until 2018. We follow Hasan et al. (2017) as well as Shu et al. (2012) to backfill the data for the missing years using the available data from the most-recent preceding year.

[20] In the literature, interpolation is a standard approach for estimating regional characteristics for non-available data points. See, e.g., Wei and Zhang (2020); Hilary and Hui (2009); Kumar et al. (2011); and Shu et al. (2012).

Likewise, MHI for each state in month t is the value of MHI at the corresponding year (in year t). Higher values correspond to higher income level.

PCI: Per capita personal income in each state. The state-level per capita personal income data is obtained from the US Census Bureau and expressed in dollars. Since data for PCI at the state level is available for 1990, 2000, 2010, we linearly extrapolate PCI for interim years, and then apply its value in 2010 to the periods after 2010 until 2018. Similarly, PCI for each state in month t is the value of PCI at the corresponding year (in year t). Higher values correspond to higher income level.

References

Aboulamer, A., Kryzanowski, L., 2016. Are idiosyncratic volatility and MAX priced in the Canadian market? Journal of Empirical Finance 37, 20-36.

Aghion, P., Algan, Y., Cahuc, P., Shleifer, A., 2010. Regulation and distrust. Quarterly Journal of Economics 125, 1015-1049.

Ahern, K.R., Daminelli, D., Fracassi, C., 2015. Lost in translation? The effect of cultural values on mergers around the world. Journal of Financial Economics 117, 165-189.

Algan, Y., Cahuc, P., 2010. Inherited trust and growth. American Economic Review 100, 2060-2092.

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

An, L., Wang, H., Wang, J., Yu, J., 2020. Lottery-related anomalies: the role of reference-dependent preferences. Management Science 66, 473-501.

Anand, A., Gatchev, V.A., Madureira, L., Pirinsky, C.A., Underwood, S., 2011. Geographic proximity and price discovery: evidence from NASDAQ. Journal of Financial Markets 14, 193-226.

Annaert, J., De Ceuster, M., Verstegen, K., 2013. Are extreme returns priced in the stock market? European evidence. Journal of Banking and Finance 37, 3401-3411.

Baars, M., Mohrschladt, H., 2021. An alternative behavioral explanation for the MAX effect. Journal of Economic Behavior and Organization 191, 868-886.

Bali, T.G., Cakici, N., Whitelaw, R.F., 2011. Maxing out: stocks as lotteries and the cross-section of expected returns. Journal of Financial Economics 99, 427-446.

Bali, T.G., Hirshleifer, D., Peng, L., Tang, Y., 2019. Attention, social interaction, and investor attraction to lottery stocks. Unpublished working paper. Georgetown University.

Barbi, M., Febo, V., Giudici, G., 2023. Community-level social capital and investment decisions in equity crowdfunding. Small Business Economics 61, 1075-1110.

Berggrun, L., Cardona, E., Lizarzaburu, E., 2019. Extreme daily returns and the cross-section of expected returns: Evidence from Brazil. Journal of Business Research 102, 201-211.

Bloom, N., Sadun, R., Van Reenen, J., 2012. The organization of firms across countries. Quarterly Journal of Economics 127, 1663-1705.

Boyer, B., Mitton, T., Vorkink, K., 2010. Expected idiosyncratic skewness. Review of Financial Studies 23, 169-202.

Bradrania, R., Gao, Y., 2024. Lottery demand, weather and the cross-section of stock returns. Journal of Behavioral and Experimental Finance 42, p.100910.

Brockman, P., El Ghoul, S., Guedhami, O., Zheng, Y., 2020. Does social trust affect international contracting? Evidence from foreign bond covenants. Journal of International Business Studies, 1-34.

Byun, S.-J., Goh, J., Kim, D.-H., 2020. The role of psychological barriers in lottery-related anomalies. Journal of Banking and Finance 114, 105786.

Carhart, M.M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57-82.

Cheon, Y.-H., Lee, K.-H., 2018. Maxing out globally: individualism, investor attention, and the cross section of expected stock returns. Management Science 64, 5807-5831.

Conrad, J., Kapadia, N., Xing, Y., 2014. Death and jackpot: why do individual investors hold overpriced stocks? Journal of Financial Economics 113, 455-475.

Dimson, E., 1979. Risk measurement when shares are subject to infrequent trading. Journal of Financial Economics 7, 197-226.

Drobetz, W., Mönkemeyer, M., Requejo, I., Schröder, H., 2023. Foreign bias in institutional portfolio allocation: the role of social trust. Journal of Economic Behavior and Organization 214, 233-269.

El-Attar, M., Poschke, M., 2011. Trust and the choice between housing and financial assets: evidence from Spanish households. Review of Finance 15, 727-756.

Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. Journal of Finance 47, 427-465.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56.

Fama, E.F., MacBeth, J.D., 1973. Risk and return: some empirical tests. Journal of Political Economy 81, 607-636.

Fong, W.M., Toh, B., 2014. Investor sentiment and the MAX effect. Journal of Banking and Finance 46, 190-201.

Fukuyama, F., 1995. Trust: The Social Virtues and the Creation of Prosperity. Free Press, New York, NY.

Gambetta, D., 1988. Can we trust trust? In: Gambetta, D. (Ed.), Trust: Making and Breaking Cooperative Relations. Blackwell, New York, NY, pp. 213-237.

Gao, Y., Bradrania, R., 2024. Property crime and lottery-related anomalies. Global Finance Journal 59, p.100927.

Guiso, L., Sapienza, P., Zingales, L., 2003. People's opium? Religion and economic attitudes. Journal of Monetary Economics 50, 225-282.

Guiso, L., Sapienza, P., Zingales, L., 2004. The role of social capital in financial development. American Economic Review 94, 526-556.

Guiso, L., Sapienza, P., Zingales, L., 2006. Does culture affect economic outcomes? Journal of Economic Perspectives 20, 23-48.

Guiso, L., Sapienza, P., Zingales, L., 2008. Trusting the stock market. Journal of Finance 63, 2557-2600.

Guiso, L., Sapienza, P., Zingales, L., 2011. Civic capital as the missing link. Handbook of social economics 1, 417-480.

Gupta, A., Raman, K., Shang, C., 2018. Social capital and the cost of equity. Journal of Banking and Finance 87, 102-117.

Harvey, C., Siddique, A., 2000. Conditional skewness in asset pricing tests. Journal of Finance 55, 1263-1295.

Hasan, I., Hoi, C.K., Wu, Q., Zhang, H., 2017. Social capital and debt contracting: evidence from bank loans and public bonds. Journal of Financial and Quantitative Analysis 52, 1017-1047.

Hilary, G., Hui. K., 2009. Does religion matter in corporate decision making in America? Journal of Financial Economics 93, 455-473.

Hung, W., Yang, J.J., 2018. The MAX effect: lottery stocks with price limits and limits to arbitrage. Journal of Financial Markets 41, 77-91.

Inglehart, R., Haerpfer, C., Moreno, A., Welzel, C., Kizilova, K., Diez-Medrano J., M. Lagos, P. Norris, E. Ponarin & B. Puranen et al. (eds.), 2020. World Values Survey: All Rounds – Country-Pooled Datafile. Madrid, Spain & Vienna, Austria: JD Systems Institute & WVSA Secretariat. http://www.worldvaluessurvey.org/WVSDocumentationWVL.jsp.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. Journal of Finance 45, 881-898.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. Journal of Finance 48, 65-91.

Knack, S., Keefer, P., 1997. Does social capital have an economic payoff? A cross-country investigation. Quarterly Journal of Economics 112, 1251-1288.

Kumar, A., 2009. Who gambles in the stock market? Journal of Finance 64, 1889-1933.

Kumar, A., Page, J., Spalt, O., 2011. Religious beliefs, gambling attitudes, and financial market outcomes. Journal of Financial Economics 102, 671-708.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 1997. Trust in large organizations. American Economic Review 87, 333-338.

Limbach, P., Rau, P.R., Schürmann, H., 2021. The death of trust across the U.S. finance industry. Unpublished working paper. University of Cologne, University of Cambridge, and University of Wuppertal.

Lin, T.-C., Liu, X., 2018. Skewness, individual investor preference, and the cross–section of stock returns. Review of Finance 22, 1841-1876.

Loughran, T., Schultz, P., 2004. Weather, stock returns, and the impact of localized trading behavior. Journal of Financial and Quantitative Analysis 39, 343-364.

Meng, Y., Yin, C., 2019. Trust and the cost of debt financing. Journal of International Financial Markets, Institutions and Money 59, 58-73.

Nartea, G.V., Kong, D., Wu, J., 2017. Do extreme returns matter in emerging markets? Evidence from the Chinese stock market. Journal of Banking and Finance 76, 189-197.

Nartea, G.V., Wu, J., Liu, H., 2014. Extreme returns in emerging stock markets: evidence of a MAX effect in South Korea. Applied Financial Economics 24, 425-435.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703-708.

Nguyen, H.T., Truong, C., 2018. When are extreme daily returns not lottery? At earnings announcements! Journal of Financial Markets 41, 92-116.

Pevzner, M., Xie, F., Xin, X., 2015. When firms talk, do investors listen? The role of trust in stock market reactions to corporate earnings announcements. Journal of Financial Economics 117, 190-223.

Putnam, R.D., 1993. Making Democracy Work: Civic Traditions in Modern Italy. Princeton University Press, Princeton, NJ.

Scholes, M., Williams, J., 1977. Estimating betas from nonsynchronous data. Journal of Financial Economics 5, 309-327.

Schultz, P., 2003. Who makes markets? Journal of Financial Markets 6, 49-72.

Seif, M., Docherty, P., Shamsuddin, A., 2018. Limits to arbitrage and the MAX anomaly in advanced emerging markets. Emerging Markets Review 36, 95-109.

Shao, R., Wang, N., 2021. Trust and local bias of individual investors. Journal of Banking & Finance 133, 106273.

Shu, T., Sulaeman, J., Yeung, P.E., 2012. Local religious beliefs and mutual fund risk-taking behaviors. Management Science 58, 1779-1796.

Walkshäusl, C., 2014. The MAX effect: European evidence. Journal of Banking and Finance 42, 1-10.

Wei, C., Zhang, L., 2020. Trust and local bias. Journal of Financial and Quantitative Analysis 55, 2211-2245.

Zak, P., Knack, S., 2001. Trust and growth. Economic Journal 111, 295-321.

Zhong, A., Gray, P., 2016. The MAX effect: an exploration of risk and mispricing explanations. Journal of Banking and Finance 65, 76-90.

Table 1. Summary statistics

The table reports summary statistics for the 10 US geographical regions and the main variables used in our analysis. Panel A provides the details of 10 US geographical regions, the values of trust index (TRUST) for each region during the five survey years, as well as the distribution of the number of Nasdaq-listed firms across regions. In each region year, we recode the response to the World Value Survey (WVS) survey question regarding the social trust to 1 if a respondent answers that most people can be trusted and 0 otherwise and then calculate the mean of the response as the measure of trust – TRUST. Panel B shows the summary statistics of regional variables in our sample. TRUST is the social trust index. CATH (in percent) is the state-level of the proportion of Catholic adherents. EDU (in percent) is the state-level of the percentage of population over 25 years old with a bachelor's degree or higher. MHI (in dollars) is the state-level of the median household income. PCI (in dollars) is the state-level of the per capita personal income. Panel C presents the summary statistics for stock variables of interest in our study. MAX (in percent) is the maximum daily return over a month. ISKEW is the idiosyncratic skewness. BETA is the market beta. SIZE is the natural log of market capitalization in millions of dollars. BTM is the book-to-market ratio. MOM (in percent) is the momentum. REV (in percent) is the short-term reversal. ILLIQ (scaled by 10^6) is Amihud (2002) measure of illiquidity. The detailed definitions of all variables are presented in the Appendix. The sample includes Nasdaq-listed stocks headquartered in 10 US geographical regions. The sample period is from January 1996 to December 2018.

Panel A: Trust index by region across survey years and the number of Nasdaq-listed firms within each region

Region	States	TRUST					Number of Nasdaq-Listed Firms
		1995	1999	2006	2011	2017	
1 New England	Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut	0.331	0.433	0.425	0.415	0.487	848
2 Middle Atlantic	New York, Pennsylvania, and New Jersey	0.364	0.405	0.389	0.362	0.416	1492
3 South Atlantic	Delaware, Maryland, Washington, D.C., Virginia, West Virginia, North Carolina, South Carolina, Georgia, Florida	0.246	0.311	0.382	0.342	0.359	1452
4 East South Central	Kentucky, Tennessee, Mississippi, Alabama	0.263	0.214	0.231	0.291	0.271	246
5 West South Central	Oklahoma, Texas, Arkansas, Louisiana	0.417	0.313	0.378	0.299	0.367	799
6 East North Central	Wisconsin, Michigan, Illinois, Indiana, Ohio	0.394	0.406	0.389	0.350	0.396	901
7 West North Central	Missouri, North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa	0.315	0.472	0.407	0.514	0.504	467
8 Rocky Mountain	Montana, Wyoming, Nevada, Utah, Colorado, Arizona, New Mexico, Idaho	0.275	0.367	0.434	0.394	0.382	565

Continued on next page…

...Continued

Region	States	TRUST					Number of Nasdaq-Listed Firms
		1995	1999	2006	2011	2017	
9 Northwest	Oregon, Washington	0.508	0.458	0.531	0.573	0.429	276
10 California	California	0.346	0.333	0.421	0.421	0.387	1829
Total	49 states	-	-	-	-	-	8875

Panel B: Summary Statistics of Regional Variables

Variables	Mean	St.Dev	25th Percentile	Median	75th Percentile
TRUST	0.38	0.06	0.35	0.38	0.41
CATH	23.93	11.62	15.50	26.38	30.92
EDU	27.59	5.15	24.05	27.17	30.91
MHI	48726.19	9263.15	41937.60	47517.00	55521.50
PCI	24741.23	4905.31	20940.00	24260.50	28190.00

Panel C: Summary Statistics of Stock Variables

Variables	Mean	St.Dev	25th Percentile	Median	75th Percentile
MAX	9.23	11.85	3.83	6.37	10.89
ISKEW	0.24	0.96	-0.27	0.20	0.72
BETA	0.88	4.13	-0.10	0.75	1.81
SIZE	5.03	1.80	3.78	4.95	6.17
BTM	0.72	0.86	0.29	0.54	0.89
MOM	14.79	88.34	-25.84	3.32	33.91
REV	1.20	20.79	-7.60	0.00	7.71
ILLIQ	3.65	14.18	0.01	0.07	0.85

Table 2. Returns and alphas of portfolios sorted on MAX

The table reports the value-weighted and equal-weighted average monthly returns as well as the CAPM alphas, Fama-French three-factor alphas (FF3 alpha) and Fama-French-Carhart four-factor alphas (FFC4 alpha) on the portfolios. Decile portfolios are formed every month from January 1996 to December 2018 by sorting stocks based on the maximum daily return (MAX) over the previous month. Decile 1 (10) is the portfolio of stocks with the lowest (highest) MAX. 10−1 is the zero-cost portfolio, which is long the decile 10 portfolio (High MAX) and short the decile 1 portfolio (Low MAX). The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Average returns and alphas are given in percentage. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

	Value-Weighted Portfolios				Equal-Weighted Portfolios			
Decile	Average return	CAPM alpha	FF3 alpha	FFC4 alpha	Average return	CAPM alpha	FF3 alpha	FFC4 alpha
1 (Low MAX)	1.28	0.71	0.62	0.62	1.31	0.75	0.65	0.67
2	1.33	0.65	0.55	0.58	1.38	0.71	0.60	0.65
3	1.19	0.42	0.35	0.39	1.28	0.53	0.45	0.51
4	1.04	0.19	0.12	0.20	1.12	0.29	0.22	0.33
5	1.04	0.12	0.08	0.17	1.12	0.22	0.17	0.29
6	0.93	-0.05	-0.06	0.09	1.08	0.14	0.11	0.30
7	0.95	-0.10	-0.10	0.07	1.13	0.13	0.11	0.31
8	0.79	-0.31	-0.30	-0.06	0.99	-0.06	-0.06	0.22
9	0.86	-0.27	-0.25	-0.03	1.14	0.06	0.06	0.33
10 (High MAX)	0.25	-0.86	-0.81	-0.54	0.72	-0.36	-0.32	0.03
10-1	-1.03	-1.57	-1.42	-1.16	-0.59	-1.11	-0.97	-0.64
	(-1.88)	(-3.34)	(-4.70)	(-3.87)	(-1.05)	(-2.30)	(-2.79)	(-1.81)

Table 3. Trust and MAX effect: univariate analysis

The table reports the value-weighted (Panel A) and equal-weighted (Panel B) average monthly returns as well as the CAPM alphas, Fama-French three-factor alphas (FF3 alpha) and Fama-French-Carhart four-factor alphas (FFC4 alpha) on the portfolios for high-TRUST and low-TRUST subsamples (regions with high and low level of trust). We classify the sample stocks into two subsample groups (high-TRUST or low-TRUST) based on the firm's region's previous month TRUST ranking. The ranking of TRUST is created within each region where firms are headquartered and over time. The thresholds used in ranking include the median and mean of TRUST. If a firm's region's monthly TRUST is above (below) thresholds of TRUST, the firm-month is classified into the high-TRUST (low-TRUST) subsamples. For each subsample, decile portfolios are formed every month from January 1996 to December 2018 by sorting stocks based on the maximum daily return (MAX) over the previous month. Decile 1 (10) is the portfolio of stocks with the lowest (highest) MAX. 10−1 is the zero-cost portfolio, which is long the decile 10 portfolio (High MAX) and short the decile 1 portfolio (Low MAX). The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Average returns and alphas are given in percentage. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

	Panel A: Value-Weighted Portfolios				Panel B: Equal-Weighted Portfolios			
	Thresholds of TRUST used to define subsamples				Thresholds of TRUST used to define subsamples			
Decile	Median		Mean		Median		Mean	
	High-TRUST	Low-TRUST	High-TRUST	Low-TRUST	High-TRUST	Low-TRUST	High-TRUST	Low-TRUST
1 (Low MAX)	1.26	1.33	1.30	1.30	1.29	1.35	1.34	1.32
2	1.27	1.29	1.24	1.31	1.32	1.33	1.29	1.34
3	1.08	1.23	1.14	1.15	1.14	1.32	1.20	1.25
4	1.12	1.05	1.09	0.99	1.19	1.12	1.15	1.05
5	0.97	1.15	0.94	1.21	1.07	1.25	1.04	1.33
6	0.88	0.90	0.87	0.88	1.01	1.03	1.00	1.03
7	0.84	1.09	0.88	1.00	1.06	1.20	1.09	1.14
8	0.67	0.75	0.67	0.84	0.85	1.00	0.83	1.06
9	0.76	0.94	0.74	0.96	1.07	1.23	1.05	1.27
10 (High MAX)	-0.08	0.46	0.02	0.30	0.38	0.91	0.47	0.79
10-1	-1.34	-0.87	-1.29	-1.00	-0.91	-0.45	-0.86	-0.53
	(-2.49)	(-1.54)	(-2.42)	(-1.72)	(-1.70)	(-0.75)	(-1.64)	(-0.86)
CAPM alpha	-1.85	-1.40	-1.79	-1.52	-1.39	-0.96	-1.34	-1.04
	(-3.91)	(-2.82)	(-3.84)	(-2.93)	(-2.95)	(-1.82)	(-2.91)	(-1.88)
FF3 alpha	-1.72	-1.25	-1.65	-1.40	-1.26	-0.81	-1.21	-0.91
	(-5.21)	(-3.78)	(-5.17)	(-3.72)	(-3.51)	(-2.13)	(-3.48)	(-2.14)
FFC4 alpha	-1.46	-0.97	-1.39	-1.11	-0.97	-0.45	-0.91	-0.54
	(-4.37)	(-3.10)	(-4.29)	(-3.14)	(-2.53)	(-1.21)	(-2.45)	(-1.31)

Table 4. Fama-MacBeth regressions in subsamples

The table reports the time-series average of the slope coefficients from cross-sectional regressions over high-TRUST and low-TRUST subsamples (regions with high and low levels of trust). We classify the sample stocks into two subsample groups (high-TRUST or low-TRUST) based on a firm's region's previous month TRUST ranking. The ranking of TRUST is created within each region where firms are headquartered and over time. If a firm's region's monthly TRUST is above (below) thresholds of TRUST, the firm-month is classified into the high-TRUST (low-TRUST) subsamples. The thresholds used in ranking are the median and mean of TRUST. For each subsample and every month from January 1996 to December 2018, we run the Fama-MacBeth regression of the monthly stock returns (in percent) on one-month lagged independent variables that include the maximum daily return (MAX) and a set of control variables. The control variables include market beta (BETA), natural log of market capitalization (SIZE), natural log of book-to-market ratio (BM), momentum (MOM), short-term reversal (REV) and illiquidity (ILLIQ). All variables are defined in the Appendix. The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

Variables	Threshold of TRUST used to define high-TRUST and low-TRUST subsamples							
	Median				Mean			
	High-TRUST		Low-TRUST		High-TRUST		Low-TRUST	
MAX	-0.054	-0.050	-0.028	-0.019	-0.051	-0.045	-0.025	-0.020
	(-2.87)	(-3.00)	(-1.41)	(-1.10)	(-2.78)	(-2.76)	(-1.12)	(-0.97)
BETA		0.013		-0.051		-0.023		-0.045
		(0.26)		(-0.99)		(-0.49)		(-0.78)
SIZE		-0.227		-0.173		-0.221		-0.169
		(-2.91)		(-2.59)		(-2.86)		(-2.49)
BM		0.260		0.229		0.245		0.247
		(1.79)		(1.87)		(1.73)		(1.92)
MOM		0.143		0.047		0.143		0.090
		(0.46)		(0.16)		(0.47)		(0.30)
REV		-0.004		-0.008		-0.005		-0.006
		(-0.75)		(-1.39)		(-0.95)		(-0.72)
ILLIQ		0.028		0.043		0.025		0.059
		(2.70)		(1.99)		(2.57)		(2.20)

Table 5. Fama-MacBeth regressions with an interaction term

The table reports the time-series average of the slope coefficients from cross-sectional regressions across the sample when the threshold to define DTRUST is median of TRUST within each region over time. Every month from January 1996 to December 2018 we run the Fama-MacBeth regression of the monthly stock returns (in percent) on the one-month lagged independent variables that include the maximum daily return (MAX), TRUST, the interaction term of MAX and DTRUST, and control variables. DTRUST is a dummy variable based on TRUST within each region where firms are headquartered. If a firm's region's monthly TRUST is above the median of TRUST for the region over time, then DTRUST is one and zero otherwise. The control variables are market beta (BETA), natural log of market capitalization (SIZE), natural log of book-to-market ratio (BM), momentum (MOM), short-term reversal (REV) and illiquidity (ILLIQ). All variables are defined in the Appendix. The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

Model	(1)	(2)	(3)	(4)	(5)	(6)
MAX	-0.038	-0.030	-0.038	-0.030	-0.030	-0.022
	(-2.08)	(-1.93)	(-2.08)	(-1.94)	(-1.51)	(-1.32)
TRUST			0.794	0.379	1.321	1.070
			(1.21)	(0.67)	(1.87)	(1.70)
$\mathrm{MAX} \times \mathrm{DTRUST}$					-0.022	-0.025
					(-2.22)	(-2.71)
BETA		-0.021		-0.021		-0.019
		(-0.49)		(-0.49)		(-0.45)
SIZE		-0.208		-0.208		-0.208
		(-3.16)		(-3.16)		(-3.15)
BM		0.225		0.226		0.230
		(1.78)		(1.79)		(1.84)
MOM		0.097		0.099		0.099
		(0.32)		(0.34)		(0.34)
REV		-0.006		-0.006		-0.006
		(-1.15)		(-1.15)		(-1.15)
ILLIQ		0.034		0.034		0.034
		(3.18)		(3.20)		(3.24)

Table 6. Fama-MacBeth regressions, controlling for regional factors

The table reports the time-series average of the slope coefficients from cross-sectional regressions across the sample after controlling for regional factors when the threshold to define DTRUST is median of TRUST within each region over time. Every month from January 1996 to December 2018 we run the Fama-MacBeth regression of the monthly stock returns (in percent) on the one-month lagged independent variables that include the maximum daily return (MAX), TRUST, the interaction term of MAX and DTRUST, and control variables. DTRUST is a dummy variable based on TRUST within each region where firms are headquartered. If a firm's region's monthly TRUST is above the median of TRUST for the region over time, then DTRUST is one and zero otherwise. The control variables are market beta (BETA), natural log of market capitalization (SIZE), natural log of book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), and the regional factors which include the percent of Catholic population (CATH), the percent of the population aged 25 and older who attained a bachelor's degree or higher (EDU), and the median household income (MHI) measured in thousands of dollars. All variables are defined in the Appendix. The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

Model	(1)	(2)	(3)	(4)	(5)
MAX	-0.030	-0.024	-0.023	-0.024	-0.023
	(-1.51)	(-1.39)	(-1.44)	(-1.46)	(-1.41)
TRUST	1.321	0.195	0.386	0.272	0.038
	(1.87)	(0.32)	(0.70)	(0.49)	(0.06)
MAX × DTRUST	-0.022	-0.025	-0.023	-0.023	-0.025
	(-2.22)	(-2.33)	(-2.52)	(-2.52)	(-2.41)
BETA		-0.019	-0.020	-0.021	-0.020
		(-0.45)	(-0.48)	(-0.49)	(-0.48)
SIZE		-0.209	-0.205	-0.206	-0.207
		(-3.15)	(-3.14)	(-3.14)	(-3.16)
BM		0.235	0.240	0.244	0.243
		(1.93)	(2.00)	(2.04)	(2.03)
MOM		0.102	0.103	0.104	0.105
		(0.35)	(0.36)	(0.36)	(0.36)
REV		-0.006	-0.006	-0.006	-0.006
		(-1.16)	(-1.17)	(-1.16)	(-1.16)
ILLIQ		0.034	0.034	0.034	0.034
		(3.26)	(3.26)	(3.25)	(3.27)

Continued on next page…

…Continued

CATH	0.010			0.006
	(1.81)			(1.35)
EDU		0.026		-0.007
		(1.65)		(-0.66)
MHI			0.024	0.021
			(1.96)	(2.36)

Table 7. Education and the effect of trust on MAX effect

The table reports the time-series average of the slope coefficients from cross-sectional regressions over two subsamples that include regions with low education level (low-EDU) and high education level (high-EDU). EDU is the state-level percentage of the population over 25 years old with a bachelor's degree or higher. We classify the sample stocks into two subsample groups (low-EDU or high-EDU) based on a firm's state's previous month EDU ranking. The threshold used in ranking is the median of EDU. The ranking of EDU is created across all states where firms are headquartered in each month. If a firm's state's monthly EDU is below (above) the median of EDU, the firm-month is classified into the low-EDU (high-EDU) subsamples. For each subsample and every month from January 1996 to December 2018, we run the Fama-MacBeth regression of the monthly stock returns (in percent) on the one-month lagged independent variables that include the maximum daily return (MAX), TRUST, the interaction term of MAX and DTRUST, and control variables. DTRUST is a dummy variable based on TRUST within each region where firms are headquartered. If a firm's region's monthly TRUST is above the median of TRUST for the region over time, then DTRUST is one and zero otherwise. The control variables are market beta (BETA), natural log of market capitalization (SIZE), natural log of book-to-market ratio (BM), momentum (MOM), short-term reversal (REV) and illiquidity (ILLIQ). All variables are defined in the Appendix. The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

	Low-EDU			High-EDU		
Model	(1)	(2)	(3)	(1)	(2)	(3)
MAX	-0.039	-0.039	-0.021	-0.028	-0.028	-0.025
	(-2.03)	(-2.06)	(-0.95)	(-1.79)	(-1.81)	(-1.50)
TRUST		-0.442	0.436		-0.038	0.498
		(-0.61)	(0.58)		(-0.05)	(0.73)
MAX × DTRUST			-0.046			-0.017
			(-2.92)			(-1.68)
BETA	-0.018	-0.017	-0.019	-0.027	-0.027	-0.023
	(-0.32)	(-0.30)	(-0.34)	(-0.57)	(-0.58)	(-0.49)
SIZE	-0.163	-0.164	-0.164	-0.222	-0.223	-0.224
	(-2.50)	(-2.50)	(-2.52)	(-3.20)	(-3.19)	(-3.19)
BM	0.334	0.334	0.328	0.197	0.198	0.201
	(2.48)	(2.48)	(2.46)	(1.59)	(1.60)	(1.63)
MOM	0.112	0.114	0.099	0.099	0.098	0.101
	(0.36)	(0.37)	(0.32)	(0.33)	(0.32)	(0.34)
REV	0.000	0.000	0.001	-0.009	-0.009	-0.009
	(0.07)	(0.04)	(0.11)	(-1.65)	(-1.64)	(-1.65)
ILLIQ	0.023	0.023	0.023	0.042	0.043	0.043
	(2.16)	(2.13)	(2.15)	(3.18)	(3.22)	(3.25)

Table 8. Income and the effect of trust on MAX effect

The table reports the time-series average of the slope coefficients from cross-sectional regressions over two subsamples that include regions with low income (low-MHI) and high income (high-MHI). MHI is defined as the state-level median household income. We classify the sample stocks into two subsample groups (low-MHI or high-MHI) based on a firm's state's previous month MHI ranking. The threshold used in ranking is the median of MHI. The ranking of MHI is created across all states where firms are headquartered in each month. If a firm's state's monthly MHI is below (above) the median of MHI, the firm-month is classified into the low-MHI (high-MHI) subsamples. For each subsample and every month from January 1996 to December 2018, we run the Fama-MacBeth regression of the monthly stock returns (in percent) on the one-month lagged independent variables that include the maximum daily return (MAX), TRUST, the interaction term of MAX and DTRUST, and control variables. DTRUST is a dummy variable based on TRUST within each region where firms are headquartered. If a firm's region's monthly TRUST is above the median of TRUST for the region over time, then DTRUST is one and zero otherwise. The control variables are market beta (BETA), natural log of market capitalization (SIZE), natural log of book-to-market ratio (BM), momentum (MOM), short-term reversal (REV) and illiquidity (ILLIQ). All variables are defined in the Appendix. The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

	Low-MHI			High-MHI		
Model	(1)	(2)	(3)	(1)	(2)	(3)
MAX	-0.045	-0.045	-0.018	-0.026	-0.026	-0.021
	(-2.20)	(-2.23)	(-0.77)	(-1.67)	(-1.70)	(-1.24)
TRUST		-0.436	0.837		0.016	0.729
		(-0.58)	(1.13)		(0.02)	(0.97)
MAX × DTRUST			-0.061			-0.017
			(-3.95)			(-1.67)
BETA	-0.031	-0.030	-0.031	-0.021	-0.021	-0.018
	(-0.56)	(-0.53)	(-0.58)	(-0.46)	(-0.46)	(-0.39)
SIZE	-0.178	-0.177	-0.178	-0.215	-0.216	-0.217
	(-2.73)	(-2.70)	(-2.73)	(-3.14)	(-3.13)	(-3.14)
BM	0.286	0.286	0.269	0.217	0.221	0.227
	(2.03)	(2.03)	(1.91)	(1.72)	(1.77)	(1.83)
MOM	0.083	0.072	0.046	0.098	0.100	0.107
	(0.25)	(0.22)	(0.14)	(0.33)	(0.34)	(0.37)
REV	0.002	0.002	0.002	-0.008	-0.008	-0.008
	(0.31)	(0.30)	(0.39)	(-1.49)	(-1.50)	(-1.52)
ILLIQ	0.029	0.029	0.030	0.037	0.037	0.037
	(1.85)	(1.85)	(1.88)	(3.57)	(3.61)	(3.67)

Trust and Lottery-Related Anomalies

Internet Appendix

This appendix shows the results of several additional empirical analyses that are further conducted to check the robustness of our main results in the paper. In short, these additional analyses demonstrate that our main finding of the role of social trust played in the underperformance of lottery-type stocks is robust. Section IA-1 reports the results of the univariate portfolio analysis by using the orthogonal component of MAX (i.e., the portion of MAX that is orthogonal to the social trust index proxy TRUST) as the sort variable. Section IA-2 presents the results of for the univariate portfolio analysis that examines the relation between trust and the lottery demand when using two alternative approaches to create the ranking of TRUST and construct regions with the highest and lowest trust. Section IA-3 shows the results of the Fama-MacBeth (1973) cross-sectional regressions with an interaction term by using mean of TRUST as the alternative threshold to define the dummy variable for TRUST (DTRUST). Section IA-4 demonstrates that our main results are robust when instead of MAX, MAX(N), which is the average of N (N = 2, 3, 4, 5) highest daily returns over the last month, is used as the alternative proxies for lottery demand. Section IA-5 provides further support for the main results by using idiosyncratic skewness as the alternative measure of lottery demand instead of MAX. Section IA-6 confirms that our main results are robust when using mean of EDU, as the alternative threshold, to split our sample by education level and mean of TRUST, as the alternative threshold, to define DTRUST in the cross-sectional regression analysis. Section IA-7 presents our main findings continue to hold when repeating the cross-sectional regression analysis, but instead using mean of MHI, as the alternative threshold, to split the sample by the level of income and mean of TRUST, as the alternative threshold, to define DTRUST. Section IA-8 shows that the main results continue to hold when we replace MHI (median household income) with PCI (per capita personal income) as the proxy for income in each state.

IA-1. Orthogonal test

In this section, we test the robustness of our main results by conducting a univariate portfolio analysis using the component of MAX that is orthogonal to TRUST as the sort variable. The component of MAX that is orthogonal to the social trust index TRUST, denoted $MAX \perp TRUST$, is estimated as the residual from a time-series regression of MAX on TRUST for each stock. The information of the variable ($MAX \perp TRUST$) construction in this section is provided in the Appendix. Every month from January 1996 to December 2018, we calculate $MAX \perp TRUST$ using values of MAX and TRUST over the previous month and then use these orthogonalized MAX ($MAX \perp TRUST$) to sort all sample stocks into 10 decile portfolios to examine the cross-section of expected returns. The results are presented in Table IA1 of the Appendix. The Newey-West (1987) adjusted *t*-statistics are presented in parentheses using six lags.

The results in Table IA1 demonstrate that the MAX anomaly is not detected when only the portion of MAX that is orthogonal to TRUST ($MAX \perp TRUST$) is used as the sort variable in the univariate portfolio analysis. We find that the average raw returns of the zero-cost portfolios that are long the high $MAX \perp TRUST$ (decile 10) portfolio and short the low $MAX \perp TRUST$ (decile 1) portfolio are positive and statistically significant for both value-weighted and equal-weighted portfolios, with values of 0.57% per month (*t*-statistic = 2.71) and 0.46% per month (*t*-statistic = 2.16), respectively. This is opposite to the corresponding results in Table 2, which show the negative average raw returns of the zero-cost portfolios for both value-weighted (-1.03% per month with the *t*-statistic of -1.88) and equal-weighted (-0.59% per month with the *t*-statistic of -1.05) portfolios. In Table IA1, the CAPM, FF3 and FFC4 alphas of the zero-cost portfolio also present a similar pattern, in that they are positive and more statistically significant.

Therefore, the results in Table IA1 confirm that our main results are robust, suggesting that the negative relation between MAX and expected stock returns in Table 2 is largely driven by the relation between MAX and TRUST.

IA-2. Trust and the lottery demand: univariate sort for regions with the highest and lowest TRUST

In Table 3, we do the univariate portfolio analysis by creating a ranking (or threshold) of TRUST over time for each region to construct high and low trust subsamples. However, it is feasible to identify the subsamples by focusing on the cross-sectional as well as time-series variation in TRUST across all regions.

First, we consider the extreme case and define the highest and lowest trust regions using TRUST ranking in the cross-section across all regions. To do so, in each month, we select the regions with extreme values for the trust index. In other words, the subsamples include only regions with the highest and lowest TRUST in each month.

More specifically, in each month, we create a ranking of TRUST across the 10 US geographical regions where firms are headquartered and classify firms in regions where the one-month lagged value of TRUST is at the top and bottom (or the highest and lowest) ranking as the highest-TRUST and lowest-TRUST subsamples, respectively. Then, for each subsample in each month, we sort stocks into deciles based on MAX and calculate both value-weighted returns and equal-weighted average monthly raw and risk-adjusted returns for decile portfolios and for the difference between high (decile 10) and low (decile 1) MAX portfolio for the highest-TRUST and lowest-TRUST subsamples. The results are reported in Panel A of Table IA2. The numbers in parentheses are *t*-statistics, adjusted following Newey-West (1987) using six lags.

In Panel A of Table IA2, for both value-weighted and equal-weighted portfolios, the average raw returns of the zero-cost portfolios that are long the high MAX (decile 10) portfolio and short the low MAX (decile 1) portfolio tend to be more significantly negative for the highest-TRUST subsample, with values of −1.09% per month (*t*-statistic = −2.02) and −0.78% per month (*t*-statistic = −1.39), respectively. By contrast, the corresponding returns tend to be indistinguishable from zero for the lowest-TRUST subsample, with values of −0.37% per month (*t*-statistic = −0.67) and 0.01% per month (*t*-statistic = 0.01), respectively. After adjusting the risk factors, the risk-adjusted returns present a similar pattern. For instance, for value-weighted portfolios, the risk-adjusted return of the zero-cost portfolios under the Fama-French three-factor model (FF3) is −1.54% per month (*t*-statistic = −3.29) for the highest-TRUST subsample, which is more significantly negative and approximately 2.6 times larger in absolute magnitude than the corresponding return for the lowest-TRUST subsample (−0.60% per month with *t*-statistic = −1.21).

Thus, the results in Panel A of Table IA2 show a similar pattern as in Table 3. Panel A of Table IA2 indicates that the relation between MAX and expected stock returns is economically and significantly negative for the highest-TRUST subsample (regions with highest trust), however, it is insignificant for the lowest-TRUST subsample (regions with lowest trust). It implies that a univariate portfolio analysis using the cross-sectional variation in trust index (TRUST) across regions does not change our main findings.

Now, we turn to conducting a univariate portfolio analysis based on time-series mean variation in TRUST across regions. Unlike the monthly cross-sectional TRUST ranking used previously, in this approach, we use the alternative extreme case which only includes two regions with the highest and lowest average trust index (TRUST) over the sample period (276 months). More specifically, for each region, we calculate the averages of the one-month lagged TRUST over time and create a ranking of these 10 time-series averages. We then only select two regions of firms' headquarters where the time-series average of one-month lagged TRUST is at the top and bottom (or the highest and lowest) ranking: the highest-TRUST and lowest-TRUST regions, respectively. Next, for each region in each month, we sort stocks into deciles based on MAX. Panel B of Table IA2 reports both value-weighted returns and equal-weighted average monthly raw and risk-adjusted returns for decile portfolios and for the zero-cost portfolio for these two regions. The Newey-West (1987) adjusted *t*-statistics are presented in parentheses using six lags.

The results in Panel B of Table IA2 follow a similar pattern as in Panel A of Table IA2. Regardless of whether the risk factors are adjusted for returns or not, the average returns of the zero-cost portfolios for both value-weighted and equal-weighted portfolios tend to be significantly negative for the highest-TRUST region, whereas they become insignificant for the lowest-TRUST region. For example, for the highest-TRUST region, the CAPM alpha of the zero-cost portfolios for equal-weighted portfolios is approximately 5.4 times larger in absolute magnitude and more significantly negative (−1.50% per month with t-statistic = −2.07) than the corresponding return for the lowest-TRUST region (−0.28% per month with t-statistic = −0.48). The evidence in Panel B of Table IA2 shows that the MAX effect is economically and significantly negative in the highest-TRUST region, whereas it is not significant in the lowest-TRUST region. This again supports that our main results are robust when we use the time-series mean variation in TRUST across regions for a univariate portfolio analysis.

In summary, Table IA2 shows that our main results in Table 3 are robust when separately using the cross-sectional variation and time-series mean in trust index (TRUST) across regions to form portfolios and conduct univariate portfolio analyses. It provides additional evidence for our main results that the MAX anomaly is stronger for regions with high trust than for regions with low trust.

IA-3. Mean of TRUST as the alternative threshold to define the dummy variable for TRUST (DTRUST)

In our main cross-sectional regression analysis in Table 5, we use the median of TRUST of the firm's headquarter region over time as the threshold to define the dummy variable for TRUST (DTRUST). In this section, we test whether our main results in Table 5 are robust when using mean of TRUST as the alternative threshold to define DTRUST.

We replace median of TRUST with mean of TRUST to define DTRUST and repeat the Fama-MacBeth (1973) cross-sectional regressions analysis in Table 5. The results are reported in Table IA3. We find the results in Table IA3 are qualitatively similar to those in Table 5. When we include the interaction term ($MAX \times DTRUST$) to the regression specification, the significant estimated coefficients on MAX become insignificant, with the values of −0.032 (t-statistic = −1.53) and −0.024 (t-statistic = −1.41) in models (5) and (6), respectively. However, the coefficients on the interaction terms ($MAX \times DTRUST$) are significantly negative except for the one in model (5), suggesting that the high level of social trust plays a significant role in the MAX effect. For example, the estimated coefficient on the interaction term ($MAX \times DTRUST$) in model (6) is −0.018 (t-statistic = −1.85), which implies that MAX effect becomes weaker and statistically insignificant (coefficient estimate = −0.024) among firms' regions with low trust, whereas it tends to be significant and stronger among firms' regions with high trust, with the estimated coefficient of −0.018 (formally, (−0.018) × 1). Although the coefficient on interaction term in model (5) of Table IA3 is weaker and insignificant (coefficient = −0.016 and t-statistic = −1.45) compared to the coefficient on interaction term in Table 5, it does not impact the interpretation of the results. Therefore, the results in Table IA3 show that our main results in Table 5 are robust when using mean of TRUST as the alternative threshold to define DTRUST in the cross-sectional regression analysis, suggesting that high social trust is associated with the stronger MAX effect.

IA-4. Alternative constructions of MAX

In the main tests, we use a single day of maximum return from the last month (MAX) as the proxy for lottery demand. In this section, we examine whether our main results are robust when replacing

MAX with MAX(N) (N = 2, 3, 4, 5) as the proxy for lottery demand. MAX (N) is defined as the average of the N (N = 2, 3, 4, 5) highest daily returns over the previous month. With the concerns of the seemingly arbitrary measure of a single day of maximum return (MAX) from the previous month, Bali et al. (2011) also introduce MAX(N) as the alternative constructions of MAX to check the robustness of their main results. We replace MAX with MAX (N) (N = 2, 3, 4, 5) to repeat the Fama-MacBeth (1973) cross-sectional regression analysis in Table 4.

The results are presented in Table IA4. Panel A and Panel B separately report the results using the median and mean of TRUST as thresholds to define high-TRUST and low-TRUST groups. The patterns obtained in Table IA4 are similar to the results in Table 4, showing that the MAX effect is associated with social trust and is more negative and statistically significant among regions with a high level of social trust than among regions with a low level of social trust. For instance, in Panel A of Table IA4, for the high-TRUST group, the average slope coefficients on MAX(2) without and with control variables are −0.080 (*t*-statistics = −2.90) and −0.080 (*t*-statistics = −3.18), respectively. However, for the low-TRUST group, the coefficients on MAX(2) without and with control variables are −0.047 (*t*-statistic = −1.62) and −0.039 (*t*-statistic = −1.55), respectively. We find that the slope coefficients of MAX(2) for the high-TRUST group are approximately 1.7 to 2.1 times larger in absolute magnitude than those for the low-TRUST group. In comparison to Table 4, Table IA4 also shows that the MAX effect tends to be more pronounced as the number of days for calculating MAX (N) increases, regardless of the level of trust.

We next use MAX(N) (N = 2, 3, 4, 5) instead of MAX to repeat Fama-MacBeth (1973) cross-sectional regressions with interaction terms in Table 5 and Table IA3, which use different thresholds, median and mean of TRUST, respectively, to define the dummy variables for TRUST (DTRUST). For brevity, we only repeat analysis for the main specifications of Table 5 and Table IA3. The results of these analyses are presented in Table IA5. We report the results with the median and mean of TRUST used as thresholds to define DTRUST in Panel A and Panel B, respectively.

We find that the results of Panel A and Panel B in Table IA5 are consistent with those shown in Table 5 and Table IA3. Particularly, the significant slope coefficients on MAX(N) become weaker and less significant after introducing the interaction term between MAX(N) and the trust dummy variable (DTRUST). The coefficients on the interaction terms ($MAX(N) \times DTRUST$) are significantly negative across all specifications except for the one in model (3) of Panel B in Table IA5, suggesting that a high level of social trust contributes to the MAX effect. Similarly, compared to Table 5 and Table IA3, we find that the MAX effect becomes more significant, both economically and statistically, and the coefficients on the interaction terms ($MAX(N) \times DTRUST$) are more negative and statistically significant as we average more days to calculate MAX(N).

Overall, the results in Tables IA4 and IA5 show that our main findings do not change after replacing MAX with MAX(N), confirming that social trust plays a significant role in the MAX effect, and that this effect is stronger among the regions with a high level of social trust in comparison to regions with a low level of social trust.

IA-5. Alternative proxy for lottery demand: idiosyncratic skewness

In this section, we examine whether our main results still hold when we use idiosyncratic skewness instead of MAX as the proxies for lottery demand.[21]

The literature on lottery-related anomalies suggests that skewness measures can also be used as the proxies for lottery demand, since similar to MAX, they capture one dimension of a return distribution, that is, the small probability of a large payoff. We follow Bali et al. (2011) to construct idiosyncratic skewness (ISKEW), at the end of each month. We then measure ISKEW as the skewness (or third moment) of daily residuals by running a two-factor time-series regression model regarding the daily stock returns within the month. Detailed information on the variable is provided in the variable definitions of the Appendix.

We next replace MAX with idiosyncratic skewness (ISKEW) to repeat the analysis in Table 5 and Table IA3; that is, the Fama-MacBeth (1973) cross-sectional regressions with an interaction term using different thresholds, median and mean of TRUST to define the dummy variables for TRUST (DTRUST).[22] Table IA6 presents the results when ISKEW is used as the measure for lottery demand. We only report the key results of the regression models reported in Table 5 and Table IA3 for brevity. Panel A (Panel B) shows the results when median (mean) of TRUST is used as the threshold to define DTRUST.

The results of Panel A and Panel B in Table IA6 present a similar pattern to those in Table 5 and Table IA3. When we include the interaction term of the idiosyncratic skewness and the dummy variable for TRUST ($ISKEW \times DTRUST$) to the regression specification, the significant slope coefficients of the idiosyncratic skewness become weaker and less significant. The slope coefficients for the interaction terms are significantly negative at the 10% significance level, indicating that lottery-related anomalies are influenced by the high level of social trust. Thus, the results in Table IA6 provide additional support that our main results are robust when replacing MAX with skewness measure as the proxy for lottery demand.

IA-6. Mean of EDU as the alternative threshold to split sample by education level

In the main tests, we introduce the education level measured by EDU and find that the effect of trust on the MAX effect varies across regions with different education levels. In our main analysis in Table 7, we use median of EDU as the threshold to divide our sample stocks into two groups (low-EDU and high-EDU) by education level. For each group, we run the monthly Fama and MacBeth (1973) cross-sectional regressions using the median of TRUST of the firm's headquarter region over time to define the dummy variable for TRUST (DTRUST). In this section, as a robustness test, we use

[21] In unreported analyses, we replace MAX with total skewness and repeat the analysis in Tables 5 and IA3. While the coefficients for the interaction term of the total skewness and the dummy variable for trust (DTRUST) are less significant compared to the results using idiosyncratic skewness, our main findings continue to hold.

[22] In unreported analyses, we replace MAX with skewness measures (idiosyncratic skewness and total skewness, respectively) and repeat the Fama-MacBeth (1973) cross-sectional regression analysis in Table 4 for high-TRUST and low-TRUST groups, respectively. The results are robust. Although for the low-TRUST group, the average slope coefficients on skewness measures tend to be significantly negative after including control variables, they are less significant, both economically and statistically, in comparison to those coefficients for the high-TRUST group, and our main findings continue to hold.

alternative thresholds of EDU and TRUST to examine whether the main results in Table 7 persist. We repeat the Fama and MacBeth (1973) cross-sectional regression analysis in Table 7 using mean of EDU as the alternative threshold to split our sample by education level as well as mean of TRUST as the alternative threshold to define the dummy variable for TRUST (DTRUST).

Table IA7 presents the results. The results in Table IA7 are qualitatively similar to those in Table 7. The coefficient on interaction term ($MAX \times DTRUST$) in model (3) for the low-EDU group is significantly negative (coefficient = −0.032 and t-statistic = −2.26), however, for the high-EDU group, it is insignificant (coefficient = −0.012 and t-statistic = −0.92). This does not change the interpretation of the main results, and Table IA7 provides a further support for our main findings, indicating that a higher level of social trust is associated with the stronger MAX effect, depending on the education level. Table IA7 suggests that when considering the different levels of education, the effect of trust on the MAX effect is stronger when the region's education level is lower, indicating that less educated people possess less reliable information and rely more on trust in making economic or financial decisions. In Table IA7, the results support Kumar (2009) who shows that less educated investors exhibit a greater propensity to invest in stocks with lottery features, whereas we show that less educated investors invest disproportionately more in lottery-type stocks only in high trust regions.

IA-7. Mean of MHI as the alternative threshold to split sample by income level

In our main analysis in Table 8, we introduce the income level proxied by MHI to investigate how the effect of trust on the MAX effect varies across regions with different income levels. We use median of MHI as the threshold to divide our sample into low-MHI and high-MHI groups by the level of income. Then we run the monthly Fama and MacBeth (1973) cross-sectional regressions using the median of TRUST to define the dummy variable for TRUST (DTRUST) for each group. In this section, we use alternative thresholds of MHI and TRUST to examine whether our main findings in Table 8 continue to hold. We repeat the Fama and MacBeth (1973) cross-sectional regression analysis in Table 8, but using mean of MHI as the alternative threshold to split the sample by the level of income as well as mean of TRUST as the alternative threshold to define the dummy variable for TRUST (DTRUST). The results are reported in Table IA8.

In Table IA8, the results show a similar pattern to those presented in Table 8. The coefficient on the interaction term ($MAX \times DTRUST$) in model (3) for the high-MHI group is insignificant (coefficient = −0.013 and t-statistic = −0.88), whereas that of the low-MHI group is significantly negative (coefficient = −0.034 and t-statistic = −2.21). The results in Table 8 remain robust when we use mean of MHI as the threshold to split our sample by the income level and mean of TRUST to define DTRUST. In summary, Table IA8 shows that a high level of social trust contributes to the MAX effect, which depends on the income level. Again, Table IA8 shows that the effect of trust on the MAX effect is more pronounced in regions with lower income, suggesting social trust matters more for less wealthy people who possess less reliable information to make economic or financial decisions. Also, the results in Table IA8 support Kumar (2009) who shows that low-income investors exhibit a greater propensity to invest in lottery-type stocks. However, we show that less wealthy investors invest disproportionately more in stocks with lottery features only in high trust regions.

IA-8. Alternative proxies for income: per capita personal income, and the effect of trust on MAX effect

In our analyses related to the relation between income level and the effect of trust on the MAX effect in Table 8 and Table IA8, we use MHI (median household income) as the proxy for income level in each state and run the Fama and MacBeth (1973) cross-sectional regressions using different thresholds: median (mean) of MHI as the threshold to split the sample by the level of income as well as median (mean) of TRUST as the threshold to define the dummy variable for TRUST (DTRUST) in Table 8 (Table IA8). We show the effect of income levels on the relation between the MAX effect and social trust. In this section, as the robustness test, we use PCI (per capita personal income) as the proxy for income in each state instead of MHI (median household income) to repeat the analyses in Tables 8 and IA8. Similarly, we conduct the cross-sectional regression analyses with different thresholds: median (mean) of PCI as the threshold to split the sample by the level of income as well as median (mean) of TRUST as the threshold to define DTRUST. The results are presented in Table IA9. For brevity, Panel A and Panel B show the results for median of PCI with median of TRUST for DTRUST and mean of PCI with mean of TRUST for DTRUST, respectively. The results of Panels A and B in Table IA9 are substantially same as those presented in Tables 8 and IA8, indicating that replacing MHI with PCI does not change our main finding that the effect of social trust on the MAX effect is stronger among low-income regions in comparison to high-income regions.

Table IA1. Univariate portfolios sorted on orthogonalized MAX ($MAX \perp TRUST$)

The table reports the value-weighted and equal-weighted average monthly returns as well as the CAPM alphas, Fama-French three-factor alphas (FF3 alpha) and Fama-French-Carhart four-factor alphas (FFC4 alpha) on the portfolios. Decile portfolios are formed every month from January 1996 to December 2018 by sorting stocks based on the portion of the maximum daily return (MAX) that is orthogonal to the social trust index TRUST ($MAX \perp TRUST$) over the previous month. Decile 1 (10) refers to the portfolio of stocks with the lowest (highest) $MAX \perp TRUST$. 10−1 is the zero-cost portfolio, which is long the decile 10 portfolio (High $MAX \perp TRUST$) and short the decile 1 portfolio (Low $MAX \perp TRUST$). The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Average returns and alphas are in percentage. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

	Value-Weighted Portfolios				Equal-Weighted Portfolios			
Decile	Average return	CAPM alpha	FF3 alpha	FFC4 alpha	Average return	CAPM alpha	FF3 alpha	FFC4 alpha
1 (Low $MAX \perp TRUST$)	0.17	-0.86	-0.83	-0.66	0.54	-0.47	-0.46	-0.23
2	0.88	-0.09	-0.08	0.01	1.08	0.15	0.14	0.27
3	1.11	0.24	0.21	0.28	1.26	0.42	0.37	0.47
4	1.16	0.31	0.26	0.33	1.25	0.43	0.36	0.46
5	1.19	0.37	0.31	0.38	1.28	0.49	0.42	0.51
6	1.10	0.27	0.21	0.31	1.21	0.41	0.34	0.47
7	1.21	0.35	0.29	0.38	1.33	0.49	0.41	0.55
8	1.06	0.15	0.10	0.25	1.18	0.29	0.22	0.41
9	0.97	0.00	-0.01	0.18	1.14	0.21	0.18	0.43
10 (High $MAX \perp TRUST$)	0.75	-0.27	-0.25	-0.02	0.99	-0.01	0.01	0.29
10-1	0.57	0.59	0.58	0.64	0.46	0.46	0.46	0.52
	(2.71)	(2.80)	(2.76)	(3.08)	(2.16)	(2.21)	(2.17)	(2.42)

Table IA2. Trust and MAX effect: univariate analysis using different approach to define highest and lowest trust regions

The table reports the average monthly returns CAPM alphas, Fama-French three-factor alphas (FF3 alpha) and Fama-French-Carhart four-factor alphas (FFC4 alpha) on the portfolios for highest-TRUST and lowest-TRUST subsamples defined using two approaches. In Panel A, we classify the sample stocks into subsamples based on a firm's region's previous month TRUST ranking created across all regions where firms are headquartered in each month. If a firm's region's monthly TRUST is at the highest (lowest) ranking, the firm-month is classified into the highest-TRUST (lowest-TRUST) subsample. In Panel B, we calculate the average of the one-month lagged TRUST over time for each region where firms are headquartered and create a ranking of the regions' time-series averages. If the time-series average of one-month lagged TRUST for a region of a firm's headquarter is at the highest (lowest) ranking, the firm is classified into the highest-TRUST (lowest-TRUST) subsample. For each subsample, decile portfolios are formed every month from January 1996 to December 2018 by sorting stocks based on the maximum daily return (MAX) over the previous month. Decile 1 (10) is the portfolio of stocks with the lowest (highest) MAX. 10−1 is the zero-cost portfolio, which is long the decile 10 portfolio (High MAX) and short the decile 1 portfolio (Low MAX). The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Average returns and alphas are in percentage. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

	Panel A: Regions sorted based on cross-sectional ranking of TRUST				Panel B: Regions sorted based on time-series mean of TRUST			
	Value-Weighted Portfolios		Equal-Weighted Portfolios		Value-Weighted Portfolios		Equal-Weighted Portfolios	
Decile	Highest-TRUST	Lowest-TRUST	Highest-TRUST	Lowest-TRUST	Highest-TRUST	Lowest-TRUST	Highest-TRUST	Lowest-TRUST
1 (Low MAX)	1.32	1.15	1.31	1.11	1.42	1.18	1.38	1.13
2	1.43	1.05	1.52	1.13	1.56	1.09	1.63	1.15
3	1.23	1.64	1.23	1.72	1.15	1.57	1.07	1.66
4	1.02	1.12	1.08	1.13	1.02	1.11	1.06	1.14
5	1.04	1.04	1.16	1.25	0.92	1.02	1.16	1.23
6	1.42	0.63	1.41	0.73	1.37	0.67	1.36	0.76
7	1.09	0.84	1.10	0.90	1.27	0.87	1.24	0.90
8	1.11	0.43	1.30	0.59	0.91	0.46	1.23	0.64
9	1.45	0.56	1.54	0.73	1.18	0.47	1.44	0.61
10 (High MAX)	0.24	0.78	0.52	1.12	-0.07	0.85	0.32	1.13
10-1	-1.09	-0.37	-0.78	0.01	-1.49	-0.33	-1.06	0.00
	(-2.02)	(-0.67)	(-1.39)	(0.01)	(-2.47)	(-0.60)	(-1.54)	(-0.01)
CAPM alpha	-1.61	-0.61	-1.30	-0.26	-1.97	-0.58	-1.50	-0.28
	(-3.22)	(-1.11)	(-2.49)	(-0.45)	(-3.31)	(-1.04)	(-2.07)	(-0.48)
FF3 alpha	-1.54	-0.60	-1.22	-0.27	-1.90	-0.56	-1.42	-0.28
	(-3.29)	(-1.21)	(-2.45)	(-0.50)	(-3.46)	(-1.13)	(-2.08)	(-0.54)
FFC4 alpha	-1.18	-0.44	-0.79	-0.04	-1.59	-0.41	-1.00	-0.06
	(-2.41)	(-0.89)	(-1.34)	(-0.07)	(-2.68)	(-0.82)	(-1.25)	(-0.11)

Table IA3. Fama-MacBeth regressions with an interaction term: using mean of TRUST as the threshold to define DTRUST

The table reports the time-series average of the slope coefficients from cross-sectional regressions across the sample when the threshold to define DTRUST is mean of TRUST within each region over time. Every month from January 1996 to December 2018, we run the Fama-MacBeth regression of the monthly stock returns (in percent) on the one-month lagged independent variables that include the maximum daily return (MAX), TRUST, the interaction term of MAX and DTRUST, and control variables. DTRUST is a dummy variable based on TRUST within each region where firms are headquartered. If a firm's region's monthly TRUST is above the mean of TRUST for the region over time, then DTRUST is one and zero otherwise. The control variables are market beta (BETA), natural log of market capitalization (SIZE), natural log of book-to-market ratio (BM), momentum (MOM), short-term reversal (REV) and illiquidity (ILLIQ). All variables are defined in the Appendix. The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

Model	(1)	(2)	(3)	(4)	(5)	(6)
MAX	-0.038	-0.030	-0.038	-0.030	-0.032	-0.024
	(-2.08)	(-1.93)	(-2.08)	(-1.94)	(-1.53)	(-1.41)
TRUST			0.794	0.379	1.219	0.939
			(1.21)	(0.67)	(1.65)	(1.49)
$\text{MAX} \times \text{DTRUST}$					-0.016	-0.018
					(-1.45)	(-1.85)
BETA		-0.021		-0.021		-0.020
		(-0.49)		(-0.49)		(-0.46)
SIZE		-0.208		-0.208		-0.208
		(-3.16)		(-3.16)		(-3.15)
BM		0.225		0.226		0.228
		(1.78)		(1.79)		(1.83)
MOM		0.097		0.099		0.099
		(0.32)		(0.34)		(0.34)
REV		-0.006		-0.006		-0.006
		(-1.15)		(-1.15)		(-1.17)
ILLIQ		0.034		0.034		0.034
		(3.18)		(3.20)		(3.20)

Table IA4. Fama-MacBeth regressions using MAX (N)

The table reports the time-series average of the slope coefficients from cross-sectional regressions of four alternative MAX measures over high-TRUST and low-TRUST subsamples (regions with high and low level of trust). We classify the sample stocks into two subsamples based on the firm's region's previous month TRUST ranking. The ranking of TRUST is created within each region where firms are headquartered and over time. The thresholds used in ranking include the median and mean of TRUST. If a firm's region's monthly TRUST is above (below) thresholds of TRUST, the firm-month is classified into the high-TRUST (low-TRUST) subsamples. For each subsample and every month from January 1996 to December 2018, we run the Fama-MacBeth regression of the monthly stock returns (in percent) on one-month lagged independent variables that include the alternative MAX measures (MAX(N)) and a set of control variables. MAX(N) is the average of N (N=2, 3, 4, and 5) highest daily returns over a month. The control variables include market beta (BETA), natural log of market capitalization (SIZE), natural log of book-to-market ratio (BM), momentum (MOM), short-term reversal (REV) and illiquidity (ILLIQ). All variables are defined in the Appendix. Panel A (Panel B) reports the results when the threshold used to define high-TRUST and low-TRUST subsamples is median (mean) of TRUST within each region over time. The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

Panel A: Median of TRUST as the threshold to define high-TRUST and low-TRUST subsamples

Variables	N=2				N=3				N=4				N=5			
	High-TRUST		Low-TRUST		High-TRUST		Low-TRUST		High-TRUST		Low-TRUST		High-TRUST		Low-TRUST	
MAX(N)	-0.080	-0.080	-0.047	-0.039	-0.102	-0.108	-0.065	-0.061	-0.122	-0.134	-0.082	-0.079	-0.141	-0.160	-0.098	-0.097
	(-2.90)	(-3.18)	(-1.62)	(-1.55)	(-2.94)	(-3.40)	(-1.77)	(-1.90)	(-2.96)	(-3.53)	(-1.85)	(-2.03)	(-2.98)	(-3.62)	(-1.93)	(-2.15)
BETA		0.029		-0.038		0.039		-0.030		0.044		-0.024		0.047		-0.020
		(0.63)		(-0.75)		(0.87)		(-0.60)		(0.98)		(-0.50)		(1.05)		(-0.41)
SIZE		-0.238		-0.181		-0.245		-0.187		-0.248		-0.189		-0.250		-0.190
		(-3.12)		(-2.78)		(-3.23)		(-2.91)		(-3.30)		(-2.95)		(-3.31)		(-2.98)
BM		0.254		0.221		0.249		0.215		0.246		0.212		0.244		0.210
		(1.80)		(1.85)		(1.79)		(1.82)		(1.78)		(1.80)		(1.77)		(1.79)
MOM		0.131		0.042		0.122		0.037		0.119		0.036		0.117		0.033
		(0.42)		(0.14)		(0.38)		(0.13)		(0.37)		(0.12)		(0.37)		(0.11)
REV		-0.005		-0.008		-0.005		-0.009		-0.006		-0.009		-0.006		-0.009
		(-0.84)		(-1.49)		(-0.91)		(-1.54)		(-0.96)		(-1.60)		(-0.99)		(-1.65)
ILLIQ		0.030		0.044		0.031		0.045		0.032		0.046		0.032		0.046
		(2.81)		(2.02)		(2.90)		(2.05)		(2.94)		(2.07)		(2.98)		(2.08)

Continued on next page…

...Continued

Panel B: Mean of TRUST as the threshold to define high-TRUST and low-TRUST subsamples

Variables	N=2				N=3				N=4				N=5			
	High-TRUST		Low-TRUST		High-TRUST		Low-TRUST		High-TRUST		Low-TRUST		High-TRUST		Low-TRUST	
MAX(N)	-0.077	-0.074	-0.042	-0.039	-0.099	-0.102	-0.059	-0.060	-0.118	-0.127	-0.076	-0.078	-0.138	-0.150	-0.095	-0.101
	(-2.85)	(-3.00)	(-1.36)	(-1.35)	(-2.91)	(-3.25)	(-1.52)	(-1.65)	(-2.94)	(-3.37)	(-1.65)	(-1.82)	(-2.96)	(-3.46)	(-1.77)	(-2.04)
BETA		-0.006		-0.033		0.004		-0.026		0.010		-0.021		0.013		-0.017
		(-0.14)		(-0.58)		(0.09)		(-0.46)		(0.22)		(-0.37)		(0.29)		(-0.30)
SIZE		-0.232		-0.178		-0.240		-0.184		-0.243		-0.186		-0.244		-0.189
		(-3.07)		(-2.72)		(-3.19)		(-2.84)		(-3.25)		(-2.89)		(-3.27)		(-2.95)
BM		0.238		0.237		0.233		0.231		0.230		0.229		0.228		0.226
		(1.73)		(1.89)		(1.72)		(1.86)		(1.71)		(1.84)		(1.70)		(1.81)
MOM		0.133		0.089		0.124		0.090		0.121		0.090		0.120		0.088
		(0.43)		(0.29)		(0.40)		(0.30)		(0.39)		(0.30)		(0.38)		(0.29)
REV		-0.006		-0.006		-0.006		-0.006		-0.007		-0.007		-0.007		-0.007
		(-1.04)		(-0.73)		(-1.11)		(-0.78)		(-1.15)		(-0.83)		(-1.18)		(-0.89)
ILLIQ		0.026		0.062		0.028		0.063		0.029		0.064		0.029		0.065
		(2.67)		(2.23)		(2.75)		(2.25)		(2.79)		(2.28)		(2.83)		(2.31)

Table IA5. Fama-MacBeth regressions with an interaction term and MAX (N)

The table reports the time-series average of the slope coefficients from cross-sectional regressions of four alternative MAX measures across the sample. Every month from January 1996 to December 2018, we run the Fama-MacBeth regression of the monthly stock returns (in percent) on the one-month lagged independent variables that include the alternative MAX measures (MAX(N)), TRUST, the interaction term of MAX(N) and DTRUST, and control variables. MAX(N) is the average of N (N=2, 3, 4, and 5) highest daily returns over a month. DTRUST is a dummy variable based on TRUST within each region where firms are headquartered. If a firm's region's monthly TRUST is above the threshold of TRUST for the region over time, then DTRUST is one and zero otherwise. The control variables are market beta (BETA), natural log of market capitalization (SIZE), natural log of book-to-market ratio (BM), momentum (MOM), short-term reversal (REV) and illiquidity (ILLIQ). All variables are defined in the Appendix. Panel A (Panel B) reports the results when the threshold used to define DTRUST is median (mean) of TRUST within each region over time. The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

Panel A: Median of TRUST as the threshold to define DTRUST

	N=2			N=3			N=4			N=5		
Model	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
MAX(N)	-0.053	-0.053	-0.044	-0.076	-0.077	-0.066	-0.097	-0.098	-0.085	-0.117	-0.118	-0.104
	(-2.21)	(-2.23)	(-1.73)	(-2.49)	(-2.51)	(-2.06)	(-2.63)	(-2.65)	(-2.21)	(-2.74)	(-2.76)	(-2.33)
TRUST		0.377	1.140		0.379	1.178		0.379	1.200		0.378	1.206
		(0.66)	(1.79)		(0.67)	(1.85)		(0.67)	(1.88)		(0.66)	(1.88)
MAX(N) × DTRUST			-0.030			-0.035			-0.040			-0.045
			(-2.54)			(-2.45)			(-2.46)			(-2.45)
BETA	-0.007	-0.007	-0.005	0.002	0.002	0.004	0.007	0.007	0.009	0.011	0.011	0.013
	(-0.17)	(-0.17)	(-0.12)	(0.04)	(0.04)	(0.09)	(0.17)	(0.18)	(0.22)	(0.27)	(0.27)	(0.32)
SIZE	-0.217	-0.217	-0.217	-0.223	-0.223	-0.223	-0.226	-0.226	-0.226	-0.227	-0.227	-0.227
	(-3.39)	(-3.38)	(-3.37)	(-3.52)	(-3.52)	(-3.51)	(-3.58)	(-3.57)	(-3.57)	(-3.61)	(-3.60)	(-3.59)
BM	0.218	0.219	0.214	0.213	0.214	0.219	0.210	0.211	0.216	0.207	0.209	0.213
	(1.78)	(1.80)	(1.85)	(1.76)	(1.77)	(1.82)	(1.74)	(1.76)	(1.81)	(1.72)	(1.74)	(1.80)
MOM	0.088	0.090	0.090	0.080	0.082	0.082	0.076	0.078	0.078	0.073	0.074	0.075
	(0.29)	(0.30)	(0.31)	(0.26)	(0.27)	(0.28)	(0.25)	(0.26)	(0.26)	(0.24)	(0.25)	(0.25)
REV	-0.007	-0.007	-0.007	-0.007	-0.007	-0.007	-0.007	-0.007	-0.007	-0.007	-0.008	-0.008
	(-1.25)	(-1.26)	(-1.26)	(-1.31)	(-1.32)	(-1.33)	(-1.36)	(-1.37)	(-1.38)	(-1.40)	(-1.41)	(-1.42)
ILLIQ	0.035	0.035	0.035	0.036	0.036	0.036	0.036	0.037	0.037	0.037	0.037	0.038
	(3.23)	(3.25)	(3.29)	(3.27)	(3.29)	(3.34)	(3.29)	(3.31)	(3.36)	(3.30)	(3.32)	(3.38)

Continued on next page…

...Continued

Panel B: Mean of TRUST as the threshold to define DTRUST

	N=2			N=3			N=4			N=5		
Model	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
MAX(N)	-0.053	-0.053	-0.047	-0.076	-0.077	-0.071	-0.097	-0.098	-0.091	-0.117	-0.118	-0.112
	(-2.21)	(-2.23)	(-1.82)	(-2.49)	(-2.51)	(-2.15)	(-2.63)	(-2.65)	(-2.30)	(-2.74)	(-2.76)	(-2.45)
TRUST		0.377	1.012		0.379	1.052		0.379	1.069		0.378	1.075
		(0.66)	(1.57)		(0.67)	(1.63)		(0.67)	(1.65)		(0.66)	(1.65)
MAX(N) × DTRUST			-0.022			-0.025			-0.029			-0.031
			(-1.73)			(-1.68)			(-1.69)			(-1.63)
BETA	-0.007	-0.007	-0.005	0.002	0.002	0.003	0.007	0.007	0.009	0.011	0.011	0.012
	(-0.17)	(-0.17)	(-0.13)	(0.04)	(0.04)	(0.08)	(0.17)	(0.18)	(0.22)	(0.27)	(0.27)	(0.31)
SIZE	-0.217	-0.217	-0.217	-0.223	-0.223	-0.224	-0.226	-0.226	-0.226	-0.227	-0.227	-0.228
	(-3.39)	(-3.38)	(-3.37)	(-3.52)	(-3.52)	(-3.50)	(-3.58)	(-3.57)	(-3.56)	(-3.61)	(-3.60)	(-3.58)
BM	0.218	0.219	0.222	0.213	0.214	0.217	0.210	0.211	0.214	0.207	0.209	0.212
	(1.78)	(1.80)	(1.83)	(1.76)	(1.77)	(1.81)	(1.74)	(1.76)	(1.80)	(1.72)	(1.74)	(1.78)
MOM	0.088	0.090	0.091	0.080	0.082	0.083	0.076	0.078	0.079	0.073	0.074	0.076
	(0.29)	(0.30)	(0.31)	(0.26)	(0.27)	(0.28)	(0.25)	(0.26)	(0.26)	(0.24)	(0.25)	(0.25)
REV	-0.007	-0.007	-0.007	-0.007	-0.007	-0.007	-0.007	-0.007	-0.007	-0.007	-0.008	-0.008
	(-1.25)	(-1.26)	(-1.27)	(-1.31)	(-1.32)	(-1.33)	(-1.36)	(-1.37)	(-1.38)	(-1.40)	(-1.41)	(-1.43)
ILLIQ	0.035	0.035	0.035	0.036	0.036	0.036	0.036	0.037	0.037	0.037	0.037	0.037
	(3.23)	(3.25)	(3.25)	(3.27)	(3.29)	(3.29)	(3.29)	(3.31)	(3.31)	(3.30)	(3.32)	(3.33)

Table IA6. Fama-MacBeth regressions with an interaction term and alternative measure for lottery demand

The table reports the time-series average of the slope coefficients from cross-sectional regressions across the sample when idiosyncratic skewness is used as the measure for lottery demand. Every month from January 1996 to December 2018, we run the Fama-MacBeth regression of the monthly stock returns (in percent) on the one-month lagged independent variables that include ISKEW, TRUST, the interaction term of ISKEW and DTRUST, and control variables. ISKEW is the idiosyncratic skewness over a month. DTRUST is a dummy variable based on TRUST within each region where firms are headquartered. If a firm's region's monthly TRUST is above the threshold of TRUST for the region over time, then DTRUST is one and zero otherwise. The thresholds are the median and mean of TRUST within each region over time. The control variables include market beta (BETA), natural log of market capitalization (SIZE), natural log of book-to-market ratio (BM), momentum (MOM), short-term reversal (REV) and illiquidity (ILLIQ). All variables are defined in the Appendix. Panel A (Panel B) reports the results when (median) mean of TRUST is used as the threshold to define DTRUST. The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

	Panel A: Median of TRUST as the threshold to define DTRUST			Panel B: Mean of TRUST as the threshold to define DTRUST		
Model	(1)	(2)	(3)	(1)	(2)	(3)
ISKEW	-0.147	-0.148	-0.117	-0.147	-0.148	-0.109
	(-2.37)	(-2.37)	(-1.84)	(-2.37)	(-2.37)	(-1.51)
TRUST		0.386	0.473		0.386	0.463
		(0.68)	(0.83)		(0.68)	(0.82)
ISKEW × DTRUST			-0.106			-0.125
			(-1.79)			(-1.83)
BETA	-0.051	-0.051	-0.050	-0.051	-0.051	-0.051
	(-1.03)	(-1.03)	(-1.02)	(-1.03)	(-1.03)	(-1.03)
SIZE	-0.189	-0.189	-0.188	-0.189	-0.189	-0.188
	(-2.47)	(-2.46)	(-2.46)	(-2.47)	(-2.46)	(-2.45)
BM	0.235	0.237	0.239	0.235	0.237	0.239
	(1.64)	(1.66)	(1.68)	(1.64)	(1.66)	(1.67)
MOM	0.113	0.115	0.114	0.113	0.115	0.113
	(0.37)	(0.39)	(0.38)	(0.37)	(0.39)	(0.38)
REV	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005
	(-0.88)	(-0.89)	(-0.90)	(-0.88)	(-0.89)	(-0.90)
ILLIQ	0.032	0.032	0.032	0.032	0.032	0.032
	(3.00)	(3.02)	(3.02)	(3.00)	(3.02)	(3.02)

Table IA7. Education and the effect of trust on MAX effect: using mean of EDU as the threshold to define subsamples

The table reports the time-series average of the slope coefficients from cross-sectional regressions over two subsamples that include regions with low education level (low-EDU) and high education level (high-EDU). EDU is the state-level percentage of the population over 25 years old with a bachelor's degree or higher. We classify the sample stocks into two subsample groups (low-EDU or high-EDU) based on the firm's state's previous month EDU ranking. The threshold used in the ranking of EDU is its mean across all states where firms are headquartered in each month. If a firm's state's monthly EDU is below (above) the mean of EDU, the firm-month is classified into the low-EDU (high-EDU) subsamples. For each subsample and every month from January 1996 to December 2018, we run the Fama-MacBeth regression of the monthly stock returns (in percent) on the one-month lagged independent variables that include the maximum daily return (MAX), TRUST, the interaction term of MAX and DTRUST, and control variables. DTRUST is a dummy variable based on TRUST within each region where firms are headquartered. If a firm's region's monthly TRUST is above the mean of TRUST for the region over time, then DTRUST is one and zero otherwise. The control variables are market beta (BETA), natural log of market capitalization (SIZE), natural log of book-to-market ratio (BM), momentum (MOM), short-term reversal (REV) and illiquidity (ILLIQ). All variables are defined in the Appendix. The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

	Low-EDU			High-EDU		
Model	(1)	(2)	(3)	(1)	(2)	(3)
MAX	-0.040	-0.040	-0.023	-0.028	-0.028	-0.026
	(-2.19)	(-2.20)	(-1.04)	(-1.82)	(-1.83)	(-1.42)
TRUST		-0.389	0.520		-0.415	-0.137
		(-0.54)	(0.71)		(-0.59)	(-0.20)
MAX × DTRUST			-0.032			-0.012
			(-2.26)			(-0.92)
BETA	-0.010	-0.010	-0.010	-0.026	-0.026	-0.021
	(-0.19)	(-0.18)	(-0.19)	(-0.57)	(-0.57)	(-0.45)
SIZE	-0.163	-0.163	-0.168	-0.228	-0.228	-0.230
	(-2.63)	(-2.63)	(-2.72)	(-3.16)	(-3.15)	(-3.16)
BM	0.342	0.342	0.331	0.184	0.185	0.186
	(2.65)	(2.65)	(2.59)	(1.45)	(1.46)	(1.48)
MOM	0.134	0.135	0.128	0.083	0.081	0.086
	(0.42)	(0.42)	(0.40)	(0.28)	(0.27)	(0.30)
REV	-0.002	-0.002	-0.002	-0.009	-0.009	-0.009
	(-0.29)	(-0.31)	(0.27)	(-1.64)	(-1.62)	(-1.65)
ILLIQ	0.024	0.024	0.023	0.043	0.043	0.044
	(2.31)	(2.29)	(2.27)	(3.20)	(3.24)	(3.28)

Table IA8. Income and the effect of trust on MAX effect: using mean of MHI as the threshold to define subsamples

The table reports the time-series average of the slope coefficients from cross-sectional regressions over two subsamples that include regions with low income (low-MHI) and high income (high-MHI). MHI is defined as the state-level median household income. We classify the sample stocks into two subsample groups (low-MHI or high-MHI) based on the firm's state's previous month MHI ranking. The threshold used in the ranking of MHI is its mean across all states where firms are headquartered in each month. If a firm's state's monthly MHI is below (above) the mean of MHI, the firm-month is classified into the low-MHI (high-MHI) subsamples. For each subsample and every month from January 1996 to December 2018, we run the Fama-MacBeth regression of the monthly stock returns (in percent) on the one-month lagged independent variables that include the maximum daily return (MAX), TRUST, the interaction term of MAX and DTRUST, and control variables. DTRUST is a dummy variable based on TRUST within each region where firms are headquartered. If a firm's region's monthly TRUST is above the mean of TRUST for the region over time, then DTRUST is one and zero otherwise. The control variables are market beta (BETA), natural log of market capitalization (SIZE), natural log of book-to-market ratio (BM), momentum (MOM), short-term reversal (REV) and illiquidity (ILLIQ). All variables are defined in the Appendix. The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

	Low-MHI			High-MHI		
Model	(1)	(2)	(3)	(1)	(2)	(3)
MAX	-0.038	-0.039	-0.021	-0.029	-0.029	-0.026
	(-2.06)	(-2.08)	(-0.93)	(-1.87)	(-1.88)	(-1.28)
TRUST		-0.415	0.071		0.040	0.636
		(-0.68)	(0.11)		(0.05)	(0.90)
MAX × DTRUST			-0.034			-0.013
			(-2.21)			(-0.88)
BETA	-0.033	-0.032	-0.033	-0.018	-0.019	-0.013
	(-0.62)	(-0.61)	(-0.65)	(-0.39)	(-0.40)	(-0.29)
SIZE	-0.172	-0.172	-0.174	-0.220	-0.220	-0.221
	(-2.78)	(-2.78)	(-2.84)	(-3.08)	(-3.08)	(-3.07)
BM	0.337	0.334	0.325	0.187	0.189	0.194
	(2.60)	(2.58)	(2.52)	(1.44)	(1.47)	(1.52)
MOM	0.141	0.139	0.132	0.082	0.082	0.088
	(0.44)	(0.43)	(0.41)	(0.28)	(0.28)	(0.31)
REV	-0.001	-0.001	-0.001	-0.009	-0.009	-0.009
	(-0.15)	(-0.16)	(-0.14)	(-1.63)	(-1.62)	(-1.66)
ILLIQ	0.027	0.027	0.027	0.040	0.040	0.041
	(2.14)	(2.12)	(2.12)	(3.64)	(3.69)	(3.76)

Table IA9. Income and the effect of trust on MAX effect: using per capita personal income as the proxy for income

The table reports the time-series average of the slope coefficients from cross-sectional regressions over two subsamples that include regions with low income (low-PCI) and high income (high-PCI). PCI is defined as the state-level per capita personal income. We classify the sample stocks into two subsample groups (low-PCI or high-PCI) based on the firm's state's previous month PCI ranking. The ranking of PCI is created across all states where firms are headquartered in each month. The thresholds used in ranking include the median and mean of PCI. If a firm's state's monthly PCI is below (above) the threshold of PCI, the firm-month is classified into the low-PCI (high-PCI) subsamples. For each subsample and every month from January 1996 to December 2018, we run the Fama-MacBeth regression of the monthly stock returns (in percent) on the one-month lagged independent variables that include the maximum daily return (MAX), TRUST, the interaction term of MAX and DTRUST, and control variables. DTRUST is a dummy variable based on TRUST within each region where firms are headquartered. If a firm's region's monthly TRUST is above the threshold of TRUST for the region over time, then DTRUST is one and zero otherwise. The thresholds to define DTRUST are median and mean of TRUST within each region over time. The control variables are market beta (BETA), natural log of market capitalization (SIZE), natural log of book-to-market ratio (BM), momentum (MOM), short-term reversal (REV) and illiquidity (ILLIQ). All variables are defined in the Appendix. Panel A (Panel B) reports the results when the threshold used to define low-PCI and high-PCI subsamples is median (mean) of PCI and the threshold to define DTRUST is median (mean) of TRUST within each region over time. The sample includes Nasdaq-listed stocks headquartered in the 10 US geographical regions. Newey-West (1987) adjusted *t*-statistics using six lags are reported in parentheses.

Panel A: Median of PCI as the threshold to define low-PCI and high-PCI subsamples

	Low-PCI			High-PCI		
Model	(1)	(2)	(3)	(1)	(2)	(3)
MAX	-0.038	-0.038	-0.021	-0.030	-0.030	-0.023
	(-1.98)	(-1.99)	(-1.04)	(-1.88)	(-1.91)	(-1.37)
TRUST		0.457	1.206		-0.223	0.620
		(0.62)	(1.60)		(-0.31)	(0.94)
MAX × DTRUST			-0.047			-0.020
			(-2.52)			(-1.97)
BETA	-0.065	-0.063	-0.064	-0.011	-0.011	-0.008
	(-1.12)	(-1.10)	(-1.12)	(-0.23)	(-0.24)	(-0.18)
SIZE	-0.163	-0.164	-0.162	-0.214	-0.214	-0.213
	(-2.94)	(-2.96)	(-2.98)	(-2.97)	(-2.97)	(-2.95)
BM	0.342	0.341	0.336	0.188	0.190	0.194
	(2.93)	(2.93)	(2.88)	(1.45)	(1.47)	(1.51)
MOM	0.252	0.253	0.242	0.053	0.052	0.056
	(0.80)	(0.80)	(0.78)	(0.18)	(0.17)	(0.19)
REV	0.002	0.002	0.002	-0.009	-0.009	-0.009
	(0.34)	(0.32)	(0.35)	(-1.62)	(-1.62)	(-1.66)
ILLIQ	0.035	0.035	0.035	0.037	0.038	0.038
	(1.66)	(1.65)	(1.67)	(3.67)	(3.73)	(3.78)

Continued on next page…

…Continued

Panel B: Mean of PCI as the threshold to define low-PCI and high-PCI subsamples

	Low-PCI			High-PCI		
Model	(1)	(2)	(3)	(1)	(2)	(3)
MAX	-0.040	-0.040	-0.021	-0.028	-0.028	-0.024
	(-2.20)	(-2.22)	(-1.02)	(-1.77)	(-1.78)	(-1.19)
TRUST		-0.052	0.334		0.054	0.688
		(-0.08)	(0.47)		(0.07)	(0.97)
MAX × DTRUST			-0.039			-0.017
			(-2.29)			(-1.10)
BETA	-0.058	-0.057	-0.056	-0.013	-0.013	-0.008
	(-1.04)	(-1.02)	(-1.01)	(-0.28)	(-0.29)	(-0.19)
SIZE	-0.155	-0.155	-0.158	-0.215	-0.214	-0.215
	(-2.79)	(2.80)	(2.86)	(-2.95)	(-2.94)	(-2.92)
BM	0.331	0.328	0.318	0.204	0.206	0.211
	(2.83)	(2.81)	(2.75)	(1.58)	(1.61)	(1.66)
MOM	0.117	0.116	0.102	0.104	0.105	0.112
	(0.36)	(0.35)	(0.31)	(0.35)	(0.36)	(0.39)
REV	0.001	0.001	0.001	-0.010	-0.010	-0.010
	(0.11)	(0.10)	(0.14)	(-1.71)	(-1.72)	(-1.76)
ILLIQ	0.032	0.032	0.032	0.038	0.038	0.039
	(2.28)	(2.25)	(2.26)	(3.53)	(3.58)	(3.66)