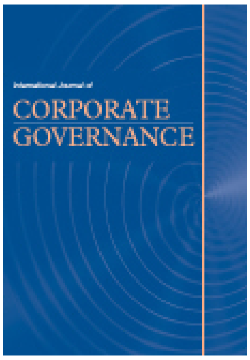

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Do unhealthy cities produce unhealthy returns?

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Abstract: We examine how firms headquartered in poor health communities affect their stock returns and valuations. We find that poor health throughout a community, measured through obesity rates, self-reported poor health status, and self-reporting poor physical or mental health, lowers stock returns and creates lower valuations. Specifically, we find that a 1% increase in overweight rates is associated with $100 billion in lost value to the USA stock market. Furthermore, this effect is more prominent in stocks with more retail investors. This suggests that poor community health influences local investor behaviour more strongly than employees affect local stock returns. These results have important implications as obesity rates continue to rise throughout the world.

Keywords: stock performance; health; obesity; mental health; physical health.

JEL codes: E70, G10, G40.

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1 Introduction

Health impacts a person's quality of life and can be his or her most significant asset. Good health is related to improved cognitive function in old age (Case and Paxton, 2009), greater longevity (Peeters et al., 2003), and enhanced quality of life (Schwimmer et al., 2003). Despite this evidence, the USA and most of the world are currently experiencing a health crisis. For example, the National Institute of Health (NIH) finds that nearly 70 percent of the American population is either overweight or obese (NIH, 2017), while the World Health Organization (2016) shows that the number of adults that are obese worldwide has more than doubled since 1980. The COVID-19 pandemic has impacted markets worldwide (Kapar et al., 2021) and has likely exacerbated the health crisis. However, there is limited evidence on how poor health directly influences corporate performance despite the growing concern about the economic impact of the population's poor health.

Several papers explore how community health affects company policies and productivity. For example, Agrawal and Lim (2018) examine the impact of community obesity on firm policies and find that firms located in areas with higher obesity rates tend to invest less and grow more slowly, which they interpret as consistent with a risk averse and myopic demographic effect. However, there is more to poor health than just obesity rates, like health quality and mental health. Moreover, a company is reliant on the people within its geographical community for providing employees and customers, and, as we argue, local investors. Our paper is the first to explore how the local community's general health affects a firm's stock performance and valuation.

There is evidence that companies located together experience similar corporate performance and policies. For example, Pirinsky and Wang (2006) and Parsons et al. (2020) find that the stock returns of firms headquartered in the same location have strong co-movement with each other. While not examining health per se, Kedia and Rajgopal (2009) find that the local labour markets influence local firm decisions. Additionally, research finds significant local spillover in corporate growth (Dougal et al., 2015), innovation (Mathers and Shank, 2024), and corporate responsibility (Nofsinger et al., 2022). We posit that the health of the local community is one source causing these geographical spillovers. Furthermore, we posit that there are two potential mechanisms in which areas of poor health can adversely affect local firms: the investor clientele effect and the employee effect.

First, the investor clientele effect argues that the poor health of investors will cause lower stock returns and valuations. The literature documents that poor health is related to impaired cognitive function (Smith et al., 2011; Naderali et al., 2009; Farr et al., 2008; Kanoski and Davidson, 2011), less optimism, and higher depression (Stunkard et al., 2003; Gariepy et al., 2010), and lower risk taking (Addoum et al., 2017; Bogan and Fertig, 2013; Bressan et al., 2014; Nofsinger and Shank, 2019; Patterson and Shank, 2020). Depression can be a side effect of poor health or a primary symptom of mental illness. Depression causes people to fear risks and thus increases risk aversion. Consistent with this notion, Lindeboom and Melnychuk (2015) use the Survey of Health, Ageing, and Retirement in Europe data to explore the association between depression and holding risky investment assets. They find that suffering the symptoms of depression lowers the probability that they will own risk assets like stocks. In addition, using the Health and Retirement Study that follows 7,000 heads of households over many survey years, Rosen and Wu (2004) report that self-reported healthy people are more likely to hold retirement plans, individual bonds, and risk assets like individual stocks and mutual funds, while less healthy people are less likely to hold all three groups of investment assets. In addition, the literature robustly demonstrates that investors have a local bias and are more likely to purchase stocks that are headquartered close to where they live (Coval and Moskowitz, 1999; Grinblatt and Keloharju, 2001; Huberman, 2001; Ivković and Weisbenner, 2005; Chen et al., 2007; Nofsinger and Varma, 2012). Therefore, firms in areas of poor health could have a preponderance of local investors who are more risk averse and may not even participate in the stock market. Thus, their stock returns and valuations may suffer.

As such, the result of unhealthy local investors is likely to lower stock returns and valuations for those local firms. In fact, research demonstrates that poor health measured through transient environmental factors such as the flu (McTier et al., 2013) and allergies (Pantzalis and Ucar, 2018) cause decreased trading volume, volatility, and stock returns due to the impact of decreased cognitive function and risk tolerance. Unlike transitory health issues like the flu or allergies, poor health tends to be quasi-permanent and unlikely to change quickly, if at all. Therefore, the firms in areas plagued by poor health should have consistently lower stock returns.[1] Consistent with this idea, Agrawal and Lim (2018) find that the investor clientele effect is a contributing factor to why firms in areas of high obesity take less risk. One possible reason for this is that obesity is related to lower testosterone levels (Kelly and Jones, 2015), which are related to less risk taking (Nofsinger et al., 2018, 2021).

Second, research argues that healthier populations have higher labour productivity (Bloom and Canning, 2000; Bloom et al., 2004; Strauss and Thomas, 1998), which could increase stock returns and valuations through employee productivity. Thus, the employee effect argues that employees in poor health will hinder firm performance as the employees will be less productive and efficient due to absenteeism (not being able to work) and presenteeism (at work but not being productive) (Wolf and Colditz, 1996; Weil, 2007; Konnopka et al., 2011; Finkelstein et al., 2009, 2010; Ford et al., 2011; Goettler et al., 2017). For example, Finkelstein et al. (2009) find that individuals suffering from morbid obesity, on average, miss almost one week of work more per year than those of a healthy weight. Ricci and Chee (2005) find that obese individuals are more likely to engage in the five following behaviours: losing concentration, repeating a task, working more slowly than others, feeling fatigued, and doing nothing at work.

Finkelstein et al. (2010) find that the cost of presenteeism due to morbid obesity is about $3,792 per worker per year, which equates to more than one month's lost productivity while at work. Similarly, research has examined the impact of poor mental health. In a Meta review examining the impact of psychological health, including depression, anxiety, life satisfaction, and physical health, Ford et al. (2011) find consistent results that being in poor mental health is related to a substantial reduction in work performance. Wang et al. (2004) examine the effects of depression, along with allergies, arthritis, back pain, headaches, high blood pressure, and asthma on work performance and find that depression is the only condition that is significantly related to decreased work performance, demonstrating the importance of examining mental health. This reduced work performance equates to 2.3 days absent per month. Therefore, if companies employ more employees from areas with a higher prevalence of poor health, the firm should be less profitable and have lower stock returns. Additionally, Agrawal and Lim (2018) argue that even if the employees themselves are not in poor health, living in a poor health community will decrease the risk preferences for the community as a whole through social norms.

Our study first establishes that the health of local communities affects firm performance by employing data collected from the Centers for Disease Control and Prevention (CDC) to determine areas characterised by poor health and examine its impact on firm stock performance. Precisely, we analyse the impact of obesity and self-perceived health status in metropolitan and micropolitan statistical areas (MMSAs) and match the health variables to stock returns and stock valuations of companies headquartered in the same MMSA. We find that a community being more overweight and in poorer health than other communities is associated with lower stock returns for local firms. In terms of estimates of the economic magnitude, we find that a 1% increase in overweight rates is associated with $100 billion in lost value to the USA stock market. Our results hold under the robustness tests of changing both independent and dependent variables. For independent variables, our results are consistent with the health variables changing from weight-based measures and self-reported health status to self-reported days per year when the average resident is in poor mental health or poor physical health. For dependent variables, our results hold using the market to book ratio to measure firm valuation.

We then assess the mechanism that drives poor community health to cause lower stock returns. We hypothesise that the investor clientele effect is the primary link between community health and corporate performance. We use retail stock ownership to examine this hypothesis as retail ownership is shown to be related to investment in local companies (Coval and Moskowitz, 1999; Grinblatt and Keloharju, 2001; Huberman, 2001; Nofsinger and Varma, 2012; Chen et al., 2007). Note that institutional investors dominate the US market. For individual investors to influence equity pricing, the firm would have to have a substantial level of retail ownership. Thus, we investigate the investor clientele effect by conducting our analysis in firm samples of low and high retail ownership. If the impact of poor health communities on lower returns and valuations mostly comes from firms with greater retail ownership, then there is support for the investor clientele effect.

We also investigate the competing hypothesis of the employee effect by adopting Giroud and Mueller's (2011) employee productivity variable of industry adjusted sales divided by the number of employees deflated by CPI. If the employee effect is causing lower firm performance, it would be more prevalent in firms that have less productive employees. Mitchell and Bates (2011) estimate the productivity costs of various types of employee health risks, including weight related and mental health conditions. They conclude that lifestyle risk factors and health conditions are associated with workplace productivity loss. Therefore, we conduct our analysis in samples of high and low productivity firms.

The results of our split samples provide support for the investor clientele effect. For example, we find that poor health, as measured as community obesity rates or the percentage of the population in fair or poor health, has a significantly greater negative effect on both stock returns and valuations when retail ownership is higher. Conversely, when exploring the split sample based on high and low employee productivity, we find that the impact of poor health is consistently negative in both samples. Overall, our results suggest that the poor health of a community influences how retail investors invest.

We contribute to the health literature by documenting a relation between local community health and company stock valuation. Our paper also contributes to the behavioural finance literature that shows that individual characteristics, specifically health, influence financial decision making. For example, laboratory experiments find individuals in poor health display risk averse behaviour (Koritzky et al., 2012). Similarly, the portfolio choice literature demonstrates that individuals in poor health are less likely to hold risky securities (Addoum et al., 2017; Rosen and Wu, 2004; Edwards, 2010; Pang and Warshawsky, 2010; Goldman and Maestas, 2013; Yogo, 2016). This literature primarily focuses on large datasets that can only examine stock market participation and equity versus debt allocations without examining the fine details of stock selection. We contribute to this literature by examining firm level stock returns using local health as a proxy for retail investor health.

The paper progresses as follows. In Section 2, we describe the data and methodology. Our primary results are presented in Section 3, with robustness tests in Section 4. We conclude the paper in the final section.

2 Methodology

2.1 Data

We match each company to the health characteristics of the community surrounding its headquarters using yearly data from January 2002 to December 2017. The health data are from the Behavioral Risk Factor Surveillance System (BRFSS), which is a phone survey conducted by the CDC that collects data on USA residents regarding their health condition. Employing the CDC dataset from MMSAs, we have an average of nearly 1,500 interviews per year per MMSA. In 2002, the CDC conducted interviews in 98 MMSAs but expanded to 136 MMSAs by 2017. We aggregate each variable for all of the individual data into an average for each MMSA by year. For example, we examine each individual interview to determine if the respondent is obese. We then cumulate the number of obese respondents in the MMSA and divide it by the total number of respondents in the MMSA to calculate the obesity rate for the MMSA for the given year. We then match the firm level data to the health data based on the location of the firm's headquarters from Compustat.

Company stock returns are collected from CRSP and matched with firm characteristics from Compustat. We delete observations outside of the 50 States within the USA (i.e., Puerto Rico, Guam, etc.), exclude financial (SIC 6000-6999) and utilities (4900-4999) firms due to them being highly regulated, and only use common stocks (share code 10 and 11) as typically found in the literature. Furthermore, we collect data about air pollution from the US Environmental Protection Agency (EPA) and data on Medicaid Expansion from the Kaiser Family Foundation at KFF.org. Finally, we collect demographic control variables about each MMSA from the US census.

2.2 Variables of interest

The goal of this paper is to examine the impact of poor community health on stock returns and valuations. So, we describe several health variables that are commonly and not commonly found in the financial literature. To start, we use the BRFSS questionnaire to assess many facets of poor health in each MMSA community. One of the most studied health issues is the impact of weight. The body mass index (BMI) is a formula that provides a numerical value on how heavy an individual is compared to their height. Weight and height are asked on the survey. A healthy BMI is between 18.5 and 25. Someone who has a BMI under 18.5 is considered underweight, while someone with a BMI over 25 is deemed to be overweight. Finally, a BMI over 30 is considered obese.[2] Another popular health research method is to examine the percentage of people in poor health or poor or fair health as a variable (Miilunpalo et al., 1997; Bize et al., 2007; Hu et al., 2016). This variable is constructed as one of the questions on the BRFSS asks the participant how they perceive their health on a five-point Likert scale (poor, fair, good, very good, excellent). We also use this self-reported health status to assess the general health of communities, as individuals with healthy BMIs can have poor health, and overweight individuals can feel they are in good health.

Furthermore, health quality can be broken into both physical and mental health. Individuals may suffer from physical ailments such as headaches, hypertension, gastrointestinal problems, infection, chronic pain, or other common ailments that could inhibit them from performing their duties. Moreover, friction on job performance can also result from mental health issues, including depression, anxiety, stress, tension, or other issues. The BRFSS asks a question about the number of days per month that the individual's physical health was poor and the number of days per month the individual's mental health was poor. We use these poor mental health days and poor physical health days in robustness tests. The variables descriptions utilised in this paper are displayed in Table 1.

2.3 Control variables

We employ firm and MMSA control variables to control for known drivers of firm performance. We use the standard control variables, including firm size, market to book ratio, leverage, and research and development to control for firm effects that could impact stock returns or valuations following previous literature (Chan et al., 2001; Edmans, 2011; Belo et al., 2013; Dasgupta et al., 2011).

Table 1 Description of variables

Variable	*Definition*	*Source*
Panel A: health variables		
Fair/poor health	Self-reported health index that takes the value of 1 if the respondent reports they are in fair or poor health or the value of 0 if they report being in excellent, very good, or good health.	Behavioral Risk Factor Surveillance System
Obese	The sample average of individuals who report having a body mass index of greater than 30.	Behavioral Risk Factor Surveillance System
Overweight	The sample average of individuals who report having a body mass index of greater than 26.	Behavioral Risk Factor Surveillance System
Poor health	The sample average of self-reported health index that takes the value of 1 if the respondent reports they are in poor health or the value of 0 otherwise.	Behavioral Risk Factor Surveillance System
Poor mental health days	The sample average of self-reported days per month that their mental health is not good.	Behavioral Risk Factor Surveillance System
Poor physical health days	The sample average of self-reported days per month that their physical health is not good.	Behavioral Risk Factor Surveillance System
Panel B: dependent variables		
Excess returns	Company stock return – S&P 500 return	CRSP and Compustat
Excess M/B	Market equity / book equity – industry market equity / industry book equity. Book equity = shareholders' equity – preferred stock + balance sheet deferred taxes. Shareholders' equity = stockholders' equity or total common equity + preferred stock par value if previous is missing or total assets – total liabilities if previous is missing. Preferred stock = redemption value, liquidating value, or carrying value, in that order as available. Market equity = market equity if available or stock price times shares outstanding.	CRSP and Compustat
Panel C: firm level control variables		
Employee productivity	sales divided by employees adjusted by 2digit sic industry and deflated by CPI.	CRSP and Compustat
Leverage	Total debt / total assets.	CRSP and Compustat
M/B missing	dummy variable that equals 1 if the company has missing or negative M/B ratio.	CRSP and Compustat
R&D	Research and development.	CRSP and Compustat
R&D missing	Dummy variable that equals 1 if the company has missing or negative R&D.	CRSP and Compustat
Retail investor	1 – percentage of stock owned by institutional investors.	Thompson Reuter 13f
ROE	Income before extraordinary items for common shareholders/book equity.	CRSP and Compustat
Size	Natural log of market equity.	CRSP and Compustat

Notes: This table presents the variable names, definitions, and data sources of the variables used in this paper.

Table 1 Description of variables (continued)

Panel D: instrumental variables		
AQI	Index of daily air quality. Calculated for five major air pollutions: ground-level ozone, particle pollution (PM), carbon monoxide, sulphur dioxide, and nitrogen dioxide.	US Environmental Protection Agency
Medicaid Expansion	A dummy variable that equals 1 if the state has implemented an expanded Medicaid or 0 otherwise.	KFF.org
Panel E: MMSA control variables		
Age	Natural log of the median age of the population in the MMSA.	US Census
Education	The percent of the population who report having an undergraduate or graduate degree.	US Census
Income	Natural log of the median income of the population in the MMSA.	US Census
Married	The percent of the population who report being married.	US Census
Population	Natural log of the population in the MMSA.	US Census
Unemployment	The percent of the population who report being unemployed.	US Census
White	The percent of the population who report being white (non-Hispanic).	US Census

Notes: This table presents the variable names, definitions, and data sources of the variables used in this paper.

We use demographic information provided by the US Census to control for non-health factors in each MMSA. Age and income are included because they are frequently found to affect financial decisions (for example, see Campbell, 2006; Addoum et al., 2017). Additionally, we control for income because it is possible that areas with lower health are likely more impoverished and could influence the valuation of local companies (Hong et al., 2008). Following previous research, we include college graduation rates as a proxy for financial sophistication and cognitive abilities (for example, see Addoum et al., 2017; Lusardi and Mitchell, 2007, 2011).

After winsorising all variables at the 1% and 99% level, we still have a significant number of outliers. For example, our excess return variable (firm annual return less S&P 500 Index annual return) had a mean of 18.78 basis points with a standard deviation of 86.12. However, the maximum, 1,042 basis points, is nearly 12 standard deviations from the mean. Similar statistics can be seen with numerous other variables. Therefore, we winsorise all data at the 5% and 95% level to ensure outliers are not driving our results following recent research (Jacobs and Hillert, 2016; Bian et al., 2018; Berzins et al., 2019; Kostovetsky, 2017; Evans and Outlaw, 2017; Griffith et al., 2020).

Table 2 displays the summary statistics of the variables used in the analysis. Panel A shows that throughout our sample period, about 30% of the population was obese, with 63% of the population being overweight. Nearly 5% of the population self-reported being in poor health. Similarly, the average person self-reported being in poor mental health and poor physical health about ten days per month. Panel B shows that the average yearly excess return is about 14 basis points, with the average market to book ratio being 3.0.

Panel C shows that the market to book ratio is either negative or missing for about 6% of the sample. Furthermore, on average, 40% of shares outstanding are owned by retail investors.

Table 2 Summary statistics

Variables	*Mean*	*SD*	*Min*	*Max*
Panel A: health variables				
Fair/poor health	16.55	4.127	7.047	34.05
Obese	29.09	6.116	11.16	66.29
Overweight	62.77	6.883	26.17	83.19
Poor health	4.418	1.481	1.674	10.48
Poor mental health days	9.928	1.236	5.468	12.89
Poor physical health days	10.43	1.44	5.767	17.46
Panel B: firm level dependent variables				
Excess returns	14.54	62.45	–89.65	362.7
M/B	3.001	2.731	0	14.53
Panel C: firm level control variables				
Employee productivity	0.534	0.517	0.0492	2.431
Leverage	0.202	0.201	0	0.759
M/B missing	0.0599	0.237	0	1
R&D	0.0828	0.246	–0.0374	12.84
R&D missing	0.466	0.499	0	1
ROE	0.25	0.267	0	1.389
Retail ownership	0.395	0.321	0	1
Size	6.106	1.867	1.529	10.15
Panel D: instrumental variables				
Medicaid Expansion	0.137	0.344	0	1
AQI	56.2	11.53	21	140
Panel E: MMSA control variables				
Age	36.44	2.249	23.3	47.6
Education	29.3	7.62	9	50.8
Income	605.5	120.2	320.1	1,100
Married	49.09	2.947	33.1	62.1
Population	5,022,000	4,171,000	116,383	20,320,000
Unemployment	7.374	2.21	2.2	17
White	57.83	15.92	12.27	95.77

Notes: This table displays the mean, standard deviation (SD), minimum (min), and maximum (max) for the summary statistics. Panel A shows the independent health variables. Panel B shows the dependent variables of interest. Panel C shows the firm level control variables. Panel D shows the MMSA level control variables. The sample contains 28,035 observations from 2002 to 2017. All variables from CRSP or Compustat are winsozorised at the 5% and 95% level.

Panel D displays our two instrumental variables, Air Quality Index (AQI) and Medicaid Expansion used in later analysis. AQI describes how clean or polluted the air is on a range of 0 to 500. The EPA calculates the AQI for five of the largest air pollutants regulated by the Clean Air Act. These pollutants include carbon monoxide, ground-level ozone, nitrogen dioxide, particle pollution (commonly known as particulate matter), and sulphur dioxide. Levels from 0 to 50 represent good air quality, 51 to 100 represent moderate, 101 to 150 describe air quality that is unhealthy for sensitive groups, and over 151 depicts different levels of unhealthy conditions for all individuals. Overall, the average MMSA in our sample has moderate air quality.

In 2010, President Obama signed the Affordable Care Act (ACA) into law. This law allowed states to expand Medicaid coverage to households who earn below 133% of the federal poverty level from the previous level of 100% of the federal poverty level. The Medicaid Expansion went into effect in 2014 for 27 states, with Pennsylvania, Indiana, and Alaska implementing it in 2015 and Montana and Louisiana in 2016. Table 2 shows that 14% of our sample was covered under the expanded Medicaid policy.

Finally, panel E shows that the average age of each MMSA was 36 years old, with about 29% of the population holding a college degree. Furthermore, the unemployment rate was about 7%, with nearly 58% of the population being white (non-Hispanic).

2.4 *Model*

Table 3 presents the correlation matrix of all health related variables. The table shows that the correlation between being obese and overweight to being in poor health is 0.25 and 0.27. As such, an individual's BMI can only explain a fourth of their quality of health, which shows the need to examine more than just the obesity or overweight variable. However, the table indicates that all the variables we employ to measure poor health are highly correlated. Therefore, we examine each of the variables independently to avoid multi-collinearity concerns.

Table 3 Correlation table

	Obese	*Overweight*	*Poor health*	*Fair/poor health*	*Poor physical health*
Overweight	0.68				
Poor health	0.25	0.27			
Fair/poor health	0.44	0.42	0.66		
Poor physical health	0.37	0.31	0.51	0.59	
Poor mental health	0.4	0.38	0.38	0.42	0.57

Notes: This table presents the correlation matrix for the health variables of interest in the paper. See Table 1 for variable definitions.

One potential issue we need to address is the matter of reverse causation. While we investigate community health impacting firm stock performance, there is some evidence that economic and stock market performance impacts health (Schwandt, 2018; McInerney et al., 2013; Nandi et al., 2012; Cotti et al., 2015). For example, Cotti et al. (2015) find a positive relation between stock market declines and unhealthy behaviours such as smoking, binge drinking, and self-reported poor mental health. Additionally, Ratcliffe and Taylor (2015) find a positive relation between stock price increases and improved mental health and those mental well-being decreases as market volatility increases. Schwandt (2018) finds that positive wealth shocks lead to an improvement in physical health, mental health, and mortality rates. McInerney et al. (2013) show depression and anxiety tend to be higher in recessions, while Nandi et al. (2012) find that suicides increase during poor economic conditions. Similarly, Deaton (2012) finds that the stock market crash of 2008–2009 increased worry and stress in American adults.

Furthermore, Ruhm (2000) finds that obesity is inversely related to state unemployment rates, and a 1% increase in the state unemployment rate is related to a 1.3% increase in suicides. Similarly, Kalcheva et al. (2021) find a relationship between economic uncertainty and drinking and smoking. However, the aforementioned literature uses contemporaneous data, making it hard to draw causal relationships in some instances. Engelberg and Parsons (2016) overcome this issue and find that poor stock returns of firms in the state result in more hospital admissions in those states for both physical and mental ailments in the days following the stock price declines.

Due to this issue of reverse causality, we lag all independent variables, similar to Engelberg and Parsons (2016), as the stock performance of a given year cannot cause health issues in the previous year. As such, we present the following models to examine the impact of health on future firm stock performance and value:

$$\begin{aligned} Excess\ Ret_{s,t} &= \alpha_0 + Health_{s,t-1} + \phi_{s,t-1} + \Psi_{s,t-1} + B/M_{s,t-1} \\ &\quad + B/M\ Missing_{s,t-1} + MMSA_{s,t-1} \\ &\quad + State_{s,t-1} + Industry_{s,t-1} + \varepsilon_{s,t} \end{aligned} \tag{1}$$

$$\begin{aligned} Excess\ Val_{s,t} &= \alpha_0 + Health_{s,t-1} + \phi_{s,t-1} + \Psi_{s,t-1} + ROE_{s,t-1} \\ &\quad + MMSA_{s,t-1} + State_{s,t-1} + Industry_{s,t-1} + \varepsilon_{s,t} \end{aligned} \tag{2}$$

where *Excess Ret* is the firm stock return minus the return of the S&P 500.[3] $Health_{s,t-1}$ is one of the health variables (obese, overweight and obese, poor health, poor physical health, and poor mental health) lagged one year. The natural log of all individual health measures is taken for ease of interpretation. ϕ‘s are firm level controls lagged one year, including size, leverage, research and development, research and development missing, employee productivity, and retail ownership. Ψ is one-year lagged MMSA control variables, including population size, population age, unemployment rate, median income, married, white, and education. B/M is the firm’s lagged book-to-market ratio, and B/M missing is a dummy variable equal to 1 if the firm is missing its B/M ratio or 0 otherwise.[4] *Excess Val* is the book to market ratio, minus the two-digit SIC industry average book to market ratio. Additionally, return on equity lagged one year is included when examining firm valuations following Edmans (2011) and Hong and Kacperczyk (2009). MMSA fixed effects, industry fixed effects, and robust standard errors clustered by firm are used in all analyses. MMSA fixed effects are used as research shows that firms located in the same area have co-movement (Dougal et al., 2015; Parsons et al., 2020), state laws or tax codes, and to control for unobservable differences between cities. Finally, industry fixed effects are employed using two-digit SIC codes to control for specific industries having higher or lower returns following Agrawal and Lim (2018) and Dougal et al. (2015) and the fact that there may be a higher concentration of specific industries in individual states and cities.

3 Empirical evidence

3.1 Health and stock returns

Table 4 presents the results on how poor health impacts stock returns. The estimated coefficient on the percentage of obesity in the MMSA (column 1) is negative and significant at the 1% level, with a coefficient of –19.2. This result suggests that a 1% increase in obesity rates translates to approximately a 19-basis point lower stock return per year. Furthermore, when using the percentage of overweight individuals (column 2), the coefficient nearly doubles. As an illustration of the potential nationwide magnitude of this effect, consider that the overall stock market capitalisation in the USA was over 28 trillion dollars in 2017. So, each 1% increase in the portion of the population being overweight equates to a \$100 billion loss in the stock market. Furthermore, note that during our data sample, from 2002 to 2017, the CDC estimates that obesity rates increased by 9.25%, equating to over a \$900 billion reduction in market capitalisation in just the USA. Furthermore, the percentage of individuals in poor health (model 3) has a significantly adverse effect on local firm stock returns as poor health has a coefficient of –11.4 and is significant at the 1% level, while the percentage of the population being in fair or poor health is negative and significant at the 10% level.

Table 4 The impact of health on firm stock returns

	1	*2*	*3*	*4*
Obese	–19.2***			
	(2.908)			
Overweight		–36.1***		
		(4.776)		
Poor health			–11.4***	
			(1.529)	
Fair/poor health				–3.7*
				(2.085)
Retail ownership	–13.5***	–13.6***	–13.5***	–13.5***
	(1.602)	(1.605)	(1.606)	(1.606)
Employee productivity	1.4*	1.4*	1.4*	1.5**
	(0.732)	(0.729)	(0.735)	(0.735)
Size	–4.1***	–4.1***	–4.1***	–4.1***
	(0.306)	(0.307)	(0.307)	(0.307)
M/B	–1.7***	–1.8***	–1.7***	–1.8***
	(0.165)	(0.165)	(0.165)	(0.165)

Notes: This table reports the OLS regressions on multiple poor health variables and other known determinants of stock returns for the sample period of 2002 to 2017. All variables are lagged one year and defined in Table 1. All models include MMSA and two-digit SIC fixed effects. Robust standard errors clustered by firm are reported below the coefficient estimates that display significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 4 The impact of health on firm stock returns (continued)

	1	*2*	*3*	*4*
M/B missing	–5.4**	–5.4**	–5.5**	–5.6**
	(2.292)	(2.295)	(2.293)	(2.296)
Leverage	18.9***	18.9***	19.2***	19.1***
	(2.382)	(2.384)	(2.391)	(2.389)
R&D	8.2***	8.3***	8.4***	8.3***
	(2.913)	(2.908)	(2.893)	(2.905)
R&D missing	–2.3**	–2.4**	–2.3**	–2.4**
	(1.074)	(1.077)	(1.076)	(1.077)
Population	–60.3***	–58.9***	–66.2***	–61.7***
	(9.888)	(9.916)	(9.978)	(9.908)
Age	103.5***	105.6***	88.0**	105.5***
	(38.246)	(38.265)	(38.095)	(38.330)
Unemployment	3.9***	4.2***	4.1***	4.0***
	(0.275)	(0.278)	(0.275)	(0.275)
Income	154.8***	159.4***	153.5***	149.8***
	(12.152)	(12.205)	(12.080)	(12.045)
Married	–2.5***	–2.2***	–2.3***	–2.1***
	(0.470)	(0.469)	(0.468)	(0.476)
White	4.5***	4.9***	4.7***	4.8***
	(0.420)	(0.420)	(0.421)	(0.421)
Education	1.0***	1.0***	0.9***	1.0***
	(0.096)	(0.096)	(0.097)	(0.097)
Observations	22,363	22,363	22,363	22,363
R-squared	0.058	0.059	0.058	0.056

Notes: This table reports the OLS regressions on multiple poor health variables and other known determinants of stock returns for the sample period of 2002 to 2017. All variables are lagged one year and defined in Table 1. All models include MMSA and two-digit SIC fixed effects. Robust standard errors clustered by firm are reported below the coefficient estimates that display significance at the 10% (*), 5% (**), and 1% (***) levels.

When examining the control variables, we find that size and the market to book ratio are inversely related to stock returns, which is consistent with prior research (for example, Fama and French, 1993). The leverage, research and development spending, and employee productivity coefficients are positively related to stock returns, while retail ownership is inversely related to stock returns. Furthermore, higher unemployment rates, income, and white populations are related to higher stock returns. When local unemployment rates are high, labour wages, and thus labour costs, are likely lower, making firms more profitable.

3.2 An instrumental variable approach

In order to overcome the potential issue of endogeneity, we implement an instrumental variable approach. An instrumental variable must be an exogenous shock not correlated with the error term while being correlated with the explanatory variables, in our case, poor health. The biggest problem with the instrumental variable approach is that finding a good instrument and the data for it can be difficult. Agrawal and Lim (2018) use the ‘fatty foods’ tax that several states have adopted to reduce obesity and the density of fast-food restaurants in the given communities. However, these two variables are not exogenous shocks. The states that have elected to implement this tax are typically those with higher obesity issues, making the variable endogenous. Furthermore, while this tax may reduce the amount of certain foods or beverages people are consuming, it does not appear that it is affecting actual obesity rates because people switch to other unhealthy foods that are not taxed (Fletcher et al., 2010a, 2010b, 2010c; Powell et al., 2009; Sturm et al., 2010; Restrepo and Cantor, 2020) or pay the tax and have a reduced budget for other activities like exercise. Finally, if this tax were an appropriate measure for obesity rates, it does not seem like it would be appropriate for overall poor health measures or mental health measures. Additionally, fast food density is likely driven by demand. Given that a poor-health community demands more fast food, which leads to more supply, the variable does not measure an exogenous shock.

Therefore, we use the AQI and Medicaid Expansion as instrumental variables in a two staged least squared model to overcome the potential issue of endogeneity. Our choice of AQI as an exogenous instrumental variable is due to research showing it has a negatively significant impact on BMI (Sun et al., 2009; Jerrett et al., 2014; Ustulin et al., 2018) and overall health (Anderson et al., 2011; Brook et al., 2010; Kampa and Castanas, 2008; Mustafíc et al., 2012; Tzivian, 2011). Our choice of Medicaid Expansion as an exogenous instrumental variable is due to Chou et al. (2004), who use data from the BRFSS and show that obesity and poor health are inversely related to income. Therefore, Medicaid Expansion should improve the health quality of those at the highest risk. In fact, Sommers et al. (2017) find that uninsured rates for low-income adults dropped more than 20% for states that expanded Medicaid and a 23% increase in adults who report being in excellent self-reported health. One potential concern about using the Medicaid Expansion as an instrumental variable is that states with higher obesity rates may be more likely to adapt. However, anecdotal evidence shows this is not the case and that Democratic leaning states have adopted the Medicaid Expansion while Southern Republican leaning states have not. For example, in 2017, the ten MMSAs with the lowest obesity[5] rates had adopted the Medicaid Expansion while 8 of the 10 cities with the highest obesity rates had not.[6] Furthermore, there is no evidence that air pollution and Medicaid Expansion impact stock returns. Therefore, the two instruments satisfy the exclusion condition (Roberts and Whited, 2013). As such, we specify our model as:

$$Health_{s,t-1} = Medicaid\ Expansion_{s,t-1} + Air\ Quality_{s,t-1} \tag{3}$$

$$\begin{aligned} Execess\ Ret_{s,t} = \alpha_0 + \widehat{Health}_{s,t-1} + \phi_{s,t-1} + \Psi_{s,t-1} + B/M_{s,t-1} + B/M\ Missing_{s,t-1} \\ + MMSA_{s,t-1} + State_{s,t-1} + Industry_{s,-t1} + \varepsilon_{s,t} \end{aligned} \tag{4}$$

$$Health_{s,t-1} = Medicaid\ Expansion_{s,t-1} + Air\ Quality_{s,t-1} \tag{5}$$

$$\begin{aligned} Excess\ Val_{s,t} = \alpha_0 + \widehat{Health}_{s,t} + \phi_{s,t-1} + \Psi_{s,t-1} + ROE_{s,t-1} + MMSA_{s,t-1} \\ + State_{s,t-1} + Industry_{s,t-1} + \varepsilon_{s,t} \end{aligned} \tag{6}$$

where $\widehat{Health}_{s,t-1}$ is the fitted health status variable from the first stage regression. Medicaid Expansion is a dummy variable that equals 1 if the state has implemented the expanded Medicaid following ACA or 0 otherwise. Air Quality is the median AQI for the MMSA for the given year.

Table 5 The impact of health on firm stock returns and valuation using instrumental variables

	Panel A: first stage regression			
	Obese	*Overweight*	*Poor health*	*Fair/poor health*
Medicaid	0.0826***	0.0364***	0.0706***	0.0251***
	(0.004)	(0.002)	(0.005)	(0.003)
AQI	–0.0007***	–0.0005***	0.0018***	–0.0010***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	21,014	21,014	21,014	21,014
R-squared	0.549	0.419	0.466	0.469
	Panel B: second stage regression			
	1	*2*	*3*	*4*
Obese	–253.8***			
	(18.771)			
Overweight		–550.5***		
		(45.164)		
Poor health			–225.4***	
			(24.639)	
Fair/poor health				–476.3***
				(74.209)
Observations	20,833	20,833	20,833	20,833
	Panel C: second stage regression for valuation			
	1	*2*	*3*	*4*
Obese	–2.63**			
	(1.154)			
Overweight		–5.86**		
		(2.525)		
Poor health			–1.72	
			(1.197)	
Fair/poor health				–6.03**
				(2.677)
Observations	20,979	20,979	20,979	20,979

Notes: This table reports the 2SLS regressions on multiple poor health variables and other known determinants of stock returns for the sample period of 2002 to 2017 using Medicaid Expansion and Air Quality Index as instruments. Panel A displays the first stage regression results. Panel B displays the second stage regression results for excess returns and panel C shows results for valuation. All variables are lagged one year and defined in Table 1. All models include MMSA and two-digit SIC fixed effects. Robust standard errors clustered by firm are reported below the coefficient estimates that display significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 6 The impact of health on firm valuations based on retail ownership

	1		*2*		*3*		*4*		*High–low*
	Low	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*	*T-test*
Panel A: stock returns									
Obese	–183***	–318***							–135***
	(23.642)	(30.456)							[–3.50]
Overweight			–476***	–596***					–120
			(65.306)	(61.589)					[–1.34]
Poor health					–224***	–216***			8
					(37.596)	(33.767)			[0.16]
Fair/poor health							–276***	–626***	–350***
							(88.048)	(100.144)	[–2.62]
Observations	11,249	9,584	11,249	9,584	11,249	9,584	11,249	9,584	
	1		*2*		*3*		*4*		*High–low*
	Low	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*	*T-test*
Panel B: market to book ratio									
Obese	0.25	–4.80***							–5.025**
	(1.486)	(1.636)							[–2.28]
Overweight			0.57	–10.26***					–10.83**
			(3.782)	(3.170)					[–2.19]
Poor health					–0.27	–1.46			[–1.19
					(1.833)	(1.451)			–0.51]
Fair/poor health							1.44	–11.97***	–13.41***
							(3.378)	(3.749)	[–2.66]
Observations	11,266	9,713	11,266	9,713	11,266	9,713	11,266	9,713	

Notes: This table reports the second stage of 2SLS regressions on multiple poor health variables and other known determinants of stock returns (panel A) and market to book ratio (panel B) for the sample period of 2002 to 2017 using Medicaid Expansion and Air Quality Index as instruments. All variables are lagged one year and defined in Table 1. All models include MMSA and two-digit SIC fixed effects. Robust standard errors clustered by firm are reported below the coefficient estimates that display significance at the 10% (*), 5% (**), and 1% (***) levels. The last column reports coefficient difference and an associated t-test [shown in brackets].

Table 7 The impact of health on firm valuations based on employee productivity

	1		2		3		4		High–low
	Low	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*	*T-test*
Panel A: stock returns									
Obese	−257***	−247***							10
	(29.958)	(24.946)							[0.26]
Overweight			−505***	−592***					−87
			(63.988)	(68.831)					[−0.93]
Poor health					−149***	−344***			−195***
					(25.756)	(52.193)			[−3.35]
Fair/poor health							−424***	−485***	−61
							(91.772)	(108.718)	[−0.43]
Observations	10,366	10,309	10,366	10,309	10,366	10,309	10,366	10,309	
	1		2		3		4		High–low
	Low	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*	*T-test*
Panel B: market to book ratio									
Obese	−3.08*	−2.73*							0.35
	(1.825)	(1.438)							[0.15]
Overweight			−6.80*	−6.47*					0.33
			(3.597)	(3.492)					[0.07]
Poor health					−0.25	−4.30**			−4.05
					(1.330)	(2.155)			[−1.60]
Fair/poor health							−8.33**	−4.50	12.83***
							(3.787)	(3.510)	[2.48]
Observations	10,461	10,349	10,461	10,349	10,461	10,349	10,461	10,349	

Notes: This table reports the second stage of 2SLS regressions on multiple poor health variables and other known determinants of stock returns (panel A) and market to book ratio (panel B) for the sample period of 2002 to 2017 using Medicaid Expansion and Air Quality Index as instruments. All variables are lagged one year and defined in Table 1. All models include MMSA and two-digit SIC fixed effects. Robust standard errors clustered by firm are reported below the coefficient estimates that display significance at the 10% (*), 5% (**), and 1% (***) levels. The last column reports coefficient difference and an associated t-test [shown in brackets].

Table 8 The impact of health on firm valuations based on retail ownership or employee productivity

	Retail ownership					*Employee productivity*				
	5		*6*		*High–low*	*5*		*6*		*High–low*
	Low	*High*	*Low*	*High*	*T-test*	*Low*	*High*	*Low*	*High*	*T-test*
Panel A: stock returns										
Poor mental health	–327***	–987***			–660***	–541***	–561***			–20
	(70.411)	(177.271)			[–3.46]	(107.116)	(98.303)			[–0.14]
Poor physical health			–637***	–764***	–127			–650***	–702***	–52
			(109.548)	(109.547)	[–0.82]			(111.137)	(92.062)	[–0.36]
Observations	11,246	9,578	11,249	9,583		10,361	10,305	10,365	10,309	
	Retail ownership					*Employee productivity*				
	5		*6*		*High–low*	*5*		*6*		*High–low*
	Low	*High*	*Low*	*High*	*T-test*	*Low*	*High*	*Low*	*High*	*T-test*
Panel B: market to book ratio										
Poor mental health	1.13	–19.33***			–20.56***	–10.30**	–5.59			–15.89***
	(3.231)	(6.362)			[–2.88]	(4.581)	(3.793)			[–2.67]
Poor physical health			0.84	–14.66***	–15.5**			–10.37**	–7.72*	2.65
			(4.990)	(4.547)	[–2.30]			(4.904)	(4.213)	[0.41]
Observations	11,263	9,707	11,266	9,712		10,456	10,345	10,460	10,349	

Notes: This table reports the second stage of 2SLS regressions on multiple poor health variables and other known determinants of stock returns (panel A) and market to book ratio (panel B) for the sample period of 2002 to 2017 using Medicaid Expansion and Air Quality Index as instruments. All variables are lagged one year and defined in Table 1. All models include MMSA and two-digit SIC fixed effects. Robust standard errors clustered by firm are reported below the coefficient estimates that display significance at the 10% (*), 5% (**), and 1% (***) levels. The last column reports coefficient difference and an associated t-test [shown in brackets].

Table 5 presents the results for the impact of poor health on stock returns using a 2SLS model with the two instrumental variables. Panel A displays the first stage regressions and shows that our two instrumental variables are highly correlated to health. To save space, we only show the instrumental variables of interest, even though we include all demographic, firm characteristics, and fixed effects in the model. Panel B shows the second stage regression results. We find that all four of our poor health variables have a negative and significant impact on stock returns at the 1% level, consistent with Table 4. As such, we conclude that poor local health has a negative causal impact on local stock returns.

Corporate stock returns are not the only way to examine stock valuation. As such, we explore the impact of poor health on the firm's relative value, as measured using the firm's book-to-market ratio following previous literature (e.g., Lin and Liu, 2015; Kumar and Sujit, 2022). Additionally, as one may argue that there is an endogeneity issue as firm returns could impact community health, it is doubtful that a firm's market to book ratio would impact community health.

A low ratio suggests that the company has a lower relative value, all else equal. We argue that being headquartered in a community plagued by poor health is an intangible liability for the firm. Edmans (2011) explains that firms that treat their employees better have higher valuation measures, which is consistent with the idea that investors partially value this beneficial intangible asset. Other intangible assets are also studied in the drift literature. For example, the drift literature demonstrates that firm assets such as research and development (Chan et al., 2001), corporate governance (Gompers et al., 2003), being in the sin industry (Hong and Kacperczyk, 2009), and dividend initiations (Michaely et al., 1995) cause long run drifts in higher abnormal returns. Therefore, if investors believe there will be lower excess returns in the long run due to being headquartered in a poor health area, the firm will have a lower valuation measure.

Panel C of Table 5 reports our results where we change the dependent variable to the market to book ratio rather than stock returns. We find that all of our poor health variables have a negative impact on the market to book ratio, with overweight, poor health, and fair/poor health being significant. As such, we confirm that poor local health is a detriment to firm value.

3.3 The channel

The investor clientele effect stipulates that the negative stock returns and lower stock valuations on companies located in areas in poor health may be due to unhealthy local retail investors affecting local company asset pricing. If these retail investors are in poor health like their neighbours, they may be risk averse due to personal health-related financial needs, which impacts their participation in the stock market and the stocks they buy. Also, their cognitive function may be impaired, making it so they cannot accurately forecast future stock returns, creating miss-valued stocks. Furthermore, locals may have more information about the firm (Farooq and Tauouss, 2012). However, the aim of this paper is not to determine why firms located in poor health communities with high retail ownership have lower valuations but to demonstrate if retail investors are the mechanism causing our previous results. Therefore, we split our sample into firms that have high or low retail ownership and rerun our regressions. If the investor clientele effect is driving the poor firm performance, poor health will be stronger in the high retail ownership sample.

Table 6 presents our results of the split sample using the 2SLS regressions for stock returns in panel A. In the final column, we examine the difference in the coefficients based on the firm having high or low retail ownership and determine if there is a significant difference between the two samples using a standard t-test. We find that poor health has a negative and significant impact on stock returns regardless of whether the firm has high or low retail ownership. However, we find a significant difference between our split samples. For obesity, we find a coefficient of –183 for the low retail ownership sample and a coefficient of –318 for the high retail ownership sample. This difference of 135 is significant at the 1% level with a t-statistics of 3.50. Moreover, we find a significant difference in high versus low retail ownership for fair and poor health.

We find consistent results when examining the market to book ratio in panel B. We find that coefficients for obesity, overweight, and fair/poor health are negative and significant at the 1% level for firms with high retail ownership while insignificant in the low retail ownership sample. When examining obesity, we find a coefficient difference between the high and low retail ownership sample of –5.025, which is significant at the 5% level. These results are confirmed when exploring the overweight variable. Finally, we find that the fair/poor health coefficient for the market-to-book ratio analysis in panel B is 13.41 lower in the high retail ownership than the low retail ownership sample, which is significant at the 1% level. Overall, these results support the investor clientele effect.

The competing employee effect hypothesis comes from unhealthy employees being less productive than healthy employees due in part to absenteeism and presenteeism. We aggregate employee productivity by adopting Giroud and Mueller's (2011) employee productivity estimate of a firm. The variable is defined as the industry adjusted sales divided by the number of employees deflated by CPI. If the employee effect is causing lower firm performance, our poor health variables would be more prevalent in firms that have less productive employees. Mitchell and Bates (2011) estimate the productivity costs of various types of employee health risks, including weight related and mental health conditions. They conclude that lifestyle risk factors and health conditions are associated with workplace productivity loss. To test the competing hypothesis of the employee effect, we analyse our health variables in firm samples of low and high employee productivity.

Table 7 presents the results on the impact of poor health in firms with low and high employee productivity. Again, panel A shows that poor health has a negative and significant impact on stock returns regardless of the split sample. The t-test for the difference between the samples is shown in the last column. There is a statistically significant difference in only one health variable, poor health. However, the difference is in the wrong direction. That is, to support the employee effect hypothesis, the low productivity sample should have a more negative coefficient than the high productivity sample. As such, we do not find evidence to support the hypothesis that the health status of the employees is driving lower excess returns. Panel B shows that all poor health variables are inversely related to market to book ratio, with most of them being significant in each high and low productivity sample. Only the fair/poor health analysis shows a statistical difference between low and high productivity samples. As such, we fail to find evidence that the lower valuation of these firms located in poor health areas is caused by employee productivity.

4 Robustness tests

4.1 Poor mental and physical health days

In our analysis, we have used common estimates of poor health used in previous literature, namely weight-based measures and self-reported health status. For a robustness check, we re-examine our results using the number of days individuals are in poor mental health or poor physical health per month. In Table 8, we repeat the analysis of Tables 6 and 7 using poor mental health days and poor physical health days. Furthermore, the results for the first stage regression are consistent with Table 5 but omitted to save space. Panel A for excess returns shows that these new poor health measures are negative and significant in high and low retail ownership and employee productivity samples. Consistent with our previous results, we find that these poor health measures are more negative in the high retail ownership sample, with poor mental health being significant at the 1% level. Furthermore, there is no difference in the high and low employee productivity samples. This supports the previous evidence that the investor clientele effect is more important than the employee effect when examining the cause of lower stock returns. In Panel B for valuation, we find that both poor mental and physical health have a more negative and significant impact on the high retail ownership samples. Note that there is some evidence for the employee effect on poor mental health as it affects valuation more in low productivity firms than high productivity firms. Overall, these results support that poor health causes lower stock returns and valuation, especially in high retail ownership firms.

5 Conclusions

We examine how firms headquartered in MMSAs are affected by the local population's poor health. We find that local communities in poor health, proxied by obesity rates, poor self-reported health, or the number of days the average person is in poor physical or mental health, causes local companies to have lower stock returns and relative valuation in the following year. In fact, we find that a 1% increase in overweight rates would equate to more than $100 billion in stock market losses. We also explore the mechanism by which poor health might influence firm performance. Specifically, we examine the investor clientele effect and the employee effect. Evidence to support the investor effect is stronger, suggesting that local retail investors are causing firm's lower performance. Our findings have important implications for where firms locate their headquarters. For example, it is important for firms to weigh factors such as local obesity and health and the tradeoffs against labour costs, productivity, quality of infrastructure, and other local norms. Thus, future research may look to examine the impact of local health on firms that move headquarters. Additionally, future papers may explore the relation between city characteristics like size, density, education, ethnicity, religion, etc. on the influence of health quality on ensuing firm performance.

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Notes

1 For a greater discussion on the biology of financial decisions see Nofsinger and Shank (2020).

2 Maukonen et al. (2018) find that individuals often overstate their height while underestimating the weight. As such, the overweight and obesity rates may actually be higher than what are provided. This bias would have us misidentifying obese individuals as non-obese. However, this misclassification would bias our results against finding significant effects.

3 We use excess return rather than the three-factor or five-factor model because we are using yearly data.

4 We include a dummy variable for firms missing values for book-to-market and R&D following the literature (e.g., Chen et al., 2017; Brisker and Wang, 2017) in order not to have to drop them from the sample. R&D is frequently missing in Compustat (roughly 50%), so it is important not to drop these firms from the sample. Additionally, some firms have missing or negative book-to-market ratios, so this allows us to incorporate them into the sample.

5 The ten MMSA's are Portland (OR), Reno (NV), Denver (CO), Philadelphia (PA), Kahului (HI), Colorado Springs (CO), Oakland (CA), Seattle (WA), Los Angeles (CA) and Billings (MT).

6 The eight MMSA's are Charleston (WV), Tuscaloosa (AL), Grand Island (NE), Topeka (KS), Wichita Falls (TX), Florence (SC), Memphis (TN), and Augusta (GA).