Local Obesity Prevalence and Corporate Policies

Anup Agrawal and Yuree Lim*

Current draft: September 2016

Comments welcome

* Agrawal: University of Alabama, Culverhouse College of Commerce, Tuscaloosa, AL 35487-0224, aagrawal@cba.ua.edu, (205) 348-8970; Lim: University of Wisconsin-La Crosse, College of Business Administration, La Crosse, WI 54601, ylim@uwlax.edu, (205) 765-6620. We thank Vineet Bhagwat, Susan Chen, David Cicero, Doug Cook, Cam Harvey, Danling Jiang, Chuck Knoeber, Shawn Mobbs, Alexandra Niessen-Ruenzi, Raghu Rau, and seminar participants at the University of Alabama for helpful comments. We also thank Vineet Bhagwat, Andrea Eisfeldt, Danling Jiang, and Scott Yonker for sharing their data. Agrawal acknowledges financial support from the William A. Powell, Jr. Chair in Finance and Banking. Lim acknowledges financial support from a summer research grant from the Culverhouse College of Commerce.

Local Obesity Prevalence and Corporate Policies

Abstract

Consistent with prior findings that obese individuals tend to be more risk-averse, we find that firms headquartered in areas with greater obesity prevalence adopt less risky corporate policies. Using a dataset of obesity prevalence in US counties, we find that the obesity rate in a county is related negatively to investment, growth and profitability, and positively to stock volatility, of firms located there. We use time-varying state taxes on ‘fatty foods’ and the density of fast food restaurants in a county as instruments for local obesity to examine a causal link between local obesity and corporate policies. We provide evidence that both local managers and shareholders appear to be channels through which obesity prevalence gets transmitted to the lower-risk policies of local firms. The mechanisms underlying this transmission appear to be education, health, race, and marital status. Finally, adding to the nature vs. nurture debate, both genetic and environmental factors appear to contribute to our findings.

JEL classification: G02, G30, I12

Keywords: Obesity, Corporate policies, Risk-taking

Local Obesity Prevalence and Corporate Policies

1. Introduction

A large literature in economics and psychology has related physical characteristics of individuals to their economic behavior and outcomes. The literature has focused on three such characteristics: height, weight, and beauty. For example, Persico, Postlewaite, and Silverman (2004) find that taller teenagers are more likely to be social and earn higher wages as adults. Harper (2000) finds that obese individuals tend to earn lower wages. Hamermesh and Biddle (1994) find that more attractive workers earn higher wages. Our paper focuses on one particular physical attribute, namely obesity, which combines height and weight, and contributes to perceptions of beauty.

Prior studies discussed in section 2 find that the preferences of obese individuals differ from those of the general population in two key respects: they tend to be more risk-averse and myopic. Obesity is related to several observable individual characteristics, unobservable traits, and social experiences that are known to influence risk-taking behaviors. Obese individuals are also known to be myopic, i.e., they have a preference for immediate utility over delayed utility. Consistent with greater risk-aversion in personal financial choices, Addoum, Korniotis, and Kumar (2016) find that obese individuals are less likely to participate in the stock market and invest less in risky assets. Van Praag and Booij (2003) find experimental evidence that obesity is strongly related to higher risk-aversion. If obese individuals take less risk and are myopic, it is reasonable to ask whether obesity of key individuals connected to a firm (such as managers and shareholders) affect corporate policies and actions. There is no prior empirical evidence on this question.

An empirical examination of this issue is challenging because systematic data on weight and height of managers and shareholders are not publicly available for a broad sample of companies. We tackle this difficulty by using the prevalence of obesity in the local area around corporate headquarters (henceforth, 'local obesity') as a proxy for the prevalence of obesity-induced risk-aversion among a firm's managers and shareholders, who often tend to be drawn from the local area. Even if these individuals in a firm are not obese themselves, they are likely influenced by the local culture of risk-aversion.

We provide, to our knowledge, the first empirical study that examines how the prevalence of obesity in an area affects the policies of firms located there. Our study contributes to a growing recent literature suggesting that traits of the local population can be important determinants of firm behavior (see, e.g., Hilary and Hui (2009), Becker, Ivković and Weisbenner (2011), and Cohen, Gurun and Malloy (2016)). Local culture can affect corporate policies because local individuals are more likely to be shareholders and managers of firms located in an area. This approach enables us to examine the policies and actions of all firms headquartered in the United States. Specifically, we examine whether firms located in areas with greater prevalence of obesity choose lower-risk policies and actions. This question is important because geography is crucial to understanding the drivers of economic growth (see, e.g., Clark, Gertler, Feldman and Williams, 2003). This topic is of particular interest to policy makers because characteristics of the local environment can attract businesses, thereby creating jobs and fostering capital formation and economic growth.

Motivated by the existing literature, we posit that higher local obesity leads to less risky corporate actions such as less investment and lower growth. Limbach and Sonnenburg (2015) find that CEOs who finish a marathon lead more profitable firms and make better merger and acquisition decisions. They attribute these findings to the positive impact of physical fitness on CEOs' cognitive abilities, performance, and stress control functions. Extensive prior evidence of behavioral consistency between managers' actions on personal and corporate accounts (see, e.g., Cronqvist, Makhija and Yonker (2012), and Hutton, Jiang and Kumar (2014)) suggests that obesity-induced risk-aversion of managers can seep into firms' policies, actions and outcomes.

To shed some light on this issue, we examine how the prevalence of obesity in a U.S. county is related to various corporate actions and outcomes such as investment, growth, stock volatility and profitability of companies headquartered in the county. We employ a sample of 29,752 firm-year observations during the period from 2004 to 2012. Our regressions control for observable firm characteristics and demographic characteristics of the county. Our baseline tests show that local obesity is related negatively to firm investment in tangible assets and innovation, growth rates, and profitability; and positively to stock volatility (more on this later). Thus, we find that firms located in more obese areas take less risk and experience lower growth rates and profitability.

A causal interpretation of our results is that managers and shareholders in more obese areas tend to be more risk-averse and their preference gets reflected in lower risk-taking by local firms. This interpretation is consistent with extensive prior findings that obese individuals tend to be more risk-averse and that individuals in a community tend to acquire the community's attitudes and preferences. There are two main identification challenges to this interpretation. First, local obesity and lower-risk corporate policies can be simultaneously determined by omitted variables. Second, conservative firms may choose to locate in areas that have a culture of risk-aversion, such as areas with greater prevalence of obesity. While identification concerns are generally difficult to completely rule out, we try to mitigate them using several approaches. First, to reduce the concern about spurious correlation caused by omitted variables, we control for a number of county characteristics, in addition to the firm characteristics that have been found to be important determinants of the corporate policies that we examine. Second, we employ an instrumental variables approach in an attempt to introduce exogenous variation in local obesity. This approach helps overcome the difficulty with potentially omitted variables as well as establishes the direction of causality. Third, we test and find support for several secondary implications of our story, which makes it more difficult for an alternative story to explain all of our results. Specifically, we provide evidence on two potential channels and several underlying mechanisms though which local obesity can affect risk-taking by firms located in the area. Finally, we rule out several alternative explanations in robustness checks, thereby favoring a causal interpretation of our results.

We use two instruments for local obesity: (1) the staggered adoption of taxes on 'fatty foods' by several states to reduce obesity, and (2) the density of fast food restaurants in a county. Both variables are expected to directly affect local obesity and empirically they do so significantly. However, neither variable should directly affect corporate policies. This is because state tax policy on unhealthy foods is clearly exogenous to the corporate policies about investment, growth and risk-taking of firms located there. Similarly, there is no reason why the density of fast food restaurants in a county should directly affect these corporate decisions by local firms. Using these instruments, we find that firms with higher local obesity rates tend to invest less, have lower R&D expenditures, and grow more slowly.

Next, we delve into the channels through which local obesity affects corporate policies. We focus on two potential channels: local managers and local shareholders. Our focus on local managers is motivated by findings that firms often hire managers, even CEOs, locally (see, e.g., Yonker (2016)). We provide two pieces of evidence to support a managerial channel. First, consistent with obesity-induced risk-aversion, managers of firms in more obese areas choose lower risk-incentives, as measured by the vega of their compensation. Our baseline findings that local obesity is negatively (positively) related to the rates of investment, R&D and growth (stock volatility) continue to hold after we control for CEOs' pay-performance incentives measured by delta and their risk-taking incentives measured by vega. Second, within our subsample of exogenous CEO turnovers, if a firm goes from being led by a CEO who grew up in a non-obese place to a CEO who grew up in an obese place, the firm reduces its industry-adjusted investment rate. There is essentially no change in investment rate for firms that experience the opposite type of CEO change. The difference between the two changes is statistically significant.

Local obesity can also affect corporate policies via obesity-induced risk aversion of local shareholders because investors are more likely to hold the stock of local firms (see, e.g., Coval and Moskowitz (1999)). We examine this channel by investigating the behavior of firms for which local investors are likely to be more important. We find that the effects of local obesity on investment, asset growth, and profitability are more pronounced in smaller firms, for which local investors are likely more important.

Digging deeper, we next try to uncover the mechanisms that link local obesity to the policies of companies located there. Motivated by the prior literature discussed in section 2, we consider education, race, health, income, and marital status as potential mechanisms that could drive the relations between local physical attributes and corporate policies. Our finding of a negative effect of local obesity on firm risk-taking is more pronounced in counties with larger shares of less-educated, minority, diabetic and single populations, which can foster a local risk-averse culture in these areas. Thus, education, race, health and marital status appear to be mechanisms driving our findings.

Finally, obesity can be attributable to either genetic or environmental factors. Addoum, Korniotis, and Kumar's (2016) findings suggest that the relation between physical attributes and risk-aversion reflects factors that are fixed at birth, such as genetics or the prenatal environment. Similarly, Cronqvist, Previtero, Siegel, and White (2016) show that higher prenatal testosterone exposure leads to greater financial risk-taking during adulthood. In addition to genetic factors, Christakis and Fowler (2007) find that environmental factors such as social networks facilitate the spread of obesity. Specifically, people who live in obese communities are more likely to become obese themselves because they tend to acquire the lifestyles of their friends and neighbors. Moreover, even if they do not become obese, they are likely to acquire the local culture, including an obesity-induced culture of risk-aversion. We analyze which of the two sources of obesity explains its effects on corporate decisions. Using the birth-weight of babies born in the county to predict the genetic component of local obesity prevalence and treating the residual from this regression as the environmental component, we find that environmental factors can explain the negative effects of local obesity on firm investment, asset growth, and profitability. Genetic factors appear to drive the negative (positive) relation between local obesity and R&D expenditure (profitability). Lastly, both factors drive the positive relation between local obesity and stock volatility.

Our study contributes to several strands of research. First, prior literature in economics and finance examines the implications of individuals' physical appearance on their economic decisions and success in the labor market. For example, taller stature is associated with higher wages (see, e.g., Mankiw and Weinzierl (2010), and Persico, Postlewaite, and Silverman (2004)), while obesity is generally associated with lower earnings (see, e.g., Hamermesh and Biddle (1994), Harper (2000), and Johansson, Böckerman, Kiiskinen, and Heliövaara (2009)). Case and Paxson (2008) suggest that height is related to cognitive abilities. Our paper complements Addoum, Korniotis, and Kumar (2016), who find that individuals who are taller and of normal weight are more likely to take personal financial risks by holding stocks in their portfolios. While prior studies find a relation between obesity and *individual* decisions, to our knowledge, no prior study has examined the relation between obesity and *corporate* decisions. We try to fill this gap in the literature.

A second strand of research relates managers' physical attributes (such as height, fitness and beauty) to corporate policies. For example, Graham, Harvey, and Puri (2013) examine the effect of CEO height on corporate policies. Adams, Keloharju, and Knűpfer (2015) find that larger companies are more likely to have taller CEOs. Graham, Harvey, and Puri (2016) find that competent-looking individuals are more likely to be hired as CEOs and paid more. Similarly, Cook and Mobbs (2014) find that executives with more attractive faces are more likely to be appointed CEO, especially when the qualified labor pool is larger. Our paper adds to this literature by showing that physical attributes such as obesity of the local population are also related to the policy choices of firms located in the area. As discussed earlier, managers and shareholders of a firm are often from the local area, and even if they are not obese themselves, they are likely influenced by the local culture of risk-aversion.

Finally, our study contributes to another strand of the literature that examines the impact of local demographics on corporate policies. For example, Hilary and Hui (2009), Becker, Ivković and Weisbenner (2011), and Adhikari and Agrawal (2016) investigate the effect of religiosity, age and religious composition of the local population on corporate policies. Cohen, Gurun and Malloy (2016) relate the ethnic composition of the local population to foreign trade links of firms located there. Our study extends this literature by showing that physical characteristics of the local population also affect corporate policies.

The remainder of the paper is organized as follows. Section 2 reviews the pertinent literature and develops testable hypotheses. In Section 3, we describe the data and variables used in the study. Section 4 reports our baseline empirical findings. Section 5 describes our instrumental variables approach. Section 6 discusses the channels through which local traits get transmitted to corporate policies. Section 7 discusses the underlying mechanisms that can explain our results. Section 8 reports several robustness checks, and section 9 concludes.

2. Related Literature and Hypotheses

Our main conjecture is that firms headquartered in counties with greater prevalence of obesity are likely to choose lower risk policies. The reason is that obesity is related to observable individual characteristics such as health, marital status, education, income and race; unobservable traits such as cognitive abilities, sociability, optimism and self-esteem; and social experiences such as discrimination and being trusted that are known to influence risk-taking behaviors.

A large body of research in health sciences finds that obesity is related to adverse health events such as stroke, cancers and mental disorders (see, e.g., Sturm (2002), Mokdad, et al. (2003), Sobal (2004), and Dixon (2010)). Combined with recent studies in finance that find that individuals with poor health or mental disorders choose less risky personal investment portfolios (see, e.g., Rosen and Wu (2004), and Bogan and Fertig (2013)), these studies imply that obese individuals are likely to be more risk-averse.

Obesity is also related to lower marriage rates for women (Harper, 2000), which in turn leads them to take fewer risks (Love (2010)). Obese individuals are more likely to be lower- income and single (see, e.g., Chou, Grossman, and Saffer, 2004), which reduces their ability to bear risk, and consequently makes them more risk-averse. Obese individuals tend to be less-educated (see, e.g., Wardle, Waller, and Jarvis (2002)) and are more likely to belong to minority communities in the U.S. (see Wang and Beydoun (2007) for a review). Hong, Kubik, and Stein (2004) find that these groups have lower stock market participation rates, reflecting their greater risk-aversion.

Moreover, recent literature in psychology, economics and finance suggests that obese individuals tend to have lower self-esteem and suffer from depression (see, e.g., Mocan and Tekin (2009), and Dong, Sanchez, and Price (2004)), which suggests that they are likely to be less optimistic. Combined with Puri and Robinson's (2007) finding that pessimistic individuals tend to be more risk-averse, these studies imply that obese individuals are likely to take less risk.

Obese individuals are more likely to have cognitive impairments (see, e.g., Farr et al. (2008), and Li et al. (2008)), which are associated with greater risk aversion and impatience (see, e.g., Dohmen, Falk, Huffman, and Sunde (2010)) and lead to lower stock market participation (see, e.g., Christelis, Jappelli, and Padula (2010), and Grinblatt, Keloharju, and Linnainmaa (2011), (2012)). Thus, obese individuals are likely to take less risk.

Social experience can be another reason that obesity affects human decisions. Obese borrowers face discrimination in peer-to-peer lending markets (see, e.g., Pope and Sydnor (2011), and Duarte, Siegel, and Young (2012)). Guthrie and Sokolowsky (2014) find that obese borrowers represent greater credit risk. Obesity is also related to negative treatment in hiring and promotion decisions (see, e.g., Kirkland (2008), Bhattacharya and Bundorf (2009), and Lundborg, Nystedt, and Rooth (2010)). Individuals who are not trusted take less risk (see, e.g., Guiso, Sapienza, and Zingales (2008), and Jiang and Lim (2014)), leading them to be more risk-averse. Obese individuals also prefer to stay home, causing them to be less sociable. Hong, Kubik, and Stein (2004) find that less social individuals are less likely to participate in the stock market and invest less in risky assets. These negative social experiences can lead them to take fewer risks in investment and be reluctant to borrow.

In addition to risk aversion, time preference is another reason why obese individuals invest less and take fewer risks. Time preference is the preference for immediate utility over delayed utility (see, e.g., Frederick et al. (2002)). Individuals with a high rate of time preference place more emphasis on the present and discount the future heavily (see Zhang and Rashad (2008)). Sutter et al. (2013) find that more impatient children, who develop higher BMIs, are less likely to save money. Using a large sample of individual responses to preferences between sure vs. uncertain payoffs, Van Praag and Booij (2003) find that obesity is strongly related to higher risk-aversion. They argue that overeating can be explained by a precautionary motive, i.e., fear of going hungry, representing risk-aversion. The positive relation between obesity and time preference is quite intuitive. For instance, most weight control methods require one to limit current consumption to reap future health benefits. Obese individuals generally have a strong preference for immediate consumption that makes them gain weight and can lead them to invest less for future consumption.

Therefore, obese individuals tend to be risk-averse. We expect local communities with greater incidence of obesity to have a more risk-averse culture, which would get reflected in lower risk-taking by firms located there via local managers and shareholders. This is our main hypothesis. Specifically, we examine the following corporate actions and outcomes:

H1: Investment: Investment is associated with uncertainty about its payoff, so firms located in more obese communities would make lower rates of investment, both in tangible assets and R&D.

H2: Growth: Due to lower investment, we expect these firms to have lower growth rates.

H3: Profitability: If firms in more obese areas forgo profitable investment opportunities due to higher risk-aversion, it could lead to lower profitability. On the other hand, these firms may be more profitable if they only accept projects with higher positive NPV.

H4: Volatility: If firms located in more obese areas choose policies and actions aimed at generating stable outcomes, we would expect them to have lower stock return volatility. But outside investors may consider these firms riskier due to greater health problems and behavioral instabilities in their local communities, implying higher return volatility. Since stock volatility is determined by actions of both a firm and its outside investors, volatility can be lower or higher for such firms.

3. Data and Variables

We obtain data on firm characteristics from several sources. Specifically, firm financials and location data come from Compustat annual files. Stock return volatility is computed using daily stock returns obtained from the Center for Research in Security Prices (CRSP). We exclude firms from the financial (SIC codes between 6000 and 6999) and utility sectors (SIC codes between 4900 and 4999) since these industries are subject to greater government regulation. We delete firms headquartered in Puerto Rico or outside the US.

We obtain data on institutional ownership from the Thomson Reuters database, analyst data from IBES, and CEO-related data from Risk Metrics. We compute CEO delta and vega as in Coles, Daniel, and Naveen (2013). In addition, we obtain data on CEO's place of origin from Bernile, Bhagwat, and Rau (2016) and Yonker (2016) and exogenous CEO turnovers from Eisfeldt and Kuhnen (2013).

County-level demographic data come from the U.S. Census Bureau.[1] We linearly interpolate values for the intermediate years. Our sample contains 29,752 firm-year observations from 2004 to 2012.

3.1 Obesity Data

We obtain annual data on obesity prevalence in each US county during 2004 to 2012 from the Centers for Disease Control and Prevention (CDC) website, based on residents' self-reported height and weight information collected by the Behavioral Risk Factor Surveillance System (BRFSS) and data from the U.S. Census Bureau's Population Estimates Program.[2] State health departments operate BRFSS in collaboration with the CDC. Starting in 1984, BRFSS collects data monthly to measure behavioral risk factors for the adult population in each county, using telephone interviews of individuals selected randomly from households. Estimates are restricted to adults 20 years of age or older to be consistent with the population estimates program. Individuals are considered obese if their body mass index (BMI = weight in kg / (height in meters)^2) is 30 or greater.

[1] http://www.census.gov/

[2] CDC data begins in 2004 and ended in 2012 when we collected it.

3.2 Variables

3.2.1. Dependent Variables: Corporate Policies and Outcomes

We use six variables to measure corporate policies and outcomes. We measure firm investment by *INV* and *RD*; firm growth by *SaleG* and *AssetG*; stock volatility by *VOL*; and profitability by *ROA*. Dependent variables are defined as follows: *INV* = Capital expenditure / Lagged total assets; *RD* = R&D expenditure / Lagged total assets; *SaleG* (*AssetG*) is the sales (asset) growth rate over the prior year; *VOL* is annualized daily stock return volatility; and *ROA* is the return on assets. All the variables are defined in the Appendix.

3.2.2. Treatment Variable: Obesity

We define the variable *OBE* as the age-adjusted obesity prevalence obtained from BRFSS, which equals the percentage of adults who are obese in each county in each year, adjusted to reduce the effect of age which can confound comparisons between counties with different age profiles. Since reported obesity rates are based on self-reported height and weight of representative individuals in a county, they are subject to measurement error which CDC estimates to be between $\pm$ 6%. Since obesity-prevalence rates for most counties do not vary much during the sample period, our analysis focuses on cross-sectional and basic panel estimation.

3.2.3. Control Variables

Following Hutton, Jiang, and Kumar (2014), we control for firm characteristics such as the market-to-book ratio (*MB*), the log of total assets (*SIZE*), leverage (*TDA*), and an indicator variable for negative ROA (*LOSS*). To reduce the effect of outliers, we winsorize all firm variables at the 1st and 99th percentiles. We estimate regressions with both year and industry (two-digit SIC) fixed effects and report t-statistics obtained using standard errors clustered at the firm, county, and year level. In addition, we control for county-level demographics such as per capita income (*Income*), total population (*Totpop*), median age (*Age*), the lack of urbanization (*Rural*), and the percentages of males (*Male*), whites (*White*), and married people (*Married*).

3.3 Summary Statistics

We present summary statistics of all the variables used in our baseline regressions in Table 1. Panel A shows mean and median values of obesity prevalence by state for our sample period. In addition, Figure 1 shows a graphic of the 2010 data by county on the US map. Obesity is generally more prevalent in the Eastern half of the country than in the Western half. Specifically, Alabama, Indiana, Kentucky, Louisiana, Mississippi, Missouri, Tennessee, and West Virginia have mean obesity rates of 28% or higher, while California, Colorado, Connecticut, Maine, New Mexico, and New York have mean obesity rates below 20%. Panel B shows that the average obesity rate in a county is 23% during our sample period.

Panel A of Table 2 presents a correlation matrix for obesity-prevalence and various demographic county-characteristics. Obesity-prevalence is negatively (positively) correlated with income and population (lack of urbanization), while its correlations with other demographic variables are relatively low. In Panel B of Table 2, we partition the sample into three obesity-prevalence terciles and report for each group the mean and median values of our six corporate policy variables. Across the three groups with increasing obesity rates, the mean values of R&D expenditure, sales growth and asset growth decrease monotonically, and profitability (i.e., ROA) increases. The mean differences between the high and the low obesity groups are statistically significant. These initial sorting results suggest that firms located in obese communities invest less in R&D and experience lower levels of growth, but higher profitability. But these results do not control for other things, a task we turn to next.

4. Baseline Results

We estimate the following panel regression to examine the effect of local obesity on corporate policies:

$$Policy_{i,t} = \alpha_0 + \alpha_1 OBE_{i(j),t} + \alpha_2 FirmControls_{i,t} + \alpha_3 CountyControls_{i(j),t} + \alpha_t Year_t + \alpha_h Industry_{h,t} + \varepsilon_{i,t} \quad (1)$$

where *Policy* is one of the corporate policies (*INV, RD, SaleG, AssetG, VOL*, and *ROA)*, *FirmControls* is a vector of the firm characteristics (*SIZE, LOSS, TDA,* and *MB),* and *CountyControls* is a vector of county-level demographic characteristics (*Income, TotPop, Age, Male, White, Married,* and *Rural*). We include these demographic variables to capture the net effect of obesity after controlling for other demographic characteristics. We also include year and industry fixed effects to control for time-varying macroeconomic effects and industry effects. The subscripts *i*, *j*, *h*, and *t* denote firm, county, industry and year, respectively. We report t-statistics based on standard errors clustered at the firm, county, and year levels; these are shown in parentheses below the coefficient estimates in Table 3. We expect obesity to be negatively related to investment in tangible and intangible assets and to growth in sales and assets, while its relations with return volatility and profitability are empirical issues.

Consistent with the investment hypothesis, the estimated coefficients of *OBE* in regressions of *INV* and *RD* are significantly negative in Table 3. The estimated coefficients of *OBE* in regressions of *SaleG* and *AssetG* are also negative and highly significant, consistent with the growth hypothesis. Since our hypothesis has clear predictions about OBE's effect on these four dependent variables, we use the method of testing multiple hypotheses, which adjusts for a data snooping bias. Following Harvey, Liu and Zhu (2016), we use Holm's adjustment to compute the cut-off value of the t-statistic. The last row in Table 3 shows these cut-off t-values for the coefficient of OBE in columns (1) to (4) at the 5% level in 2-tailed tests. The t-values of OBE exceed these cut-off values in all four cases, indicating that the coefficient of OBE is statistically significant even under this more rigorous criterion. We also find that local obesity is positively related to stock return volatility (*VOL*) and negatively related to firm profitability (*ROA*). Since we do not have clear predictions about these latter two relations, the issue of testing multiple hypotheses does not apply here.

We also evaluate the economic significance of our results. The slope estimate on *OBE* in *INV* regression is -0.042, which implies that a one standard deviation change in OBE (4%) is associated with a reduction in investment of 0.17% (= 4% × 0.042), or about 2.8% (= 0.17% / 6%) of the mean INV of 6%. Similar computations show reductions of 0.49% in *RD* (i.e., 8.2% of the sample mean), 1.25% in *SaleG* (8.3% of the sample mean), 0.86% in *AssetG* (8.6% of the sample mean), 0.38% in *ROA* (6.3% of the sample mean), and an increase of 0.03% in *VOL* (1% of the sample mean).[3]

Coefficient estimates of the control variables measuring firm characteristics are statistically significant and have signs generally consistent with the prior literature (see, e.g., Hilary and Hui (2009), and Hutton, Jiang, and Kumar (2014)). For example, larger firms invest less, grow more slowly and are more profitable and less volatile, while more leveraged firms invest more in tangible assets and less in R&D, grow rapidly, and are riskier and less profitable. The results for demographic variables are also generally consistent with our expectations. For instance, firms located in young, male, white and rural counties invest more in tangible assets. Urban counties invest more in intangible assets. On average, our pooled regressions explain about 43% of the variation in corporate policies.

The results from our baseline regressions are consistent with our main conjecture that firms headquartered in more obese counties choose less risky policies. Specifically, these firms tend to invest less and grow slowly. Adoption of lower risk policies does not seem to benefit shareholders, as reflected in these firms' higher stock volatility and lower profitability.

[3] We also perform these tests using male and female obesity prevalence separately and find that our results are driven by the prevalence of obesity among men. This finding is consistent with greater representation of men in top management positions (see, e.g., Adhikari, Agrawal and Malm (2016)) and among shareholders (see, e.g., Barber and Odean (2001)). Section 6 presents evidence that both managers and shareholders are channels through which obesity-induced risk-aversion of a local population gets transmitted to the policies of firms headquartered there.

5. Identification: Instrumental Variables Approach

So far, we find that local obesity is related to lower risk corporate policies. Does this imply that local obesity cause firms to adopt less risky policies and actions? There are two difficulties in making this causal interpretation. First, the relation could be caused by omitted variables. Second, it may be due to reverse causality, driven by conservative firms and obese people, who tend to be risk-averse, moving to conservative places. In other words, there may be self-selection or matching between obese local populations and conservative firms. To identify a causal effect of local obesity on conservative corporate policies, we use an instrumental variables (IV) approach.

Our first instrument for local obesity prevalence is the density of fast food restaurants in a county, which equals the number of fast food restaurants in the county divided by county population (*Den_FFR*). We obtain county-level data on fast food restaurants from the Food Atlas of the U.S. Department of Agriculture for the years 2007 and 2011. We linearly interpolate values for the intermediate years. Our second instrument is state taxes on 'fatty foods' such as soda, candy, gum, chips, pretzel, ice cream, popsicles, milkshakes, and baked goods (*Exo_Tax*).[4] These state taxes are aimed at reducing the consumption of these products to reduce obesity. We compute the instrument, *Exo_Tax*, as *DisfavoredTax* (i.e., the number of disfavored taxes a state adopts to reduce obesity) × *LevelDisfavoredTax* (the sum of disfavored tax rates).[5]

A good instrument needs to satisfy the relevance and exclusion conditions. Here, the relevance condition requires the instrument to be correlated with the prevalence of obesity in a county. Chou, Grossman, and Saffer (2004) find that higher density of fast food restaurants in an area is positively related to the local obesity prevalence. We would expect states that are more concerned about obesity,

[4] We obtain this data from Bridging the Gap, http://www.bridgingthegapresearch.org/, a research program on the effects of public policies and environmental factors on diet, physical activity and obesity among youth.

[5] We also tried using (1) *DisfavoredTax* and (2) the average disfavored tax rate as two separate instruments, instead of *Exo_Tax*. But (1) and (2) are highly correlated (Pearson $\rho = 0.5179$, p-value < 0.01) and the Hansen J-statistic for over-identification is significant in that specification.

such as states with higher obesity rates, to be more likely to adopt higher taxes on fatty foods, and the consumption of fatty foods to reduce in response to tax-induced price increases, leading to lower obesity rates. So observed obesity rates can be higher or lower in state-years with such taxes. Empirically, our first-stage regression estimates reported in Table 4 show that both *Exo_Tax* and *Den_FFR* positively and significantly predict local obesity prevalence, with t-statistics of 15.44 and 3.46, respectively. The F-statistic for the joint significance of the two variables has a p-value of 0.0000, which implies that the instruments are not weak. To save space, we only tabulate the key variables, although the regression specifications include our usual demographic and firm characteristics together with year and industry fixed effects.

The exclusion condition requires the instruments not to be correlated with the error term in the second stage regression. Here, this means that the density of fast food restaurants in an area and any unfavorable state tax on fatty foods should not directly affect corporate policies of local firms. There is no reason to expect the density of fast food restaurants in an area to directly affect risk-taking by local firms, except via its positive effect on local obesity. An exception is the small number of firms in the fast food industry. Similarly, the state tax on fatty foods is clearly exogenous to risk-taking by firms in the state, except for fast food firms. Our IV results are almost identical to those reported in Table 4 when we omit the 260 firm-year observations that belong to the fast food restaurant industry from our sample of 14,754 firm-years.

Table 4 reports the estimates from the second-stage regressions of corporate policies, where we use the predicted *OBE* from the first-stage regression as the main explanatory variable. The estimates show that, as expected, the predicted *OBE* has significantly negative coefficients on *INV, RD*, and *SaleG*. As in Table 3, we use Holm's adjustment to compute the cut-off value of the t-statistic for the coefficient of OBE for columns (1) to (4). The last row of Table 4 shows these cut-off t-values at the 5% level in 2-tailed tests. The t-values of OBE exceed these cut-off values in regressions of INV, RD and SaleG. As is common (see, e.g., Angrist and Pischke (2009)), the estimates of *OBE* are considerably higher in the IV framework than in the OLS regressions. We conclude from these findings that an obesity-induced culture of risk-aversion prompts firms to invest less in tangible assets and innovation projects and consequently experience lower sales growth.

6. Channels

We next delve into potential channels through which local obesity affects corporate policies of local firms. We focus on two obvious possibilities: local managers and local shareholders. The focus on local managers is motivated by Yonker's (2016) finding that firms often hire the CEO locally. The focus on local shareholders is motivated by the extensive literature that finds that investors are more likely to hold the stock of local firms (see, e.g., Coval and Moskowitz (1999)). Local managers or shareholders in obese areas are more likely to adopt the local risk-averse culture, even if they are not obese themselves.

To examine the CEO channel, we take two tacks. First, we ask whether CEOs of firms in more obese areas choose lower risk-incentives (vega) in their compensation. We obtain the delta and vega of compensation for the CEOs in our sample from Coles, Daniel, and Naveen (2013). Table 5 shows the results. We find that local obesity negatively predicts managerial risk-taking incentives, consistent with the idea that CEOs of firms in more obese areas are more risk-averse and so choose lower risk-incentives. We then add CEOs' performance and risk incentives (delta and vega) as explanatory variables to the baseline regressions of Table 3. We find that higher local obesity negatively predicts investment, R&D expenditure, sales growth and asset growth, and positively predicts stock volatility, consistent with our baseline regressions; but it positively predicts ROA, suggesting that obesity-induced risk-aversion increases firm profitability because these firms accept only more profitable projects, consistent with their greater risk-aversion.[6]

Second, we use Eisfeldt and Kuhnen's (2013) data on exogenous CEO turnovers to examine changes in firm behavior when a firm switches from a CEO who comes from a non-obese area to one

[6] As in Table 3, inferences about the significance of the coefficient of OBE in regressions of INV, RD, SaleG and AssetG (columns (2) to (5) in Table 5) are based on Holm's adjustment. The last row of Table 4 shows Holm's cut-off t-values at the 5% level in 2-tailed tests. The t-values of OBE exceed these cut-off values in all four of these regressions.

from an obese area. For each CEO turnover event, we identify the place of origin of the outgoing and incoming CEO, using two alternate definitions of the CEO's place of origin: their birthplace (using data from Bernile, Bhagwat and Rau (2016)) and the place where they received their social security card, usually around age 16 (using data from Yonker (2016)). Using either definition, we find that if the firm goes from being led by a CEO who grew up in a non-obese place to a CEO who grew up in an obese place, the firm reduces its industry-adjusted investment rate. There is essentially no change in investment rate for firms that experience the opposite type of CEO change. Despite small sample sizes (31 and 40 for the two types of switches based on the first definition of the CEO's place of origin, and 134 and 124 for the switches based on the second definition), the difference between the two changes is statistically significant. These results are not shown in a table for brevity.

To examine the shareholder channel for the effect of local obesity on lower-risk corporate policies, we examine whether the effects we find are more pronounced for firms that are more reliant on local shareholders for financing, such as smaller firms (see, e.g., Becker, Ivković and Weisbenner (2011)). We do not have a clear prediction regarding this channel. While investors in more obese areas likely prefer lower risk corporate policies, obese individuals are less likely to participate in the stock market (see Addoum, Korniotis, and Kumar (2016)). Thus, it is not clear which effect will dominate. We partition our sample into small and large firms using the median market capitalization in each year as the cut-off. We then re-estimate our baseline regressions in Table 3 separately for the two sub-samples. We expect the results we find in Table 3 to be more pronounced in the subsample of small firms. Table 6 reports the results. We find that our baseline results on the effects of local obesity on investment, asset growth, and profitability are more pronounced in smaller firms. We interpret this as partial evidence in support of the shareholder channel.

7. Mechanisms

We next investigate potential underlying mechanisms that drive the relations between local obesity and lower risk corporate policies that we find. The prior literature reviewed in section 2 suggests several possible mechanisms driving these relations. Following Campbell (2006), we analyze education, race, health, income, and marital status as potential mechanisms, which are related to individuals' risk preferences.

We partition our sample based on each potential mechanism. For example, the *Low Edu* group contains firms headquartered in areas where the proportion of residents with at least a bachelor's degree is lower than the sample median in a given year. We analyze the health mechanism using the prevalence of diabetes in a county. Table 7 reports the results. Panel A shows that the effects of local obesity on R&D expenditure and sales growth are more pronounced in less educated areas, suggesting that education is a mechanism for the effect of obesity on these policies. Panel B shows that the effects of local obesity on R&D expenditure, sales and assets growth, and volatility are more pronounced in areas with lower portions of white residents, pointing to race as a mechanism for these policies. In Panel C, the health mechanism can explain the effect of obesity on investment and profitability. In Panel D, income appears to be a mechanism for firm growth. In Panel E, marital status appears to be a mechanism for all corporate policies and outcomes we examine, except for profitability.

Finally, obesity can be attributable to both genetic and environmental factors. Addoum, Korniotis, and Kumar (2016) find that the association between physical attributes and risk-aversion appears to reflect factors that are fixed at birth, such as genetics or the prenatal environment. Cronqvist, Previtero, Siegel, and White (2016) find that higher prenatal testosterone exposure leads to greater financial risk-taking during adulthood. Christakis and Fowler (2007) find that environmental factors such as social networks also facilitate the spread of obesity. We try to shed some light on this issue by analyzing which of the two sources of local obesity prevalence can explain the relations we observe between local obesity and lower risk corporate policies and outcomes.

Prior studies find that high birth weight (> 4,000 grams) significantly and positively predicts obesity from childhood to early adulthood (see Yu, et al. (2011) for a review). We obtain birth weight data from CDC.[7] We define *HighBW* as the proportion of babies whose birth weights are greater than 4,000 grams in a given county and year. To isolate the genetic and environmental components of obesity, we employ two-stage regressions. For each county *j* in year *t*, we first estimate the regression (3) of local obesity, using *HighBW* and county and year fixed effects as explanatory variables:

$$OBE_{j,t} = \alpha_0 + \alpha_1 HighBW_{j,t} + \underline{\alpha_2} County_j + \underline{\alpha_3} Year_t + \epsilon_{i,t}. \qquad (2)$$

We then obtain the predicted value of local obesity and the residuals from this regression. By construction, the residual captures the portion of local adults' obesity (*OBE*) that is not explained by genetic factors and county and year fixed effects. The predicted value of local obesity measures its genetic portion, while the residual measures the environmental portion of OBE. We then replace *OBE* in our baseline regressions in Table 3 by its predicted value and the residuals.

The results, reported in Table 8, suggest that environmental factors can explain the negative effects of obesity on investment in tangible and intangible assets, asset growth, and profitability; genetic factors drive the negative (positive) relation between obesity and R&D expenditure (profitability); and both factors drive the positive relation between obesity and stock volatility.

8. Robustness Checks

We next conduct several checks on the robustness of our baseline results, summarized in Table 9. For brevity, we report only the coefficient estimates and t-statistics on our main explanatory variable of interest, *OBE*, for these tests.

---

[7] http://wonder.cdc.gov/natality.html.

We first address the concern that our results may be driven by a few states with very high or very low levels of obesity. When we exclude from our sample the five most or the five least obese states, our results remain quite similar to the baseline results, as shown in the first two rows in Table 9. Second, we address the possibility that our results could be driven by a few industries located in areas with very high or very low levels of obesity. We address this concern by identifying and deleting the observations from the five industries based on 2-digit SIC code that have the highest or the lowest mean of local obesity. The results, shown respectively in rows 3 and 4 of Table 9, are qualitatively similar. A third concern is that our results could be driven by firms in the technology sector, which tend to invest aggressively and grow faster and are located in less obese areas. When we delete observations for technology firms, as defined by Loughran and Ritter (2004), our baseline results remain virtually unchanged, as seen in row 4 of Table 9.

Fourth, we re-estimate our models in homogenous subsamples in order to mitigate a potential bias driven by cultural and physical variation. In particular, we examine whether our results hold after excluding high-tech counties where immigrants are likely to be a high percentage of the residents. Following Adhikari and Agrawal (2016), these high-tech counties are Silicon Valley (FIPS = 6085, 6075), Suffolk county (25025), the New York City metro area (36061, 36047, 36081, 36005), Washington D.C. (11001), and Dallas and Fort Worth (48113). The results, in row 5 of Table 9, remain virtually unchanged. The results are also similar when we add controls for local religiosity or political preferences in rows 6 and 7 of Table 9.

Finally, another endogeneity concern is measurement error in obesity rates, caused by a potential bias in self-reported data on height and weight or because of recording errors in this data. Our untabulated results are similar when we re-estimate our baseline regressions using raw (rather than age-adjusted) obesity prevalence rates, and either the upper-limit or the lower-limit of age-adjusted rates.

9. Summary and Conclusions

It is natural to expect that firms with risk-averse managers and shareholders will take less risk. A major difficulty in testing this proposition empirically is that risk-aversion is an unobserved individual trait. In this paper, we take a novel approach to this problem by using the prevalence of obesity in a county as a proxy for the risk-aversion of local residents, who contribute managers and shareholders to firms headquartered in the county. Our main hypothesis is that firms headquartered in counties with higher obesity prevalence are more likely to choose lower-risk policies and actions. This conjecture is based on extensive prior findings that obese individuals tend to be more risk-averse, firms often hire managers locally, and investors tend to hold more shares in local firms.

To test this hypothesis, we obtain annual data on obesity prevalence in each U.S. county from CDC for the years 2004 to 2012, match it with financial and location data on a large sample of public companies, and employ several econometric techniques to analyze the predicted relations. We find that firms headquartered in counties with greater prevalence of obesity invest at significantly lower rates in tangible assets and innovation projects, experience lower growth rates and are less profitable. They also have more volatile stock returns. These findings are robust to controls for other firm characteristics and demographic characteristics of the county that can affect these policies. To establish a causal relation between local obesity and lower-risk corporate policies, we adopt an instrumental variables approach. We use states taxes on fatty foods and the density of fast food restaurants in a county as instruments for the prevalence of obesity in the county. The results from this approach favor a causal explanation of our findings, i.e., obesity-induced risk-aversion of residents in a county leads to local firms adopting lower-risk policies and actions. Our findings are also robust to a variety of empirical specifications.

Next, we find some evidence that both local managers and local shareholders are channels through which obesity-induced risk-aversion gets transmitted to the policies and actions of local firms. CEOs of firms located in more obese areas accept lower risk-incentives in their compensation. And firms that switch from having a CEO from a non-obese place to one from an obese place in an exogenous CEO turnover reduce their industry-adjusted investment rate. And several of the effects we find are more pronounced in smaller firms, for which local shareholders are more important.

We then try to find the underlying mechanisms that link obesity prevalence in an area to the policies of companies located there. Based on the prior literature in health sciences, psychology, sociology, economics and finance, we consider education, race, health, income, and marital status as potential mechanisms that could drive the relations between local obesity and corporate policies. Our finding of a negative effect of local obesity on firm risk-taking is more pronounced in counties with larger shares of less-educated, minority, diabetic and single populations, which can foster local risk-averse cultures in these areas. Thus, education, race, health and marital status appear to be mechanisms driving our findings.

Finally, obesity can be attributable to either genetic or environmental factors. We analyze which of the two sources of obesity explains its effects on corporate decisions. We isolate the genetic and the environmental components of obesity and find that environmental factors can explain the negative effects of obesity on firm investment, asset growth, and profitability, while genetic factors drive the negative (positive) relation between obesity and R&D expenditure (profitability). Lastly, both factors contribute to the positive relation between obesity and stock volatility.

In conclusion, this study extends the literatures on the roles of individuals' physical appearance on their economic behavior, the effect of managerial attributes on corporate finance, and the effect of local demographics on corporate policies. We provide surprising new evidence that the physical attributes of local residents can affect the policies and actions of firms located in the area. Our findings suggest that the prevalence of obesity in an area has implications beyond the health of local residents. Local obesity prevalence also affects the risk-taking behavior of firms headquartered in the area, and thereby affects broader economic development and growth.

Appendix

Variable Definitions

Variable	Definition
County Variables	**Data Source: U.S. Census**
OBE	The age-adjusted obesity prevalence (%) / 100
Totpop	Natural logarithm of a county's population in a given year
Income	Per capita income / 1,000
Male	Percentage of male population in a county
Married	Percentage of married households in a county
White	Percentage of White population to total population
Age	Median age of the population in a county
Edu	The share of adults who received a bachelor's or higher degree
Rural	Lack of urbanization, scaled from 1 to 9 in which a higher number indicates more rural: 1-3 (metro), 4-9 (non-metro). The classification distinguishes metropolitan (metro) counties by the population size of their metro area, and nonmetropolitan counties by the degree of urbanization and adjacency to a metro area or areas.
Exo_Tax	= DisfavoredTax (the number of disfavored taxes a state implements to reduce obesity) × LevelDisfavoredTax (the sum of disfavored tax rates) in each state
Den_FFR	Density of fast food restaurants in a county.
High Diabetes	= 1 if a firm headquartered in a county with higher diabetes prevalence areas than the median in a given year.
HighBW	Proportion of babies whose birth weight is greater than 4,000 grams.
Religiosity	A higher value reflects more than average religion interests in the community. The factor that has been used in the creation of this estimate is the number of employees working in Religious Organizations (NAICS 8131).
Political culture index	Corporate political culture index from Hutton, Jiang, and Kumar (2015)
Firm Variables	**Data Source: Compustat, CRSP, Thomson Reuter, IBES**
INV	CAPX / lag_AT. (Compustat variables are upper capitals)
RD	XRD / lag_AT. Coded as zero if missing
SaleG	(SALE-lag_SALE) / lag_SALE
AssetG	(AT-lag_AT) / lag_AT
VOL	The standard deviation of daily stock returns during the fiscal year
ROA	OIBDP / lag_AT

MB	(AT+CSHO*PRCC_F-CEQ) / lag_AT
SIZE	Ln (lag_AT)
LOSS	= 1 if ROA < 0
TDA	DLC+DLTT / lag_AT
Tech Stocks	Are defined as those in SIC codes 3571, 3572, 3575, 3577, 3578 (computer hardware), 3661, 3663, 3669 (communications equipment), 3671, 3672, 3674, 3675, 3677, 3678, 3679 (electronics), 3812 (navigation equipment), 3823, 3825, 3826, 3827, 3829 (measuring and controlling devices), 3841, 3845 (medical instruments), 4812, 4813 (telephone equipment), 4899 (communications services), and 7371, 7372, 7373, 7374, 7375, 7378, and 7379 (software).
Small_Firm	= 1 if a firm has a smaller market value than the median of all firms, zero otherwise.
CEO Variables	**Data Source: Riskmetrics**
Delta	CEO compensation delta (pay-performance sensitivity), computed as in Coles, Daniel, and Naveen (2013)
Vega	CEO compensation vega (risk-taking incentives), computed as in Coles, Daniel, and Naveen (2013)

References

Adams, R. B., Keloharju, M., & Knüpfer, S. (2015). Match Made at Birth? What Traits of a Million Swedes Tell Us about CEOs. Working Paper, SSRN.

Addoum, J. M., Korniotis, G. M., & Kumar, A. (2016). Stature, Obesity, and Portfolio Choice. *Management Science*, Forthcoming.

Adhikari, B. K., & Agrawal, A. (2016). Religion, gambling attitudes and corporate innovation. *Journal of Corporate Finance*, 37, 229-248.

Adhikari, B. K., Agrawal, A. and Malm, J. (2016). Do Women Stay Out of Trouble? Evidence from Corporate Litigation. Working Paper, SSRN.

Angrist, J. D., Pischke, J. S., & Pischke, J. S. (2009). Mostly harmless econometrics: an empiricist's companion (Vol. 1). Princeton: Princeton university press.

Barber, B.M. and Odean, T. (2001) Boys will be Boys: Gender, Overconfidence, and Common Stock Investment. *Quarterly Journal of Economics*, 116(1), 261-292.

Becker, B., Ivković, Z., & Weisbenner, S. (2011). Local dividend clienteles. *Journal of Finance*, 66(2), 655-683.

Bernile, G., Bhagwat, V., & Rau, P. R. (2016). What Doesn't Kill You Will Only Make You More Risk-Loving: Early-Life Disasters and CEO Behavior. *Journal of Finance*, Forthcoming.

Bhattacharya, J., & Bundorf, M. K. (2009). The incidence of the healthcare costs of obesity. *Journal of Health Economics*, 28(3), 649-658.

Bogan, V. L., & Fertig, A. R. (2013). Portfolio choice and mental health. *Review of Finance*, 17(3), 955-992.

Campbell, J. Y. (2006). Household finance. *Journal of Finance*, 61(4), 1553-1604.

Case, A., & Paxson, C. (2008). Stature and Status: Height, Ability, and Labor Market Outcomes. *Journal of Political Economy*, 116(3).

Chou, S. Y., Grossman, M., & Saffer, H. (2004). An economic analysis of adult obesity: results from the Behavioral Risk Factor Surveillance System. *Journal of Health Economics*, 23(3), 565-587.

Christakis, N. A., & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine*, 357(4), 370-379.

Christelis, D., Jappelli, T., & Padula, M. (2010). Cognitive abilities and portfolio choice. *European Economic Review*, 54(1), 18-38.

Clark, G. L., Gertler, M. S., Feldman, M. P., & Williams, K. (2003). *The Oxford Handbook of Economic Geography*. Oxford University Press.

Cohen, L, Gurun, U. and Malloy, C. J. (2016). Resident networks and corporate connections: Evidence from World War II internment camps. *Journal of Finance*, forthcoming.

Coles, J. L., Daniel, N. D., & Naveen, L. (2013). Calculation of compensation incentives and firm-related wealth using Execucomp: Data, program, and explanation. Working Paper, SSRN.

Cook, D. O., & Mobbs, S. (2014). CEO Selection and Executive Appearance. Working Paper, SSRN.

Coval, J. D. and T. J. Moskowitz. (1999). Home bias at home: Local equity preference in domestic portfolios, *Journal of Finance*, 54, 2045-2073.

Cronqvist, H., Makhija, A. K., & Yonker, S. E. (2012). Behavioral consistency in corporate finance: CEO personal and corporate leverage. *Journal of Financial Economics*, *103*(1), 20-40.

Cronqvist, H., Previtero, A., Siegel, S., & White, R. E. (2016). The Fetal Origins Hypothesis in Finance: Prenatal Environment, the Gender Gap, and Investor Behavior. *Review of Financial Studies*, 29(3), 739-786.

Dixon, J. B. (2010). The effect of obesity on health outcomes. *Molecular and Cellular Endocrinology*, 316(2), 104-108.

Dohmen, T., Falk, A., Huffman, D., & Sunde, U. (2010). Are risk aversion and impatience related to cognitive ability? *The American Economic Review*, 100(3), 1238-1260.

Dong, C., Sanchez, L. E., & Price, R. A. (2004). Relationship of obesity to depression: A family-based study. *International Journal of Obesity*, 28(6), 790-795.

Duarte, J., Siegel, S., & Young, L. (2012). Trust and credit: the role of appearance in peer-to-peer lending. *Review of Financial Studies*, 25(8), 2455-2484.

Eisfeldt, A. L., & Kuhnen, C. M. (2013). CEO turnover in a competitive assignment framework. *Journal of Financial Economics*, 109(2), 351-372.

Farr, S. A., Yamada, K. A., Butterfield, D. A., Abdul, H. M., Xu, L., Miller, N. E., ... & Morley, J. E. (2008). Obesity and hypertriglyceridemia produce cognitive impairment. *Endocrinology*, 149(5), 2628-2636.

Frederick, S., Loewenstein, G., & O'donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of Economic Literature*, 351-401.

Gariepy, G., Nitka, D., & Schmitz, N. (2010). The association between obesity and anxiety disorders in the population: a systematic review and meta-analysis. *International Journal of Obesity*, 34(3), 407-419.

Graham, J. R., Harvey, C. R., & Puri, M. (2013). Managerial attitudes and corporate actions. *Journal of Financial Economics*, 109(1), 103-121.

Graham, J. R., Harvey, C. R., & Puri, M. (2016). A corporate beauty contest. *Management Science*, Forthcoming.

Grinblatt, M., Keloharju, M., & Linnainmaa, J. (2011). IQ and stock market participation. *Journal of Finance*, 66(6), 2121-2164.

Grinblatt, M., Keloharju, M., & Linnainmaa, J. T. (2012). IQ, trading behavior, and performance. *Journal of Financial Economics*, 104(2), 339-362.

Guiso, L., Sapienza, P., & Zingales, L. (2008). Trusting the stock market. *Journal of Finance*, 63(6), 2557-2600.

Guthrie, K., & Sokolowsky, J. (2014). Obesity and Household Financial Distress. Working Paper, SSRN.

Hamermesh, D. S., & Biddle, J. E. (1994). Beauty and the Labor Market. *American Economic Review*, 84(5), 1174-1194.

Harper, B. (2000). Beauty, stature and the labour market: a British cohort study. *Oxford Bulletin of Economics and Statistics*, 62(s1), 771-800.

Harvey, C.R., Liu Y., and Zhu, H. (2016) …and the cross-section of expected returns. *Review of Financial Studies*, 29(1), 5-68.

Hilary, G., & Hui, K. W. (2009). Does religion matter in corporate decision making in America? *Journal of Financial Economics*, 93(3), 455-473.

Hong, H., Kubik, J. D., & Stein, J. C. (2004). Social interaction and stock-market participation. *Journal of Finance*, 59(1), 137-163.

Hutton, I., Jiang, D., & Kumar, A. (2014). Corporate policies of Republican managers. *Journal of Financial and Quantitative Analysis*, 49(5-6), 1279-1310.

Hutton, I., Jiang, D., & Kumar, A. (2015). Political values, culture, and corporate litigation. *Management Science*, 61(12), 2905-2925.

Jiang, D., & Lim, S. S. (2014). Trust and Household Finance. Working Paper, SSRN.

Johansson, E., Böckerman, P., Kiiskinen, U., & Heliövaara, M. (2009). Obesity and labour market success in Finland: The difference between having a high BMI and being fat. *Economics and Human Biology*, 7(1), 36-45.

Kirkland, A. (2008). Fat Rights: Dilemmas of Difference and Personhood, New York University Press.

Li, Y., Dai, Q., Jackson, J. C., & Zhang, J. (2008). Overweight is associated with decreased cognitive functioning among school-age children and adolescents. *Obesity*, 16(8), 1809-1815.

Limbach, P., & Sonnenburg, F. (2015). CEO fitness and firm value. Working Paper, SSRN.

Loughran, T. and Ritter, J. (2004). Why has IPO underpricing changed over time? *Financial Management* 33, 5-37.

Love, D. A. (2010). The effects of marital status and children on savings and portfolio choice. *Review of Financial Studies*, 23(1), 385-432.

Lundborg, P., Nystedt, P., & Rooth, D. O. (2010). No country for fat men? Obesity, earnings, skills, and health among 450,000 Swedish men, IZA Discussion Paper No. 4775.

Mankiw, N. G., & Weinzierl, M. (2010). The Optimal Taxation of Height: A Case Study of Utilitarian Income Redistribution. *American Economic Journal: Economic Policy*, 2(1), 155.

Mocan, N. H., & Tekin, E. (2009). Obesity, self-esteem and wages. Working Paper, National Bureau of Economic Research.

Mokdad, A. H., Ford, E. S., Bowman, B. A., Dietz, W. H., Vinicor, F., Bales, V. S., & Marks, J. S. (2003). Prevalence of obesity, diabetes, and obesity-related health risk factors, 2001. *Journal of the American Medical Association*, 289(1), 76-79.

Persico, N., Postlewaite, A., & Silverman, D. (2004). The Effect of Adolescent Experience on Labor Market Outcomes: The Case of Height. *Journal of Political Economy*, 112(5).

Pope, D. G., & Sydnor, J. R. (2011). What's in a Picture? Evidence of Discrimination from Prosper.com. *Journal of Human Resources*, 46(1), 53-92.

Puri, M., & Robinson, D. T. (2007). Optimism and economic choice. *Journal of Financial Economics*, 86(1), 71-99.

Rosen, H. S., & Wu, S. (2004). Portfolio choice and health status. *Journal of Financial Economics*, 72(3), 457-484.

Sobal, Jeffery (2004). Sociological Analysis of the Stigmatisation of Obesity. In John Germov and Lauren Williams (Editors), A Sociology of Food and Nutrition. The Social Appetite, Oxford, Oxford University Press

Sturm R. (2002). The effects of obesity, smoking and drinking on medical problems and costs. *Health Affairs*, 21(2): 245-53

Sutter, M., Kocher, M. G., Glatzle-Rutzler, D., & Trautmann, S. T. (2013). Impatience and uncertainty: Experimental decisions predict adolescents' field behavior. *American Economic Review*, 103(1), 510-531.

Van Praag, B. M., & Booij, A. S. (2003). Risk aversion and the subjective time discount rate: A joint approach. CESifo Working Paper number 923.

Wang, Y., & Beydoun, M. A. (2007). The obesity epidemic in the United States—gender, age, socioeconomic, racial/ethnic, and geographic characteristics: a systematic review and meta-regression analysis. *Epidemiologic Reviews*, 29(1), 6-28.

Wardle, J., Waller, J., & Jarvis, M. J. (2002). Sex differences in the association of socioeconomic status with obesity. *American Journal of Public Health*, 92(8), 1299-1304.

Yonker, S. E. (2016). Geography and the market for CEOs. *Management Science*, Forthcoming.

Yu, Z. B., Han, S. P., Zhu, G. Z., Zhu, C., Wang, X, J., Cao, X. G., & Guo, X.R. (2011). Birth weight and subsequent risk of obesity: a systematic review and meta-analysis. *Obesity Review*, 12(7), 525-42.

Zhang, L. E. I., & Rashad, I. (2008). Obesity and time preference: the health consequences of discounting the future. *Journal of Biosocial Science*, 40(01), 97-113.

Figure 1

Obesity Prevalence in USA

This figure illustrates obesity prevalence in each U.S. County in 2010 as reported by the CDC.

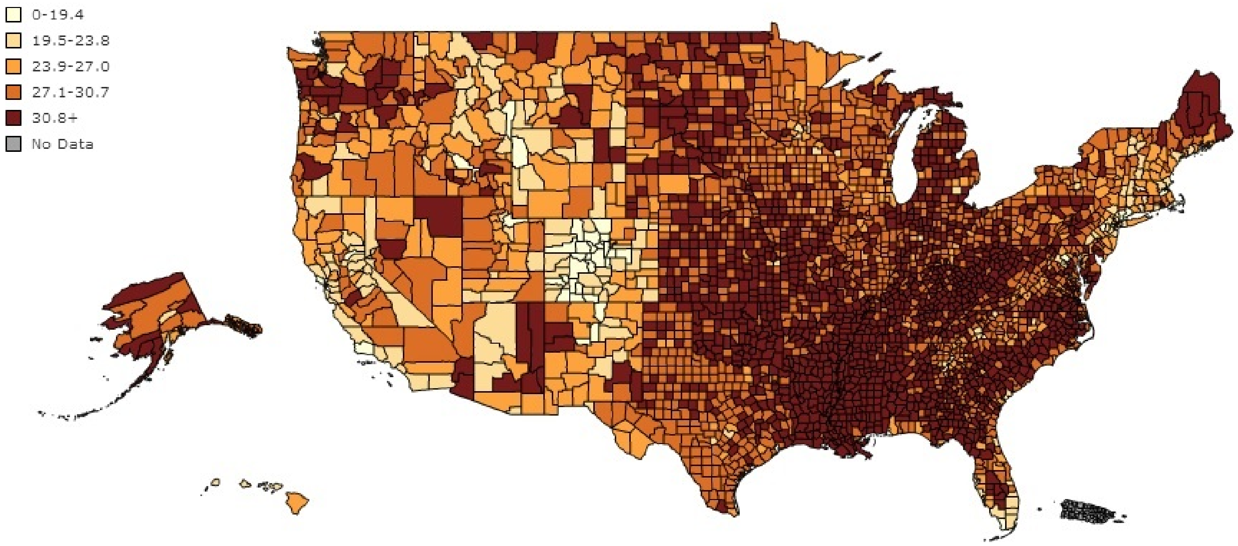

Table 1

Obesity prevalence by state and summary statistics

Panel A presents the mean, median, and standard deviation for the variables *OBE* in our dataset. Panel B show the summary statistics for firm variables and county demographic characteristics. The sample is based on the data from Centers for Disease Control and Prevention (CDC) from 2004 to 2012. Variables are defined in the Appendix.

Panel A: Prevalence of obesity (%) by state

	Mean	Median	Std.dev.
Alabama	29.53	29.90	1.96
Alaska	25.51	25.50	0.61
Arizona	21.40	21.40	1.76
Arkansas	27.38	27.65	3.00
California	19.69	19.60	1.95
Colorado	16.88	17.00	2.64
Connecticut	19.40	18.10	2.84
Delaware	26.13	26.50	3.22
District of Columbia	21.38	21.40	0.52
Florida	22.61	22.20	2.87
Georgia	24.22	23.70	1.86
Hawaii	20.89	21.15	1.60
Idaho	22.61	22.40	2.27
Illinois	23.68	23.50	1.88
Indiana	28.00	28.20	2.42
Iowa	26.28	26.20	2.28
Kansas	23.99	22.95	4.35
Kentucky	28.43	27.30	2.82
Louisiana	28.36	28.10	3.06
Maine	19.49	19.20	1.76
Maryland	21.86	20.60	4.62
Massachusetts	21.20	21.30	2.03
Michigan	27.46	26.50	3.77
Minnesota	22.65	22.40	2.13
Mississippi	32.30	31.70	3.47
Missouri	28.20	27.90	2.51
Montana	23.48	21.80	7.72
Nebraska	26.48	26.40	1.60
Nevada	22.64	22.60	2.54
New Hampshire	23.86	23.30	2.19
New Jersey	21.34	21.10	2.54

New Mexico	18.17	18.30	1.65
New York	18.77	16.60	4.41
North Carolina	25.37	25.30	2.55
North Dakota	27.19	27.20	0.66
Ohio	27.60	27.40	1.94
Oklahoma	27.48	27.20	2.32
Oregon	22.74	22.60	2.11
Pennsylvania	24.82	25.00	3.40
Rhode Island	23.06	23.20	2.95
South Carolina	27.34	27.70	3.86
South Dakota	26.61	26.50	1.72
Tennessee	28.21	28.00	3.23
Texas	25.55	25.60	2.47
Utah	22.59	22.60	2.29
Vermont	21.85	21.60	2.70
Virginia	23.75	22.20	3.50
Washington	22.35	21.40	3.35
West Virginia	31.15	31.30	2.12
Wisconsin	27.17	27.40	2.96
Wyoming	22.63	24.55	6.23

Panel B: Summary statistics

Variable	Mean	S.D.	p25	p50	p75	N
OBE	0.23	0.04	0.20	0.23	0.26	29,752
INV	0.06	0.08	0.01	0.03	0.06	28,177
RD	0.06	0.13	0.00	0.00	0.07	29,752
SaleG	0.15	0.48	-0.02	0.08	0.21	27,723
AssetG	0.10	0.37	-0.05	0.04	0.16	24,663
VOL	0.03	0.02	0.02	0.03	0.04	29,602
ROA	0.06	0.25	0.03	0.11	0.18	28,193
MB	2.32	2.08	1.16	1.67	2.61	28,207
SIZE	5.93	2.01	4.45	5.88	7.32	28,242
LOSS	0.20	0.40	0.00	0.00	0.00	29,752
TDA	0.22	0.26	0.00	0.16	0.34	28,108
Income	49.73	15.73	39.53	46.31	54.98	29,278
Totpop	13.78	1.05	13.23	13.77	14.36	29,752
Age	35.48	2.72	33.36	35.44	37.25	29,752
Male	48.98	0.90	48.41	49.06	49.64	29,752
White	73.36	12.92	65.78	73.59	83.22	29,752
Married	49.42	7.82	45.60	50.17	55.03	29,748
Rural	1.25	0.67	1.00	1.00	1.00	29,752

Table 2

Correlation matrix and sorts on obesity rates

Panel A reports the pairwise correlation coefficients among the variables. * indicates statistical significance at the 5% level. Panel B presents the mean and median values of variables for firms sorted by the obesity rates (OBE) as reported by CDC. The t-statistic in the last column is for the difference between the high and low OBE groups.

Panel A: Correlation matrix

	OBE	Income	Totpop	Age	Male	White	Married	Rural
OBE	1							
Income	-0.5896*	1						
Totpop	-0.2857*	0.1531*	1					
Age	-0.0970*	0.2953*	-0.3172*	1				
Male	-0.0757*	-0.3256*	0.0692*	-0.4212*	1			
White	0.0214*	-0.2320*	-0.3752*	0.1623*	0.2005*	1		
Married	0.0200*	-0.2960*	-0.2169*	0.1073*	0.4306*	0.5132*	1	
Rural	0.2644*	-0.2451*	-0.6198*	0.1392*	0.0737*	0.3140*	0.1214*	1

Panel B: Sorts on Obesity

	Low		Medium		High		T-statistics
Variable	Mean	Median	Mean	Median	Mean	Median	High-Low
INV	0.05	0.03	0.05	0.03	0.07	0.04	15.58
RD	0.09	0.02	0.07	0.01	0.03	0.00	-34.70
SaleG	0.18	0.09	0.16	0.08	0.11	0.07	-9.87
AssetG	0.12	0.05	0.10	0.04	0.09	0.04	-3.71
VOL	0.04	0.03	0.03	0.03	0.03	0.03	-2.40
ROA	0.02	0.09	0.05	0.11	0.11	0.13	24.46

Table 3

Relation between obesity and corporate policies

The table reports the estimates from regressions of corporate policies and outcomes. Dependent variables are: INV is the rate of investment in tangible assets, RD is the rate of investment in intangible assets, SaleG is the sale growth, AssetG is the asset growth, VOL is annualized daily return volatility, and ROA is return on assets. OBE is the age-adjusted prevalence obesity rates in a county as reported by the CDC. All regressions include year and industry (two-digit SIC) fixed effects. The t-statistics, reported in parentheses below the coefficient estimates, are computed using standard errors corrected for clustering at the firm, county, and year levels. All regressions include intercepts (not tabulated). The sample period is from 2004 to 2012. Variables are defined in the Appendix. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, in 2-tailed tests. The last row shows cut-off t-values under Holm's adjustment for tests of multiple hypotheses on the coefficient of OBE for columns (1) to (4) at the 5% level in 2-tailed tests.

	(1) INV	(2) RD	(3) SaleG	(4) AssetG	(5) VOL	(6) ROA
OBE	-0.042**	-0.123***	-0.312***	-0.215***	0.008**	-0.096**
	(-2.51)	(-5.45)	(-2.75)	(-3.01)	(2.54)	(-2.49)
SIZE	-0.001***	-0.006***	-0.017***	-0.018***	-0.004***	0.015***
	(-6.86)	(-18.96)	(-11.26)	(-16.51)	(-77.10)	(26.98)
LOSS	-0.015***	0.087***	-0.050***	-0.166***	0.011***	-0.387***
	(-13.51)	(42.87)	(-4.63)	(-27.79)	(38.22)	(-110.88)
TDA	0.032***	-0.020***	0.203***	0.402***	0.009***	-0.020***
	(13.71)	(-6.61)	(11.73)	(26.67)	(23.69)	(-3.38)
MB	0.006***	0.017***	0.064***	0.103***	-0.001***	-0.005***
	(21.27)	(29.61)	(23.52)	(50.00)	(-14.91)	(-4.49)
Income	-0.000**	0.000**	0.000	-0.000**	0.000***	-0.000***
	(-2.32)	(2.08)	(0.05)	(-1.99)	(3.17)	(-3.09)
Totpop	-0.002***	-0.003***	0.007*	0.003	0.001***	-0.002
	(-3.73)	(-4.89)	(1.86)	(1.09)	(4.73)	(-1.36)
Age	-0.001***	0.001***	0.001	-0.001	0.000	-0.002***
	(-3.88)	(4.80)	(0.49)	(-0.74)	(0.48)	(-4.81)
Male	0.002***	0.008***	0.006	-0.005	0.000***	-0.003**
	(2.79)	(7.93)	(1.16)	(-1.59)	(2.69)	(-2.04)
White	0.000***	-0.001***	0.000	0.000***	-0.000*	0.000
	(3.22)	(-16.56)	(0.90)	(2.70)	(-1.92)	(0.67)
Married	-0.000***	0.001***	-0.000	-0.000	-0.000	0.000
	(-3.50)	(11.91)	(-0.66)	(-0.71)	(-0.69)	(1.45)
Rural	0.003***	-0.005***	-0.003	-0.004	0.000	0.008***
	(3.53)	(-5.84)	(-0.70)	(-1.19)	(0.32)	(4.41)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	27608	27648	27159	24151	27528	27622
Adjusted R^2	0.399	0.516	0.133	0.438	0.517	0.588
Holm's adj.	1.96	2.50	2.24	2.395		

Table 4

Identification: Instrumental variable regression estimates

The table reports the estimates from the two-stage least square (2SLS) instrumental variable regressions. It reports the first-stage estimates, where the dependent variable is the prevalence obesity in a county (OBE). We instrument OBE with the *Exo_Tax*, DisfavoredTax (the number of disfavored taxes a state implements to reduce obesity) × LevelDisfavoredTax (the sum of disfavored tax rates), and Den_FFR, density of fast food restaurants in a county from 2007 to 2011, along with all control variables used in the second-stage regressions. All the statistics (F or J) for tests reports its p-value. The right table reports the second-stage estimates. The t-statistics reported in parentheses below the respective estimates are computed using standard errors corrected for heteroscedasticity. Variables are defined in the Appendix. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The last row shows cut-off t-values under Holm's adjustment for tests of multiple hypotheses on the coefficient of OBE for columns (1) to (4) at the 5% level in 2-tailed tests.

First-Stage Regression		Second-stage Regression						
Dep. Var.	OBE		INV	RD	SaleG	AssetG	VOL	ROA
Exo_Tax	0.000***	OBE	-0.624***	-1.481***	-2.692**	-0.750	0.025	-0.108
	(15.44)		(-4.47)	(-5.77)	(-2.25)	(-1.11)	(0.68)	(-0.27)
Den_FFR	7.431***							
	(3.46)							
Firm Var	Yes		Yes	Yes	Yes	Yes	Yes	Yes
County Var	Yes		Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes		Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes		Yes	Yes	Yes	Yes	Yes	Yes
F-stat.	0.0000	*J-stat.*	0.3620	0.0144	0.4622	0.7924	0.5999	0.1141
N	14754	*N*	14754	14782	14475	14781	14768	14771
Adj. R^2	0.672	Adj. R^2	0.356	0.461	0.110	0.438	0.509	0.582
		Holm t	2.395	2.50	2.24	1.96		

Table 5

Role of managers

The table reports estimates from OLS regression of CEO vega six corporate policies and outcomes. Dependent variables are defined as follows: INV is the rate of investment, RD is the rate of investment in intangible assets, SaleG is the sale growth, AssetG is the asset growth, VOL is annualized daily return volatility, and ROA is return on assets. OBE is the age-adjusted prevalence obesity rates in a county as reported by the CDC. Delta (pay-performance sensitivity) and Vega (risk-taking incentives) for executives are calculated as in Coles, Daniel, and Naveen (2013). All regressions include year and industry (two-digit SIC) fixed effects and control for firm and county characteristics. The t-statistics reported in parentheses below the coefficient estimates are computed using standard errors corrected for clustering at the firm, county, and year level. All regressions include the intercept term. The sample period is from 2004 to 2012. Variables are defined in the Appendix. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The last row shows cut-off t-values under Holm's adjustment for tests of multiple hypotheses on the coefficient of OBE for columns (1) to (4) at the 5% level in 2-tailed tests.

	(1) Vega	(2) INV	(3) RD	(4) SaleG	(5) AssetG	(6) VOL	(7) ROA
OBE	-136.349***	-0.051**	-0.189***	-0.222**	-0.169**	0.008**	0.097***
	(-4.46)	(-2.55)	(-10.11)	(-2.42)	(-1.98)	(2.10)	(3.08)
Delta		-0.000	0.000***	0.000	0.000*	-0.000***	0.000***
		(-1.47)	(3.90)	(0.03)	(1.85)	(-4.21)	(3.44)
Vega		0.000	0.000	0.000***	0.000**	0.000***	-0.000
		(0.66)	(1.33)	(4.67)	(2.17)	(2.63)	(-1.35)
N	12587	5927	5932	5932	5092	5932	5932
Adjusted R^2	0.287	0.478	0.412	0.282	0.446	0.606	0.534
Holm's adj. t-value		2.395	2.50	2.24	1.96		

Table 6

Local shareholder channel

The table reports the results of OLS regressions of local obesity, *OBE*, on corporate policies on samples partitioned by firm size. We create a dummy variable, *Small_Firm*, which equals one if the market capitalization of a firm (MarketCap = csho*prcc_f) is less than the median market cap of all the sample firms in a given year, and zero if above the median market cap. Refer to Variables are defined in the Appendix. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Small	Large	Small	Large	Small	Large
Dependent Variable	INV	INV	RD	RD	SaleG	SaleG
OBE	-0.052**	-0.029	-0.077*	-0.175***	-0.312	-0.302**
	(-2.11)	(-1.25)	(-1.93)	(-8.76)	(-1.58)	(-2.53)
N	13645	13957	13672	13970	13263	13890
Adjusted R^2	0.341	0.449	0.529	0.529	0.101	0.215
Dependent Variable	AssetG	AssetG	VOL	VOL	ROA	ROA
OBE	-0.236**	-0.140	0.006	0.006**	-0.213***	0.058
	(-2.10)	(-1.55)	(0.98)	(2.09)	(-3.25)	(1.56)
N	11943	12202	13558	13964	13654	13962
Adjusted R^2	0.428	0.455	0.416	0.516	0.615	0.498
Firm & County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7

Possible mechanisms

The table reports test results on possible mechanisms where the effect of local obesity on corporate policies come from. The panels present results from OLS regressions of corporate policies on local obesity and other determinants. We only report coefficients of local obesity for brevity, while the basic controls are the same as Table 3. We split the sample into two groups: *Low* groups contain firms with mechanism values less than the median in a given year, and *High* groups with values above the median. Variables are defined in the Appendix. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Education

	INV		RD		SaleG	
	Low Edu	High Edu	Low Edu	High Edu	Low Edu	High Edu
OBE	0.021	-0.058**	-0.117***	-0.087**	-0.442***	-0.093
	(0.88)	(-2.32)	(-3.65)	(-1.97)	(-2.95)	(-0.45)
N	13960	13648	13981	13667	13773	13386
Adjusted R^2	0.428	0.355	0.453	0.543	0.175	0.105
	AssetG		VOL		ROA	
	Low Edu	High Edu	Low Edu	High Edu	Low Edu	High Edu
OBE	-0.152	-0.190	0.004	0.004	0.104*	-0.136*
	(-1.41)	(-1.46)	(0.76)	(0.67)	(1.81)	(-1.91)
N	12210	11941	13921	13607	13968	13654
Adjusted R^2	0.464	0.422	0.524	0.519	0.564	0.604

Panel B: Race

	INV		RD		SaleG	
	Low White	High White	Low White	High White	Low White	High White
OBE	0.025	-0.027	-0.164***	0.032	-0.622***	-0.065
	(1.03)	(-1.12)	(-4.69)	(0.92)	(-3.78)	(-0.39)
N	13486	14122	13513	14135	13256	13903
Adjusted R^2	0.405	0.409	0.553	0.487	0.133	0.134
	AssetG		VOL		ROA	
	Low White	High White	Low White	High White	Low White	High White
OBE	-0.477***	-0.084	0.015***	-0.005	0.062	-0.144**
	(-4.09)	(-0.80)	(2.75)	(-1.07)	(1.01)	(-2.46)
N	11800	12351	13449	14079	13496	14126
Adjusted R^2	0.454	0.426	0.531	0.512	0.591	0.590

Panel C: Health

	INV		RD		SaleG	
	High Diabetes	Low Diabetes	High Diabetes	Low Diabetes	High Diabetes	Low Diabetes
OBE	-0.070**	0.038*	-0.037	-0.128***	-0.009	-0.453***
	(-2.43)	(1.69)	(-0.77)	(-4.39)	(-0.04)	(-3.12)
N	13069	14539	13088	14560	12788	14371
Adjusted R^2	0.340	0.434	0.518	0.485	0.106	0.168

	AssetG		VOL		ROA	
	High Diabetes	Low Diabetes	High Diabetes	Low Diabetes	High Diabetes	Low Diabetes
OBE	-0.220	-0.263***	-0.018***	0.009*	-0.206***	0.091*
	(-1.59)	(-2.58)	(-2.81)	(1.94)	(-2.62)	(1.74)
N	11443	12708	13038	14490	13074	14548
Adjusted R^2	0.428	0.452	0.510	0.532	0.599	0.566

Panel D: Income

	INV		RD		SaleG	
	Low Income	High Income	Low Income	High Income	Low Income	High Income
OBE	-0.011	-0.053*	-0.109***	-0.193***	-0.416***	-0.008
	(-0.51)	(-1.81)	(-3.89)	(-4.72)	(-2.94)	(-0.04)
N	14206	13402	14229	13419	13988	13171
Adjusted R^2	0.409	0.389	0.470	0.540	0.161	0.112
	AssetG		VOL		ROA	
	Low Income	High Income	Low Income	High Income	Low Income	High Income
OBE	-0.200**	-0.115	0.003	0.004	-0.066	-0.081
	(-2.10)	(-0.95)	(0.71)	(0.66)	(-1.26)	(-1.21)
N	12449	11702	14158	13370	14215	13407
Adjusted R^2	0.439	0.440	0.527	0.515	0.572	0.600

Panel E: Marriage

	INV		RD		SaleG	
	High Single	Low Single	High Single	Low Single	High Single	Low Single
OBE	-0.053**	0.012	-0.192***	0.077*	-0.533***	0.075
	(-2.38)	(0.44)	(-6.83)	(1.86)	(-3.58)	(0.38)
N	14140	13468	14168	13480	13933	13226
Adjusted R^2	0.447	0.328	0.495	0.528	0.155	0.114
	AssetG		VOL		ROA	
	High Single	Low Single	High Single	Low Single	High Single	Low Single
OBE	-0.432***	0.022	0.016***	0.000	-0.063	-0.142**
	(-4.57)	(0.18)	(3.59)	(0.02)	(-1.28)	(-2.02)
N	12399	11752	14099	13429	14154	13468
Adjusted R^2	0.451	0.428	0.534	0.507	0.576	0.600

Table 8

Genetic or environmental obesity

The table reports the estimates from regressions to separate the effects of genetic (yhat) and environmental (e) obesity on corporate policies. We follow a two-stage regression approach. In the first stage, we obtain residuals of local obesity that are purged of the effects of time-invariant county characteristics. Specifically, for each county j in year t, we first run a regression on local obesity using year and county fixed effects and the high birth weight rates:

$$OBE_{j,t} = \alpha_0 + \alpha_1 HighBW_{j,t} + \underline{\alpha_2} County_j + \underline{\alpha_3} Year_t + \epsilon_{i,t}.$$

By construction, $\epsilon_{i,t}$ (the residual) captures the portion of local adults' obesity (*OBE*) that is orthogonal to (or purged of) county and year fixed effects. We also obtain the predicted value of local obesity (yhat) from the regression. Thus, the predicted values of local obesity account for the genetic portion, and the residuals account for environmental portion of *OBE*. We then estimate regressions of the corporate policy variables after replacing OBE by its two components as the main explanatory variables. We only report coefficients of predicted OBE and the residuals, while the basic controls are the same as in Table 3.

	(1) INV	(2) RD	(3) SaleG	(4) AssetG	(5) VOL	(6) ROA
yhat	1.572***	-6.068***	-3.118	0.551	0.314***	2.200***
	(5.34)	(-13.90)	(-1.39)	(0.37)	(4.97)	(2.94)
e	-0.096***	-0.105*	-0.048	-0.423**	0.017**	-0.296***
	(-2.74)	(-1.92)	(-0.18)	(-2.24)	(2.12)	(-3.03)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	26583	26623	26147	23254	26515	26597
Adjusted R^2	0.404	0.521	0.133	0.439	0.518	0.589

Table 9

Robustness checks

The table reports the coefficients of OBE from several robustness tests performed on the corporate policy regressions. Panel A summarizes several robustness checks. Each row represents a separate regression. We report the estimates of OBE only for simplicity. Although unreported, the control variables are the same as in Table 3. The t-statistics reported in parentheses are computed using standard errors corrected for clustering at the firm, county, and year. Variables are defined in the Appendix. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.	(1) INV	(2) RD	(3) SaleG	(4) AssetG	(5) VOL	(6) ROA
Excl. 5 most obese States	-0.045*** (-2.62)	-0.126*** (-5.45)	-0.312*** (-2.69)	-0.203*** (-2.80)	0.008** (2.48)	-0.118*** (-3.01)
Excl. 5 least obese States	0.007 (0.40)	-0.159*** (-6.03)	-0.266** (-2.15)	-0.188** (-2.30)	0.009** (2.51)	-0.070 (-1.55)
Exclude 5 industries with highest OBE	-0.015 (-0.73)	-0.046* (-1.82)	-0.349*** (-2.65)	-0.106 (-1.28)	0.005 (1.22)	-0.105** (-2.32)
Exclude 5 industries with lowest OBE	-0.045*** (-2.62)	-0.122*** (-5.33)	-0.319*** (-2.76)	-0.224*** (-3.09)	0.007** (2.21)	-0.104*** (-2.65)
Exclude tech industries	-0.047** (-2.39)	-0.058** (-2.34)	-0.378*** (-2.84)	-0.245*** (-3.06)	0.009** (2.38)	-0.109** (-2.51)
Exclude high-tech counties	-0.037** (-2.06)	-0.096*** (-3.96)	-0.241** (-1.96)	-0.226*** (-2.98)	0.003 (0.98)	-0.129*** (-3.11)
Religiosity	-0.033* (-1.68)	-0.121*** (-4.53)	-0.310** (-2.26)	-0.186** (-2.07)	-0.186** (-2.07)	-0.085* (-1.83)
Political Culture Index	-0.172*** (-2.73)	-0.218*** (-4.27)	-0.149 (-0.84)	-0.388 (-1.53)	-0.003 (-0.50)	0.199** (2.16)