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Local Obesity Prevalence and Corporate Policies

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Consistent with prior findings that obese individuals tend to be more risk-averse and myopic, we find that firms located in areas with higher obesity rates invest less, grow more slowly, are less profitable, and have higher stock volatility. We mitigate identification concerns by using an instrumental variables approach, testing for local managers and local shareholders as channels for these effects, and ruling out several alternative explanations, thereby favoring a causal interpretation of our results. Finally, both genetic and environmental factors appear to contribute to these effects. Our findings suggest that physical characteristics of the local population also affect the policies of local firms.

Keywords: Obesity; corporate policies; risk-taking; myopia.

JEL Classifications: G02, G30, I12

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.

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For example, Persico *et al.* (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; and Hamermesh and Biddle (1994) find that more attractive workers have better labor market outcomes. Our paper focuses on one particular physical attribute, namely obesity, which combines height and weight, and contributes to perceptions of beauty.

Prior studies find that obese individuals tend to be more risk-averse and myopic. As we discuss in Sec. 2, obesity has been found to be related to several observable individual characteristics, unobservable traits, and social experiences that are known to influence risk-taking behaviors. Consistent with greater risk-aversion in personal financial choices, Addoum *et al.* (2017) find that obese individuals are less likely to participate in the stock market and invest less in risky assets. Obese individuals are also known to be myopic, i.e., they have a preference for immediate utility over delayed utility. Sutter *et al.* (2013) find that more impatient children, who develop higher body mass indexes (BMIs), are less likely to save money. If obese individuals take less risk and are myopic, it is reasonable to ask whether these traits of obese managers and shareholders seep into lower-risk and myopic 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, measured as the proportion of adults who are obese, 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 *et al.* (2011), and Cohen *et al.* (2017)).

Local culture can shape corporate policies in at least two ways. First, firms tend to hire managers, even chief executive officers (CEOs), locally (see, e.g., Yonker (2017)). Managers from communities that have a myopic and risk-averse culture are more likely to have these traits themselves. Extensive prior evidence of behavioral consistency between managers' actions on personal and corporate accounts (see, e.g., Cronqvist *et al.* (2012), and Hutton *et al.* (2014)) suggests that obesity-induced risk-aversion and myopia of managers can get transmitted to firms' policies, actions and outcomes. Second, the literature on local bias suggests that investors tend to over-invest in stocks of local firms (see, e.g., Coval and Moskowitz (1999), Grinblatt and Keloharju (2001), and Ivković and Weisbenner (2005)). Furthermore, firms tend to cater to the preferences of their investor-base (see, e.g., Becker *et al.* (2011)). So firms located in more obese communities have incentives to cater to their local investors by adopting lower-risk and myopic policies such as less investment and lower growth. This approach enables us to examine the policies and actions of all the firms headquartered in the United States.

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. An example illustrates the idea. Consider the two largest firms in the soft drinks industry: Coca Cola Company and Pepsico, Inc. Coke is headquartered in Fulton county, GA, a county whose obesity rates over our 2004–2012 sample period averaged 23.1. Pepsi is headquartered in Westchester county, NY, whose obesity rates averaged 17.7 over the same time period. Pepsi has higher rates of investment (6.2% vs. 4.2%), research and development (R&D) (0.8% vs. 0), sales growth (10.8% vs. 10%), and higher return on assets (ROA) (25.0% vs. 22.7%) than Coke over this time period. While this is simply an example and these are just univariate comparisons, these differences in investment, R&D and ROA are statistically significant at the 5% level based on a matched-pairs t-test.

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 prevalence is negatively related to firm investment in tangible assets and innovation, growth rates, and profitability; it is positively related to stock volatility (more on this in Sec. 2). 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 myopic, and their preferences get reflected in lower risk-taking and myopic behavior 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 rates and lower-risk corporate policies can be simultaneously determined by omitted variables. Second, conservative and myopic firms may choose to locate in areas that have a culture of risk-aversion and myopia, 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 through 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 be related to local obesity and empirically they are significantly related. However, neither variable should directly affect corporate policies. This is because state tax policy on unhealthy foods is clearly exogenous to corporate policies on investment, growth and risk-taking of firms located in the state. Similarly, there is no reason why the density of fast food restaurants in a county should directly affect these corporate decisions by local firms. While fast food restaurant density is likely correlated with county demographics, which may also be related to local obesity rates and to corporate policies, our regressions control for them. 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 locally. 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 myopia and risk-aversion of local shareholders because investors are more likely to hold the stock of local firms. We examine this channel by investigating the behavior of firms for which local investors are likely to be more important, such as smaller firms. We find that the effects of local obesity on investment, asset growth, and profitability are more pronounced in smaller firms.

Finally, obesity can be due to either genetic or environmental factors. The findings of Addoum *et al.* (2017) suggest that the relation between physical attributes and risk-aversion reflects factors that are fixed at birth, such as genetics or the prenatal environment. 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 myopia and risk-aversion. We analyze which of the two sources of obesity explains its effects on corporate decisions. Tyrrell *et al.* (2016) find that several traits related to maternal obesity are causally related to birth weight, which implies that birth weight is at least partially determined by genetic factors. 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 prevalence on firm investment, asset growth, and profitability. Genetic factors appear to drive the negative (positive) relation between local obesity prevalence and R&D expenditure (profitability). Lastly, both factors drive the positive relation between local obesity prevalence 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., Persico *et al.* (2004), and Mankiw and Weinzierl (2010)), while obesity is generally associated with lower earnings (see, e.g., Hamermesh and Biddle (1994), Harper (2000), and Johansson *et al.* (2009)). Our paper complements Addoum *et al.* (2017), who find that obese individuals are less likely to take personal financial risks by holding stocks in their portfolios. While prior studies find a relation between obesity and *individual* decisions and outcomes, to our knowledge, no prior study has examined the relation between obesity and *corporate* decisions and outcomes. 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 *et al.* (2013) examine the effect of CEO height on corporate policies. Adams *et al.* (2015) find that larger companies are more likely to have taller CEOs. Graham *et al.* (2016) find that competent-looking individuals are more likely to be hired as CEOs and paid more. Similarly, Cook and Mobbs (2017) find that executives with more attractive facial characteristics are more likely to be appointed CEO, especially when the qualified labor pool is larger. 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. 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 and outcomes for firms located in the area.

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 *et al.* (2011), and Adhikari and Agrawal (2016a) investigate the effect of religiosity, age and religious composition of the local population on corporate policies. Cohen *et al.* (2017) 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 examines whether the relations we find are due to obesity induced by nature or nurture. Section 8 reports several robustness checks, and Section 9 concludes.

2. Hypotheses

Prior literature discussed in Appendix 1 suggests that obese individuals tend to be risk-averse and myopic. 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 have 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 net present value (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 Institutional Brokers' Estimate System (I/B/E/S), and CEO-related data from Risk Metrics. We compute CEO delta and vega as in Coles *et al.* (2013). In addition, we obtain data on CEO's place of origin from Bernile *et al.* (2017) and Yonker (2017), 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. The sample contains 518 (of the 3,007) U.S. counties with at least one firm-year of data.

3.1. *Obesity data*

We obtain annual data on obesity prevalence in each U.S. 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 kilograms/(height in meters)^2) is 30 or greater.

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

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

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

(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 Appendix 2.

3.2.2. *Treatment variable*: *Obesity*

BRFSS reports two obesity rates for each county for each year: the raw obesity rate and an age-weighted obesity rate. The latter is a weighted-average of the obesity rate for each of three age groups (20–44, 45–64, and 65+) in a county, weighted by the proportion of each age group in the U.S. population from the latest prior decennial census. The age-weighted obesity rate allows comparisons across different counties regardless of the county's age distribution. 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 ±6%. Following prior studies (von Hinke Kessler Scholder, 2008; Cawley and Maclean, 2012; Salois, 2012), we define the variable *OBE* as the age-weighted obesity rate.[3] 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 *et al.* (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-level variables at the 1st and 99th percentiles. We estimate regressions with both year and industry (two-digit SIC) fixed effects[4] 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] Our regressions control for the average age in the county. And as discussed in Section 8 later, our results are similar to those reported in the paper when we instead use the raw obesity rates, and either the upper-limit or the lower-limit of age-adjusted obesity rates.

[4] We cannot use state-year fixed effects because there is insufficient variation in obesity rates across the counties in our sample within a state. As noted earlier in this section, only 518 of the 3,007 U.S. counties house the headquarters of a Compustat firm in at least one year in our sample.

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

Table 1. Obesity prevalence by state and summary statistics.

Panel A: Obesity prevalence (%) 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

Table 1. (*Continued*)

Panel A: Obesity prevalence (%) by state

	Mean	Median	Std. Dev.
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 of county-year observations

Variable	Mean	S.D.	p25	p50	p75	*N*
OBE	0.26	0.04	0.23	0.26	0.29	3,940
Totpop	12.40	1.08	11.62	12.41	13.19	3,940
Age	36.34	3.25	34.03	36.30	38.40	3,940
Male	49.03	0.87	48.45	49.04	49.59	3,940
Rural	2.07	1.26	1.00	2.00	3.00	3,940
White	81.53	13.74	73.81	85.79	92.24	3,940
Income	39.94	10.36	33.04	37.74	44.06	3,847
Married	51.85	7.05	47.77	52.41	56.53	3,936
*Den*_FFR($\times$ 100)	0.07	0.01	0.06	0.07	0.08	2,082

Panel C: Summary statistics of firm-year observations

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

Table 1. (*Continued*)

Panel C: Summary statistics of firm-year observations

Rural	1.25	0.67	1.00	1.00	1.00	29,752
*Exo*_Tax	38.40	38.93	10.50	21.00	75.00	29,752
*Den*_FFR($\times$ 100)	0.08	0.02	0.07	0.08	0.08	15,542

Notes: Panel A presents mean, median, and standard deviation for the *OBE* variable. Panel B shows summary statistics of county-level variables for the county-years in our sample. Panel C shows summary statistics of firm- and county-level variables for the firm-years in our sample. The sample is based on data from the Centers for Disease Control and Prevention (CDC) from 2004 to 2012. All the variables are defined in Appendix 2.

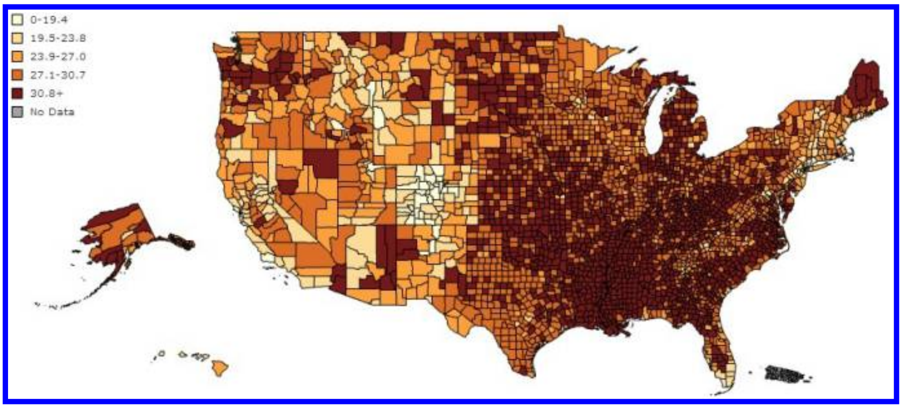

Fig. 1. Obesity prevalence in USA.

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

prevalence by state for our sample period. In addition, Fig. 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 summary statistics of county characteristics for the 3,940 county-years in our sample. Panel C shows summary statistics of the variables for the 29,752 firm-years in our sample. The average obesity rate in our sample is 23%.

Panel A of Table 2 presents Pearson correlations among the variables in our sample of firm-years. Obesity-prevalence is negatively (positively) correlated with income and population (lack of urbanization), while its correlations with other demographic variables are relatively low.

Table 2. Correlation matrix.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. *OBE*	1.00																			
2. *Totpop*	−0.28	1.00																		
3. *Age*	−0.10	−0.32	1.00																	
4. *Male*	−0.08	0.07	−0.42	1.00																
5. *Rural*	0.26	−0.62	0.14	0.07	1.00															
6. *White*	0.02	−0.38	0.16	0.20	0.31	1.00														
7. *Income*	−0.59	0.15	0.30	−0.33	−0.25	−0.23	1.00													
8. *Married*	0.02	−0.22	0.11	0.43	0.12	0.51	−0.30	1.00												
9. *SIZE*	0.13	0.00	−0.01	−0.10	−0.02	−0.09	0.05	−0.10	1.00											
10. *LOSS*	−0.15	0.05	0.00	0.07	−0.05	−0.02	0.07	0.04	−0.45	1.00										
11. *TDA*	0.08	−0.03	−0.02	−0.05	0.02	0.01	−0.03	−0.04	0.24	−0.13	1.00									
12. *MB*	−0.13	0.03	−0.01	0.05	−0.03	0.00	0.03	0.03	−0.23	0.14	0.01	1.00								
13. *Exo*_Tax	0.09	−0.01	0.12	−0.16	−0.03	0.04	0.06	0.01	0.01	−0.04	0.05	−0.03	1.00							
14. *Den*_FFR	−0.36	0.10	−0.02	−0.40	−0.19	−0.32	0.65	−0.63	0.06	−0.01	0.02	−0.01	−0.12	1.00						
15. *INV*	0.08	−0.01	−0.14	0.08	0.06	0.02	−0.07	−0.04	0.06	−0.11	0.21	0.13	0.02	−0.02	1.00					
16. *RD*	−0.18	0.05	0.04	0.08	−0.08	−0.05	0.10	0.09	−0.36	0.49	−0.14	0.40	−0.08	−0.04	−0.15	1.00				
17. *SaleG*	−0.07	0.03	−0.01	0.04	−0.02	0.01	0.01	0.01	−0.10	0.03	0.11	0.30	−0.01	0.00	0.17	0.15	1.00			
18. *AssetG*	−0.03	0.02	−0.02	0.03	−0.01	0.01	−0.01	0.01	−0.06	−0.11	0.28	0.56	0.00	0.00	0.28	0.11	0.35	1.00		
19. *VOL*	−0.01	0.04	−0.04	0.06	−0.02	0.01	0.03	0.01	−0.45	0.41	−0.01	−0.02	−0.01	−0.01	−0.05	0.23	0.01	−0.13	1.00	
20. *ROA*	0.14	−0.05	−0.03	−0.04	0.06	0.02	−0.08	−0.03	0.42	−0.74	0.09	−0.18	0.03	0.01	0.17	−0.66	−0.02	0.07	−0.42	1.00

Notes: This table reports pairwise correlation coefficients among the variables.

4. Baseline Results

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

$$\begin{aligned} Policy_{i,t} = {} & \alpha_0 + \alpha_1 OBE_{i,t} + \alpha_2 FirmControls_{i,t} + \alpha_3 CountyControls_{h,t} \\ & + \alpha_t Year_t + \alpha_h Industry_{j,t} + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

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, industry, county 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 *et al.* (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

Table 3. Relation between obesity and corporate policies.

	(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	27,608	27,648	27,159	24,151	27,528	27,622
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		

Notes: 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 sales growth rate, *AssetG* is asset growth rate, *VOL* is annualized daily stock return volatility, and *ROA* is return on assets. *OBE* is the age-adjusted obesity prevalence 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 Appendix 2. *, **, 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.

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).[5]

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 *et al.* (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.

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 causes 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

[5] 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 *et al.* (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.

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*).[6] 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) $\times$ *LevelDisfavoredTax* (i.e., the sum of disfavored tax rates).[7]

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 *et al.* (2004) find that higher density of fast food restaurants in an area is positively related to the local prevalence of obesity. Similarly, we would expect states that are more concerned about obesity rates to adopt taxes on fatty foods. So obesity rates should be related to these 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. State tax policy on fatty foods is clearly exogenous to investment policies of firms located in the state, except for fast food firms. Similarly, 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.[8] An exception is the small number of firms in the fast food industry. Our IV results are almost identical to those reported in Table 4 when we omit the 260

[6] 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.

[7] 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.

[8] Fast food restaurant density is likely correlated with county demographics, which may also be related to local obesity rates and to corporate policies. But our regressions include extensive controls for county demographics.

Table 4. Identification: Instrumental variable regression estimates.

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	14,754	*N*	14,754	14,782	14,475	14,781	14,768	14,771
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		

Notes: The table reports estimates from two-stage least squares (2SLS) instrumental variable regressions. It reports the first-stage estimates, where the dependent variable is the obesity prevalence rate in a county (*OBE*). We instrument *OBE* with (1) *Exo*_Tax = *DisfavoredTax* (i.e., the number of disfavored taxes a state implements to reduce obesity) × *LevelDisfavoredTax* (i.e., the sum of disfavored tax rates), and (2) *Den*_FFR = density of fast food restaurants in a county from 2007 to 2011, along with all the control variables used in the second-stage regressions. All the statistics (*F* or *J*) for tests reports its *p*-value. The right side of the 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 Appendix 2. *, **, 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.

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 findings that firms often hire managers 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 compute the delta and vega of compensation for the CEOs in our sample as in Coles *et al.* (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

Table 5. Role of managers.

	(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	12,587	5,927	5,932	5,932	5,092	5,932	5,932
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		

Notes: The table reports estimates from OLS regressions of CEO vega and 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 sales growth rate, *AssetG* is asset growth rate, *VOL* is annualized daily stock return volatility, and *ROA* is return on assets. *OBE* is the age-adjusted obesity prevalence rates in a county as reported by CDC. Delta (pay-performance sensitivity) and Vega (risk-taking incentives) for executives are calculated as in Coles *et al.* (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 levels. All regressions include the intercept term. The sample period is from 2004 to 2012. Variables are defined in Appendix 2. *, **, 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 (2) to (5) at the 5% level in 2-tailed tests.

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.[9]

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 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 *et al.* (2017)) and the place where they received their social security card, usually around age 16 (using data from Yonker (2017)). 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.[10]

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 *et al.* (2011)). We partition our sample into small and large firms using the median market capitalization in each year

[9] 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.

[10] We also tried to do a similar experiment by inferring CEO obesity directly by looking at pictures of their faces and doing a survey of college students to rate whether the CEOs were obese or not. For a sample of 50 exogenous CEO turnover events within our sample, we were able to obtain facial pictures of the outgoing and incoming CEOs. Very few of these 100 CEOs looked to us like they could be obese, so we did not pursue this approach further. Perhaps this is not surprising given that being physically fit appears to be almost a job requirement for becoming a CEO (see, e.g., Kwoh (2013)).

Table 6. Local shareholder channel.

Dependent Variable	Small *INV*	Large *INV*	Small *RD*	Large *RD*	Small *SaleG*	Large *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	13,645	13,957	13,672	13,970	13,263	13,890
Adjusted R^2	0.341	0.449	0.529	0.529	0.101	0.215
Dependent Variable	Small *AssetG*	Large *AssetG*	Small *VOL*	Large *VOL*	Small *ROA*	Large *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	11,943	12,202	13,558	13,964	13,654	13,962
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

Notes: The table reports the results of OLS regressions of local obesity rates (*OBE*) on corporate policies, on samples partitioned by firm size. We create a dummy variable, *Small_Firm*, which equals 1 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 otherwise. Variables are defined in Appendix 2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

as the cut-off. We then re-estimate our baseline regressions in Table 3 separately for the two sub-samples. 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. Nature vs. Nurture

Finally, obesity can be attributed to both genetic and environmental factors. Addoum *et al.* (2017) find that the relation between obesity and financial risk-taking by individuals appears to reflect factors that are fixed at birth, such as genetics or the prenatal environment. Cronqvist *et al.* (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 investigating which of these two sources of obesity can explain the relations we observe between local obesity and lower risk corporate policies and outcomes.

Table 7. Genetic or environmental obesity.

	(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	26,583	26,623	26,147	23,254	26,515	26,597
Adjusted R^2	0.404	0.521	0.133	0.439	0.518	0.589

Notes: 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 estimate a regression on local obesity using year and county fixed effects and the rates of high birth weight:

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

By construction, $\epsilon_{i,t}$ (the residual) captures the portion of local adults' obesity rates (*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. Control variables are as in Table 3.

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). Tyrrell *et al.* (2016) find that several obesity-related traits of mothers are related to their babies' birth weights, suggesting that birth weight is affected by genetic factors. We obtain birth weight data from CDC.[11] 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 regression (2) of local obesity rates, using *HighBW* and county and year fixed effects as explanatory variables:

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

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

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 7, 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 8. For brevity, we report only the coefficient estimates and t-statistics on our main explanatory variable of interest, *OBE*, for these tests.

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 8. 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 8, 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 5 of Table 8.

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 constitute higher percentages of local residents. Following Adhikari and Agrawal (2016a), these high-tech counties

Table 8. Robustness checks.

Dep. Var.	(1) *INV*	(2) *RD*	(3) *SaleG*	(4) *AssetG*	(5) *VOL*	(6) *ROA*
Excl. 5 most obese States	−0.045***	−0.126***	−0.312***	−0.203***	0.008**	−0.118***
	(−2.62)	(−5.45)	(−2.69)	(−2.80)	(2.48)	(−3.01)
Excl. 5 least obese States	0.007	−0.159***	−0.266**	−0.188**	0.009**	−0.070
	(0.40)	(−6.03)	(−2.15)	(−2.30)	(2.51)	(−1.55)
Exclude 5 industries with highest *OBE*	−0.015	−0.046*	−0.349***	−0.106	0.005	−0.105**
	(−0.73)	(−1.82)	(−2.65)	(−1.28)	(1.22)	(−2.32)
Exclude 5 industries with lowest *OBE*	−0.045***	−0.122***	−0.319***	−0.224***	0.007**	−0.104***
	(−2.62)	(−5.33)	(−2.76)	(−3.09)	(2.21)	(−2.65)
Exclude tech industries	−0.047**	−0.058**	−0.378***	−0.245***	0.009**	−0.109**
	(−2.39)	(−2.34)	(−2.84)	(−3.06)	(2.38)	(−2.51)
Exclude high-tech counties	−0.037**	−0.096***	−0.241**	−0.226***	0.003	−0.129***
	(−2.06)	(−3.96)	(−1.96)	(−2.98)	(0.98)	(−3.11)
Religiosity	−0.033*	−0.121***	−0.310**	−0.186**	−0.186**	−0.085*
	(−1.68)	(−4.53)	(−2.26)	(−2.07)	(−2.07)	(−1.83)
Political Culture Index (PCI)	−0.172***	−0.218***	−0.149	−0.388	−0.003	0.199**
	(−2.73)	(−4.27)	(−0.84)	(−1.53)	(−0.50)	(2.16)
Religiosity and PCI	−0.179***	−0.213***	−0.151	−0.503**	−0.001	0.179***
	(−3.90)	(−5.68)	(−0.91)	(−2.04)	(−0.21)	(2.68)

Notes: The table reports the coefficients of *OBE* from several robustness tests performed on the corporate policy regressions. Each cell represents a separate regression. We only report the estimates of *OBE* for brevity. 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 levels. Variables are defined in Appendix 2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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 6 of Table 8, remain virtually unchanged. Prior studies find that firms located in more religious areas and Republican-leaning firms adopt lower-risk policies and actions (see, e.g., Hilary and Hui (2009), Adhikari and Agrawal (2016b), and Hutton *et al.* (2014, 2015)). Our results on the effects of local obesity on lower-risk corporate policies survive controls for local religiosity or Republican-leaning political culture or both, shown in rows 7, 8 and 9 of Table 8.

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 myopic and risk-averse managers and shareholders will make myopic decisions and take less risk. A major difficulty in testing this proposition empirically is that myopia and risk-aversion are unobserved individual traits. 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 myopia and 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 myopic and lower-risk policies and actions. This conjecture is based on extensive prior findings that obese individuals tend to be more myopic and 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. We mitigate identification concerns by using an instrumental variables approach, testing for local managers and local shareholders as channels for our findings, and ruling out several alternative explanations, thereby favoring a causal interpretation of our results.

Next, we find some evidence that both local managers and local shareholders are channels through which obesity-induced myopia and risk-aversion get transmitted to the policies and actions of local firms. CEOs of firms located in more obese areas accept lower risk-incentives in their compensation. In addition, 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. Also, several of the effects we find are more pronounced in smaller firms, for which local shareholders are more important.

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 local obesity prevalence 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, 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 impedes investment, growth and profitability of firms headquartered in the area, and thereby affects broader economic development and growth.

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Appendix 1: Related Literature

Our main conjecture is that firms headquartered in counties with greater prevalence of obesity are likely to choose lower risk and myopic policies. The reason is that obesity is related to observable individual characteristics (e.g., health, marital status, education, income and race); unobservable traits (e.g., cognitive abilities, sociability, optimism and self-esteem); and social experiences (e.g., discrimination and being trusted) that are known to influence their risk-taking and time-preference 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 *et al.*, 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 *et al.* (2002)) and are more likely to belong to minority communities in the U.S. (see Wang and Beydoun (2007) for a review). Hong *et al.* (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 *et al.* (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 *et al.* (2010)) and lead to lower stock market participation (see, e.g., Christelis *et al.* (2010), and Grinblatt *et al.* (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 *et al.* (2012)). Guthrie and Sokolowsky (2017) 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 *et al.* (2010)). Individuals who are not trusted take less risk (see, e.g., Guiso *et al.* (2008), and Jiang and Lim (2018)), leading them to be more risk-averse. Obese individuals also prefer to stay home, causing them to be less sociable. Hong *et al.* (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.

Appendix 2: 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* (i.e., the number of disfavored taxes a state implements to reduce obesity) $\times$ *LevelDisfavoredTax* (i.e., 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 is headquartered in a county with higher diabetes prevalence rates than the median in a given year
HighBW	Proportion of babies whose birth weight is greater than 4,000 grams

Appendix 2. (*Continued*)

Variable	Definition
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 *et al.* (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 *et al.* (2013)
Vega	CEO compensation vega (risk-taking incentives), computed as in Coles *et al.* (2013)

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