The Agglomeration of Bankruptcy*

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Abstract

This paper identifies a new channel through which bankrupt firms impose negative externalities on non-bankrupt peers. The bankruptcy and liquidation of a retail chain weakens the economies of agglomeration in any given local area, reducing the attractiveness of retail centers for remaining stores leading to contagion of financial distress. We find that companies with greater geographic exposure to bankrupt retailers are more likely to close stores in affected areas. We further show that the effect of these externalities on non-bankrupt peers is higher when the affected stores are smaller and are operated by firms with poor financial health.

I. Introduction

How does bankruptcy spread? While research on bankruptcy and financial distress has documented how bankruptcy reorganizations affect firms that file for Chapter-11 themselves, there is limited evidence on the effect of bankruptcies and financial distress on competitors and industry peers. In this paper, we identify a new channel by which bankrupt firms impose negative externalities on their non-bankrupt competitors, namely, through their impact on peer firm sales and on the propensity to close stores.

Research in industrial organization has argued that the geographic concentration of stores and the existence of clusters of stores can be explained by consumers' imperfect information and their need to search the market (Wolinsky (1983)). Indeed, both practitioners and academics argue that economies of agglomeration exist in retail since some stores – those of national name-brands or anchor department stores, in particular – draw customer traffic not only to their own stores but also to nearby stores. As a result, store level sales may depend on the sales of neighboring stores for reasons that are unrelated to local economic conditions (Gould and Pashigian (1998) and Gould, Pashigian and Prendergast (2005)).

We conjecture that the externalities that exist between neighboring stores, and the economies of agglomeration they create, can be detrimental during downturns, propagating and amplifying the negative effects of financial distress and bankruptcies among firms in the same locality. Our main prediction is that, due to agglomeration economies, retail stores in distress impose negative externalities on their neighboring peers: store sales tend to decrease with the reduction in sales, and ultimately the closure, of neighboring stores. If such negative externalities are sufficiently strong, bankruptcies, and the store closure they involve, will lead to additional store closures and bankruptcies, propagating within a given area.

Identifying a causal link, however, from the bankruptcy and financial distress of one retailer to the sales and closure decisions of its neighboring retailers is made difficult by the fact that bankruptcy filings and financial distress are correlated with local economic conditions. Correlation in sales among stores in the same vicinity may therefore simply reflect weak demand in an area. Similarly, the fact that store closures tend to cluster locally may often be the outcome of underlying difficulties in the local economy, rather than the effect of negative externalities among stores. Local economic conditions will naturally drive a correlation in outcomes among stores located in the same area.

Using a novel and detailed dataset of all national chain store locations and closures across the United States from 2005 to 2010, we provide empirical evidence that supports the view that bankruptcies of retail companies impose negative externalities on neighboring stores owned by solvent companies. Our identification strategy consists of analyzing the effect of Chapter 11 bankruptcies of large national retailers, such as Circuit City and Linens n Things, who liquidated their entire store chain during the sample period. Using Chapter 11 bankruptcies of national retailers alleviates the concern that local economic conditions led to the demise of the company: it is unlikely that a large retail chain will suffer major financial difficulties because of a localized economic downturn in one of its many locations. Supporting this identification assumption, we show that stores of retail chains that eventually end up in Chapter 11 bankruptcy are not located in areas that are worse than the location of stores operated by chains that do not end up in bankruptcy, along a host of economic characteristics.

We then show that stores located in proximity to stores of national chains that are liquidated are more likely to close themselves. Importantly, we find that this effect is stronger for stores in the same industry of the liquidating national chain as compared to stores in industries different from that of the liquidating chain. For example, focusing on stores located in the same address (usually mall locations), the probability that a store will close in the year following the closure of a store belonging to a liquidating national chain is approximately two times larger when operating in the same industry as compared to when the stores operate in different industries.

Finally, we study the interaction between the geographical effect of store closures and the financial health of solvent owners of neighboring stores. We hypothesize that the impact of national chain store liquidations will be stronger on firms in weaker financial health, as these stores are expected to suffer more from the reduction in customer traffic. Focusing on stores owned by a parent company, and measuring financial health using the profitability of the parent, we find that, consistent with our hypothesis, the geographical effect of store closures on neighboring stores is indeed more pronounced in financially weaker firms. For example, when located within a 50 meter radius of a closing national chain store, stores belonging to parent firms in the 25th percentile of profitability are between 16.9 and 22.2 percent more likely to close. In contrast, if the parent firm is in the 75th percentile of profitability there is no statistical significant effect on the likelihood of store closure. Along the same lines, we also find that larger stores are more resilient to the closure of neighboring stores, exhibiting a lower likelihood of closure following the closure of neighboring stores.

Our paper is closely related to a large body of work on agglomeration economies that studies how the proximity of firms and individuals in urban areas increases productivity. Prior work has shown that increases in productivity can arise for a variety of reasons, including reduced transport costs of goods, increased ability of labor specialization , better matching quality of workers to firms, and knowledge spillovers.[1] Within the retail sector, agglomeration economies may arise because of the increased productivity stemming from reduced consumer search costs. By utilizing micro-level data on store locations and closures our paper contributes in two ways to this important literature.

The first contribution is our focus on the way in which downturns and bankruptcies damage economies of agglomeration and the productivity enhancements they create. In contrast, prior work has focused on the creation of agglomeration economies through firm entry and employment decisions (See, for example, Ellison and Glaeser (1997), Glaeser et al (1992), Henderson et al 1995, and Rosenthal and Strange 2003). By focusing on downturns, our work shows how agglomeration economies can be understood to propagate bankruptcies and financial distress. Indeed, firm closures will naturally reduce proximity between agents in an urban environment, which will tend to reduce the productivity of remaining firms due to dis-economies of agglomeration. To the extent that replacing closed stores with new ones takes time – for example due to credit constraints during downturns – the reduction in productivity may have long term consequences.[2]

The second contribution of the paper is the empirical identification of agglomeration economies. The standard difficulty in identifying agglomeration effects is the endogeneity of firms' location decisions. Namely, is firm proximity causing high productivity or, alternatively, is the proximity simply a by-product of firms choosing to locate in areas naturally pre-disposed to high productivity? Employing micro-level data on store locations, we address the endogeneity concern by instrumenting for variation in store location with our large retail-chain bankruptcy instrument.[3] As described above, to the extent that national chain store closures are not driven by highly localized demand-side effects, we can measure the impact of store closures on nearby stores. Agglomeration effects,

[1]Important contributions include Krugman 1991(a,b), Becker and Murphy 1992, Helsley and Strange (1990), and Marshall (1920)).

[2]There have been few studies analyzing how firms in bankruptcy or financial distress affect their industry peers. One exception is Benmelech and Bergman (2011) who use data from the airline industry to examine how firms in financial distress impose negative externalities on their industry peers by increasing their cost of debt capital.

[3]Rosenthal and Strange (2008) instrument for the location of firms with the presence of bedrock. Other efforts to deal with the endogeneity concern involve analyzing coagglomeration effects (see for example Ellison et al, 2010).

and the degree to which they attenuate with distance to other stores, are therefore estimated at a micro level.

Our paper also adds to the growing literature in finance on the importance of peer effects and networks for capital structure (Leary and Roberts, 2013), acquisitions and managerial compensation (Shue, 2013), entrepreneurship (Lerner and Malmendier (2013)) and portfolio selection and investment (Cohen, Frazzini and Malloy (2008)). In particular, our paper is closely related to Almazan, De Motta, Titman and Uysal (2010) who link financial structure to economies of agglomeration. In particular, Almazan, De Motta, Titman and Uysal (2010) show that firms that are located in industry clusters are more likely to maintain financial slack in order to facilitate acquisitions within these clusters.

The rest of the paper is organized as follows. Section II explains our identification strategy. Section III describes our data sources and provides summary statistics and Section IV describes the initial location of stores in our sample. Section V presents the empirical analysis of the relation between bankrupt store and neighboring store closures. Section VI analyzes the effects of store size and firm profitability on store closures. Section VII concludes.

II. Identification Strategy

Our main prediction is that, due to economics of agglomeration, the closure of retail stores imposes negative externalities on their neighbors – that is, store sales tend to decrease with a decline in customer traffic in their area. If this effect is sufficiently large, store closures will tend to propagate geographically. However, identifying a causal link from the financial distress or bankruptcy of retailers to the decision of a neighboring solvent retailer to close its stores is difficult because financial distress is potentially correlated with underlying local economic conditions. For example, the fact that local retailers are in financial distress can convey information about weak local demand. Similarly, the fact that store closures tend to cluster locally does not imply in and of itself a causal link but rather may simply reflect difficulties in the local economy.

Our identification strategy consists of analyzing the effect of Chapter 11 bankruptcies of large national retailers, such as Circuit City and Linens n Things, who liquidate their entire store chain during the sample period. Using Chapter 11 bankruptcies of national retailers alleviates the concern that local economic conditions led to the demise of the company: it is unlikely that a large retail chain will suffer major financial difficulties because of a localized economic downturn in one of its many locations. Still, it is likely that national chains experiencing financial distress will restructure their operations and cherry-pick those stores they would like to remain open. According to this, financially distressed retailers will shut down their worst performing stores while keeping their best stores open, implying that a correlation between closures of stores of bankrupt chains may merely reflect poor local demand rather than negative externalities driven by financial distress. We address this concern directly by only utilizing variation driven by bankruptcy cases that result in the liquidation of the entire chain. In these cases, there is clearly no concern of cherry-picking of the more successful stores; all stores are closed regardless of local demand conditions.

In examining national chain liquidations, one concern that remains is that the stores of the liquidating chain were located in areas that experienced negative economic shocks – for example, because of poor store placement decisions made on the part of headquarters – and that it was these shocks that eventually drove the chain into bankruptcy. We address this concern in two ways. First, based on observables, we show empirically that stores of chains that eventually file for Chapter 11 bankruptcy and end up in full liquidations are not located in areas that are worse than the location of stores operated by chains that do not end up in bankruptcy. Second, due to our precise data on the location of each store and our use of area fixed effects (either county, zip code, or zip-by-year), our identification strategy enables us to net out local economic shocks and relies on variation within the relevant geographic area. As such, the relevant endogeneity concern is not that the stores of liquidating national chains were located in areas that suffered more negative economic shocks, but rather that these stores were somehow positioned in the worse locations *within each county or zip code*. Given their firms' success in forming a national chain of stores, this seems highly unlikely.

To further alleviate concerns about store locations we also perform a placebo test. We define a "placebo" variable that counts for each store in our sample the number of neighboring stores that are part of a national chain that will liquidate in the *following* year but that are currently not in bankruptcy. We find that the effect of store liquidation on subsequent store closures is not driven by the location of the retail chain-stores that will later become bankrupt but rather by the timing in which they were actually closed which is consistent with the existence of a causal effect of store closures.

III. Data and Summary Statistics

A. Sample Construction and Data Sources

Our dataset is composed of several sources which we describe in turn in this section. The main source is Chain Store Guide (CSG), a database that contains detailed information on retail store locations in the US and Canada. CSG data is organized in the form of annual snapshots of almost the entire retail industry at the establishment level.[4] The information on each location contains the store name, its address (street number, street name, city, state, and zip code) and phone number, the parent company, and a CSG-defined industry.[5] Our sample covers the 2005-2010 period and includes 828,792 store-year observations in the U.S. in the following CSG-defined industries: Apparel Stores, Department Store, Discount Stores, General Merchandise Store, Home Centers & Hardware Chains, and Value-Priced Apparel Store. Figures 1 and 2 demonstrates the coverage of our data by plotting the locations of all stores in our dataset for the first year (2005 in Figure 1) and the last year of our sample (2010 in Figure 2).

We clean the data and and streamline store names and parent names for consistency. Large chain stores account for the bulk of the data. For example, in 2010, the 50 largest retail chains accounted for 111,655 of the 166,045 stores in the dataset, representing 67.2% of the stores in the data for that year.

Our empirical strategy requires us to compute distances between retail locations. To do so we convert all street addresses into geographic coordinates using ArcGIS software. If an address is not contained in the address locator used by ArcGIS, we pass it through Google Maps API in an additional attempt to geocode it. As a result, we successfully map street addresses to geographic coordinates for 97% of the data. The information on longitudes and latitudes of full addresses – up to a street number – makes it possible for us to compute distances between retail locations to a very high precision. Since our analysis focuses on stores that are in close proximity to each other, we use the standard formula for the shortest distance between two points on a sphere (see Coval and Moskowitz (1999)) without adjusting for the fact that the Earth's surface is geoid-shaped.

We supplement the CSG store-level data with information on the number of employees accessible

[4]CSG does not track locations operated by companies that have annual revenues below a certain industry-specific threshold. For example, to be included into the database, apparel retailers and department stores are required to have annual sales of at least $500,000 and $250,000, respectively.

[5]The parent company is essentially the name of the retail chain. Some companies operate stores under different brands which we then match to the parent company.

through Esri's Business Analyst. Esri's data structure is very similar to that of CSG. We carefully merge these two databases by store/parent name and address; questionable cases are checked manually. The majority of information on the number of employees available is collected by Esri by reaching out individually to every store on a yearly basis; about 10% of the data though is populated according to the data provider's proprietary models based on observable characteristics of a retail location. In our analysis, we use only the actual data points and discard modeled figures.

We also use Esri's Major Shopping Centers, which is a panel of major U.S. shopping centers, to group stores in our sample into malls where applicable. The included mall-level pieces of information are mall name and its address (usually up to a street intersection), gross leasable area (GLA), total number of stores, and names of anchor tenants (up to four). We merge Esri's Major Shopping Centers to CSG data using the following multi-step procedure. First, we find anchor stores in the data using the information on store/parent name and zip code. If several anchor stores pertaining to the same mall are identified, we confirm the match if the average distance from anchors to the implied center of the mall is less than 200 meters. By doing so, we increase our confidence that we do not erroneously label stores as anchor tenants in zip codes containing a large number of stores. Stores located within 25 meters of anchors are assigned to the same mall. Second, we geocode addresses of malls that were not found in the data using anchor tenants – e.g., information on their anchors is missing – to be able to compute distances between malls and stores. All stores within 100 meters of the mall are assigned to that mall. At all stages of the algorithm, we manually check questionable cases by looking up store addresses and verifying whether they are part of a shopping mall.

Next, we use SDC Platinum to identify retail Chapter 11 bankruptcies since January 2000 within the following SIC retail trade categories: general merchandise (SIC 4-digit codes 5311, 5331 and 5399), apparel (5600, 5621 and 5651), home furnishings (5700, 5712, 5731, 5734 and 5735) and miscellaneous (5900, 5912, 5940, 5944, 5945, 5960, 5961 and 5990). There were 93 cases of retail Chapter 11 liquidations between 2000 and 2011. The largest bankruptcies in recent years include Circuit City, Goodys, G+G Retail, KB Toys, Linens n Things, Mervyns, and The Sharper Image. Bankruptcy stores are identified in our data by their respective parent name.

We then merge our data with Compustat Fundamental and Industry Data. We use the Compustat North America Fundamentals Annual database to construct variables that are based on operational and financial data. These include the number of employees in the firm, size (defined as the natural log of total assets), market-to-book ratio (defined as the market value of equity and book value of assets less the book value of equity, divided by the book value of assets), profitability (defined as earnings over total assets), and leverage (defined as total current liabilities plus long-term debt, divided by the book value of assets).

We supplement our database with information pertaining to the local economies from the Census, IRS, Zillow, and the BLS. We rely on the 2000 Census survey for a host of demographic variables available by zip code. We also use the Internal Revenue Service (IRS) data which provides the number of filed tax returns (a proxy for the number of households), the number of exemptions (a proxy for the population), adjusted gross income (which includes taxable income from all sources less adjustments such as IRA deductions, self-employment taxes, health insurance, alimony paid, etc.), wage and salary income, dividend income and interest income at the zip code level. We use data on house prices from Zillow, an online real estate database that tracks valuations throughout the United States. We construct annual county-level and zip-code median house values as well as annual changes in housing prices.

B. Individual Store Closings

In order to construct our main dependent variable of store closings we compare the data from one year to the next. We define a store closure if a store entry appears in a given year but not in the subsequent one. Given that our data span the years 2005-2010 we can identify store closings for each year from 2005 up to 2009. Panel A of Table 1 provides summary statistics on store closings during our entire sample-period as well as, individually, for each of the years in the sample. The number of stores in the data ranges from 84,388 individual stores in 2005 to 155,114 stores in 2009. The rate of annual store closure ranges between 1.4% in 2007 to 11.0% in 2008. During the entire sample period of 2005-2009, 6.1% of store-years represent store closures, with a standard deviation of 23.9%. Figures 3 and 4 displays the geographical distribution of store closings (red dots) relative to stores that stay open (blue dots) for the years 2007 and 2008, respectively.

There are 30 retail companies that filed for bankruptcy and were matched to our 2005-2010 data set. Table 2 provides a chronological list of the bankrupt companies, the date in which they filed for bankruptcy, whether they emerged from bankruptcy, and the number of stores operated by the firm. Table 2 clearly demonstrates the wave of retail bankruptcies during the economic contraction of 2007-2009 as consumer consumption and expenditure declined sharply. In forming the sample of liquidating national chains used in our identification we include only those chains where upon bankruptcy of the chains all stores were closed, and in which the retail chains operated in several states.

Panel B of Table 1 provides summary statistics for stores that operated while their company was in a Chapter-11 restructuring. As Panel B shows, 2.1% of the 827,156 observations were stores that their companies were operating under Chapter-11 protection. The number of bankrupt stores increased sharply from 4,231 stores in 2007 (representing 2.9% of total stores) to 6,167 bankrupt stores in 2008 (4.2% of total stores). By 2009 many of the bankrupt retailers were liquidated and their stores disappeared resulting in fewer bankrupt stores (3,963 stores representing 2.6% of the stores in our sample). By 2010 most of the remaining bankrupt companies that were not liquidated emerged from Chapter-11 and the number of bankrupt stores fell to 652 or 0.4% of the stores in our sample.

Finally, we calculate the number of stores that were closed in bankruptcies of chains that were fully liquidated. As we argue previously, these bankruptcy cases are not driven by the specific location of their stores but rather because of a failure of their business plan. Hence, as described in the Identification Strategy section, we use store closures resulting from the chain-wide liquidation of the parent firm to capture the negative externalities of bankruptcy. Panel C of Table 1 displays summary statistics for these chain-wide liquidating stores. The number of stores closed by chains that were fully liquidated in bankruptcy increases from 160 stores in 2007 (0.10% of total stores) to 2,650 (1.86% of total stores) and 2,987 (1.93% of total stores), in 2008 and 2009, respectively.[6]

C. Neighboring Store Closures

We construct three main measures of neighboring store closures that are driven by liquidation of national retail chains. To do this, for each store in our sample and for every year we measure the distance to any other store in our sample. Specifically, for each store we define its neighboring stores in a series of concentric circles. We consider neighboring stores that are: (1) located in the same address; (2) located in a different address but are within a 50 meters radius of the store under consideration; and (3) stores that are located in a different address and are located in a radius of more than 50 meters but less or equal than 100 meters from the store under consideration.[7] In

[6] As in Panel A of Table 1 we cannot calculate stores closing for 2010 given that it is the last year in our panel dataset.

[7] Different stores that are operating in the same address are usually indicative of a shopping mall.

each of these three geographical units, for each store and each year, we then count the number of stores that were closed as a result of a full liquidation of a large retail chain.

Table 3 provides summary statistics for the three measures associated with each of the three geographical units, as well as for counts of neighboring stores that are outside of the 100 meters radius. Panel A of Table 3 displays summary statistics for same address stores that were closed in chain liquidations. During the 2005-2010 same-address liquidated stores ranged from 0 to 3 with an unconditional mean of 0.028 and a standard deviation of 0.181. For any given store, therefore, the maximum number of stores operating in the same address that were closed as a result of a retail-chain liquidation is three. Panel A also displays the evolution of the *same-address* measure over time. For example, on average *same-address* equals 0 and 0.002 in 2005 and 2006, respectively.[8] As the number of bankruptcies rose in 2007 *same-address* increased to 0.038 in 2007 (range between 0 and 2) and peaked at 0.085 (range between 0 and 3) in 2009.

Panels B and C present similar statistics for the $0 < distance \leq 50$ and the $50 < distance \leq 100$ measures, respectively. As can be seen, both measures display similar patterns over time ranging from 0 to 3 and averaging approximately 0.01. Finally, Panel D expands the concentric rings beyond 100 meters, and displays summary statistics for distances up to 500 meters, at 50 meter interval.

IV. Stores Locations

A. The Geographical Dispersion of Liquidated Chain Stores

One of the main pillars of our identification strategy is the conjecture that large bankruptcy cases of national retail chains are less likely to be driven by localized economic conditions given their diversity and geographical dispersion. We present the case for the geographical dispersion of these chains in Table 4 by listing information on the geography of operation of the retail chain bankruptcies utilized in our empirical strategy.[9] In choosing these cases we focus on those bankruptcy cases of retail chains that operated in several states and that end up in full liquidation of all the stores.

There are 21 such cases in the data affecting a total of 6,418 individual stores in our sample. The mean (median) number of stores of these retail chains is 305.6 (113) and ranges from 18 stores (KS Merchandise Mart) to 2,831 (Movie Gallery). All retail chains operate in more than one state,

[8] The first statistic here simply reflects the fact that there were no store closures as a result of retail-chain liquidations in 2005.

[9] Note that the Discovery Channel Retail Stores liquidation did not result from a Chapter-11 filing but rather from a voluntary closure of the entire chain.

with the least diversified chain operating in only two states (Joe's Sports Outdoors More) and the most geographically dispersed chain operating in all fifty states (Movie Gallery). Finally, as the last two columns of Table 4 demonstrate, all chain except Joe's Sports Outdoors More operate in more than one region of the U.S. For example, eight chains have operations in all nine census divisions, and 19 out of the 21 retail chain operate stores in at least four different census divisions. While two retailers seem to be less geographically dispersed (Joe's Sports Outdoors More and Gottschalks) they do not drive our results and excluding them from the calculation of liquidated stores does not affect our findings. Furthermore, Figures 5, 6 and 7 illustrate the geographical dispersion of the initial stores locations of three firms that ended up in full liquidation used in the empirical identification: Circuit City, Linens 'N Things, and The Sharper Image. As the figures demonstrate, and consistent with the statistics in Table 4, these retail companies had dispersed geographical operation.

Given their geographic dispersion, it is unlikely that the collapse of these chains is driven by localized economic shocks related to a particular store or sub-area. Of course, this does not rule out the concern that nation-wide, liquidating stores were positioned in worse locations. We address this concern in the next section.

B. The Initial Location of Liquidated Chain Stores

The previous section presents evidence that most liquidated chains are geographically dispersed across states and U.S. regions. In this section we show that stores of liquidated chains were not located in zip codes with worse economic characteristics than the location of stores operated by non-bankrupt chains. In order to estimate the relation between local economic conditions and store location, we run a linear probability model of future store liquidation. Specifically, we test the relation between belonging to a chain that eventually ends up in liquidation and the following measures of zip code level economics variables: (i) median income, (ii) median house value, and (iii) median house price growth from 2002 to 2006. We estimate the following regression:

$$\begin{aligned} Liquidated_{i,z,t} &= \alpha + \beta_1 \times log(median\ income)_{z,2000} + \beta_2 \times log(house\ value)_{z,2000} \\ &+ \beta_3 \times \%\Delta house\ price_{2002-2006,z} + \beta_4 \times Mall_i + \mathbf{b_i}\boldsymbol{\delta} + \epsilon_{\mathbf{i,t}} \end{aligned} \tag{1}$$

where the dependent variable is an indicator variable equal to one if a store is operated by a national retail chain that will end up in liquidation at some point in the future, and zero otherwise;

log(median income)$_{z,2000}$ is the natural log of median household income at the zip code in the 2000 Census; log(house value)$_{z,2000}$ is the natural log of median house value at the zip code in the 2000 Census; %Δ house price$_{2002-2006,z}$ is the percentage change in median house price during the period 2002-2006 in the zip code and is based on data from Zillow; Mall is a dummy variable that takes the value of one if the store is located in a large shopping mall, and zero otherwise; and **b** is a vector of either state or county fixed-effects. The coefficients of interest are β_1, β_2 and β_3 which measure the effect of local economic conditions on store location. Table 5 presents the results from estimating different variants of the model and displays standard errors (in parentheses) that are clustered at the zip code level as we do throughout the paper. Given that the location of a specific store does not change over time we estimate cross-sectional rather than panel regressions for each of the years 2005, 2006 and 2007, separately.[10]

As the first column of Panel A of Table 5 demonstrates, stores of national retail chains that end-up in liquidation after the year 2005 are located in zip codes with economic characteristics that are either not statistically different or actually better than zip codes of stores belonging to chains that do not end up in liquidation. While the two variables that pertain to house prices reported in the first column of Panel A are statistically insignificant, log(median household income) is higher in zip codes where liquidated stores are located. We obtain similar results in Column 2 where we use county instead of state fixed-effects.[11] Columns 3 and 4 repeat the store location analysis in Columns 1 and 2 but for the year 2006 rather than 205. Again, the results show that stores of retail chains that end up in liquidation are located in zip codes that are similar to the location of other stores in terms of median house value, and house price appreciation.[12] As the table demonstrates, the difference between the location of liquidated chain stores and the location of non-liquidated chain stores is that stores of liquidated chains are located in zip-codes with slightly higher median household income (as indicated by the positive coefficients on log median household income). Finally, in the last two columns of Panel A, we study the location of stores of liquidated chain stores in the year 2007 and obtain similar results. We repeat the analysis in Panel B using IRS data on county level median adjusted gross income per household. We obtain similar results to those reported in Panel A indicating that liquidated chain stores are located in counties with

[10]We stop at 2007 given that almost all these stores ended up in liquidation in either 2008 or 2009.

[11]We cannot control for zip-code fixed-effects since the census data, which is at the zip code-level, are only for the year 2000.

[12]While β_2 is negative and marginally significant in this specification its economic magnitude is small.

higher median household income.

In summary, Table 5 demonstrates that along the observables there are little significant differences between the location of liquidated chain stores and the location of stores belonging to retail chains that do not undergo liquidation. Moreover, the only slight difference in terms of location is that liquidated chain stores are more likely to be located in zip codes with slightly higher median household income. These results confirm that the initial location of stores of national chains that end up in liquidation is not a likely cause of their failure. Thus, given the geographical dispersion of these chains and the zip codes in which they are located, closures of these stores are unlikely to be driven by worse local economic conditions. However, one remaining concern is that the locations of liquidating national chains suffered more during the economic downturn even though their initial location was no worse. As discussed below we address this point directly through the inclusion zip-by-year fixed effects.

V. The Effect of Bankruptcy on Store Closures

A. Baseline Regressions

We begin with a simple test of the negative externalities hypothesis by estimating a linear probability model of store closures conditional on the liquidation of neighboring stores that result from a national retailer chain-wide liquidation. We estimate different variants of the following baseline specification.

$$
\begin{aligned}
Closed_{i,t} \quad &= \quad \alpha + \beta_1 \times n(same\ address)_{i,t-1} + \beta_2 \times n(0 < distance \leq 50)_{i,t-1} \\
&+ \quad \beta_3 \times n(50 < distance \leq 100)_{i,t-1} + \beta_4 \times log(income\ per\ capita)_{z,t} \\
&+ \quad \beta_5 \times income\ growth_{z,t} + \mathbf{b_i}\boldsymbol{\delta} + \mathbf{d_t}\boldsymbol{\theta} + \epsilon_{\mathbf{i,t}} \qquad (2)
\end{aligned}
$$

where the dependent variable is an indicator variable equal to one if a store is closed in a given year, and zero otherwise; n(same address), n(0<distance≤50) and n(50<distance≤100) are the number of stores that were closed in bankruptcies of chains that were fully liquidated and that are (1) located in the same address; (2) located in a different address but are within a 50 meters radius of the store under consideration; and (3) stores that are located in a radius of more than 50 meters but less than 100 meters from the store under consideration, respectively. log(income per capita) is the county level median adjusted gross income per capital; income growth is the annual growth

rate in adjusted gross income per capita within a zip code, both income measures are constructed from the IRS data. **b** is a vector of either state, county or zip code fixed-effects; **d** is a vector of year fixed-effects and ϵ is a regression residual. We focus our analysis on stores of chains that are not currently undergoing a national liquidation to avoid mechanical correlation between the dependent and explanatory variables.[13] That is, we eliminate from the sample stores that are operated by the retail chains reported in Table 4 during their bankruptcy years. Table 6 presents the results from estimating different variants of the model and displays standard errors (in parentheses) that are clustered at the zip code level.

Column 1 of Table 6 presents the results of regression (2) using only year fixed effects. As can be seen, there is a positive relation between the number of stores closed as part of a national chain-wide liquidation and the probability that stores of non-bankrupt firms in the same address will close. Thus, consistent with the externalities conjecture, increases in bankruptcies and store closures are associated with further closings of neighboring stores. The effect is economically sizable: being located in the same address as a liquidating retail-chain store increases the probability of closure by 0.36 percentage points, or 5.9 percent of the sample mean. We also find that the negative effect of store closures is confined to stores located in the same address given that the coefficients on both n($0<\text{distance}\leq 50$) and n($50<\text{distance}\leq 100$) are not statistically different from zero. As shown below, once heterogeneity is added to the analysis we capture effects at longer distances.

Column 2 of the table repeats the analysis in Column 1 while adding state fixed effects to the specification. As can be seen, the results remain qualitatively and quantitatively unchanged: bankruptcy induced stores closures lead to additional closings of stores in the same area. Columns 3 and 4 repeat the analysis but add either county or zip-code fixed effects to the specification and hence control for unobserved heterogeneity at a finer geographical level. As can be seen in the table, we continue to find a positive relation between stores that are closed in full liquidation bankruptcies and subsequent store closures in the same address.

Further, the inclusion of either county or zip-code fixed effects increases the marginal effect of same address store closures considerably from 0.0036 and 0.0037 to 0.0042 and 0.0065 in the county and zip fixed-effects specifications, respectively. Thus, Table 6 demonstrates that having one neighboring store close down as part of a national retail liquidation increases the likelihood that stores in the same address will close by between 5.9 and 10.7 percent relative to the unconditional

[13]See Angrist and Pischke (2009) page 196.

mean.[14] The results point to agglomeration economies in retail, as the reduction of store density in a given locality exhibits a negative effect on other stores in the area, increasing their likelihood of closure. This is consistent with evidence in Gould and Pashigian (1998) and Gould, Pashigian and Prendergast (2005) which show that store level sales may depend on the sales of neighboring stores.

Finally, Columns 5 and 6 include county-by-year or zip-code-by-year fixed effects and hence control for unobserved *time-varying* heterogeneity at a fine geographical level. The inclusion of these fixed effects soaks-up any time-varying local economic conditions that may be correlated with the likelihood of store closures. As can be seen in Columns 5 and 6 we continue to find a positive relation between stores that are closed in full liquidation bankruptcies and subsequent store closures in the same address. These results alleviate concerns that the locations of liquidating national chains suffered more during the economic downturn even though their initial location was no worse.

Turning to the control variables in Table 6, in the first three columns the coefficient of log(income per capita) is either positive or not statistically significant in explaining individual store closures. Moreover, as would be expected, the first three columns of Table 6 also suggest that stores are less likely to be closed in zip codes in which income grows over time. Furthermore, in our specifications that include zip-code fixed effects in which we control for unobserved geographical heterogeneity at a finer level (Column 4) we find that income per capita has a negative and significant effect on the likelihood that a store closes down, again, as one would expect.

A.1 Neighboring Bankrupt Stores and Closing of Stores by Distance

We next turn to estimate the externalities effects of further away store closures. We supplement the analysis in Table 6 by adding additional distance ranges to the specification in regression (2).

[14]The fact that the relevant coefficients rise after including county or zip level fixed effects may be suggestive of the fact that stores of liquidating retail chains are located, if anything, in better areas on average, as seen above.

Specifically, we estimate the following model:

$$\begin{aligned}
Closed_{i,t} &= \alpha + \beta_1 \times n(same\ address)_{i,t-1} + \beta_2 \times n(0 < distance \leq 50)_{i,t-1} \\
&+ \beta_3 \times n(50 < distance \leq 100)_{i,t-1} + \beta_4 \times n(100 < distance \leq 150)_{i,t-1} \\
&+ \beta_5 \times n(150 < distance \leq 200)_{i,t-1} + \beta_6 \times n(200 < distance \leq 250)_{i,t-1} \\
&+ \beta_7 \times n(250 < distance \leq 300)_{i,t-1} + \beta_8 \times n(300 < distance \leq 350)_{i,t-1} \\
&+ \beta_9 \times n(350 < distance \leq 400)_{i,t-1} + \beta_{10} \times n(400 < distance \leq 450)_{i,t-1} \\
&+ \beta_{11} \times n(450 < distance \leq 500)_{i,t-1} + \beta_{12} \times log(income\ per\ capita)_{z,t} \\
&+ \beta_{13} \times income\ growth_{z,t} + \mathbf{b_i}\boldsymbol{\delta} + \mathbf{d_t}\boldsymbol{\theta} + \epsilon_{\mathbf{i,t}} \qquad (3)
\end{aligned}$$

Table 7 reports the results of regression (3) using the four different fixed-effects specifications used in Table 6. As the table demonstrates, out of the eleven distance measures, β_1 – the coefficient on n(same address) – is the only estimate that is both statistically and economically significant. While β_1 ranges from 0.004 (in the year fixed-effects specification) to 0.007 (in the zip-code fixed-effects specification), almost all the other estimates are much smaller and are not statistically different from zero. Only the coefficient on n(300<distance≤350) is negative and marginally significant. The results in Table 7 confirm our baseline results and demonstrate that when analyzing average effects the negative externality of store closures is mostly driven by very near stores. However, we return to this result below when analyzing the externality effect of store closures on neighboring stores belonging to chains of differing financial health and differing industries.

B. Falsification Exercise: Placebo Regressions

We supplement our analysis by performing a placebo exercise, the results of which are reported in Table 8. For each of the distance measures in Regression (2) and Table 6 we define a "placebo" variable which counts for each store in our sample the number of neighboring stores that are part of a national chain that will liquidate in the *following* year but that are currently not in liquidation. Following our baseline regression, we define these placebo variables for each of the three distance groups – same address, up to 50 meters and above 50 meters but below 100 meters. Thus, the falsification variables are simply the distance based liquidating store closure counter variables forwarded one period ahead. We then run the following variant of our baseline specification:

$$\begin{aligned} Closed_{i,t} &= \alpha + \beta_1 \times n(same\ address)_{i,t-1} + \beta_2 \times n(0 < distance \leq 50)_{i,t-1} \\ &+ \beta_3 \times n(50 < distance \leq 100)_{i,t-1} \\ &+ \beta_4 \times n(same\ address)_{i,t+1} + \beta_5 \times n(0 < distance \leq 50)_{i,t+1} \\ &+ \beta_6 \times n(50 < distance \leq 100)_{i,t+1} \\ &+ \beta_7 \times log(income\ per\ capita)_{z,t} + \beta_8 \times income\ growth_{z,t} \\ &+ \mathbf{b_i}\boldsymbol{\delta} + \mathbf{d_t}\boldsymbol{\theta} + \epsilon_{\mathbf{i,t}} \end{aligned} \tag{4}$$

where the first three variables are the lagged store closure counter variables and the following three variables are the forwarded store closure counter variables. By including both lagged and forwarded variables, we attempt to uncover the time-stamp of the store-closure externality separately from the endogenous (soon to be bankrupt) retail-chain store location. Since the externality of store closure is likely to arise only *after* the store closes – as only then does costumer traffic drop – the externality effect predicts that the forwarded variables will not be significant while the lagged variables will be significant. In contrast, if the locations of liquidating chain stores were endogenous and correlated with omitted variables that predict local store closure, we would expect to find the forwarded variables positively related to store closure.

As can be seen in Table 8, the results are consistent with an externality effect. The coefficients on the lagged variables, β_1, β_2, and β_3, are identical to our baseline results in Table 6. The coefficient on the fourth variable – i.e. the forwarded n(same address)$_{i,t+1}$ – is negative and significant in the first two models. However, once we move to the preferred specification which includes both year and zip-code fixed-effects this coefficient becomes much smaller (-0.0022 in Column 3 as compared to -0.0060 in Column 1) and is no longer statistically significant. Further, the forwarded variables using the greater distance store closure counters are not statistically significant. Taken together the results show that the effect of store liquidation on subsequent store closures is not driven by the location of the retail chain-stores that will later become bankrupt but rather by the timing in which they were actually closed.

C. Stores Closings Inside Shopping Malls

Prior work has shown that anchor stores in shopping malls create positive externalities on other non-anchor stores by attracting customer traffic. Mall owners internalize this externality by providing rent subsidies to anchor stores. Indeed, the rent subsidy provided to anchor stores as compared to non-anchor stores estimated at no less than 72 percent suggests that these positive externalities are economically large. Given the importance of anchor stores within malls, we next focus our analysis on the potential externalities that arise when an anchor store in a shopping mall closes. To maintain our identification strategy, we focus only on the effects of anchor store closures that are a result of the liquidation of a national retail chain.

We match our data on retail chain stores to Esri's Major Shopping Centers, a panel dataset of major U.S. shopping centers that lists the name and address of each of the malls and includes data on gross leasable area in the mall, the number of stores, and the names of up to four anchor tenants in the mall. There are 4,421 unique malls that are matched to 104,217 store-year observations. The average mall has a gross leasable area (GLA) of 474,019 square feet (median=349,437) and ranges from a 25th percentile of 259,086 sqf to a 75th percentile of 567,000 sqf. The matched malls span all of the fifty states and the District of Columbia. Figure 8 presents the geographical distribution of the malls that are matched to our data as well as the shopping mall gross leasable area.

Next, to estimate the externality generated by store closures within malls, we rerun our baseline regressions only on stores that have been matched to the Esri Mall database. Similar to the baseline regressions, our main dependent variable in this regression, *same mall*, is simply the number of retail-chain stores in the mall that close due to the liquidation of the entire chain. Our data enable us to control for mall fixed-effects (as opposed to just zip-code fixed effects) in addition to the year dummies which further alleviates concerns about the initial location of stores of chains that end-up in liquidation.

As Column 1 of Table 9 shows, we find that store closings within a mall lead to further store closures within a mall. When a store closes in a mall, the subsequent annual closure rate of other stores in the mall increases by 0.3 percentage points, or 4.9% of the sample mean. In Column 2 we add a second variable that counts the number of anchor stores within a mall that are closed as a result of the liquidation of a national retail chain. As the table shows, we find that most of the effect within malls is coming from anchor stores: The coefficient on *same mall* becomes insignificant while that on the number of national liquidating anchor stores rises to 0.009. The effect of anchor store closure is thus triple that of the average effect of non-anchor stores, consistent with prior research pointing to the impact of anchor stores in drawing in costumers. The economic effect is sizable with an anchor store closure causing a 14.7% increase in the probability of store closures within the mall relative to the unconditional mean.

One caveat that should be noted in regards to this effect is that some firms insert co-tenancy clauses into their lease contracts, which provide them the option to terminate their leases when certain stores close. Thus, the increase in the externality effect could be explained both by the greater importance of anchor stores in drawing traffic to malls, as well as the higher flexibility that fellow stores enjoy in terminating their leases when an anchor store closes.

In a separate set of regressions, we also analyze the effect of store closures on stores located outside malls. Table 10 repeats our baseline analysis in Table 6 for stores that were not matched to the Esri's Mall database. There are 550,364 stores in our data that are not part of matched malls. Such stores are either not located in shopping malls, or are located in smaller malls that are not matched to the Esri Mall database. As the table demonstrates, the coefficient on n(same address)$_{i,t-1}$ is positive and significant statistically indicating once again a negative externality of store closure on stores located in the same address.[15] Comparing the coefficients on the *same-address* variable in Table 10 to those in Table 9 indicates that the effect of store closure outside shopping malls on other stores located in the same address is similar to that of the effect of an anchor store closure.[16] One potential reason for this is that due to the small number of stores in small shopping malls or in buildings where stores collocate, any store closure will have a relatively large impact on other stores nearby.[17]

VI. Heterogeneity in the Response to Store Closures

In order to understand better the mechanisms through which store closures spread to further closing of stores, we add heterogeneity to our empirical analysis. In this section we investigate the transmission of negative externalities that are imposed by bankruptcies of neighboring stores further by studying the differential effect of store closures along the following three peer characteristics: (i) across industries; (ii) conditional on a firm's financial strength; and (iii) store size.

[15]Note that retail stores collocating in the same address could either be stores not in a mall but in the same building, or stores located in a mall which was not matched to the Esri database.

[16]Taking into account the standard errors of these coefficients shows that the coefficients are not statistically different for one another.

[17]This also explains why the coefficient on *same address* is larger when focusing on stores not matched to malls than the sample-wide effect of *same address*; The latter effect includes the impact of non-anchor store closure within malls, which as Table 9 shows, is small.

A. The Effect of Bankrupt Stores by Industry

We begin by analyzing whether the effect of store closures on neighboring store closures depends on the industrial composition of stores in the same vicinity. Some spatial models of imperfect competition predict that firms will choose to locate as far from their newest competitors as possible (Chamberlin (1933), Nelson (1970), Salop (1979), Stuart (1979)). The key result of these models is that the further away other stores are from a particular store, the greater market power that specific store will have with respect to the consumers located near it. If so-called centrifugal competition is the main factor driving stores locations in the U.S., we should expect that store closures will benefit nearby stores that are in the same retail segment. This is simply because the remaining stores will end up facing less competition.

Alternative spatial models suggest that it may be optimal for stores in the same industry to locate next to one another. According to this view, the geographical concentration of similar stores is driven by consumers' imperfect information. For example, Wolinsky (1983) writes:

> *"[I]mperfectly informed consumers are attracted to a cluster of stores because that is the best setting for search. A store may thus get more business and higher profits when it is located next to similar stores. This effect may outweigh centrifugal competitive forces..."*[18]

Indeed, research in urban economics have provided a good deal of evidence for the existence of economies of agglomeration and industrial clusters.[19]

To test how product substitutability and similarity influences the effect of retail store closures on neighboring retail stores, we use the North American Industry Classification System (NAICS) definition of an industry. To assign firms into industries, we employ two definitions that are based on 5-digit and 6-digit NAICS codes.

Specifically, for each store in our sample we define *same industry* analogs of n(same address), n(0<distance≤50), and n(50<distance≤100) which count only the number of liquidating retail-chain stores that are in the same industry of the given store, where industry identity is defined using either 5- or 6-digit NAICS. For each store, we also define *different industry* exposures to stores of liquidating national retail chains in an analogous manner. We then estimate, separately,

[18] Wolinsky (1983) p. 274.

[19] See for example, Ellison and Glaeser (1997), Henderson et al. (1995), and Rosenthal and Strange (2003)).

the effect of *same industry* and *different industry* store closures on subsequent store closings in their area. Results that are based on 5-digit NAICS are presented in Table 11.

As the table shows, we find that the effect of *same industry* store closures is bigger than *different industry* store closures. In the specification that controls for year and zip-code fixed-effects we find that the coefficient on n(same address) is 0.009 for *same industry* compared to 0.006 in the *different industry* regression. Moreover, we also find a positive and significant effect of our second distance measure, n($0<$distance≤ 50), in the *same industry* regressions. This effect is quite sizable: the coefficient of 0.018 (significant at the 5 percent level) in Column 3 implies that the effect of having one store close increases the likelihood of further store closure by 29.5 percent relative to the unconditional mean for stores in the same industry and that are located within a 50m radius of the closing store. In contrast, as Columns 4-6 show, there is no effect of *different industry* n($0<$distance≤ 50) on further store closures. We repeat the analysis using a 6-digit NAICS definitions and obtain very similar results.[20]

B. Store Closures and Firm Profitability

We further investigate the transmission of negative externalities that are imposed by bankruptcies of neighboring stores by studying the joint impact of a firms financial health and neighboring store closures on the likelihood that a firm will close its own store. We hypothesize that the effect of neighboring store closures on the likelihood that a store will close should be larger for stores owned by parent firms that have low profitability. Less profitable firms are financially weaker, making them more vulnerable to a decline in demand that is driven by the reduction in traffic associated with neighboring stores closing down. We therefore introduce an interaction variable between profitability and each of the local store closures into the specification estimated in the regressions reported in Table 12.[21]

In Table 12 we run the analysis separately with different fixed-effects to control for geographic heterogeneity. All regressions control for lagged values of firm size (natural log of book value of assets), leverage (defined as total debt divided by lagged assets), and profitability (EBITDA divided by assets).[22] Column 1 of the table includes year fixed-effects, Column 2 includes year and state fixed-effects, while Columns 3 and 4 each control for year and either county or zip-code fixed-effects.

[20] These results are omitted for brevity and are available upon request.
[21] See Benmelech and Bergman (2011) for a similar approach.
[22] Appendix A provides detailed definitions for each of the variables.

As in the rest of the analysis in the paper, standard errors are clustered at the zip code level.

As can be seen in Table 12, the coefficients on all three measures of bankrupt stores – n(same address), n(0<distance≤50), and n(50<distance≤100) – are positive and statistically significant, indicating that stores closed in large retail-chain liquidations lead to additional store closures in their vicinity. Consistent with the prediction of the joint effect of financial distress and store closures, we find that the effect of local store closure is amplified when the retailer operating the neighboring store is experiencing low profitability. The coefficients on the interaction terms between each of the three distance measures and profitability is negative and significant suggesting that financially stronger firms can weather the decline in revenue that is caused by store closings in the area.

More specifically, the estimates imply that a local store closure increases the likelihood that a store in the same address with a parent firm in the 25th percentile of profitability will also close by 1.03 to 1.36 percentage points, which represent an increase of 16.9 to 22.2 percent relative to the unconditional mean. In contrast, when the parent of the store is in the 75th percentile of the sample profitability, the effect of of store closure on the likelihood of same-address store closure is not statistically different from zero. Similar to the effect of store closures on same-address stores, the coefficient on the interaction term between n(0<distance≤50) and profitability is negative and statistically significant at the ten percent level (the effect ranges from -0.0471 to -0.0485) with standard errors of approximately 0.03) but only in the specification without county or zip code fixed effects.[23] Finally, the coefficient on the interaction term between n(50<distance≤100) and profitability is negative and statistically significant in all specifications, including those with zip-code fixed effects. The magnitude of the coefficients indicate that a store closure 50 to 100 meters away increases the likelihood that a store with a parent in the 25th percentile of the profitability distribution will close by 9.0 to 14.8 percent relative to the unconditional mean.

Moving to the firm-level variables, the results show that on average larger retailers are less likely to close their stores while more leveraged retailers are more likely to close their stores. Interestingly, we find that more profitable retailers are on average more likely to close their stores. One explanation for this finding could be that more profitable firms are more likely to experiment when choosing store locations, and hence are more likely to close stores which they find not to be profitable.

Taken together, our results show that stores of weaker firms are strongly affected by the closure

[23] Note, though, that the coefficient on the interaction term barely changes across all specifications.

of neighboring stores. The negative externality of store closure is greater on weaker firms than on stronger ones and, as Table 12 shows, the effect carries over larger distances. Stores of weaker firms thus seem to be more reliant on the existence of agglomeration economies. When these agglomeration are destroyed through the liquidation of neighboring stores, weaker stores are pushed towards economic inviability and shut down. Given an initial financial weakness in a geographic area, store closures can thus propagates across the area.

C. Store Size and the Effect of Bankrupt Stores

We continue by analyzing how store size affects the impact of store closures on the decision of neighboring stores to close. We hypothesize that a larger store will be more resilient to the closure of neighboring stores as compared to a smaller store since larger stores may be less reliant on neighboring stores to bring in costumer traffic. Further, to the extent that retailers act more quickly to shut down unsuccessful large stores as compared to unsuccessful small stores, for example, due to the greater impact larger stores have on retailers' bottom line, larger stores will on average be more profitable than smaller ones. Similar to the results in the prior section, we would then expect larger stores to be more resilient to local store closures.

We rerun our baseline regressions analyzing the likelihood of store closure while interacting store size, as measured by the number of employees in each store, with each of the three local store closure variables, n(same address), n(0<distance≤50), and n(50<distance≤100). We add the usual set of control variables which include the host of year and geographic fixed effects. The results are reported in Table 13.

As can be seen in the table, we find a negative coefficient on the interaction term between store size and the n(same address) variable which measures the number of store closures of liquidating national retail chains in a given address. Consistent with our hypothesis, the negative coefficient on the interaction term implies that larger stores are indeed less affected than smaller ones by the closure of stores located in the same address. The economic effect is sizable: Focusing on the specification with zip-code fixed effects, following the shutdown of a neighboring store, a store in the 25th percentile of the size distribution experiences a 47 percent rise in the probability of closure relative to the mean. In contrast, a store in the the 75th percentile of the size distribution experiences only a 8.2 percent rise in the probability of closure. The data thus support the hypothesis that larger stores are more resilient to neighboring store closures and less reliant on agglomeration economies to generate traffic.

VII. Conclusion

Most empirical work on agglomeration economies focuses on the creation of economies of agglomeration through the endogenous choice of firm entry. In this paper, rather than focusing on the endogenous creation of agglomeration economies we study how downturns damage economies of agglomeration. Our analysis shows that bankrupt firms impose negative externalities on non-bankrupt neighboring firms through the weakening of retail agglomeration economies. Store closures naturally lead to reduced attractiveness of retail areas as customers prefer to shop in areas with full vacancy. This, in turn, leads to declines in demand for retail services in the vicinity of bankrupt stores, causing contagion from financially distressed companies to stores of non-bankrupt firms. We argue that in downturns agglomeration economies may propagate bankruptcies and financial distress.

Appendix A: Variable description and construction

This section documents the definitions of the variables used in the empirical analysis.

1. *Market-to-book*: total book value of assets (AT) plus the market value of equity ($AT + CSHO * PRCC_F$) minus the book value of equity deferred taxes (CEQ+TXDB), all over total assets (AT*0.9) plus the market value of assets (MKVALT*0.1) (source: Compustat Annual Fundamental files).

2. *Leverage*: total debt (DLTT+DLC+DCLO) divided by total assets (AT) (source: Compustat Annual Fundamental files).

3. *Profitability*: EBITDA (OIBDP) divided by beginning-of-period total assets (AT) (source: Compustat Annual Fundamental files).

4. *Size*: natural log of total assets (AT) (source: Compustat Annual Fundamental files).

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Figure 1: **Store locations as of 2005.**

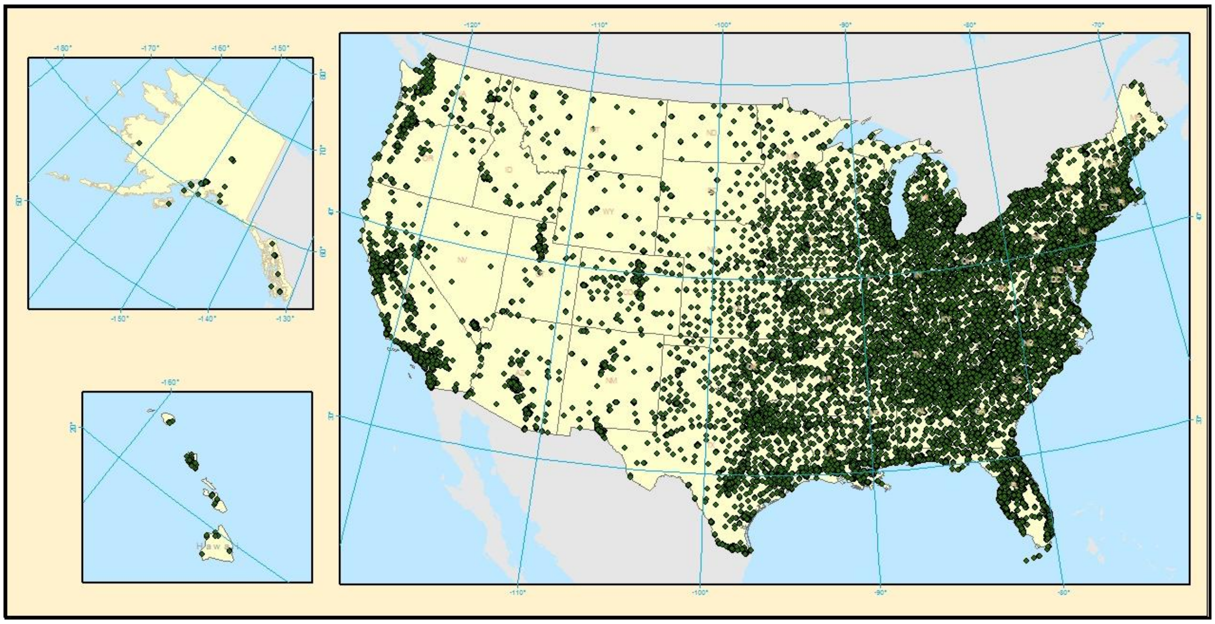

Figure 2: **Store locations as of 2010.**

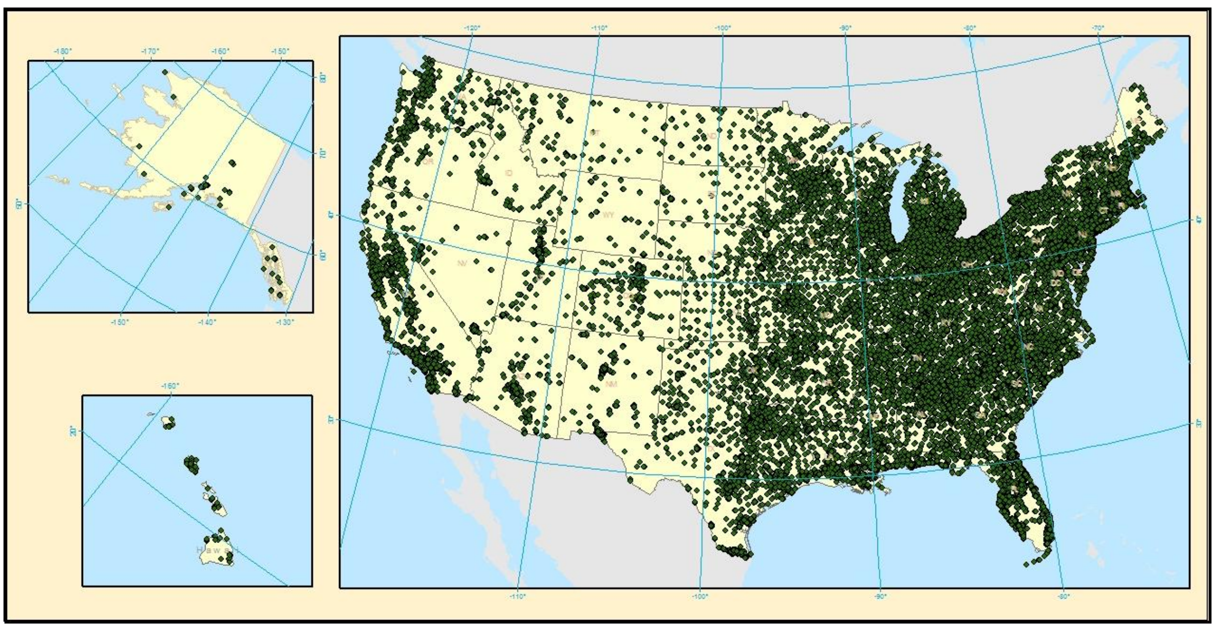

Figure 3: **Stores Closings during 2007.**

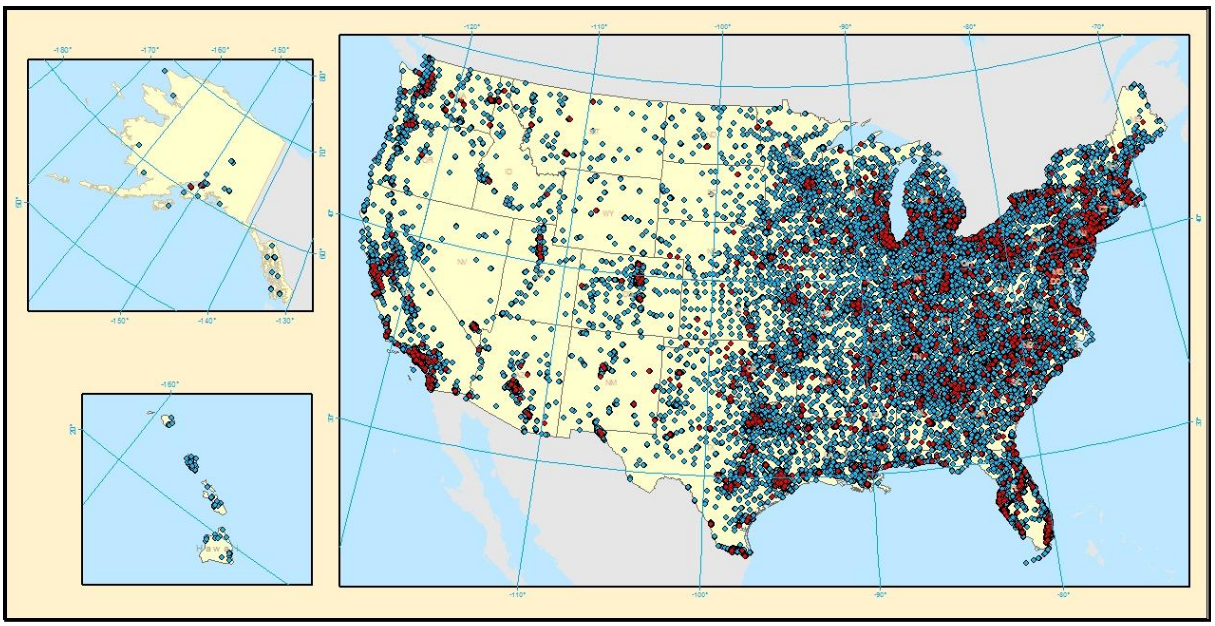

Figure 4: **Stores Closings during 2008.**

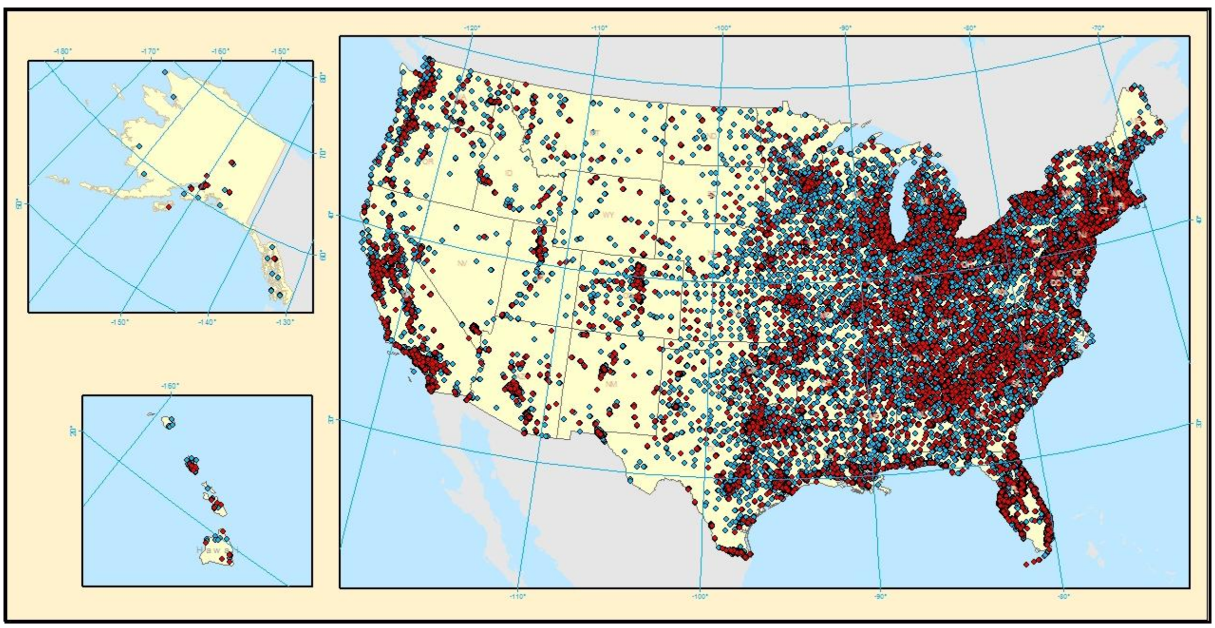

Figure 5: **Stores Locations for Circuit City.**

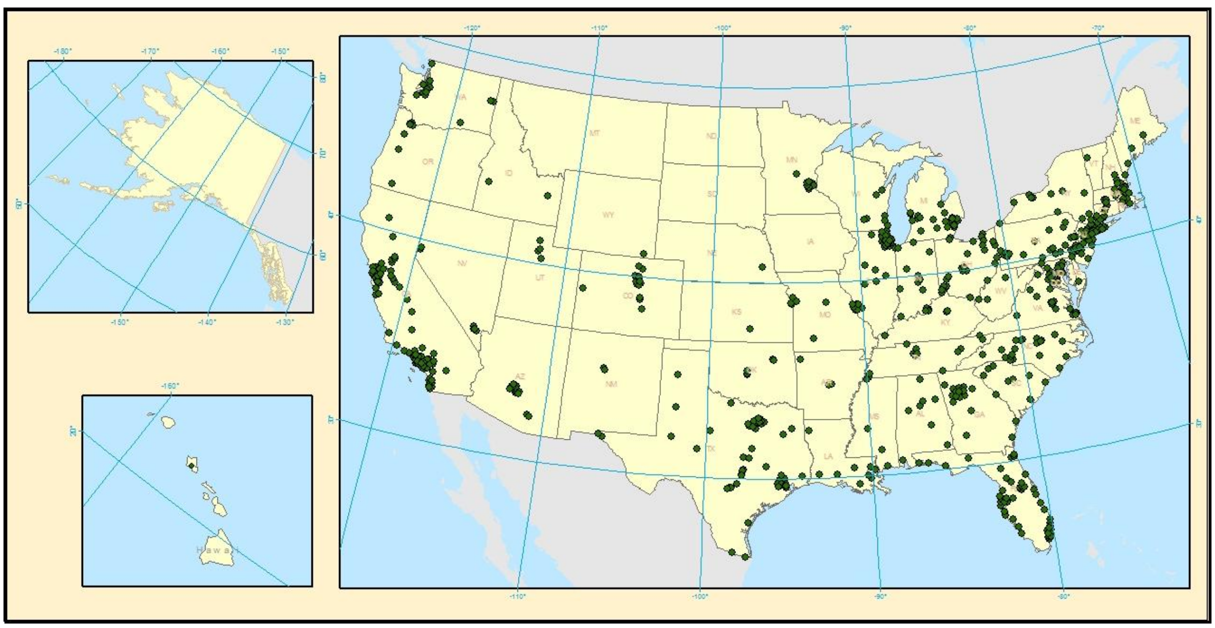

Figure 6: **Stores Locations for Linens 'N Things.**

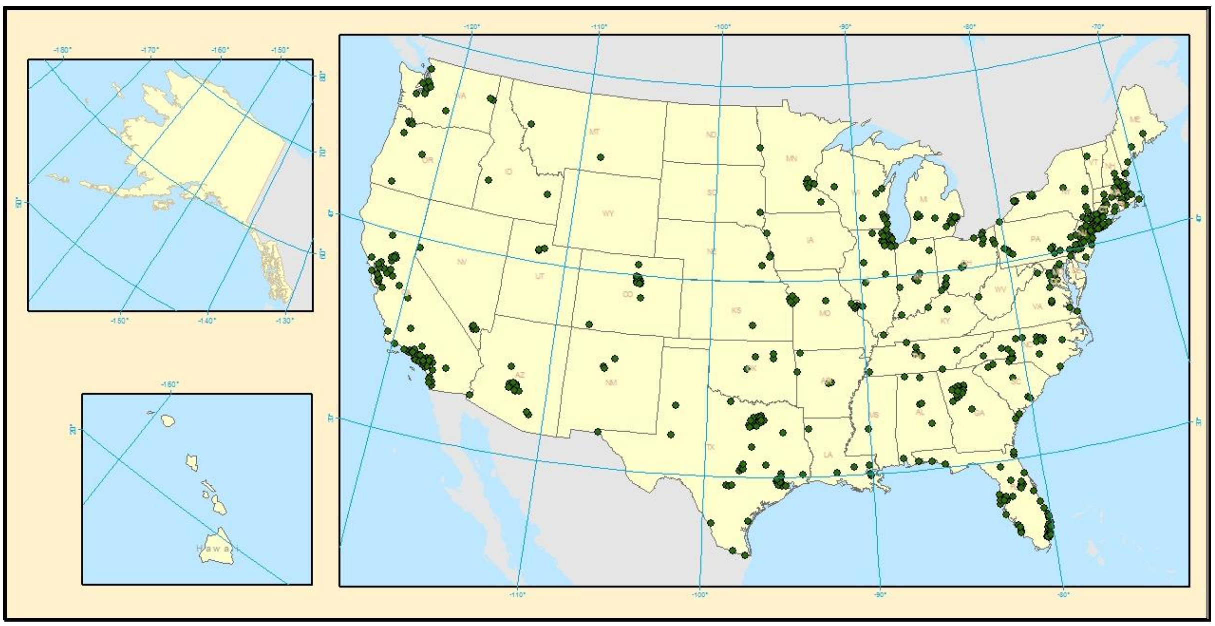

Figure 7: **Stores Locations for The Sharper Image.**

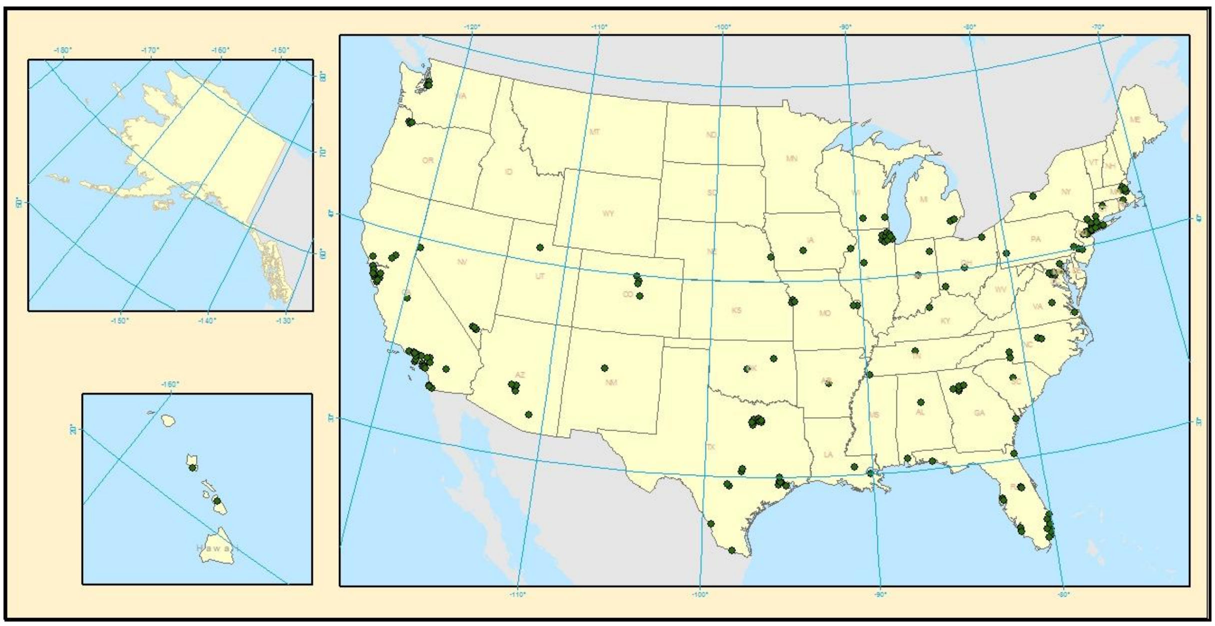

Figure 8: **Shopping Malls location and size.**

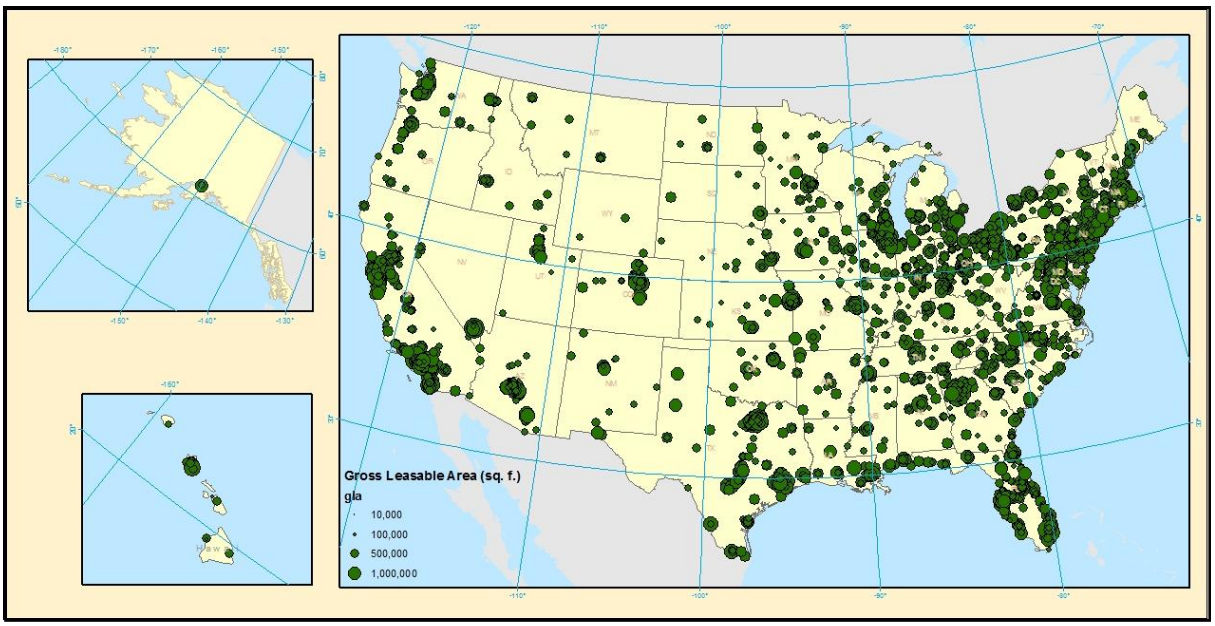

Table 1:
Individual Store Closings

This table provides descriptive statistics on store closings and bankrupt stores. Panel A displays all store closings. Panel B presents bankrupt stores, Panel C presents store closings that result from full liquidation bankruptcies. Variable definitions are provided in Appendix A.

Panel A: Closed Stores over Time

Year	Mean	25th Percentile	Median	75th Percentile	Standard Deviation	Min	Max	Observations
2005-2009	0.061	0.0	0.0	0.0	0.239	0.0	1.0	661,382
2005	0.048	0.0	0.0	0.0	0.213	0.0	1.0	84,388
2006	0.085	0.0	0.0	0.0	0.279	0.0	1.0	125,897
2007	0.014	0.0	0.0	0.0	0.116	0.0	1.0	147,551
2008	0.110	0.0	0.0	0.0	0.313	0.0	1.0	148,432
2009	0.047	0.0	0.0	0.0	0.211	0.0	1.0	155,114

Panel B: Bankrupt Stores over Time

Year	Mean	25th Percentile	Median	75th Percentile	Standard Deviation	Min	Max	Observations
2005-2010	0.021	0.0	0.0	0.0	0.142	0.0	1.0	827,156
2005	0.010	0.0	0.0	0.0	0.100	0.0	1.0	84,388
2006	0.008	0.0	0.0	0.0	0.091	0.0	1.0	125,897
2007	0.029	0.0	0.0	0.0	0.167	0.0	1.0	147,551
2008	0.042	0.0	0.0	0.0	0.201	0.0	1.0	148,432
2009	0.026	0.0	0.0	0.0	0.158	0.0	1.0	155,114
2010	0.004	0.0	0.0	0.0	0.063	0.0	1.0	165,774

Panel C: Stores Closed in Full Liquidation Bankruptcies over Time

Year	Mean	25th Percentile	Median	75th Percentile	Standard Deviation	Min	Max	Observations
2005-2009	0.010	0.0	0.0	0.0	0.100	0.0	1.0	661,382
2005	0.002	0.0	0.0	0.0	0.049	0.0	1.0	84,388
2006	0.003	0.0	0.0	0.0	0.058	0.0	1.0	125,897
2007	0.001	0.0	0.0	0.0	0.033	0.0	1.0	147,551
2008	0.0186	0.0	0.0	0.0	0.135	0.0	1.0	148,432
2009	0.0193	0.0	0.0	0.0	0.137	0.0	1.0	155,114

Table 2:
Bankrupt Retail Companies

This table provides information on the main retail bankruptcy cases used in our analysis. The table lists the name of the bankrupt company, its bankruptcy filing date, whether it emerged or not from bankruptcy, the bankruptcy outcome, the date in which the case was disposed, the time spent in bankruptcy and the number of stores operated by the company in the time of the bankruptcy filing.

Company	Filing date	Emerge?	Used in identification	Bankruptcy outcome	Date disposed	Number of stores
KB Toys	12/11/2008	No	Yes	Liquidated	2/16/2010	461
Gadzooks	2/3/2004	No	No	Acquired	2/17/2006	243
D K Stores	4/8/2005	No	Yes	Liquidated	2/9/2006	54
Norstan Apparel Shops	4/8/2005	No	Yes	Acquired	5/26/2005	229
Ultimate Electronics	1/11/2005	No	No	Acquired	12/9/2005	65
G+G Retail	1/25/2006	No	Yes	Liquidated	12/6/2006	515
KS Merchandise Mart	10/3/2006	No	Yes	Liquidated	N/A	17
Tower Record	8/20//2006	No	Yes	Liquidated	8/6/2007	89
Hancock Fabrics	3/21/2007	Yes	No	Reorganized	8/1/2008	373
Movie Gallery	2/2/2010	No	Yes	Liquidated	11/18/2010	2,415
The Dunlap	7/10/2007	No	Yes	Liquidated	N/A	38
Tweeter Home Entertainment Group	11/5/2008	No	Yes	363 sale	7/13/2007	104
The Sharper Image Corporation	2/19/2008	No	Yes	363 sale	8/13/2012	184
Linens 'n Things	5/2/2008	No	Yes	363 sale	6/12/2009	589
Mervyn's	7/29/2008	No	Yes	Liquidated	10/27/2008	177
Boscov's	8/4/2008	No	No	Liquidated	12/4/2007	49
National Wholesale Liquidators	11/10/2008	No	Yes	Liquidated	N/A	55
Value City Department Stores	10/26/2008	No	Yes	Liquidated	2/26/2009	66
Circuit City Stores	11/10/2008	No	Yes	363 sale	9/20/2010	721
Goody's	1/13/2009	No	Yes	Liquidated	7/3/2009	287
Gottschalks	1/14/2009	No	Yes	Liquidated	2/28/2011	58
S & K Famous Brands	2/9/2009	No	Yes	Liquidated	3/16/2010	136
Ritz Camera Centers	2/22/2009		No	N/A	N/A	N/A
Joe's Sports Outdoors More	3/24/2009	No	Yes	Liquidated	4/14/2009	31
Filene's Basement	5/24/2009	No	No	Liquidated	2/10/2010	25
Eddie Bauer Holdings	6/17/2009	No	No	363 sale	3/18/2010	371
Rex Stores	2/1/2009	No	Yes	Liquidated	N/A	111
Loehmann's Holdings	11/15/2010	Yes	No	Reorganized	2/9/2011	48

Table 3:
Neighboring Store Closures

This table provides descriptive statistics on full liquidation closings of neighboring stores. Panel A displays store closings in the same address. Panels B and C present store closings for 0-50 meter and 50-100 meter distances. Panel D lists summary statistics for distances that are between 150 and 500 meter. Variable definitions are provided in Appendix A.

Panel A: Same address

Year	Mean	25th Percentile	Median	75th Percentile	Standard Deviation	Min	Max	Observations
2005-2010	0.028	0.0	0.0	0.0	0.181	0.0	3.0	827,156
2005	0.0	0.0	0.0	0.0	0.0	0.0	0.0	84,388
2006	0.002	0.0	0.0	0.0	0.045	0.0	1.0	125,897
2007	0.038	0.0	0.0	0.0	0.192	0.0	2.0	147,551
2008	0.016	0.0	0.0	0.0	0.127	0.0	2.0	148,432
2009	0.085	0.0	0.0	0.0	0.327	0.0	3.0	155,114
2010	0.009	0.0	0.0	0.0	0.100	0.0	2.0	165,774

Panel B: Not Same Address and Distance $\leq$ 50 meters

Year	Mean	25th Percentile	Median	75th Percentile	Standard Deviation	Min	Max	Observations
2005-2010	0.012	0.0	0.0	0.0	0.115	0.0	3.0	827,156
2005	0.0	0.0	0.0	0.0	0.0	0.0	0.0	84,388
2006	0.002	0.0	0.0	0.0	0.044	0.0	1.0	125,897
2007	0.009	0.0	0.0	0.0	0.099	0.0	2.0	147,551
2008	0.003	0.0	0.0	0.0	0.055	0.0	2.0	148,432
2009	0.038	0.0	0.0	0.0	0.207	0.0	3.0	155,114
2010	0.010	0.0	0.0	0.0	0.111	0.0	2.0	165,774

Panel C: 50 meters $<$ distance $\leq$ 100 meters

Year	Mean	25th Percentile	Median	75th Percentile	Standard Deviation	Min	Max	Observations
2005-2010	0.008	0.0	0.0	0.0	0.094	0.0	3.0	827,156
2005	0.0	0.0	0.0	0.0	0.0	0.0	0.0	84,388
2006	0.001	0.0	0.0	0.0	0.030	0.0	1.0	125,897
2007	0.005	0.0	0.0	0.0	0.075	0.0	2.0	147,551
2008	0.002	0.0	0.0	0.0	0.044	0.0	1.0	148,432
2009	0.025	0.0	0.0	0.0	0.166	0.0	3.0	155,114
2010	0.008	0.0	0.0	0.0	0.103	0.0	2.0	165,774

Panel D: Further Away Store Closures 2005-2010

Year	Mean	25th Percentile	Median	75th Percentile	Standard Deviation	Min	Max	Observations
100 - 150 meters	0.007	0.0	0.0	0.0	0.087	0.0	3.0	827,156
150 - 200 meters	0.006	0.0	0.0	0.0	0.085	0.0	3.0	827,156
200 - 250 meters	0.020	0.0	0.0	0.0	0.151	0.0	4.0	827,156
250 - 300 meters	0.006	0.0	0.0	0.0	0.082	0.0	3.0	827,156
300 - 350 meters	0.006	0.0	0.0	0.0	0.083	0.0	4.0	827,156
350 - 400 meters	0.006	0.0	0.0	0.0	0.079	0.0	3.0	827,156
400 - 450 meters	0.006	0.0	0.0	0.0	0.081	0.0	3.0	827,156
450 - 500 meters	0.006	0.0	0.0	0.0	0.079	0.0	4.0	827,156

Table 4:
Retail Chains Fully Liquidated

This table provides information on the geographical dispersion of the liquidated retail chains used in the analysis.

Company	Number of Stores	Number of States	Number of Census Divisions	Largest Census Division
Circuit City Stores	570	44	9	S. Atlantic
D K Stores	54	5	3	Mid Atlantic
Discovery Channel Retail Stores	107	32	9	Pacific
G+G Retail	314	40	9	S. Atlantic
Goody's	377	21	5	S. Atlantic
Gottschalks	60	6	2	Pacific
Joe's Sports Outdoors More	26	2	1	Pacific
KB Toys	483	44	9	Mid Atlantic
KS Merchandise Mart	18	5	3	E. N. Central
Linens 'n Things	496	48	9	S. Atlantic
Mervyn's	169	8	3	Pacific
Movie Gallery	2,831	50	9	Pacific
National Wholesale Liquidators	44	12	4	Mid Atlantic
Norstan Apparel Shops	147	21	6	S. Atlantic
Rex Stores	113	34	9	S. Atlantic
S & K Famous Brands	43	11	5	S. Atlantic
The Dunlap	38	8	4	W. S. Central
The Sharper Image Corporation	178	38	9	Pacific
Tower Record	88	20	8	Pacific
Tweeter Home Entertainment Group	104	22	8	S. Atlantic
Value City Department Stores	105	15	5	E. N. Central

Table 5:
Store Locations

This table presents coefficient estimates and standard errors in parentheses for linear probability models of stores locations. Panel A uses zip-code level economic controls while Panel B utilize county-level controls. All regressions include an intercept, and either state or county fixed effects (not reported). Standard errors are calculated by clustering at the zip code level. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Zip-code level controls

	(1)	(2)	(3)	(4)	(5)	(6)
log(median household income)	0.017***	0.016***	0.017***	0.015***	0.011***	0.011***
	(0.005)	(0.006)	(0.003)	(0.004)	(0.003)	(0.003)
log(median house value)	-0.001	-0.001	-0.004*	-0.003	-0.002	-0.002
	(0.004)	(0.005)	(0.002)	(0.003)	(0.002)	(0.003)
Median house price growth,	0.001	0.001	0.000	-0.002	-0.0003	-0.0003
2002-2006	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)
Mall	0.034***	0.033***	0.016***	0.015***	0.014***	0.014***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)
Year	2005	2005	2006	2006	2007	2007
Fixed-effects	State	County	State	County	State	County
Observations	51,984	51,984	77,809	77,809	90,523	90,523
Adjusted-R-squared	0.008	0.013	0.004	0.007	0.003	0.006

Panel B: County level control

	(1)	(2)	(3)	(4)	(5)	(6)
log(adjusted gross income)	0.024***	0.026***	0.011***	0.009***	0.005***	0.002
	(0.003)	(0.004)	(0.002)	(0.003)	(0.001)	(0.002)
Mall	0.032***	0.031***	0.017***	0.016***	0.014***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Year	2005	2005	2006	2006	2007	2007
Fixed-effects	State	County	State	County	State	County
Observations	83,506	83,506	121,172	121,172	137,610	137,610
Adjusted R-squared	0.010	0.016	0.004	0.009	0.003	0.008

Table 6:
Neighboring Bankrupt Stores and Store Closures

This table presents coefficient estimates and standard errors in parentheses for linear probability models of store closures. All regressions include an intercept and year fixed-effects. Models 2, 3, and 4 include state, county, and zip-code fixed-effects, respectively. Model 5 includes county*year and Model 6 includes zip*year fixed effects. Standard errors are calculated by clustering at the zip code level. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Full liquidation bankrupt stores closures$_{t-1}$						
same address	0.0036**	0.0037**	0.0042***	0.0065***	0.0033	0.007
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
distance $\leq$ 50 meters	0.0003	0.0005	0.0002	-0.0024	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
50 meters $<$ distance $\leq$ 100 meters	0.0019	0.0024	0.0022	0.0007	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Ln(income per capita)	0.0066***	0.0052***	-0.0049	-0.0650***		
	(0.002)	(0.002)	(0.003)	(0.009)		
Income growth	-0.0328***	-0.0381***	-0.0304***	0.0071		
	(0.009)	(0.009)	(0.009)	(0.011)		
Fixed-effects	Year	Year+State	Year+County	Year+Zip	Year-by-County	Year-by-Zip
Observations	654,581	654,581	654,581	654,581	654,581	654,581
Adjusted R-squared	0.021	0.021	0.027	0.062	0.050	0.160

Table 7:
Neighboring Bankrupt Stores and Store Closures by Distance

This table presents coefficient estimates and standard errors in parentheses for linear probability models of store closures. All regressions include an intercept and year fixed-effects. Models 2, 3, and 4 include state, county, and zip-code fixed-effects, respectively. Standard errors are calculated by clustering at the zip code level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Full liquidation bankrupt stores closures$_{t-1}$				
same address	0.004**	0.004**	0.004***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
distance $\leq$ 50 meters	0.0002	0.0004	0.0002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
50 meters $<$ distance $\leq$ 100 meters	0.002	0.002	0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
100 meters $<$ distance $\leq$ 150 meters	0.002	0.002	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.005)
150 meters $<$ distance $\leq$ 200 meters	0.003	0.003	0.002	0.001
	(0.005)	(0.005)	(0.005)	(0.005)
200 meters $<$ distance $\leq$ 250 meters	-0.001	-0.000	-0.000	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)
250 meters $<$ distance $\leq$ 300 meters	0.003	0.004	0.003	0.001
	(0.004)	(0.004)	(0.004)	(0.004)
300 meters $<$ distance $\leq$ 350 meters	-0.003	-0.002	-0.003	-0.005*
	(0.003)	(0.003)	(0.003)	(0.003)
350 meters $<$ distance $\leq$ 400 meters	0.002	0.003	0.003	0.000
	(0.003)	(0.003)	(0.003)	(0.003)
400 meters $<$ distance $\leq$ 450 meters	0.004	0.005	0.004	0.001
	(0.004)	(0.004)	(0.003)	(0.003)
450 meters $<$ distance $\leq$ 500 meters	0.005	0.005	0.002	-0.001
	(0.007)	(0.007)	(0.006)	(0.006)
Ln(income per capita)	0.007***	0.005***	-0.005	-0.065***
	(0.002)	(0.002)	(0.003)	(0.009)
Income growth	-0.033***	-0.038***	-0.030***	0.007
	(0.009)	(0.009)	(0.009)	(0.011)
Fixed-effects	Year	Year+State	Year+County	Year+Zip
Observations	654,581	654,581	654,581	654,581
Adjusted R-squared	0.021	0.022	0.027	0.062

Table 8:
Neighboring Bankrupt Stores and Placebo Store Closures

This table presents coefficient estimates and standard errors in parentheses for linear probability placebo models of store closures. All regressions include an intercept and year fixed-effects. Models 1, 2, and 3 include state, county, and zip-code fixed-effects, respectively. Standard errors are calculated by clustering at the zip code level. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Full liquidation bankrupt stores closures$_{t-1}$			
same address	0.004***	0.005***	0.007***
	(0.002)	(0.002)	(0.002)
distance $\leq$ 50 meters	0.001	0.0002	-0.002
	(0.002)	(0.002)	(0.002)
50 meters $<$ distance $\leq$ 100 meters	0.002	0.002	0.001
	(0.003)	(0.003)	(0.003)
Placebo full liquidation bankrupt stores closures$_{t+1}$			
same address	-0.0060***	-0.0054***	-0.0022
	(0.001)	(0.001)	(0.001)
distance $\leq$ 50 meters	-0.0022	-0.0018	-0.0012
	(0.002)	(0.002)	(0.002)
50 meters $<$ distance $\leq$ 100 meters	0.0010	0.0015	0.0024
	(0.003)	(0.003)	(0.003)
Ln(income per capita)	0.0053***	-0.0046	-0.0647***
	(0.002)	(0.003)	(0.009)
Income growth	-0.0381***	-0.0305***	0.0069
	(0.009)	(0.009)	(0.011)
Fixed-effects	Year+State	Year+County	Year+Zip
Observations	654,581	654,581	654,581
Adjusted R-squared	0.022	0.027	0.062

Table 9:
Mall Bankrupt Stores and Mall Store Closures

This table presents coefficient estimates and standard errors in parentheses for linear probability models of mall-based store closures. All regressions include an intercept and year and mall fixed-effects. Standard errors are calculated by clustering at the zip code level. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Full liquidation bankrupt stores closures$_{t-1}$		
same mall	0.003*	0.002
	(0.002)	(0.002)
same mall anchor store		0.009**
		(0.004)
Ln(income per capita)	-0.046*	-0.048*
	(0.027)	(0.027)
Income growth	0.094**	0.095**
	(0.038)	(0.038)
Fixed-effects	Year+Mall	Year+Mall
Observations	104,217	104,217
Adjusted R^2	0.094	0.094

Table 10:
Non-Mall Bankrupt Stores and Non-Mall Store Closures

This table presents coefficient estimates and standard errors in parentheses for linear probability models of non-mall store closures. All regressions include an intercept and year fixed-effects. Models 2, 3, and 4 include state, county, and zip-code fixed-effects, respectively. Standard errors are calculated by clustering at the zip code level. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Full liquidation bankrupt stores closures$_{t-1}$				
same address	0.0115***	0.0118***	0.0115***	0.0087**
	(0.004)	(0.004)	(0.004)	(0.004)
distance $\leq$ 50 meters	-0.0015	-0.0013	-0.0008	-0.0034
	(0.003)	(0.003)	(0.003)	(0.003)
50 meters $<$ distance $\leq$ 100 meters	0.0053	0.0056	0.0060*	0.0039
	(0.004)	(0.004)	(0.004)	(0.003)
Ln(income per capita)	0.0089***	0.0071***	-0.0023	-0.0682***
	(0.002)	(0.002)	(0.003)	(0.009)
Income growth	-0.0442***	-0.0491***	-0.0413***	0.0002
	(0.010)	(0.011)	(0.010)	(0.011)
Fixed-effects	Year	Year+State	Year+County	Year+Zip
Observations	550,364	550,364	550,364	550,364
Adjusted R-squared	0.021	0.022	0.028	0.067

Table 11:
Bankrupt Stores Industry and Store Closures (5-digit NAICS)

This table presents coefficient estimates and standard errors in parentheses for linear probability models of store closures. The tables presents results for store closures in the same industry as well as store closures in different industries. All regressions include an intercept and year fixed-effects. Models 1, 2, and 3 include state, county, and zip-code fixed-effects, respectively. Models 4, 5, and 6 also include state, county, and zip-code fixed-effects, respectively. Standard errors are calculated by clustering at the zip code level. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Full liquidation bankrupt stores closures **same** industry$_{t-1}$						
same address	0.008*	0.008*	0.009**			
	(0.004)	(0.004)	(0.004)			
distance $\leq$ 50 meters	0.022**	0.022**	0.018**			
	(0.009)	(0.009)	(0.009)			
50 meters $<$ distance $\leq$ 100 meters	0.002	0.002	-0.004			
	(0.009)	(0.009)	(0.010)			
Full liquidation bankrupt stores closures **different** industry$_{t-1}$						
same address				0.003**	0.004**	0.006***
				(0.002)	(0.002)	(0.002)
distance $\leq$ 50 meters				-0.001	-0.001	-0.004
				(0.002)	(0.002)	(0.003)
50 meters $<$ distance $\leq$ 100 meters				0.003	0.002	0.001
				(0.003)	(0.003)	(0.003)
Ln(income per capita)	0.005***	-0.005	-0.066***	0.005***	-0.005	-0.065***
	(0.002)	(0.003)	(0.009)	(0.002)	(0.003)	(0.009)
Income growth	-0.038***	-0.030***	0.007	-0.038***	-0.030***	0.007
	(0.009)	(0.009)	(0.011)	(0.009)	(0.009)	(0.011)
Fixed-effects	Year+State	Year+County	Year+Zip	Year+State	Year+County	Year+Zip
Observations	654,581	654,581	654,581	654,581	654,581	654,581
Adjusted R^2	0.022	0.027	0.062	0.022	0.027	0.062

Table 12:
Bankrupt Stores Firm Profitability and Store Closures

This table presents coefficient estimates and standard errors in parentheses for linear probability models of store closures conditional on firm profitability. All regressions include an intercept and year fixed-effects. Models 2, 3, and 4 include state, county, and zip-code fixed-effects, respectively. Standard errors are calculated by clustering at the zip code level. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Full liquidation bankrupt stores closures$_{t-1}$				
same address	0.0329***	0.0332***	0.0345***	0.0364***
	(0.004)	(0.004)	(0.004)	(0.004)
$\times$Profitability$_{t-1}$	-0.1679***	-0.1683***	-0.1709***	-0.1698***
	(0.016)	(0.016)	(0.016)	(0.016)
distance $\leq$ 50 meters	0.0110*	0.0116**	0.0109*	0.0066
	(0.006)	(0.006)	(0.006)	(0.006)
$\times$Profitability$_{t-1}$	-0.0478*	-0.0485*	-0.0471	-0.0475
	(0.029)	(0.029)	(0.029)	(0.030)
50 meters $<$ distance $\leq$ 100 meters	0.0227***	0.0233***	0.0241***	0.0205***
	(0.008)	(0.008)	(0.008)	(0.008)
$\times$Profitability$_{t-1}$	-0.1085***	-0.1082***	-0.1123***	-0.1114***
	(0.037)	(0.037)	(0.037)	(0.038)
Size$_{t-1}$	-0.0067***	-0.0068***	-0.0067***	-0.0066***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage$_{t-1}$	0.1024***	0.1027***	0.1029***	0.1043***
	(0.003)	(0.003)	(0.003)	(0.003)
Profitability$_{t-1}$	0.0846***	0.0853***	0.0858***	0.0859***
	(0.006)	(0.006)	(0.006)	(0.006)
Ln(income per capita)	0.0076***	0.0056**	-0.0027	-0.0899***
	(0.002)	(0.002)	(0.004)	(0.011)
Income growth	-0.0116	-0.0095	-0.0089	0.0415***
	(0.013)	(0.013)	(0.013)	(0.016)
Fixed-effects	Year	Year+State	Year+County	Year+Zip
Observations	359,675	359,675	359,675	359,675
Adjusted R^2	0.030	0.030	0.040	0.090

Table 13:
Store Size and Store Closures

This table presents coefficient estimates and standard errors in parentheses for linear probability models of store closures conditional on store size. All regressions include an intercept and year fixed-effects. Models 2, 3, and 4 include state, county, and zip-code fixed-effects, respectively. Standard errors are calculated by clustering at the zip code level. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Full liquidation bankrupt stores closures$_{t-1}$				
same address	0.058***	0.059***	0.060***	0.050***
	(0.009)	(0.009)	(0.009)	(0.010)
×Store size	-0.014***	-0.014***	-0.014***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)
distance ≤ 50 meters	-0.007	-0.007	-0.006	-0.010
	(0.010)	(0.011)	(0.011)	(0.011)
×Store size	0.003	0.003	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)
50 meters < distance ≤ 100 meters	-0.001	-0.001	0.001	-0.001
	(0.009)	(0.009)	(0.009)	(0.009)
×Store size	-0.0002	-0.0001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Store size	-0.004***	-0.004***	-0.004***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(income per capita)	0.0001	-0.001	-0.007*	-0.023
	(0.002)	(0.002)	(0.004)	(0.014)
Income growth	0.032**	0.029*	0.027*	0.037**
	(0.015)	(0.015)	(0.015)	(0.015)
Fixed-effects	Year	Year+State	Year+County	Year+Zip
Observations	181,066	181,066	181,066	181,066
Adjusted R^2	0.016	0.017	0.030	0.121