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Zombie lending due to the fear of fire sales

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ABSTRACT

This paper provides evidence of a new cost of fire sales: zombie lending by banks. Banks with high market share are more likely to internalize the negative spillovers of falling collateral prices during a fire sale. To prevent prices from falling further during a fire sale, these banks do not liquidate defaulted firms and instead give zombie loans to keep them alive. Using structural breaks in real estate prices to identify periods of fire sales in different MSAs, we provide evidence that banks with high market share give zombie loans to firms with relatively higher real estate assets during a fire sale. Further, congestion due to zombie firms in an industry reduces the investment and profitability of healthier firms. Overall, we highlight a new mechanism for zombie lending resulting from reduced collateral liquidation in markets prone to fire sales.

1. Introduction

Fire sale of real assets occurs when the assets of financially distressed firms are sold at prices that are below their fair value because other specialist buyers may not have enough liquidity to buy these assets (Shleifer and Vishny, 1992). These fire sales generate negative spillover effects and reduce the value of firms holding similar assets (Kiyotaki and Moore, 1997; Brunnermeier and Pedersen, 2009). Since fire sales are both privately costly and socially inefficient because the assets are bought by nonspecialists at low prices,[1] market participants take actions to avoid it (Shleifer and Vishny, 2011).[2] Lenders may also internalize the negative externalities generated by fire-sale; for instance, Giannetti and Saidi (2019) find that lenders with large market share in an industry continue to provide liquidity to distressed firms in that industry and internalize negative spillover of industry downturns. We conjecture that if such support goes to otherwise insolvent or "zombie" firms, it may create another externality by diverting resources away from healthier firms (Caballero et al., 2008), possibly hindering creative destruction.

We use the real estate market in the US as our setting. Firms use real estate as collateral when they raise capital (Chaney et al., 2012; Gan, 2007; Cvijanović, 2014). However, real estate markets are illiquid and prone to fire-sale externalities during economic downturns (Harding et al., 2009; Campbell et al., 2011; Anenberg and Kung, 2014; Hartley, 2014). This paper examines

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[1] For evidence on the cost of fire sale, see Pulvino (1998), Campbell et al. (2011), Almeida et al. (2011), Benmelch and Bergman (2011), Carvalho (2015), among others.

[2] For example, Benmelech and Bergman (2009) show that airlines renegotiate their lease obligations downwards when they are financially stressed and the liquidation value of their aeroplanes is low. Also, see Asquith et al. (1994), Almeida et al. (2011), Schlingemann et al. (2002), Ortiz-Molina and Phillips (2010) for evidence of actions taken by agents to avoid fire sale.

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whether lenders keep credit flowing to otherwise insolvent borrowers (zombie firms) during real estate downturns to avoid fire-sale externalities in real estate markets. We show that banks that have a high market share in a metropolitan statistical area (MSA) and are therefore more exposed to a fire sale of real estate are more likely to internalize the cost of a fire sale in that MSA give zombie loans to firms with relatively high real estate assets when the local real estate market is under stress and subject to a fire sale.

We begin our analysis by building a theoretical model to illustrate this new externality of zombie lending due to fear of fire sales. Firms borrow from banks using their real estate assets as collateral. Some of these firms default when faced with a negative shock and turn into low-productivity firms, which we call zombie firms. Banks can either liquidate these firms and sell their real estate collateral or keep them alive by giving negative NPV zombie loans. Very few firms default during the *normal* state, whereas several firms default during the *adverse* state. Since very few firms default in the normal state, banks can liquidate these firms and sell their collateral at a fair price as there are enough buyers and the market is liquid. However, in the adverse state, when many firms default, buyers do not have enough liquidity to buy the assets of the defaulted firms. Hence, there will be cash-in-the-market pricing (Allen and Gale, 1994), and assets will be sold at fire-sale price, resulting in a decline in real estate price. The price decline further deteriorates the health of the local economy and affects the value of the loan portfolio of banks.

Atomistic banks take prices as given and do not internalize the effects of fire sales when they decide to liquidate a loan; hence, they liquidate all their loans. However, larger banks internalize the effect of their decision to liquidate on the price at which they will sell the collateral and also on the value of their loan portfolio. Hence, they extend zombie loans to insolvent firms instead of liquidating them. In our model, banks with higher market share give more zombie loans, particularly to firms with higher real estate collateral. This is because liquidating firms with higher real estate collateral will have a larger impact on price when there is already a fire sale going on in the market.

We conduct our empirical analysis and test the model's implications in several steps. Our model suggests that when there is a fire sale in an MSA, banks with higher market shares will give zombie loans to firms with relatively high real estate in that MSA. Since a fire sale in an MSA is not directly observable, we create two proxies for when an MSA is undergoing a fire sale. First, we assume that there is a fire sale in an MSA when the local real estate price is declining. This proxy for identifying fire sales may not be exogenous because while prices will decline when there is a fire sale in an MSA, they may also decline due to fundamental shocks, such as productivity shocks to the firms in the MSA. If these shocks are, for some reason, correlated with zombie lending in the MSA, then there will be an endogeneity problem.

To overcome this challenge, we create another exogenous proxy for fire sale in an MSA. This method of identifying fire sale and our arguments herein are closely based on Charles et al. (2018). We say that an MSA is undergoing a fire sale if there is a negative structural break in the real estate price trend of that MSA. That is, there is a *sharp* decline in the real estate price in that MSA. The structural break in the price trend of an MSA is estimated using standard methods in time-series econometrics (Bai, 1997; Bai and Perron, 1998). The underlying assumption is that these sharp price declines are not driven by changes in local fundamental factors because these factors move gradually; instead, these price declines are driven by speculative factors. The justification for our assumption comes from the emerging consensus in the existing literature, which has argued that the variation in real estate prices during the boom and bust of the global financial crisis was caused by a speculative "bubble" and not driven by fundamental factors like productivity or income. Since the sharp decline in prices are not driven by fundamentals, the real estate is effectively being sold at below their fundamental price, that is they are undergoing a fire sale.

We examine whether banks extended credit to distressed firms at subsidized rates, known as zombie lending when an MSA is undergoing a fire sale. Following Caballero et al. (2008), we identify zombie firms as those financially stressed firms that receive credit at interest rates lower than the most creditworthy firms in the economy. Firm-level analysis suggests that, indeed, banks extend credit to zombie firms, particularly firms with relatively high real estate assets. Firms with an above-median ratio of real estate assets to total assets have a 1.7% higher probability of receiving a zombie loan than firms with below-median real estate holdings when there is a price decline in an MSA. This result is in line with the predictions of our model, wherein banks are more likely to extend zombie credit to firms with higher collateral, as liquidating them would result in larger price declines. When a fire sale is identified by negative structural breaks, we find that above-median real estate firms are 2.1% more likely to be zombies than below-median real estate firms during the fire sale.

To test the model further and pin down the channel, we use data at the loan level and estimate how banks' market share in an MSA affects the probability of them giving loans to zombie firms. According to our model, a bank with a high market share will internalize the effect of price decline more than a bank with a low market share. We show that a one per cent (standard deviation) increase in a bank's market share in an MSA increases the probability of extending zombie credit to high real estate firms by 0.12% (1.3%) when there is a fire sale in that MSA as identified by a negative structural break or a price decline. Building on this channel, we conduct an alternate test and examine how bank market concentration affects zombie lending in an MSA. MSAs with higher bank concentration, as measured by the Herfindahl–Hirschman Index (HHI), are also associated with higher zombie lending to firms with high real estate assets during fire sales. In an MSA with one standard deviation (0.223 points) higher bank HHI, high real estate firms have a 6.6% (3.9%) higher likelihood of receiving a zombie loan compared to low real estate firms during a fire sale in that MSA, as identified by a negative structural break (price decline). Given that the conditional probability of a firm being a zombie is 4.2%, these magnitudes are economically significant.

Finally, we show that the presence of zombie firms harms the healthier non-zombie firms in an industry. Caballero et al. (2008) contend that zombie firms in an industry can divert resources, such as capital and labor, that would otherwise have been available to more efficient firms. Thus, they congest the market and affect the performance of healthier firms. Indeed, we find that a 1% increase in the share of zombie firms in an industry is associated with a 1.2% lower investment by healthy firms. The return on assets of non-zombie firms is also lower by 1%.

We conduct several more analyses to test the robustness of our results. First, we identify placebo fire sales by generating structural breaks and re-estimate our results 1000 times. We then compare the real coefficient estimates to the placebo estimates and find that the coefficients from the permuted data are nearer to zero than those from real data in over 95% of iterations, thus confirming the robustness of our results. We then use two alternative definitions of zombie firms. In the first alternative definition used by Acharya et al. (2019), we add a third restriction that the firm must have raised debt in the past year, and in the second zombie definition used by Banerjee and Hofmann (2018), we consider a firm as a zombie if its interest coverage ratio is less than 1 for past three years and the age of the firm is greater than five years. The new estimates using these definitions are comparable to the ones we obtained using our original definition. Additional tests include using alternative measures of real estate assets, which we call adjusted real estate used by Custódio et al. (2023), dropping firms headquartered in Delaware from the sample, excluding term-B loans from the sample, identifying high market share banks as those with above 10% market share, identifying market concentration in an MSA by the three-year average market share of top four banks and using logistic regression instead of OLS. Our results are robust even when using alternative definitions, samples and specifications.

This paper's key contribution is to show that as lenders internalize the negative externality of declining collateral prices by extending zombie credit, they create another externality by keeping unproductive firms alive. Thus, the actions that banks take may be privately or even locally optimal but may be inefficient for the economy as a whole.

Our paper contributes to several strands of literature. Prior literature has documented that fire sales exist and are costly; hence, lenders and borrowers take action to avoid fire sale of assets (Shleifer and Vishny, 2011). For example, Asquith et al. (1994) shows that distressed firms are more likely to restructure debt than liquidate their assets when the industry is facing a downturn. Schlingemann et al. (2002) find that firms divest business units from industries with more liquid markets rather than liquidating the worst-performing units. Banks with a high market share in an industry are also more likely to provide liquidity to firms during distress due to the fear of fire-sale externalities (Giannetti and Saidi, 2019).

We show that banks with a higher market share in the local market are more likely to internalize the effect of real estate price declines and extend zombie credit. Our result is analogous to Favara and Giannetti (2017), who show that banks with a higher market share are less likely to trigger foreclosures. Similarly, Gupta (2022) shows that lenders with larger market shares in mortgage markets increase the credit supply to low-quality, high-risk borrowers to prop up the house prices at the end of a boom. However, our paper highlights the *harmful* effects of keeping zombie firms alive. Our findings add to the extensive literature on the effects of bank concentration on different aspects of lending activity, such as the quantity of credit provision (Garmaise and Moskowitz, 2006) and bank–firm relationships (Petersen and Rajan, 1995). We highlight that bank concentration can affect a bank's ex-post decision to either liquidate a firm or extend zombie credit.

This paper also contributes to the literature on zombie loans. In their seminal paper, Caballero et al. (2008) show that zombie firms can make industries unproductive as they prevent creative destruction. The literature on the causes of zombie lending has shown that, in the presence of limited liability, under-capitalized banks have the incentive to engage in zombie lending (Giannetti and Simonov, 2013; Acharya et al., 2019; Blattner et al., 2018) as they are reluctant to liquidate firms and recognize losses. Our paper provides a novel channel through which zombie lending arises: to prevent the liquidation of assets in illiquid markets prone to fire sales.

Our paper also adds to the literature on the role of collateral in credit provision. Theoretical models starting with Besanko and Thakor (1987) and Hart and Moore (1994) have revealed the importance of collateral in alleviating agency frictions and increasing firms' access to credit. Companies with access to more deployable collateral receive larger loans with longer maturity and lower interest rates (Benmelech et al., 2005). Chaney et al. (2012) show that real estate is a significant source of collateral for firms and that increasing collateral value increases investments. Cvijanović (2014), on the other hand, shows that increasing real estate prices lead to an increase in firm leverage. Our paper shows that high real estate assets can help firms secure loans but for a different reason. Liquidating firms with more real estate will result in larger price externalities, and as a result, banks are prepared to extend zombie loans to such firms.

The rest of the paper is organized as follows: Section 1 presents a model of bank lending in which banks choose between liquidating firms or giving zombie loans. Section 2 discusses the data. Section 3 contains our empirical strategy. Section 4 presents the results, and Section 5 concludes.

2. Model

In our model economy, there are four kinds of agents: firms, banks, depositors and outside investors; and two dates, $t = 0$ and 1. At $t = 0$, there is a continuum of atomistic identical firms, each owns C units of real estate assets (or land) that can be used as collateral and has a positive NPV project which requires one unit of investment. There is a continuum of atomistic banks of mass one, which raise funds from insured depositors. Using these deposits, each bank finances a portfolio of 1 unit of a continuum of firms taking the real estate assets of the firm as collateral. The face value of each loan is denoted by F, which needs to be paid by the firms at $t = 1$.

The project owned by firms can either succeed or fail. There are two aggregate states of nature: normal and adverse. The probability of success is denoted by $q \in \{\alpha, \beta\}$, where α (β) is the probability of success in the normal (adverse) state. We assume $\alpha > \beta$. The project fails with the complementary probability. If the project fails, then the firm defaults and pays nothing. Now the bank has two options. First, it can liquidate the firm and sell the collateral C at prevailing market prices (to be determined later). The second option is to roll over the loan and provide the required financing to keep the firm alive. This rolled-over loan is essentially a zombie loan with a negative NPV and has a very low probability of success in the future. The total cost to the bank of giving this negative NPV zombie loan to a firm and keeping it alive is L.

If a firm's project succeeds, then it pays F to its bank. The *successful* firm is then endowed with another project that is financed by the same bank, and the process can repeat in the future. The continuation value of loans given by the bank to each successful firm is denoted by V. So we are assuming that the banks are not competitive and earn positive profits. Banks may be earning this profit because of some market power or information rent from relationship lending (Rajan, 1992).

As discussed above, if a firm fails at $t = 1$, then the bank can liquidate it and sell the collateral at the market price denoted by p. We assume that the intrinsic or fair value of one unit of land is given by Z which is independent of the aggregate state.[3] This value can be interpreted as the net present value that can be generated by the investors who buy the land. This means that an investor will never pay a price larger than Z. The economy also has outside investors who are ready to buy the land at $t = 1$. These outside investors have a total wealth of W.[4] The investors can be interpreted as experts who understand the local economy and the real estate markets. Their wealth characterizes the demand for real estate assets. One factor that could affect the size of the set of possible buyers, and thus determine W, is zoning regulation which determines the set of uses of the real estate property (Benmelech et al., 2005).

The equilibrium price is determined as follows. If a bank decides to give a zombie loan to a failed firm with probability λ and liquidate it with probability $1 - \lambda$, then the supply in the real estate market in the normal state is given by $(1 - \alpha)(1 - \lambda)C$. We assume that in the normal state very few firms fail, that is α is high enough (hence the supply is low enough) such that even if banks liquidate all their defaulted loans ($\lambda = 0$), the land is sold at the fair price Z.

Assumption 1 ($W > Z(1-\alpha)C$.)**.** The assumption says that the total wealth of outside investors is high enough to buy all liquidated collateral at price Z, which is the fair price. As the readers might have guessed, we will assume that in the adverse state many firms fail, that is β is high enough such that if all banks liquidate with probability one, then land will not be sold at the fair price.

Assumption 2 ($W < Z(1 - \beta)C$.)**.** If Assumption 2 holds, then there may be a fire sale in which case the price will be determined by cash available with the buyers, that is there will be cash-in-the-market pricing as in Allen and Gale (1994).[5] Under symmetric equilibrium, if all banks liquidate with probability $1 - \lambda$ in the adverse state, then the price is given by

$$p(\lambda) = \begin{cases} Z, & \text{if } W \geq (1-\beta)(1-\lambda)CZ. \\ \frac{W}{(1-\beta)(1-\lambda)C}, & \text{if } W < (1-\beta)(1-\lambda)CZ. \end{cases} \tag{1}$$

Thus the price is given by fair price if very few failed firms are liquidated (λ is high), else there is a fire sale and the price is determined by cash-in-the-market pricing. This price is weakly decreasing in $1 - \lambda$, i.e. weakly increasing in the number of zombie loans.

We assume that the continuation value of the loans given by a bank to successful firms, V, will be an increasing function of price which in our model depends on the number of firms operating in the economy. If more firms are operating because banks choose to roll over more loans, i.e. λ is higher, then the price is higher. There are many justifications for assuming that V increases with price. First, as the price of real estate falls, it may also reduce the home equity value of the residents in the area, who may in turn reduce their consumption (Mian et al., 2015). This reduced consumption will negatively affect the profitability of the local firms and reduce the value of loans given to them. Second, the profitability of a firm or the probability of its success depends on the number and scale of other firms functioning in the economy (Cooper and John, 1988). This is because firms use goods produced by other firms as inputs or the workers in one firm use their wage to consume goods produced by other firms. Thus, as the number of firms operating in the economy and their scale increases, the positive feedback loops on each other also increase which further increases the profitability and the probability of success. We assume that this will be true even if the firms are low-productive zombie firms as even they employ people and use inputs (see Bebchuk and Goldstein (2011)). Thus the banks have an incentive to keep zombie firms alive which also keeps the prices higher. Further, as pointed out by Benmelch and Bergman (2011), a higher price of collateral due to the prevention of bankruptcy can reduce the cost of capital and increase investment by neighboring firms. More investment would imply a larger scale of operation which will have a higher positive spillover effect on firms in the locality. We capture these ideas in a reduced form by assuming that V depends on p and is denoted by $V(p)$. Also, $V(.)$ is increasing ($V'(.) > 0$), concave ($V''(.) < 0$) and reaches its maximum at $p = Z$ ($V(Z) = \bar{V}$).

The state contingent utility function of a bank is given by

$$q(F + V(p(\lambda))) + (1-q)(1-\lambda)Cp(\lambda) - (1-q)\lambda L; \tag{2}$$

where q equals α (β) in the normal (adverse) state. The first term is the current revenue plus the continuation value of the successful firms. The second term is the revenue from the liquidation of collateral and the final term is the loss from zombie loans. There are two reasons a bank may want to give a zombie loan. The first reason is to increase the liquidation price of collateral and the second reason is to increase the continuation value which depends on the liquidation price. Next, we determine the equilibrium when all the banks are atomistic as has been assumed so far.

[3] At the cost of some notational complexity, we can relax this assumption, and instead assume that the fair value of the land at $t = 1$ depends on the state (normal or adverse), without changing the results.

[4] Again, the wealth of the investors can be taken to be state-dependent without changing the results.

[5] While in our model the supply of liquidity, W, is fixed which creates fire sale through cash-in-the-market pricing; we could alternatively have assumed the supply to be a decreasing function of price as in Diamond and Rajan (2011), and still generate fire sale and attain our results.

2.1. Equilibrium with atomistic banks

If all the banks are atomistic, then they all take the price as given and will choose their λ to maximize their utility. Since they cannot influence the price by their decision to either liquidate or give a zombie loan, they all choose not to give a negative NPV zombie loan and instead liquidate the firm in both states. So by Assumptions 1 and 2, in the normal state, the price will be equal to the fair value and in the adverse state, there will be cash-in-the-market pricing. The equilibrium is characterized by the following lemma.

Lemma 1. *When banks are atomistic, then in both states they choose $\lambda = 0$. In the normal state the price is given by Z and in the adverse state the price is given by $W/(1-\beta)C$.*

The more interesting scenario is one where all banks are not atomistic, which we analyze next.

2.2. Equilibrium when banks are not atomistic

Now let us assume that one of the banks, which we call the "large bank" has a higher fraction of market share denoted by $f < 1$ and the others are still atomistic. As before in the normal state, all banks will continue to liquidate all defaulted loans (no zombie lending), and the market price is given by Z because of Assumption 1. But in the adverse state, the large bank will internalize the effect of its liquidation strategy on the selling price of collateral as well as on the continuation value of the successful loans. The atomistic banks will continue to liquidate all loans in the adverse state since they will take the price as given. The following assumption ensures that in the adverse state, the price is below fair value.

Assumption 2' ($W < Z(1-f)(1-\beta)C$).

Assumption 2' is analogous to but stronger than Assumption 2. It implies that if all atomistic banks liquidate in the adverse state, then the supply in the adverse state is high enough that collateral will not be sold at fair price. Now if the large bank chooses the probability of zombie loan as λ, then the price is given by

$$p(\lambda) = \frac{W}{(1-\beta)C[1-\lambda f]}. \tag{3}$$

The utility function of the large bank in the adverse state is given by

$$\beta(F + V(p(\lambda))) + (1-\beta)(1-\lambda)Cp(\lambda) - (1-\beta)\lambda L.$$

This expression is the same as (2), where q takes value β; but now the price is given by (3) rather than (1). The large bank chooses λ to maximize its utility. We denote the equilibrium value of λ by λ^*. The first order condition w.r.t. λ can be written as:

$$(1-\beta)(1-\lambda)Cp'(\lambda) + \beta V'(p(\lambda))p'(\lambda) - (1-\beta)Cp(\lambda) - (1-\beta)L = 0. \tag{4}$$

As discussed above, there are two benefits of giving a zombie loan. First, it increases the price of collateral that is liquidated, as captured by the first term. Second, the increased price increases the value of V (expressed by the second term). The third term captures the cost of forgoing the cash received by liquidation and selling the collateral. The final term captures the cost of the negative NPV zombie loan. The large bank will internalize these costs and benefits and choose the optimal λ accordingly.

Clearly, if L is very large, then the banks will never do zombie lending as it will be very costly. So to simplify our analysis, we assume that L is a small number close to zero.[6] The next proposition says that large banks will give zombie loans with positive probability ($\lambda^* > 0$) under suitable conditions. Further, as the market share of the large bank increases, it gives zombie loans to a higher fraction of failed firms.

Proposition 1. *If Assumptions 1 and 2' hold true, L is close to zero and*

$$\frac{dV(p(0))}{dp} > \frac{(1-\beta)(1-f)C}{\beta f} > \frac{dV(p(1))}{dp}, \tag{5}$$

then there exists a unique $\lambda^* \in (0,1)$ which maximizes the large bank's utility. Also, λ^* increases as f increases.

Proof. See appendix.

The intuition for the result is simple. More liquidation results in a lower selling price which further results in lower continuation value of the second round of loans given to firms. As the market share of the large bank increases, it internalizes these costs more and gives zombie loans with a higher probability. Condition (5) simply gives the boundary conditions required for an interior solution. It says that $V'(.)$ should be large enough at $p(0)$ and small enough at $p(1)$ for an interior solution to exist.

We have so far assumed that all firms have the same collateral. However, in an economy, firms have different levels of collateral. So the next question is how does the level of collateral affect the likelihood of receiving a zombie loan? We turn to this issue next.

[6] This assumption is not necessary but considerably simplifies the analysis. The results will still hold as long as L is small enough.

2.3. Collateral level and the probability of zombie lending

We now assume that there are two types of firms. Half of the firms have high collateral denoted by C_H and the remaining half of the firms have low collateral denoted by $C_L < C_H$. The average size of the collateral is still C.[7] The other characteristics of the firm—V and L—remain the same.[8] As before there is a large bank with market share f and atomistic banks with a combined market share of $(1 - f)$. Each bank's portfolio is equally distributed between the two types of firms and the face value of loans remains the same.[9]

In the normal state, by Assumption 1, all banks will continue to liquidate all firms. In the adverse state, when a firm goes bankrupt, the large bank chooses to give a zombie loan to the high (low) collateral firm with probability λ_H (λ_L). The total collateral liquidated by the large bank is denoted by τ and is given by

$$\tau = f(1-\beta)((1-\lambda_H)C_H + (1-\lambda_L)C_L)/2. \tag{6}$$

The equilibrium values are denoted by λ_H^*, λ_L^* and τ^*. The atomistic banks will continue to liquidate all firms in the adverse state because they take prices as given. The price in the adverse state is given by

$$p(\lambda_H, \lambda_L) = \frac{W}{\tau + C(1-f)}; \tag{7}$$

and the utility function of the large bank in the adverse state is given by

$$\beta(F + V(p(\lambda_H, \lambda_L))) + \tau p(\lambda_H, \lambda_L) - \frac{1-\beta}{2}(\lambda_H + \lambda_L)L.$$

Given this setup, it can be shown that the high collateral firms are more likely to get a zombie loan than the low collateral firms, that is $\lambda_H^* > \lambda_L^*$.

Proposition 2. *Given Assumptions 1 and 2',*

i. *If $\tau^* \leq f(1-\beta)C_L/2$, then $\lambda_H^* = 1$ and $\lambda_L^* = \frac{\tau^*}{C_L f(1-\beta)/2}$.*
ii. *If $\tau^* > f(1-\beta)C_L/2$, then $\lambda_H^* = \frac{\tau^* - C_L f(1-\beta)/2}{C_H f(1-\beta)/2}$ and $\lambda_L^* = 0$.*

Proof. See appendix.

The proposition says that the large bank prefers to first liquidate the low-collateral firms and then the high-collateral firms. Part i. of the proposition says that if the total collateral sold by the large bank in equilibrium is less than the total collateral of the low collateral firms (this is the inequality in the if condition of part i.), then it will only liquidate the low collateral firms and all the high collateral firms get a zombie loan ($\lambda_H^* = 1$). But if the total collateral sold by the large bank in equilibrium is more than the total collateral of the low-collateral firms (this is the inequality in the if condition of part ii.), then the bank will first liquidate all the low-collateral firms ($\lambda_L^* = 0$), and the remaining collateral will come from the high-collateral firms.

The intuition is as follows. For a given number of firms that the large bank is giving zombie loans to and incurring the cost L per zombie loan, it wants to keep the price as high as possible. Liquidating the firms with a higher level of collateral will have a higher impact on price; hence it prefers to first liquidate all firms with low collateral and only then liquidate the firms with high collateral. The alternative equivalent interpretation is that, for a given amount of collateral that the large bank sells (which determines the effect on price and $V(.)$), it wants to liquidate as many firms as possible to minimize the loss from zombie lending. So it prefers to first liquidate the firms with low collateral.

3. Data

Our paper uses accounting data for listed US firms from Standard & Poor's Compustat database. Data on loans to firms is accessed from the Thompson Reuters Dealscan database. We get the House Price Index for MSAs from the Office of the Federal Housing Enterprise Oversight and the Consumer Price Index from the Bureau of Labor Statistics.

From the Compustat database, we select firms with non-missing real estate assets headquartered in the United States, and as in Chaney et al. (2012), exclude finance, insurance, real estate, construction, and mining firms. We restrict our sample period from 1993 to 2014 and to firms that have data for at least three years in this period. This leaves us with 3,280 firms and 35,243 firm–year

[7] This assumption is not necessary and merely reduces the effort of refining Assumption 1 and 2′

[8] It may seem unreasonable to assume the other characteristics of a firm do not change with the size of the collateral. However, in the empirical part of the paper, we will be comparing firms with different ratios of real estate collateral as a fraction of their total assets. Hence we can assume that the total assets of all firms are the same, but some firms have more real estate assets than others. The other characteristics of the firms, i.e. V and L, depend on total assets and not the real estate collateral. We are basically abstracting from modeling the market for non-real estate assets of the firm when it is liquidated.

[9] We can assume that the face value changes with collateral level without changing any result. Here the face value can be interpreted as the average face value of the loans. Since liquidation probability does not affect the current payoff, the face value is irrelevant to our calculations.

Table 1
Summary statistics.

Panel A: Firm-Level Data					
	Mean	Median	SD	Min	Max
Zombie	0.042	0	0.201	0	1
Real Estate	1.096	0.231	2.837	0	22.686
Sales	13.260	5.460	26.233	0	190.646
Log Assets	4.964	4.831	2.333	0	13.081
Investment	0.379	0.203	0.619	0	5.605
Leverage	0.275	0.194	0.413	0	3.852
Tobin's Q	2.544	1.519	4.513	0.534	62.878
ICR (3-yr avg)	8.430	3.332	87.518	−701.667	598.400
Number of Firms	3280				
Observations	35 243				
Panel B: MSA Level Data					
	Mean	Median	SD	Min	Max
Negative Shock	0.205	0	0.402	0	1
Structural Break	0.135	0	0.342	0	1
Bank HHI	0.191	0.107	0.223	0	1
Number of MSAs	206				
Panel C: Bank Level Data					
	Mean	Median	SD	Min	Max
Market Share	0.048	0.017	0.113	0	1
Number of Lenders	1507				
Observations	8,548				

Table 1 reports the summary statistics of our sample. Tobin's Q is calculated as the ratio of the enterprise value of a firm to its book value. *Investment* is measured as capex normalized by lagged fixed assets. *Leverage* is the ratio of total debt to assets. *Sales* is measured as the ratio of sales to lagged PPE, while *Log Assets* is the log of assets plus one. *ICR* is the three-year average of firms' interest coverage ratio, which is the ratio of firms' EBIT to interest expense. *Negative Shock* is an indicator for falling real estate prices, while *Structural Break* is an indicator for the period with significantly declining real estate prices. *Bank Market Share* is the average share of outstanding loans in the past 3 years attributed to a lender. *Bank HHI* is the Herfindahl–Hirschman Index for bank concentration in an MSA.

Table 2
Summary statistics for Zombie firms.

	Mean	Median	SD	Min	Max
RealEstate	1.088	0	3.405	0	22.686
Sales	13.459	4.766	28.171	0	190.646
Log Assets	3.635	3.384	1.925	0	13.073
Investment	0.535	0.234	0.894	0	5.605
Leverage	0.457	0.279	0.642	0	3.846
Tobin's Q	3.207	1.690	6.065	0.534	62.878
ICR (3-yr avg)	−51.422	−9.995	141.521	−701.667	1.316
Number of Firms	805				
Observations	1491				

Table 2 reports the summary statistics of zombie firms in our sample. *High Real Estate* is an indicator for above median real estate holdings, normalized by lagged PPE. Tobin's Q is calculated as the ratio of the enterprise value of a firm to its book value. *Investment* is measured as capex normalized by lagged fixed assets. *ICR* is the three-year average of firms' interest coverage ratio, which is the ratio of firms' EBIT to interest expense. *Leverage* is the ratio of total debt to assets. *Sales* is measured as the ratio of sales to lagged PPE, while *Log Assets* is the log of assets plus one.

observations. The summary statistics of these firms are shown in Table 1. The average (log) asset is 4.964, and the average leverage ratio is 0.275.

To test our hypothesis, we require information on loans given by banks to firms in different MSAs. While Dealscan provides data on loans to mostly larger firms, it is reasonable to use this in our setting as these large firms are the ones which are going to create a negative price externality in the local real estate market when they are liquidated. Following Ferreira and Matos (2012) and others, we perform our analysis at the facility level; i.e. we treat each facility as a different loan. Approximately 30% of the loans in our sample have a single lender. For the remaining loans, we ascribe a loan to a lender only if it is the Lead Arranger, Agent, Bookrunner, Manager, Underwriter or Sole Lender. This is because participants in a syndicated loan are more likely to sell their loans in the secondary market (Irani et al., 2021). Also, although both the arranger and participants commit capital to a syndicated loan, the average arranger share is four times as large as the average participant share. Further, there is poor coverage in the Dealscan database on the amount of loans given by participants in the syndicated loans. For these reasons, we follow the standard convention in the literature and consider the lead arranger as the "lender" (Ivashina and Scharfstein, 2010; Giannetti and Saidi, 2019).

We keep loans denominated in US dollars for which the information on "AllinDrawn" (AISD) is available. Since the spread is not calculated for fixed-rate loans, letters of credit, or subordinated debt, these are not included in our calculations. Following Giannetti and Saidi (2019), we keep loans that can be considered general purpose loans and exclude loans with the purpose of "takeover or acquisitions". In robustness checks, we exclude Term-B loans, which are 'institutional' facilities and, on average, have a higher interest rate than 'bank' facilities. Since Term-B loans have higher interest rates, these are less likely to be classified as zombie loans and, therefore, are more likely to reduce the magnitude of our estimates.

We merge the Dealscan database with Compustat using the link table provided by Chava and Roberts (2008). We could match 16,273 facilities (syndicated loans) to firms in our data set for 26,138 bank–firm–year observations. Using this merged data set, we calculate a bank's outstanding loans to a firm each year. We decompose syndicated loans into loan shares provided by each lender. Whenever Dealscan provides information on lending shares, we use this as the lender's share. In cases where lending shares are missing, we calculate the median share of the lead arrangers from loans with complete allocation information and split this portion equally among the lead arrangers. If the loan maturity is unavailable, we assign a maturity of 60 months to the median loan duration in the data set. Next, assuming that all of a firm's real estate is in the same MSA as its headquarters (Chaney et al., 2012), we calculate the outstanding loans of each lender in each MSA. We conduct our analysis at both the firm level and the loan level.

3.1. Identifying zombie lending

3.1.1. Identifying zombie firms using accounting data

Zombie firms are unproductive firms incapable of servicing their debt (at market rates) but continue to operate because they receive subsidized credit. To identify zombie lending, we follow the approach of Caballero et al. (2008) and Acharya et al. (2019). We identify a firm as a zombie if it is financially stressed (as measured by interest coverage ratio) but is getting credit at a cost lower than the most creditworthy firms in the economy. We calculate the interest rate paid by the most creditworthy firms in two ways. First, we calculate the median of the "average interest rate" (*total interest expense/total debt*) paid by all firms with an AAA rating in any given year. Second, we calculate the median of the "average interest rate" paid by the top decile of firms by interest coverage ratio (ICR).

To be conservative, we take the lower of the two interest rates as the rate paid by the most creditworthy firms in the economy. Given this interest rate benchmark (r^{top}) and the total debt of a firm (D_{it}), we calculate the minimum required interest payment of a firm (R^{min}) as

$$R_{it}^{min} = r_t^{top} * D_{it}.$$

Next, we calculate the excess interest paid by the firm. Excess interest is the difference between the actual interest expense of a firm (R_{it}), and the minimum required interest payment, that is

$$x_{it} = R_{it} - R_{it}^{min}.$$

Given x_{it}, a firm is classified as a zombie if it meets the following two criteria: (i) x_{it} is negative, that is, the excess interest paid by the firm is negative, which implies that its interest cost is less than that of the most creditworthy firms, and (ii) it is in the bottom tercile of firms when classified by the 3-year average of the interest coverage ratio. According to Damodaran (2024), ICR is a good proxy for the credit rating of a firm: an ICR of less than 2 corresponds to a rating of Ba2/BB or lower for large firms and a rating of B2/B for smaller firms. In the sample of firms which fall in the bottom tercile of ICR, no firm has a 3-year average ICR above 2. Thus, these firms are firms with poor ratings and should not be getting subsidized credit. We find that as per our definition, 4.2% of firm–year observations can be classified as zombie firms. The summary statistics of these firms are shown in Table 2. These zombie firms have higher leverage (median leverage is 0.279) and lower 3-year average ICR (median ICR is −9.995) compared to non-zombie firms.

3.1.2. Identifying zombie loans using dealscan data

We use the Thompson Reuters LPC Dealscan data set to identify individual loans as zombie loans. This data set has the variable "AllInDrawn" which is a composite way of reporting the pricing of facilities and is quoted as a spread over the LIBOR. This variable allows us to identify the specific loans that are "subsidized." It is comparable across facilities regardless of the underlying fee structure. As before, we classify loans as zombie loans if the interest rate spread on the loan is lower than the spread for the highest-rated firms and the firm is in the bottom tercile when classified by 3-year average ICR. The calculation of benchmark interest rate r_t^{top}, and the comparison with interest rate on loans to firms in bottom tercile, is done separately for secured and unsecured loans. In our sample, there are 16,272 facilities, of which 8,167 are secured facilities, and out of the 26,138 bank–firm loans, we find that 3.8% are zombie loans.

3.2. Real estate assets of firms

To calculate the market value of a firm's real estate, we precisely follow the method used by Chaney et al. (2012). We classify real estate as total buildings, land, improvement, and construction in progress. Real estate assets are not marked-to-market but are held on the balance sheet at historical cost. To impute the market value of the real estate, we calculate the average age of those assets and use historical prices to compute their current market value. To calculate the average age of assets, we calculate the ratio of accumulated depreciation in 1993 to the gross book value of the real estate. This measures the proportion of the cost claimed as depreciation in 1993. Assuming a depreciable life of 40 years and straight-line depreciation, we estimate the average age of a firm's real estate. We then inflate real estate assets using the MSA-level real estate inflation. For real estate purchased before 1975, we use the CPI to inflate its value till 1975 and the real estate price index after 1975. Our sample is restricted to firms active in 1993 as accumulated depreciation is unavailable in Compustat after 1993.

We use the firm's headquarters location as a proxy for the location of the real estate. As pointed out by Chaney et al. (2012), two assumptions are underlying this choice. First, headquarters and production facilities are generally clustered in the same MSA and state. Second, the headquarters account for a large fraction of corporate real estate assets.[10] According to calculations done by Campello et al. (2022), for an average firm, only 6% of their real estate assets in terms of market value are in areas outside of the location of the firm's headquarters. Thus, there is a high correlation between the market value of real estate assets based on the headquarters location and that based on actual location. Custódio et al. (2023) also highlight this point.

3.3. Bank market shares

To calculate bank market shares in an MSA, we follow the procedure in Giannetti and Saidi (2019) and use the Dealscan data.[11] As mentioned earlier, approximately 30% of the loans in our sample have a single lender. For the remaining loans, we ascribe a loan to a lender only if it is the Lead Arranger, Agent, Bookrunner, Manager, Underwriter or Sole Lender. If the arranger share data is missing, we resort to the common practice in the literature and set the loan share provided by the lead arranger as the median of our sample. In the case of more than one lead arranger, we assign each arranger an equal fraction of the lead arranger's total loan share. We also assume that a bank that arranges a loan retains it on its balance sheet. To calculate a bank's outstanding loans, we add all loans arranged by a bank that have not matured.

In our setting, lenders with higher market share in an MSA have stronger incentives to avoid price-default spirals. A bank's market share is calculated as the dollar amount of loans arranged by a bank to firms headquartered in an MSA that has not matured, divided by the dollar amount of all outstanding loans in an MSA. Formally:

$$\text{Share}_{k,MSA,t} = \sum_{t=-3}^{-1} \frac{\text{Outstanding Loans}_{k,MSA,t}}{\text{OutstandingLoans}_{MSA,t}} \tag{8}$$

The average market share is 4.8% (see panel C of Table 1). We then take the past three-year average of the bank's market share in the MSA and use this as our market share variable (Giannetti and Saidi, 2019; Saidi and Streitz, 2021). We use the above market share to compute a Herfindahl–Hirshman Index (HHI), which captures the credit concentration at the MSA-year level (Bank HHI). The average Bank HHI is 0.191.

4. Empirical analysis and results

We first conduct firm-level analysis to establish an increased incidence of zombie lending to firms with higher real estate when the local real estate market is under stress and undergoing a fire sale. Then, we move to a more granular loan-level analysis to pin down the channels that might be driving our results.

[10] Chaney et al. (2012) also provide some evidence to support these assumptions.

[11] Even though syndicated loans provided by the Dealscan database constitute a fraction of banks' total lending, they consist of the largest loans to the largest firms and thus account for a sizeable portion of total lending and have been used in previous studies (Giannetti and Saidi, 2019; Chodorow-Reich, 2014) to evaluate bank lending policies.

Table 3
Price decline, real estate assets and likelihood of zombie firms.

	(1)	(2)
Dependent variable	Zombie	
High Real Estate	0.002	0.002
	(0.007)	(0.007)
Negative Shock	−0.008	−0.007
	(0.006)	(0.006)
High Real Estate × Negative Shock	0.018***	0.017***
	(0.006)	(0.007)
Observations	35 106	34 074
Controls	No	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Table 3 estimates the probability of firms being zombies when there is a decline in local real estate prices. *Zombie* is an indicator for a firm whose average interest cost is lower than the highest rated firms in the year and is in the bottom tercile of firms by ICR. *High Real Estate* is an indicator for firms with an above-median ratio of the market value of real estate assets and lagged value of property, plant and equipment. *Negative Shock* is an indicator for MSA-years in which there is a decline in the House Price Index in an MSA, which proxies for fire sales in our setting. Column (1) shows the results with firm and time-fixed effects. Column (2) shows the results with these fixed effects and *Sales* and *Leverage* as controls. All standard errors are clustered at the firm level.

4.1. Firm-level analysis: zombie lending and real estate collateral

At the firm level, our theory suggests (see Proposition 2) that firms with higher real estate assets relative to total assets are more likely to receive zombie credit if the local real estate market is stressed and real estate assets are being sold at fire sale prices. While we cannot directly identify if there is a fire sale in the local real estate market, we create two different proxies for a fire sale in an MSA. First, we assume that there is a fire sale in the real estate market in an MSA if the local real estate price is declining that year. This is obviously not the perfect indicator of a fire sale because while prices will fall if there is a fire sale in the real estate market, they may also fall if the MSA has suffered a negative productivity shock, leading to a decline in the real value of real estate assets. Hence, we use a second way to identify a fire sale in an MSA by identifying structural breaks in real estate prices in that MSA (see Section 4.1.1). This second method will also allow us to address the endogeneity issues in our identification, which will be discussed shortly.

We test our hypothesis that firms with relatively higher real estate assets are more likely to be zombies when the real estate market is undergoing a fire sale by estimating the following OLS regression:

$$\begin{aligned}\text{Zombie}_{i,t} =&\beta_1 \cdot \text{High Real Estate}_{i,t} + \beta_2 \cdot \text{Negative Shock}_{MSA,t}\\ &+ \beta_3 \cdot \text{High Real Estate}_{i,t} \cdot \text{Negative Shock}_{MSA,t} + \text{Controls}_{i,t-1}\\ &+ \alpha_i + \delta_t + \epsilon_{i,t}\end{aligned} \tag{9}$$

$\text{Zombie}_{i,t}$ is an indicator variable that takes the value 1 if firm i is a zombie in the year t. As detailed in Section 3.1.1, we have followed the methodology used by Caballero et al. (2008) and Acharya et al. (2019) to identify zombie firms. The variable $\text{High Real Estate}_{i,t}$ is an indicator for firms with above-median real estate value, measured as the ratio of the market value of real estate held by a firm and the value of lagged property, plant and equipment. $\text{Negative Shock}_{MSA,t}$ is an indicator for an MSA-year with negative real estate price change where the price in an MSA is measured by the local house price index. As discussed above, this variable acts as a proxy for the local real estate market being under stress, where the liquidation of real estate assets may be undergoing a fire sale. Control variables included are sales and leverage. α_i and δ_t are the firm and year fixed effects and, respectively, control for the time-invariant firm-level unobservable factors and the annual shocks affecting all firms uniformly. The time-fixed effects thus control for the interest rate environment, which may be affecting zombie lending (Banerjee and Hofmann, 2018). Our main coefficient of interest is β_3, which estimates the probability of a firm with above-median real estate being a zombie firm compared to those with below-median real estate during a negative shock. β_1 estimates the probability of being a zombie firm for high real estate firms relative to low real estate firms during normal times when real estate prices are not declining.

The results of this regression are presented in Table 3. Column (1) reports the results for the specification with the fixed effects, and column (2) shows the results with fixed effects and controls. The coefficient of the interaction term, β_3, is positive and statistically significant in both specifications, indicating that firms with proportionally higher real estate assets are more likely to be zombie firms when the real estate prices are declining in that MSA. Results in column (2) imply that during a negative shock, firms with above-median real estate assets are 1.7% more likely to be zombie firms compared to firms with below-median real estate assets. Further, β_1 is close to zero and statistically insignificant in column (2), suggesting that the likelihood of being a zombie firm is the same for both above and below-median real estate firms when real estate prices are not declining.

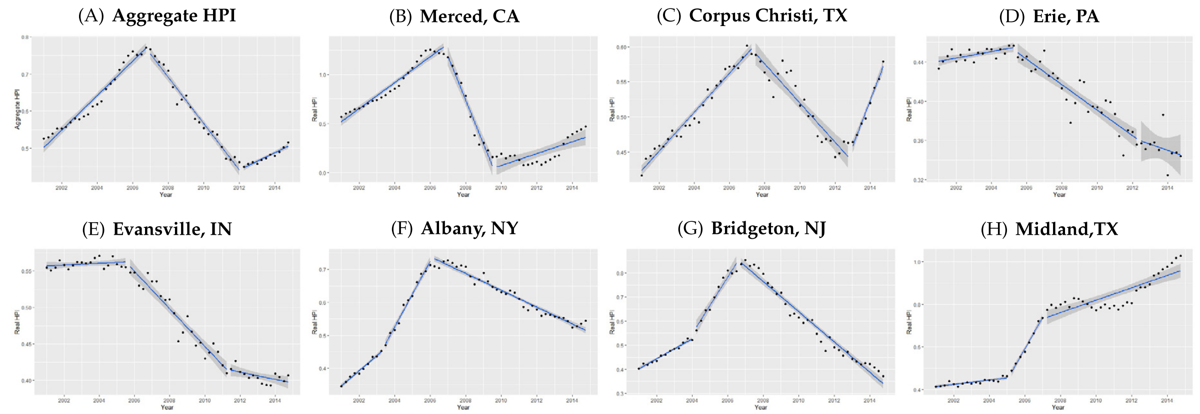

Fig. 1. shows graphs of the log of house price data for seven MSAs and the average house price index across the US. The house price index for each MSA is normalized by the CPI. The dotted lines report the house price series, while the solid lines report the estimated house price and the structural breaks. Panel A shows the average HPI. Panels B and C show the index for Merced, CA and Corpus Christi, TX, which have a negative structural break in the second period but a positive slope in the third period. Panels D and E (Erie, PA and Evansville, IN, respectively) also show MSAs that have a negative structural break in the second period. Still, the HPI continues to decline in the third period. Panels F and G (Albany, NY and Bridgeton, NJ, respectively) show a positive structural break in the second segment but a negative structural break in the third segment. The third segment is thus chosen as the period of fire sales. Finally, Panel H (Midlands, TX) shows no negative structural break and, therefore, no fire sales in any period.

4.1.1. *Identifying fire sale using structural breaks in real estate prices*

The key endogeneity concern in our estimation is that zombie lending in an MSA could be, for some reason, correlated with local fundamental unobserved factors such as productivity shocks, and these factors could also lead to a subsequent decline in real estate prices. For example, zombie lending in an MSA could be correlated with local productivity shocks to firms, which in turn could default and reduce the level of capital of banks operating in that MSA, and these undercapitalized banks, in turn, could resort to zombie lending (Caballero et al., 2008; Bruche and Llobet, 2014). These negative productivity shocks could also affect the value of local real estate, leading to a decline in prices, thus resulting in an endogeneity problem.

We address these concerns in two ways. First, we include bank-time fixed effects in our loan level regressions (see Section 4.2), which control for the health of the banks. Second, we create an indicator for a fire sale by identifying a sharp decline in real estate prices and use exogenous variation in the timing of these sharp declines in prices across different MSAs for the purpose of our identification. This identification strategy and our arguments herein are similar to those of Charles et al. (2018). The underlying assumption is that these sharp declines in prices are not driven by changes in local fundamental factors because these factors move gradually, and even if these factors move abruptly, their effects are incorporated slowly into the prices; instead, these price declines are driven by speculative factors. The justification for our assumption comes from the existing literature, which has argued that the variation in real estate prices during the boom and bust of the Great Recession in the United States was not driven by fundamental factors like productivity or income. It was rather caused by factors specific to local real estate markets, such as irrational exuberance and "bubbles" or "fads" (Shiller, 2009; Mayer, 2011; Chinco and Mayer, 2016; Burnside et al., 2016), introducing products like interest-only mortgages (Barlevy and Fisher, 2010), and changes in mortgage lending standards (Favilukis et al., 2017). So, sharp changes in real estate prices would have resulted from exogenous factors uncorrelated with local fundamental economic factors. Since the sharp decline in prices is not driven by fundamentals, the real estate is effectively being sold at below their fundamental price; that is, they are undergoing a fire sale.

Fig. 1 Panel (A) shows the quarterly average log of real estate price (normalized by the CPI) (the dotted line) of MSAs from Q1:2001 to Q4:2014. Visual inspection suggests that the price changes can be divided into three periods. The first period was from 2001 to 2006, during which the real estate price increased. This was followed by the second period from 2007 to 2012, when the prices were declining, which was then followed by the third period from 2013 to 2014, when the prices started increasing again. The second period, from 2007 to 2012, was when, on average, the real estate market was under stress with the likelihood of fire sale. However, there is significant variation across MSAs in terms of when they have a price decline. We exploit this variation for our identification as described below.

To find sharp negative changes in real estate prices in an MSA, we use the standard method of estimating structural breaks when the dates of the breaks are unknown (Bai, 1997; Bai and Perron, 1998). Using quarterly prices, we estimate Eq. (10) using OLS regression with two structural breaks for each MSA. We use two breaks as the average price trend shown in Fig. 1 Panel (A) has two breaks, first showing a decline and then a price increase.

$$HPI_{MSA,t} = \alpha_{msa} + \tau_{msa} \cdot t + \lambda^*_{msa}(t - t^*_{msa})\mathbb{1}(t > t^*) + \lambda'_{msa}(t - t'_{msa})\mathbb{1}(t > t') + \epsilon_{MSA,t} \tag{10}$$

Using this equation and quarterly house price index data from 2001:Q1 to 2014:Q4, we find the location of the two breaks, which maximizes the R^2 of the regression for each MSA, thus dividing the time series into three periods. Here, $HPI_{MSA,t}$ is the log of house

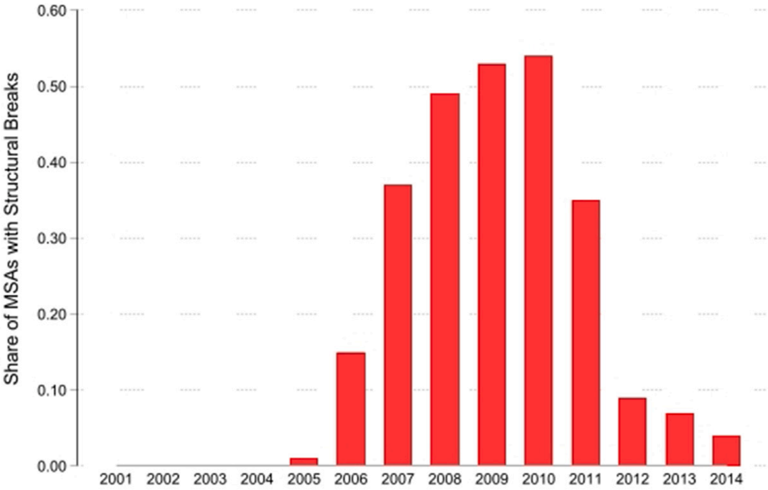

Fig. 2. shows the share of MSAs that are having a fire sale as identified by negative structural breaks.

price index in an *MSA* in quarter-year t; and t' and t^* are the timing of the first and the second structural breaks respectively. τ_{MSA} is the trend in the MSA's real estate price before the first break, and λ^* and λ' are the size of the first and second structural breaks respectively. Real estate prices had an increasing trend before the global financial crisis, which would be identified by positive τ_{msa}. To identify a fire sale in an MSA, we look for a sharp decline in real estate prices. The argument, as mentioned above, is that since these sharp declines are not driven by fundamental factors, it is reasonable to say that these MSAs are seeing a decline in prices because of fire sales. We identify three kinds of MSAs:

i. The first category is MSAs, where there is a sharp decline after the first break, i.e. in the second period, as shown in panels (B) and (C) of Fig. 1. These are identified by instances where $\tau_{msa} + \lambda^*_{msa}$ is negative and statistically significant. The prices in these MSAs resemble the average price trend, as shown in panel (A). For these MSAs, the second period is identified as having a fire sale. Panels (D) and (E) show MSAs with negative and significant structural breaks in the second period, but the HPI in these MSAs continue to decline even in the third period although the rate of decline is lower ($\lambda' > 0$). For these MSAs, we also consider the second period to be the period of fire sale. Out of a total of 206 MSAs, 183 fall in this category.
ii. If a fire sale is not identified in the second period, we check for cases where $\tau_{msa}+\lambda^*+\lambda'$ is negative and statistically significant, i.e. there is a sharp decline in the third period. These are the second kind of MSAs as shown in panels (F) and (G). For these MSAs, the third period is identified as having a fire sale. Out of a total of 206 MSAs, 22 fall in this category.
iii. Finally, the third kind of MSAs are those that do not have a statistically significant decline in prices. Panel (H) shows such an MSA. This MSA did not have a fire sale.

Fig. 2 shows the fraction of MSAs undergoing a fire sale each year as identified by this method. Having identified fire sale through structural breaks, we estimate the following OLS regression:

$$\begin{aligned} Zombie_{i,t} =& \beta_1 \cdot \text{Structural Break}_{MSA,t} + \beta_2 \cdot \text{High Real Estate}_{i,t} \\ &+ \beta_3 \cdot \text{Structural Break}_{MSA,t} \cdot \text{High Real Estate}_{i,t} + \text{Controls}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}. \end{aligned} \tag{11}$$

Here Structural Break$_{MSA,t}$ is an indicator for the period of fire sale in that MSA, i.e. it takes a value of one in the second period for the first kind of MSAs in the third period for the second kind of MSAs and never take a value of one for the MSA which did not have fire sale (third type). $Zombie_{i,t}$ is an indicator for a zombie firm. High Real Estate$_{i,t}$, as before, is the indicator for firms with above median real estate. Control variables included are sales and leverage. The coefficient of interest, β_3, allows us to estimate the impact of a fire sale as identified by the structural break in prices on the likelihood of being a zombie firm for high real estate firms.

The results for estimating Eq. (11) are presented in Table 4. As in Table 3, the coefficient of the interaction term is positive and statistically significant in both specifications, without (column(1)) and with (column (2)) controls. We find that the likelihood of being a zombie firm is 2.1% higher (column (2)) for high real estate firms during a fire sale compared to low real estate firms. The magnitude of the estimate is very similar to the magnitude estimated in Table 3. These results confirm our initial results that during a fire sale in the local real estate market, firms with a higher ratio of real estate assets to total assets are more likely to receive subsidized credit and be zombie firms. The summary statistics table (Table 1 Panel A) shows that the unconditional likelihood of a firm being a zombie firm in our sample is 4.2%. Therefore, our regression estimates show that during a fire sale, the likelihood of a high real estate firm being a zombie is higher than a low real estate firm being a zombie by almost 50% of the average likelihood of a firm being a zombie in our sample. Thus, our estimates are large and economically meaningful.

Table 4
Structural breaks, real estate assets and likelihood of zombie firms.

	(1)	(2)
Dependent variable	Zombie	
High Real Estate	0.003	0.003
	(0.005)	(0.007)
Fire Sale	−0.016**	−0.018*
	(0.006)	(0.009)
High Real Estate × Fire Sale	0.019***	0.021***
	(0.006)	(0.010)
Observations	35 106	34 074
Controls	No	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Table 4 estimates the probability of firms being zombies during a fire sale as identified by a negative structural break in HPI in an MSA. We regress an indicator for zombie firms on the structural break and an indicator for firms with above median real estate to assets ratio. *Zombie* is an indicator for zombie firms, and *High Real Estate* is an indicator for firms with above median ratio of market value of real estate and lagged value of property, plant and equipment. *Fire Sale* is an indicator for a negative structural break in real estate prices in the MSA, which proxies for fire sale in our setting. Column (1) shows the results with firm and time-fixed effects. Column (2) shows the results with these fixed effects and *Sales* and *Leverage* as controls. All standard errors are clustered at the firm level.

4.2. Bank market share and zombie lending

In this section, we conduct loan-level analysis and exploit the variation in bank market share in local markets to test our hypothesis. In our model, atomistic banks act as price takers, and their liquidation of firms does not affect the price in real estate markets; hence, they do not give negative NPV zombie loans and instead liquidate the failed firms. However, a large bank internalizes the price effect of liquidating a firm, so it does some zombie lending in equilibrium. Proposition 2 predicts that banks with higher market share are more likely to give zombie loans to firms with relatively higher real estate assets when there is a fire sale in the local real estate market. To identify this effect in the data, we estimate the following regression:

$$\begin{aligned}\text{Zombie Loan}_{i,k,t} =& \beta_1 \cdot \text{High Real Estate}_{i,t} + \beta_2 \cdot \text{Fire Sale}_{MSA,t} + \beta_3 \cdot \text{Share}_{k,MSA,t} \\ &+ \beta_4 \cdot \text{High Real Estate}_{i,t} \cdot \text{Fire Sale}_{MSA,t} \cdot \text{Share}_{k,MSA,t} \\ &+ \text{Controls}_{i,t-1} + \text{Controls}_l + \alpha_{k,t} + \gamma_i + \eta_l + \epsilon_{i,k,t}.\end{aligned} \tag{12}$$

Here Zombie Loan$_{i,k,t}$ is an indicator variable for a zombie loan (see Section 3.1.2) given by lender k to a firm i in the year t. High Real Estate$_{i,t}$, as before, indicates firms with above-median ratio of real estate assets and lagged plant, property and equipment. Share$_{k,MSA,t}$ is the market share of lender k in the MSA, where market share is defined as the past three-year average share of outstanding loans held by the bank in an MSA (see Saidi and Streitz (2021) and Giannetti and Saidi (2019)). Fire Sale$_{MSA,t}$ is an indicator variable for fire sale in an MSA in year t. As in Section 4.1, we estimate Eq. (12) separately using the two different indicators for fire sale that we have created: negative shock and structural break. γ_i is the firm fixed effect, and $\alpha_{k,t}$ is the lender-year fixed effect that, as discussed earlier, would control for the health of the banks and take care of the endogeneity problem, which could have been created by local productivity shocks affecting the health of local banks whilst also causing distress in the real estate market in the MSA. η_l is the facility-type fixed effect that controls for any variation in the borrowing cost due to the type of loan facility. Firm-level control variables include sales and leverage, while log loan amount and maturity are used as loan-level controls. The second-order interaction terms are included in the regression but not displayed in Eq. (12) above for conciseness. If positive, the coefficient of interest, β_4, would indicate that banks with higher market share are more likely to provide zombie loans to firms with relatively higher real estate assets when a fire sale occurs in the MSA.

Table 5 shows the results of estimating Eq. (12). Columns (1) and (2) show the results when we use the structural breaks to identify fire sales in the MSA, while columns (3) and (4) show the results when we use price decline in an MSA as an indicator for fire sales. Column (1) shows that banks with higher market share are not more likely to give zombie loans during fire sales. However, when we examine heterogeneity by real estate assets in column (2), we see that high real estate firms are more likely to get zombie loans from high market share firms during a fire sale. The coefficient of the triple interaction term is 0.116. A 1% (one standard deviation) increase in a bank's market share increases its probability of giving a zombie loan to high real estate firms relative to low real estate firms by 0.12% (1.3%) during a fire sale. The results are similar when we use price decline in an MSA as a proxy for fire sales, as seen in columns (3) and (4). Given that the unconditional likelihood of a firm being a zombie is 4.2%,

Table 5
Bank market share and zombie lending.

	(1)	(2)	(3)	(4)
Dependent variable:	Zombie Loan		Zombie Loan	
	Structural Break		Negative Shock	
Share	0.006	0.010	0.010	0.021
	(0.022)	(0.024)	(0.026)	(0.027)
Fire Sale	−0.018***	−0.007	0.020***	0.020***
	(0.004)	(0.004)	(0.006)	(0.004)
Fire Sale × Share	−0.028	−0.110***	−0.028	−0.116***
	(0.033)	(0.018)	(0.037)	(0.026)
High Real Estate		−0.007		−0.010
		(0.010)		(0.008)
High Real Estate × Share		−0.004		−0.013
		(0.023)		(0.023)
High Real Estate × Fire Sale		−0.016*		−0.001
		(0.008)		(0.006)
High Real Estate × Fire Sale × Share		0.116**		0.119**
		(0.050)		(0.051)
Observations	20 683	20 683	20 683	20 683
Firm Controls	Yes	Yes	Yes	Yes
Facility Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Facility Type FE	Yes	Yes	Yes	Yes
Lender × Year FE	Yes	Yes	Yes	Yes

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Table 5 estimates a linear probability model to estimate how the probability of zombie lending depends on bank market share. *Zombie Loan* is an indicator for a zombie loan to a firm by a lender in a year. The independent variables include *High Real Estate*, which is an indicator for firms with an above-median ratio of real estate to total assets, and *Share*, which is the three-year average share of outstanding loans in an MSA arranged by a bank. *Fire Sale* is an indicator for fire sale in an MSA. Fire sale in an MSA is identified by structural breaks in columns (1) and (2) and by negative price shocks in columns (3) and (4). We use *Sales* and *Leverage* as firm-level controls, while *Maturity* and *Log Amount* are included as loan-level controls. Standard errors are double clustered by lender and facility type.

these magnitudes are reasonably large and economically significant.[12]

4.2.1. Bank concentration and zombie lending in an MSA

Another obvious implication of our model is that higher bank concentration in an MSA should increase the probability of zombie lending in that MSA. We test this by estimating Eq. (13) below:

$$\begin{aligned} \text{Zombie}_{i,t} =& \beta_1 \cdot \text{High Real Estate}_{i,t} + \beta_2 \cdot \text{Fire Sale}_{MSA,t} + \beta_3 \cdot \text{Bank HHI}_{MSA,t} \\ &+ \beta_4 \cdot \text{High Real Estate}_{i,t} \cdot \text{Fire Sale}_{MSA,t} \cdot \text{Bank HHI}_{MSA,t} \\ &+ \text{Controls}_{i,t-1} + \text{Controls}_l + \alpha_{k,t} + \gamma_i + \eta_l + \epsilon_{i,k,t}. \end{aligned} \tag{13}$$

Here Bank $\text{HHI}_{MSA,t}$ is the Herfindahl–Hirschman index of bank market concentration in an MSA in year t, defined as the sum of the squares of banks' market shares in an MSA. High Real $\text{Estate}_{i,t}$ is an indicator for firms with above median ratio of real estate assets and lagged plant, property and equipment. Fire $\text{Sale}_{MSA,t}$ is an indicator for an MSA undergoing a fire sale in year t, which is identified by the two different indicators that we have created: negative shock and structural break. We include firm-fixed effects, lender-year fixed effects, facility-type fixed effects and sales and leverage as firm-level controls. Log loan amount and maturity are included as loan level controls. The second-order interaction terms are included in the regression but not displayed above in Eq. (13) for brevity. The coefficient of interest is β_4, which estimates the sensitivity of the credit concentration to the probability of zombie lending to high real estate firms relative to low real estate firms during a fire sale.

The results are presented in Table 6. Columns (1) and (2) show the results when we use the negative structural breaks to identify a fire sale in the MSA, while columns (3) and (4) show the results when we use price decline in an MSA as an indicator for fire sale. The coefficient of the interaction term in column (1) is noisy. We next examine heterogeneity by real estate assets and find the coefficient of the triple-interaction term to be 0.299 (see column (2)). This implies that in an MSA with one standard deviation (318 points) higher HHI, high real estate firms have a 9.5% higher likelihood of receiving a zombie loan than low real estate firms

12 In unreported tests, we use the five most disastrous hurricanes between 1993 and 2014 as instruments for the decline in real estate prices. We find that MSAs that experienced these hurricanes had a 3% decline in the HPI over the next two years. A 1% increase in bank market share increased the probability of zombie loans for high real estate firms in these MSAs by 0.85% compared to low real estate firms.

Table 6
Bank concentration in MSA and zombie lending.

Dependent Variable	(1)	(2)	(3)	(4)
	Zombie Loan		Zombie Loan	
	Structural Break		Negative Shock	
Bank HHI	0.032	0.042	0.039*	0.050*
	(0.020)	(0.029)	(0.019)	(0.028)
Fire Sale	−0.030***	0.001	0.016**	0.020***
	(0.004)	(0.009)	(0.007)	(0.006)
Fire Sale × Bank HHI	0.106**	−0.111	0.032	−0.067
	(0.050)	(0.065)	(0.060)	(0.048)
High Real Estate		−0.003		−0.006
		(0.008)		(0.007)
High Real Estate × Bank HHI		−0.014		−0.015
		(0.026)		(0.024)
High Real Estate × Fire Sale		−0.043***		−0.005
		(0.011)		(0.005)
High Real Estate × Fire Sale × Bank HHI		0.299***		0.132***
		(0.056)		(0.042)
Observations	20 683	20 683	20 683	20 683
Firm Controls	Yes	Yes	Yes	Yes
Facility Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Facility Type FE	Yes	Yes	Yes	Yes
Lender × Year FE	Yes	Yes	Yes	Yes

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Table 6 estimates how the probability of zombie lending varies with bank concentration. *Zombie Loan* is an indicator for a zombie loan to a firm by a lender in a year. *High Real Estate* is an indicator for firms with an above-median ratio of real estate assets to total assets. The bank concentration (Bank HHI) is measured as the sum of the squared market shares of outstanding loans in an MSA. *Fire Sale* is an indicator for fire sale in an MSA as established by either a structural break in real estate prices (columns (1) and (2)) or a decline in real estate prices in an MSA in a year (columns (3) and (4)). We use *Sales* and *Leverage* as firm-level controls, while *Maturity* and *Log Amount* are included as loan-level controls. Standard errors are double clustered by lender and facility type.

during a fire sale. Our estimates in column (4), where we use negative shocks to identify fire sales, suggest a qualitatively similar result.

5. Spillover effects of zombie firms

Most studies of zombie lending have focused on Southern Europe post the sovereign debt crisis or Japan during the lost decades of 1990–2010. Since we are studying a different country, we similarly explore the spillover effects of zombie lending on healthy firms (Caballero et al., 2008). Healthy firms in an industry can be affected by zombie firms through two channels. First, the evergreening of loans shifts the supply of credit to these zombie firms. This may lead to reduced credit available to healthier firms and may also increase their cost of credit. So, healthy firms will make lower investments in the industry with more zombie firms.

Second, the prevalence of zombies also distorts the competitive process in an industry. In a market without distortions, impaired firms would reduce employment and lose market share. This gives more productive (non-zombie) firms access to a larger talent pool, allowing them to increase market share and profitability. But, subsidized credit keeps zombie firms artificially alive, which congests the market. This reduces product market prices and corresponding markups and increases industry wages. Our regression specification follows Caballero et al. (2008) and Acharya et al. (2019):

$$\begin{aligned} y_{i,t} =& \beta_1 \times \text{Healthy Firms}_{i,t} + \beta_2 \times \%\text{Zombies}_{j,t} + \beta_3 \times \text{Healthy Firms}_{i,t} \times \%\text{Zombies}_{j,t} \\ &+ \alpha_i + \delta_{j,t} + \epsilon_{i,t}. \end{aligned} \quad (14)$$

Healthy $\text{Firms}_{i,t}$ is an indicator for firms not classified as zombies in the year t. $\%\text{Zombies}_{j,t}$ is the percentage of zombie firms in the year t in the industry j that the firm belongs to. α_i is the firm fixed effect, and $\delta_{j,t}$ is the industry-year fixed effect. The dependent variables are investment, return on assets (ROA), and change in employment. We expect zombie firms in an industry to depress these variables for healthy firms; that is, we expect the coefficient of interest β_3 to be negative.

Table 7 reports the results of this regression analysis. We have alternatively used year and industry-year fixed effects, while firm fixed effects are included in all specifications. The results suggest that the presence of zombie firms in an industry leads to healthier firms making lesser investments and having lower returns on assets ($\beta_3 < 0$). A 1% increase in zombie firms in an industry leads healthy firms to decrease their investment by 1.2% (column 2). Also, the ROA of healthy firms is lower by 1% if the zombie firms in an industry are higher by 1% (column 4). We do not observe any impact on employment by firms. Overall, our evidence suggests

Table 7
Spillover on healthy firms.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Investment		ROA		ΔEmployment	
Healthy Firms	0.019	0.021	0.079***	0.082***	−0.017***	−0.019***
	(0.028)	(0.031)	(0.024)	(0.027)	(0.006)	(0.008)
% Zombies	1.045**		0.592*		0.039	
	(0.436)		(0.310)		(0.098)	
Healthy Firms × % Zombies	−1.165***	−1.218**	−0.953***	−1.028***	0.057	0.095
	(0.445)	(0.523)	(0.326)	(0.395)	(0.100)	(0.125)
Observations	106 437	106 394	116 509	116 466	94 130	94 094
R^2	0.31	0.33	0.65	0.65	0.17	0.19
Industry × Year FE	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Table 7 explores the spillover effects of zombie lending. The specification follows Caballero et al. (2008). The regressors are an indicator for non-zombie firms (*Healthy Firms*), the percentage of zombie firms (%Zombies) in the industry and the interaction term. Our dependent variables of interest are investment, return on assets (ROA) and change in employment. *Investment* is measured as capital expenditure normalized by the lagged PPE, and ROA as EBIT normalized by lagged assets. We control alternatively for year and industry-year fixed effects while including firm fixed effects in all specifications.

that zombie firms in an industry harm healthy firms.

As seen above, zombie firms negatively impact healthy firms in their industry. However, the interaction of zombie firms with which they have a direct relationship can be positive or negative. Client firms can increase purchases from or extend trade credit to distressed firms, which may enable them to get better prices and ensure greater supplier competition.

On the other hand, they can reduce purchases from distressed firms to reduce their exposure. Custódio et al. (2023) show that client firms reduce purchases from distressed suppliers following a drop in real estate prices. This channel amplifies the shock to a firm. We derive supplier–client relationships from the Compustat segment database, which includes details on client relationships accounting for more than 10% of total sales. The database enables us to pinpoint major clients and the dollar value of their purchases. We then investigate the evolution of the supplier–client relationship for zombie firms. Specifically, we estimate the following equation

$$\begin{aligned} \Delta Sales_{i,j,t} = & \beta_1 \cdot \text{High Real Estate}_{i,t} + \beta_2 \cdot \text{Fire Sale}_{MSA,t} + \beta_3 \cdot \text{Distress}_{i,t} \\ & + \beta_4 \cdot \text{High Real Estate}_{i,t} \cdot \text{Fire Sale}_{MSA,t} \cdot \text{Distress}_{i,t} \\ & + Controls_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}. \end{aligned} \tag{15}$$

Here, $\text{Distress}_{i,t}$ is a high leverage firm (Custódio et al., 2023) in column (1) or a zombie firm in column (2). $\text{High Real Estate}_{i,t}$ is an indicator for firms with above median ratio of real estate assets and lagged plant, property and equipment. $\text{Fire Sale}_{MSA,t}$ is an indicator for an MSA undergoing a fire sale in year t, identified by a greater than 3.3% fall in real estate prices. We include firm and time-fixed effects while sales and leverage are used as controls. The second-order interaction terms are included in the regression but not displayed above for brevity. The coefficient of interest is β_4, which estimates whether the difference between the response of customers is different for firms with high real estate vs low real estate following a real estate price shock.

In Table B.1 column (1), we replicate their results and find that client purchases from firms with above median real estate holdings, which are also highly leveraged and face a greater than 3.3% fall in real estate prices decline by 11.6% following the shock (compared to a decline of 13% in Custódio et al. (2023)).

In column (2), we replace highly leveraged firms with zombie firms and observe that client purchases from zombie firms with high real estate firms do not decline and remain. This finding is consistent with our hypothesis: banks' continued support of zombie firms implies that client firms do not reduce purchases. The difference in findings for leveraged and zombie firms, as shown by the difference in columns 1 and 2, further provides an independent test of our baseline contention that zombie lending is not the same as lending to distressed firms. Indeed, our baseline zombie measure captures nuances distinct from mere firm distress.

6. Robustness tests and alternative hypothesis

Through a series of robustness checks, we show that our results are largely unchanged by alternative variable definitions or sample selection.

6.1. Alternative zombie definition

Our primary analysis defines zombie firms as highly leveraged firms with borrowing costs lower than those of the highest-rated firms. We consider alternative definitions of zombie firms in Table 8, panel (A).

Table 8
Robustness tests for the likelihood of zombie firms.

Panel A: Alternative zombie firm definition				
	Zombie 1		Zombie 2	
High Real Estate × Structural Break	0.011* (0.006)		0.028** (0.015)	
High Real Estate × Negative Shock		0.016*** (0.038)		0.052** (0.027)
Observations	34 074	34 074	34 074	34 074

Panel B: Adjusted real estate		
	Structural Break	Negative Shock
High Adjusted RE × Fire Sale	0.029*** (0.009)	0.011* (0.007)
Observations	34 074	34 074
Panel C: Excluding firms incorporated in Delaware		
	Structural Break	Negative Shock
High RE excl.-DE × Fire Sale	0.021** (0.010)	0.015** (0.007)
Observations	33 950	33 950

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Table 8 replicates the result of Tables 3 and 4 using alternative definitions of various variables. The dependent variable in all panels is an indicator for ***Zombie*** firms. ***Zombie1*** is defined as firms with excess interest < 0, $3yr$-MovAvg ICR < 1 and have issued debt in the past year (Acharya et al., 2019). ***Zombie2*** are firms that have $ICR < 1$ for the past 3 years and $Age > 5 years$ (Banerjee and Hofmann, 2018). ***Fire Sale*** is proxied by either a fall in real estate prices in an MSA or a ***Structural Break***. ***High Real Estate*** indicates firms with an above-median ratio of the market value of the real estate to assets. textitHigh RE excl.-DE is ***High Real Estate*** firms, excluding those headquartered in Delaware. ***Adjusted RE*** is the product of the ratio of PPE to total assets by the average firm-level fraction of the PPE that corresponds to buildings between 1981 and 1993. *Sales* and *Leverage* are used as controls. Standard errors are clustered at the firm level.

In columns (1) and (2), in addition to the requirements that the moving average ICR is in the bottom tercile and that the excess interest expense of a firm is negative, we add a third restriction based on Acharya et al. (2019) that the firm must have raised debt in the past year (*Zombie1*). The result shows that after a structural break, high real estate firms are 1.1% more likely to be zombie firms compared to low real estate firms. In the second row, we replace the structural break with an indicator for a fall in real estate prices and find that high real estate firms are 1.6% more likely to be classified as zombie firms following a decline in real estate prices. Though the results are similar, we believe this definition may be too restrictive for our purposes.

In columns (3) and (4), we define zombie firms as firms with an interest coverage ratio less than 1 for the past three years and an age greater than 5 years (McGowan et al., 2017; Banerjee and Hofmann, 2018). We find that a structural break in real estate prices increases the probability of a high real estate firm being identified as a zombie firm by 2.8% compared to a low real estate firm. Similarly, after a negative shock to real estate prices, high real estate firms are 5.2% more likely to be identified as zombie firms compared to low real estate firms. All these estimates are comparable to the estimates in Tables 3 and 4 and are statistically and economically significant. While this measure captures zombie firms, they more directly measure distress as opposed to subsidized lending. Since our focus is on zombie lending, we continue to use our baseline zombie definition in our analysis.

6.2. Alternative real estate definitions

We also consider an alternative definition of real estate assets, where we estimate the firm's real estate holdings as a product of the ratio of PPE to total assets in year t and the firm-level average ratio of real estate assets to PPE during the 1981–93 period (Custódio et al., 2023). Using this alternative definition of real estate assets, we define *High Adjusted RE* as an indicator for firms with above median real estate assets. The book value of RE assets is defined as the PPE net of machinery, equipment, and lease and is available for the period before 1993. In Table 8, panel (B), we replicate the results of Tables 3 and 4 using the *High Adjusted RE* measure. In Table 9, panel (B), we replicate the results of Tables 5 and 6. The results show that our findings are robust to using this alternative measure of real estate.

6.3. Excluding firms headquartered in delaware

In our analysis, we assign all the firm's real estate assets to the headquarters location. However, not all of the firm's real estate assets need to be located in the same MSA as its headquarters, which raises concerns about measurement issues. Ex-ante, it is not clear this mismeasurement will bias us toward finding an effect. If anything, the mismeasurement should bias our estimates

Table 9
Robustness tests: Impact of bank market share and concentration.

	Structural Break	Negative Shock
Panel A: Excluding Term - B loans		
High Real Estate × Fire Sale × Share	0.160***	0.052**
	(0.038)	(0.027)
High Real Estate × Fire Sale × Bank HHI	0.271***	0.037**
	(0.045)	(0.015)
Observations	20 293	20 293
Panel B: Alternative real estate definition		
High Adjusted RE × Fire Sale × Share	0.165***	0.118***
	(0.058)	(0.042)
High Adjusted RE × Fire Sale × Bank HHI	0.135	0.034
	(0.234)	(0.142)
Observations	20 768	20 768
Panel C: Excluding firms incorporated in Delaware		
High RE excl.-DE × Fire Sale × Share	0.116*	0.119**
	(0.058)	(0.042)
High RE excl.-DE × Fire Sale × Bank HHI	0.299***	0.132***
	(0.056)	(0.042)
Observations	20 768	20 768
Panel D: Alternative bank market share definition		
High Real Estate × Fire Sale × $\mathbb{1}(Share \geq 10)$	0.029***	0.018***
	(0.011)	(0.005)
Observations	20 683	20 683
Panel E: Alternative bank concentration definition		
High Real Estate × Fire Sale × Top–4 Share	0.117***	0.042**
	(0.027)	(0.020)
Observations	20 683	20 683

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Table 9 replicates Tables 5 and 6 using alternative variable definitions. The dependent variable in all panels is *Zombie Loan*, which indicates a zombie loan to a firm by a lender in a year. *Adjusted RE* is the product of the ratio of PP&E to assets and the average firm-level fraction of the PP&E corresponding to buildings in 1981–1993. *Share* is the three-year average share of outstanding loans in an MSA arranged by a bank. $\mathbf{1}(Share \geq 10)$ in panel (C) is an indicator for larger than 10% market share over the past three years. Bank concentration (Bank HHI) is measured as the sum of the squared market shares of outstanding loans in an MSA (Herfindahl Index). Panel (D) the average share of the top-4 banks in the MSA over the past 3 years is used. The remaining variables and specifications are as indicated in Table 8.

downwards to zero, and our estimates should be interpreted as a lower bound. In addition, Campello et al. (2022) shows that for an average firm, only 6% of its real estate assets in market-value terms are located outside the region of its headquarters, and hence, the true market value of real estate assets is highly correlated with the market value of assets in the headquarter. Hence, any issues due to mismeasurement of location are limited.

To further address this issue, we conduct an additional robustness test. It is well known that firms incorporate in Delaware for tax and legal purposes even when they carry their businesses outside. We remove all the firms headquartered in Delaware from our sample and re-estimate our primary results (*High RE excl.-DE*). The outcomes are displayed in Table 8, panel (C), and Table 9, panel (C). The tables confirm that our findings remain consistent even after excluding Delaware-based firms.

6.4. Excluding term-b loans

We also calculate zombie loans, bank market share and concentration after excluding term-B loans, considered 'institutional' facilities with higher interest rates than 'bank' only facilities. Banks are likelier to sell these loans, reducing their exposure to a firm or MSA (Nandy and Shao, 2010). We re-estimate Eqs. (12) and (13) and present the results in Table 9, panel (A). In column (1), we use the structural break as a proxy for the fire sale of assets, while in column (2), we use a fall in real estate prices in an MSA. The results show that, on average, banks with higher market share are more likely to give zombie loans during a fire sale to high real estate firms compared to low real estate firms. In the second row, the results show that high real estate firms in MSAs with higher bank concentration are more likely to receive zombie loans following a fire sale. All estimates are statistically and economically significant.

6.5. Alternative market share definition

In Table 9, panel (D), instead of using the past three-year average market share of a bank, we use an indicator variable which is equal to 1 when the three-year market share of a bank in an MSA is greater than 10%.[13] We use this to re-estimate Eq. (12). Similar to our main results, we find that high real estate firms are 2.9% more likely to receive a zombie loan from a bank with a greater than 10% market share in an MSA compared to a low real estate firm following a fire sale (measured using the structural break in real estate prices). When we use a fall in real estate prices as our proxy for a fire sale, the probability decreases to 1.8% but is still highly significant.

6.6. Alternative bank concentration measure

We construct a different concentration measure in an MSA, which is the past three-year average market share of the top-4 banks in an MSA (Philippon, 2019). We use these measures instead of the original HHI Index and re-estimate Eq. (13) and present the results in Table 9, panel (E). Columns (1) and (2) show the results for the regression using structural break and fall in real estate prices as proxies for fire sales, respectively. In column (1), we see that a 1% increase in the top-4 bank market share increases the probability of zombie loans in an MSA by 0.11% to high real estate firms compared to low real estate firms following a fire sale. In column (2), we see that a 1% increase in the market share of the top-4 banks increases the probability of zombie loans to high real estate firms compared to low real estate firms by 0.04% after a fall in real estate prices.

6.7. Placebo tests:

Our identification strategy relies on generating quasi-random structural breaks exogenous to local market conditions (Charles et al., 2018). Further, we include bank-by-year fixed effects, which implies that we exclusively rely on variation across firms that have a relationship with the same bank but differ in their real estate holdings. To further validate our results, in the spirit of Fisher (1935), we undertake a series of placebo tests to estimate how unlikely our regression results are if there was no impact of fire sales on the relationship between bank market share and the probability of zombie lending to high real estate firms compared to low real estate firms.[14] Using Monte Carlo simulations of 1,000 iterations, we conduct placebo tests around the null hypothesis that fire sales do not impact the relationship between the probability of zombie lending and bank market share.

Specifically, for each MSA, we take the period before the structural break and generate two random fire sales. First, we generate a placebo fire sale that lasts for 4-years. The duration is chosen to match the median duration of structural breaks in our sample. The second placebo fire sale has a random length of between 1 and 10 years. Using these two placebo fire sales, we re-estimate Eqs. (11)–(13) a thousand times and report the average estimate of the coefficients and standard errors.

In Table B.2, we replace the Structural Break variable with a placebo fire sale and estimate Eq. (11). Column (1) shows the estimate using the placebo fire sale with a 4-year duration, while column (2) shows the estimate when using a placebo fire sale of random length. The estimate of β_3 in both cases is insignificant and close to zero. It shows that the probability of a high real estate firm being identified as a zombie firm compared to a low real estate firm is not affected by a placebo fire sale. In Table B.3, we estimate Eq. (12) using the placebo fire sales and observe that increasing the market share of a bank does not increase the probability of zombie lending to high real estate firms compared to low real estate firms after a placebo structural break. Finally, in Table B.4, we show the results of estimating Eq. (13) using the placebo fire sales. The results indicate that high real estate firms in high-concentration MSAs are not more likely to receive zombie loans than low real estate firms following a placebo fire sale.

Fig. B.1 displays the kernel density graph for the estimated coefficients. Panels (A) and (B) represent the placebo estimates of β_3 from Eq. (11), as shown in Table B.2. Panels (C) and (D) depict the simulation of β_4 from Eq. (12), detailed in Table B.3, while panels (E) and (F) illustrate the estimates of β_4 from the simulation of Eq. (13), presented in Table B.4. The vertical lines indicate the coefficient estimates derived from actual data. In every instance, the coefficients from the permuted data are nearer to zero than those from the real-world data in over 95% of iterations. These tests substantiate the heterogeneous impact of bank market share on the likelihood of zombie lending to high versus low real estate firms after a fire sale and support our proposed mechanism where high market share banks are motivated to internalize the cost of fire sales.

[13] In unreported results, we use a cutoff of 5% and find similar results.

[14] We thank an anonymous referee for this suggestion.

6.8. Logistic regression

Finally, in Table B.5, we use logistic regression instead of a linear probability model to estimate the probability of zombie lending. In panel (A), we find that high real estate firms are 2.16 times (coefficient estimate of 0.772 when using *Structural Break* as a proxy for fire sale) more likely to be identified as zombie firms than low real estate firms. The estimate is statistically significant. At the same time, fire sales cause a shift in banks' behavior as they begin to subsidize high-real estate firms.

In panel (B), we see that high real estate firms are 1.15 times more likely than low real estate firms to receive a zombie loan after a structural break per 1% increase in a bank's market share. When we substitute a structural break with a fall in real estate prices, we see that high real estate firms are 1.03 times more likely than low real estate firms to receive a zombie loan after a fall in real estate prices per 1% increase in a bank's market share. This result is statistically not very significant. In panel (C), we see that a 100-unit increase in bank concentration (as measured by HHI) increases the odds of a high real estate firm receiving a zombie loan compared to a low real estate firm by 1.20 following a structural break. Using a negative shock reduces the estimate to 1.07 while both are statistically significant at the 5% level.

In the main specification, we continue to use the linear probability model (LPM). While there are some criticisms of the LPM – including that LPM does not estimate the structural parameters of a non-linear model and does not give consistent estimates of the marginal effects – Angrist and Pischke (2009) recommend LPM as a better model.

6.9. Alternative hypothesis: Bank lending across the supply chain

In our model, zombie lending is a direct strategy by banks to sustain distressed firms and mitigate fire sale risks. However, an important question remains: do banks indirectly support zombie firms by extending credit to their major clients? Such indirect lending can encourage client firms to increase purchases from zombie firms, stabilizing their revenues and reducing the likelihood of default. This mechanism, if present, represents an alternative channel for banks to support zombie firms.

To test this hypothesis, we analyze whether banks that extend zombie loans also increase lending to the client firms of these zombies, particularly during periods of fire sales. In Table B.6, column (1), we regress an indicator variable that equals 1 if a bank lends to a client firm during the same year it provides a zombie loan to a zombie firm. In column (2), the dependent variable measures the log change in the dollar value of loans extended to client firms concurrently with a zombie loan. In both cases, we find no evidence that banks increase lending to client firms as an indirect means of supporting zombie firms following a fire sale. This result challenges the expectation that banks would use indirect strategies to stabilize zombie firms' operations.

Overall, our evidence shows that firms with higher real estate values are more likely to receive zombie loans from banks with higher market share and in markets with higher bank concentration. This aligns with our theory that banks with higher market shares may be giving zombie loans to mitigate fire sales in the MSAs in which they operate.

7. Conclusion

This paper shows that banks with high market share in an MSA give zombie loans to firms with relatively high real estate collateral when there is a fire sale in the local real estate market. Any liquidation of assets during a fire sale will further depress the price. This will hurt the liquidation price of the collateral and the health of the firms in the local economy, thereby reducing the value of the portfolio of loans held by these banks. Hence, banks with high market share who do not act as price takers internalize this cost. They trade off the cost of giving zombie loans to unproductive firms against the benefit of higher prices in the local real estate markets.

Thus, while high concentration in an area can help mitigate fire sales during a crisis, it can create another negative externality of keeping unproductive firms alive by giving zombie loans. Zombie lending has negative spillovers on healthy firms in an economy. Firms in an industry dominated by zombies face a crowded market, have lower markups, and have higher labor costs. We provide evidence that this credit misallocation reduces the investment and ROA of healthy firms in industries dominated by zombie firms. While client firms tend to reduce purchases from distressed firms, the ongoing support of zombie firms by banks allows their clients not to decrease their purchases, which impedes creative destruction. These negative externalities of zombie lending can delay economic recovery after a systemic crisis. We thus highlight a new cost of market concentration apart from traditional costs such as high prices and low quantities. Policymakers, therefore, need to consider this additional cost of market concentration when designing policies to limit banks' market power. Additionally, while designing policies for economic recovery after a crisis, they need to take into account the externality cost created by zombie lending, which could delay recovery.

CRediT authorship contribution statement

Kaushalendra Kishore: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nirupama Kulkarni:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Saurabh Roy:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Proofs

A.1. Proof of Proposition 1

Taking the first order condition given in Eq. (4) and substituting $L = 0$ (since it has been assumed to be very small), we get

$$\frac{dV(p(\lambda))}{d(p(\lambda))} - \frac{(1-\beta)(1-f)C}{\beta f} = 0. \tag{A.1}$$

λ^* is given by the solution to this equation. The first term is decreasing in λ and last term is independent of λ. Hence we get a unique solution λ^* if condition (5) holds.

Next we analyze how λ^* changes with f. The derivative of the first term in (A.1) w.r.t is f equals $V''(p(\lambda))p_f(\lambda)$, where p_f is partial derivative of p w.r.t. f. Both $V''(p(\lambda))$ and $p_f(\lambda)$ are negative, hence product is positive. Thus the first term is increasing in f. The second term in (A.1) is clearly decreasing in f. Hence as f increases λ^* must increase.

A.2. Proof of Proposition 2

We prove only the first part of the proposition. The second part can be proved analogously. The proof is by contradiction. Suppose $\tau^* \leq f(1-\beta)C_L/2$ and in the optimal solution all high collateral firms have not been given zombie loan ($\lambda^*_H < 1$). Now suppose if we increase λ^*_H by ϵ and reduce λ^*_L by $\eta = \epsilon\frac{C_H}{C_L} > \epsilon$, then the total collateral liquidated remains the same but the number of zombie firms reduces. Since total collateral liquidated is same, the price will remain same and the first two terms in will be same. But the number of zombie loans will reduce increasing the utility. Thus $\lambda^* < 1$ cannot be true in equilibrium. Finally, we get λ^*_L by diving total collateral liquidated by all the collateral of the low collateral firms which failed.

Appendix B. Tables

See Tables B.1–B.6 and Fig. B.1

Table B.1
Spillover from customers.

	(1)	(2)
Dependent variable	Δ log client sales	
	High Leverage	Zombie
High Real Estate	−0.045***	−0.038**
	(0.017)	(0.017)
Fire Sale	−0.003	−0.002
	(0.017)	(0.014)
Distress	0.001	−0.026
	(0.012)	(0.021)
Fire Sale × High Real Estate	0.049	−0.010
	(0.031)	(0.024)
Fire Sale × Distress	0.016	0.133
	(0.023)	(0.095)
High Real Estate × Distress	0.022	0.080
	(0.020)	(0.052)
High Real Estate × Fire Sale × Distress	−0.116**	−0.040
	(0.045)	(0.122)
Observations	17736	17791
Year FE	Yes	Yes
Firm FE	Yes	Yes

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Table B.1 compares the spillover effects of zombie firms compared to high-leverage firms. In column (1), *Distressed* firms are identified as firms with above median leverage following Custodio (2022), while in column (2,) distressed firms are *Zombie* firms defined as firms with excess interest < 0 and 3*yr*-MovAvg ICR < 1. *Fire Sale* is an indicator for MSAs with a decline in the HPI index greater than 3.3%. *High Real Estate* is an indicator for firms with above median real estate holdings. Standard errors are clustered at the firm level.

Table B.2
Placebo test for structural breaks and the likelihood of zombie firms.

	(1)	(2)
Dependent variable	Zombie	
	Duration = 4yrs	Random duration
High Real Estate	0.006***	−0.001
	(0.001)	(0.007)
Structural Break	0.003	−0.001
	(0.008)	(0.007)
High Real Estate × Structural Break	−0.004	−0.001
	(0.006)	(0.010)
Observations	34 074	34 074
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Table B.2 re-estimates the parameters of Table 4 using a randomized structural break. The coefficients and standard errors are estimated based on 1,000 random draws of the structural break. *Structural Break* is the randomized placebo indicator for a negative structural break in real estate prices in the MSA, which proxies for fire sale in our setting. Column (1) identifies a structural break before the actual break in an MSA with a break duration of 4 years, while column (2) chooses a random break duration between 1 and 10 years. *Zombie* is an indicator for zombie firms, and *High Real Estate* is an indicator for firms with above median ratio of market value of real estate and lagged value of property, plant and equipment. Both estimates use firm and time fixed effect while *Sales* and *Leverage* are included as controls.

Table B.3
Placebo test for market share and zombie lending.

	(1)	(2)
Dependent variable:	Zombie Loan	
	Duration = 4yrs	Random duration
Share	0.020	0.018
	(0.016)	(0.019)
Fire Sale	0.000	−0.001
	(0.017)	(0.013)
Fire Sale × Share	−0.015	−0.003
	(0.098)	(0.087)
High Real Estate	−0.007***	−0.007***
	(0.002)	(0.002)
High Real Estate × Share	0.017	0.017
	(0.017)	(0.020)
High Real Estate × Fire Sale	0.003	0.002
	(0.020)	(0.015)
High Real Estate × Fire Sale × Share	0.011	0.009
	(0.111)	(0.088)
Observations	20 768	20 768
Firm Controls	Yes	Yes
Facility Controls	Yes	Yes
Firm FE	Yes	Yes
Facility type FE	Yes	Yes
Lender × Year FE	Yes	Yes

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Table B.3 re-estimates the parameters of Table 5 using a randomized structural break. The coefficients and standard errors are estimated based on 1,000 random draws of the structural break. *Fire Sale* is the randomized placebo indicator for a negative structural break in real estate prices in the MSA, which proxies for fire sale in our setting. Column (1) identifies a structural break before the actual break in an MSA with a break duration of 4 years, while column (2) chooses a random break duration between 1 and 10 years. *Zombie Loan* is an indicator for a zombie loan to a firm by a lender in a year. The independent variables include *High Real Estate*, which is an indicator for firms with an above-median ratio of real estate to total assets, and *Share*, which is the three-year average share of outstanding loans in an MSA arranged by a bank. We use *Sales* and *Leverage* as firm-level controls, while *Maturity* and *Log Amount* are included as loan-level controls.

Table B.4
Placebo test for bank concentration and zombie lending.

	(1)	(2)
Dependent variable	Zombie Loan	
	Duration = 4yrs	Random duration
Bank HHI	0.020	0.018
	(0.016)	(0.019)
Fire Sale	0.003	−0.001
	(0.020)	(0.013)
Fire Sale × Bank HHI	−0.015	−0.003
	(0.098)	(0.087)
High Real Estate	−0.007***	−0.007***
	(0.002)	(0.002)
High Real Estate × Bank HHI	0.017	−0.003
	(0.017)	(0.087)
High Real Estate × Fire Sale	0.003	0.002
	(0.020)	(0.015)
High Real Estate × Fire Sale × Bank HHI	0.011	0.009
	(0.111)	(0.088)
Observations	20 768	20 768
Firm Controls	Yes	Yes
Facility Controls	Yes	Yes
Firm FE	Yes	Yes
Facility type FE	Yes	Yes
Lender × Year FE	Yes	Yes

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Table B.4 re-estimates the parameters of Table 6 using a randomized structural break. The coefficients and standard errors are estimated based on 1,000 random draws of the structural break. *Fire Sale* is the randomized placebo indicator for a negative structural break in real estate prices in the MSA, which proxies for fire sale in our setting. Column (1) identifies a structural break before the actual break in an MSA with a break duration of 4 years, while column (2) chooses a random break duration between 1 and 10 years. *Zombie Loan* is an indicator for a zombie loan to a firm by a lender in a year. *High Real Estate* is an indicator for firms with an above-median ratio of real estate assets to total assets. Bank concentration (Bank HHI) is the sum of the squared market shares of outstanding loans in an MSA. We use *Sales* and *Leverage* as firm-level controls, while *Maturity* and *Log Amount* are included as loan-level controls.

Table B.5
Robustness tests: logit regression.

Panel A: Price decline and the likelihood of zombie firms		
	Structural Break	Negative Shock
High Real Estate × Fire Sale	0.772** (0.369)	0.622*** (0.221)
Observations	9342	9342
Panel B: Bank market share and zombie lending		
	Structural Break	Negative Shock
High Real Estate × Fire Sale × Share	0.140** (0.068)	0.0339 (0.024)
Observations	17 238	17 238
Panel C: Bank concentration and zombie lending		
	Structural Break	Negative Shock
High Real Estate × Fire Sale × Bank HHI	0.189** (0.089)	0.069** (0.030)
Observations	19 773	19 773

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Table B.5 replicates all our results using logit regression instead of a linear probability model. Panel (A) estimates the probability of a Zombie firm. In contrast, Panels (B) and (C) estimate the probability of a *Zombie Loan*. The independent variables include *High Real Estate*, which is an indicator for firms with an above-median ratio of real estate to total assets, and *Share*, which is the three-year average share of outstanding loans in an MSA arranged by a bank. The bank concentration (*Bank HHI*) is measured as the sum of the squared market shares of outstanding loans in an MSA. *Fire Sale* is an indicator for fire sale in an MSA. Fire sale in an MSA is identified by structural breaks in column (1) and by negative price shocks in column (2). We use *Sales* and *Leverage* as firm-level controls, while *Maturity* and *Log Amount* are included as loan-level controls. All regressions use firm, year and lender fixed effects. Standard errors are clustered at the lender level.

Table B.6
Spillover from banks.

	(1)	(2)
Dependent variable	𝟙(Client Loan)	Δ $Client Loan
Zombie	0.037 (0.053)	0.745 (1.106)
Fire Sale	0.006 (0.060)	−0.001 (1.194)
High Real Estate	−0.033 (0.036)	−0.645 (0.728)
Zombie × Fire Sale	−0.071 (0.202)	−1.294 (4.163)
Zombie × High Real Estate	−0.004 (0.066)	−0.071 (1.361)
Fire Sale × High Real Estate	−0.027 (0.060)	−0.474 (1.207)
Fire Sale × High Real Estate × Zombie	0.048 (0.227)	0.919 (4.629)
Observations	9774	9774
Lender × Year FE	Yes	Yes
Firm FE	Yes	Yes
Customer FE	Yes	Yes

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Table B.6 estimates a bank's propensity to lend to clients of a firm to which it has provided zombie loans. *𝟙(Client Loan)* is an indicator that equals one if a bank has extended loans to the client of a zombie firm. *Δ $Client Loan* is the dollar change in bank loan to the client of a zombie firm. *Zombie* firms defined as firms with excess interest < 0 and $3yr$-MovAvg ICR < 1. *Fire Sale* indicates MSAs experiencing a structural break in real estate prices. *High Real Estate* is an indicator for firms with above median real estate holdings. Standard errors are clustered at the lender-year level.

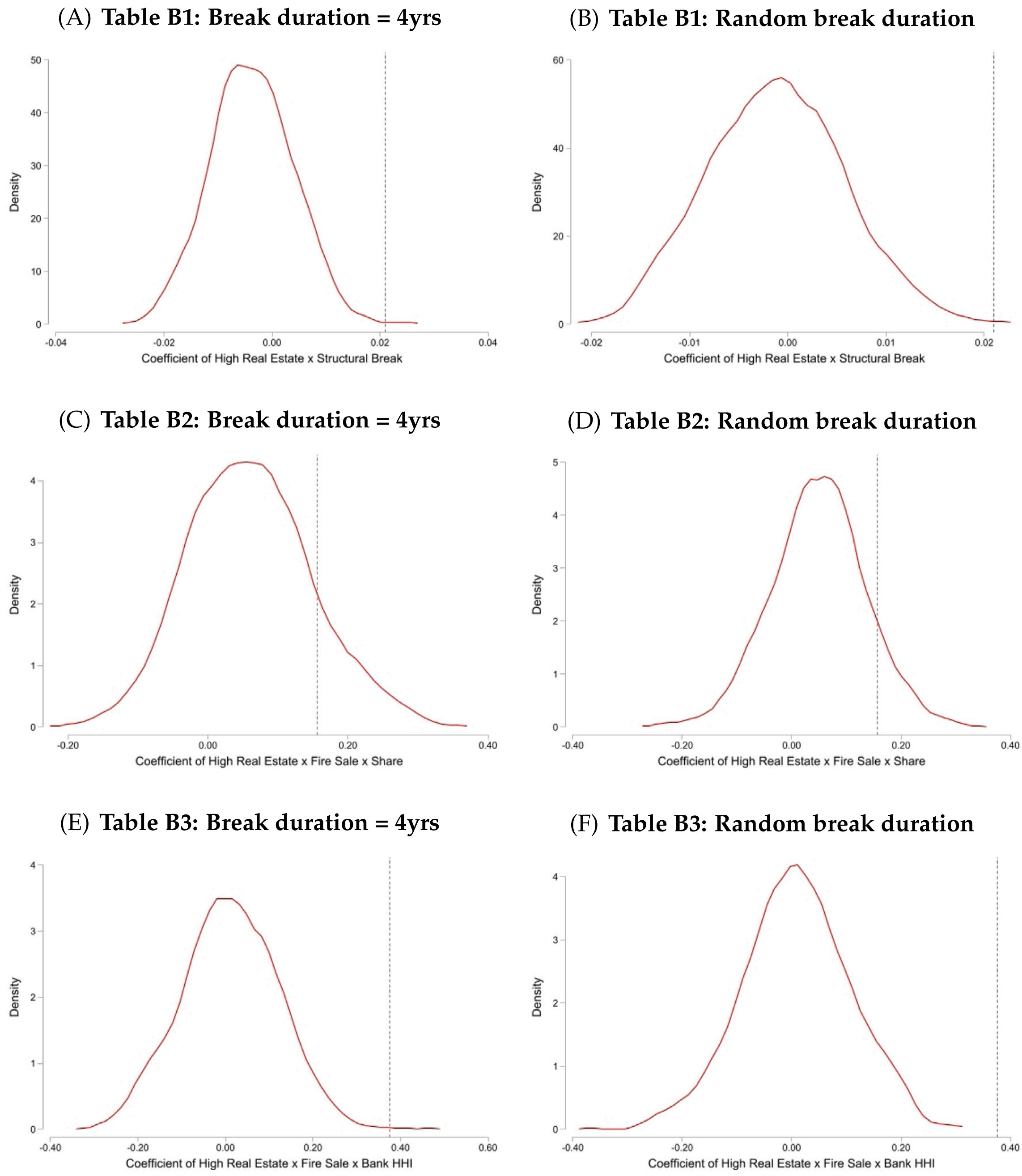

Fig. B.1. shows the kernel density graph of the placebo test estimates of Tables B1–B4. The vertical lines denote the point estimates from our main results. In all our placebo tests, the point estimate has a probability of less than 5%.

Appendix C. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jcorpfin.2024.102731.

Data availability

Data will be made available on request.

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