Zombie Lending Due to the Fear of Fire Sales

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Abstract

This paper documents a new externality stemming from the fear of fire sales: increased zombie lending during real estate price downturns. Firms use pledgeable assets such as real estate collateral to borrow. Using firm and syndicated loan data in the US, we confirm that the sensitivity of firms' debt to real estate collateral is positive. However, this sensitivity falls during real estate price declines due to an increase in lending to low-quality firms despite a fall in real estate collateral value. Zombie credit to high collateral firms increases as lenders internalize the price externalities of liquidating real estate collateral. Zombie presence depresses investment and profitability of healthier firms. Our paper highlights a new mechanism for zombie lending resulting from reduced collateral liquidation in markets prone to fire sales.

JEL Classification: G21, G33, L25

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Fire sales of assets occur during downturns, when financial institutions are forced to sell at prices below their fundamental values, triggering an even further deterioration in prices (Kiyotaki and Moore, 1997; Brunnermeier and Pedersen, 2009). Such fire sales can erode the balance sheets of financial institutions during periods of crisis (Carlson et al., 2009; French, 2010; Caballero and Simsek, 2010) and can have significant negative externalities. For instance, Benmelch and Bergman (2011) document the negative externalities on the value of other firms' assets. Lenders may also internalize such fire-sale externalities, for instance Giannetti and Saidi (2019) find that lenders continue to provide liquidity to distressed industries to avoid such externalities.

We conjecture that if such support goes to otherwise insolvent or "zombie" firms, it may end up creating another externality by hindering creative destruction and diverting resources away from healthier firms (Caballero et al., 2008).This paper thus examines a new fire-sales externality: increased zombie lending during downturns. We do this using the real estate market. Firms use real estate as collateral to alleviate agency frictions, allowing them to raise capital (Chaney et al., 2012; Gan, 2007; Cvijanovic, 2014). Real estate markets, however, are also 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 whether lenders keep credit flowing to otherwise insolvent borrowers (zombie firms) during real estate downturns to avoid fire-sale externalities in real estate markets.

This paper first builds a theoretical model that motivates lender incentives in extending zombie credit, due to the fear of fire sales during downturns. Using firm- and loan-level data from the US, we empirically show that during real estate price declines, lenders do not liquidate failing firms as they fear further deterioration in real estate prices due to fire sale externalities. Lenders instead extend zombie credit to keep these failed firms alive and arrest further declines in real estate prices. Lenders with higher exposure to the local real estate markets are more likely to extend zombie credit as they are more exposed to the negative price spillovers from liquidation. Firms with larger real estate collateral are also more likely to receive zombie loans as liquidation can create greater price externalities. Keeping inefficient zombie firms alive gives rise to another externality. It hinders creative destruction and depresses investment and profitability of healthy firms in industries congested by zombie firms.

We begin our analysis by first building a theoretical model to illustrate this new externality of fire sales. Firms borrow from banks using their real estate assets as collateral. Some of these firms eventually default when faced with a negative shock and turn into low productivity firms, which we call zombie firms. Banks can then either liquidate these firms and sell their real estate collateral, or extend zombie credit and keep them alive while bearing the cost of their negative NPV zombie loans. During the *normal* state, very few firms default, whereas during the *adverse* state, several firms default. If only a few firms default, as 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 (Brunnermeier and Pedersen, 2009; Shleifer and Vishny, 1992). However, in the adverse state, when many firms default, buyers do not have enough liquidity to buy the assets of defaulted firms. Hence, there will be cash-in-the-market pricing and assets are sold at fire-sale prices, resulting in a decline in real estate prices. Banks realize that at the margin, selling the collateral when the local real estate prices are declining can further deteriorate prices. These price declines can reduce the collateral value of nearby firms that can result in a tightening of financial constraints and a lowering of investment.

Banks, thus have an incentive to extend zombie loans to failed firms instead of liquidating them. Banks care about the value of the portfolio of loans that did not default, which in turn depends on the health of the local economy for which real estate price is a proxy. Banks also care about the price at which they sell the collateral of some of the firms they choose to liquidate. We show that during the adverse state, banks extend zombie loans to defaulted firms due to potential fire sale discounts, while during the normal state they liquidate all defaulted firms as they are able to sell their collateral at a fair price. In addition, in the adverse state, banks with higher market shares will internalize the effect of the price decline more compared to banks with lower market shares.

We conduct our empirical analysis and test the model's implications in several steps. In the model we argue that when real estate prices are declining, banks may give zombie loans to firms which have defaulted merely to keep them alive. Such lending may break down the relationship between collateral value and lending. To test this we first estimate how the value of real estate assets affects debt issuance by firms using a specification similar to Chaney et al. (2012). To test the assymetry in the relationship during good and bad times, we separately estimate the effect for periods when local real estate prices are increasing and when local real estate prices are declining. We show that the elasticity between debt and real estate prices is positive overall. However, the elasticity is 0.6 times lower when real estate prices are declining (analogous to the adverse state in our model) as compared to when real estate prices are increasing (normal state in the model). That is, the rate of deleveraging when real estate prices are declining is lower than the rate of leveraging when real estate prices are increasing. This provides suggestive evidence that banks may not be demanding as much collateral in the adverse state and may be using liberal credit policies to support firms facing negative shocks.

We test this idea further and determine whether the "excess" borrowing is by healthy or financially distressed firms. We divide firms into distressed and healthy based on their ability to service their debt. Distressed firms are defined as firms which are in the bottom tercile of interest coverage ratio (ICR), which is the ratio of profits to interest expenses. We show that in the adverse state, distressed firms raise 40% more debt compared to non-distressed firms. Potentially, banks were extending credit to financially distressed firms.

We next examine whether banks were extending credit to distressed firms at subsidized rates, also known as zombie lending. Following Caballero, Hoshi and Kashyap

(2008), we identify zombie firms based on whether they receive credit at interest rates lower than the most creditworthy firms in the economy. Indeed, banks extend credit to zombie firms, and in particular to firms with high real estate collateral. Firms with above-median real estate holdings are 2.3 times more likely to receive a zombie loan as compared to firms with below-median real estate holdings. 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.

To further test the model and to pin down the channel, we estimate how the market share of banks in a metropolitan area (MSA) affects the probability of zombie lending. A bank with higher market share will internalize the effect of price declines more than a bank with a smaller market share. We show that a one percent increase in a bank's market share increases the probability of extending zombie credit by 0.042% whereas a 1% increase in the share of collateral in an MSA held by the bank increases the probability of extending zombie credit by 0.047%.

Finally, we show that the presence of zombie firms has a negative impact on the healthier non-zombie firms. As pointed out by Caballero, Hoshi and Kashyap (2008), the presence of zombie firms in an industry can divert resources which would otherwise have been available to healthier, more efficient non-zombie firms. A 1% increase in the share of zombie firms in an industry leads to non-zombie firms reducing their investment by 1.16%. Subsequently, the profitability of non-zombie firms also declines by 0.95%.

Overall, our paper also has implications for the ongoing COVID-19 crisis, which is a systemic shock affecting firms and financial institutions. Broadly, the crisis will render two kinds of firms on the verge of bankruptcy: those with good fundamentals that become bankrupt because of the COVID-19 shock and those with poor fundamentals that would have become bankrupt even without the shock. Banks should ideally liquidate firms with poor fundamentals, but since the shock is systemic there will be few buyers in the market that can lead to fire sales of assets. Hence, banks may extend zombie loans to firms with poor future prospects so as to arrest the further deterioration of prices. This can further weaken recovery as the presence of zombie firms hinders the natural process of creative destruction and keeps otherwise insolvent firms alive. Hence, regulators needs to ensure that credit does not flow to the worse firms in the economy.

The key contribution of this paper is that it shows that as lenders internalize the negative externality of a decline in collateral prices by extending zombie credit, they create another externality by keeping unproductive firms alive which in turn hinders the process of creative destruction. Thus the actions that banks take may be optimal privately and even locally, but may be inefficient for the economy as a whole.

Our paper contributes to a number of strands of literature. Prior literature has documented that fire sales exist and are costly and hence lenders and borrowers take actions to avoid fire sale of assets (Shleifer and Vishny, 2011). For example, Asquith et al. (1994) show that distressed firms are more likely to restructure debt than liquidate their assets when the industry is facing a down turn. Schlingemann et al. (2002) provide evidence that firms divest business units from industries which have more liquid markets, rather than liquidating the worst performing units. Banks with high market share in an industry are also more likely to provide liquidity to firms in such industry during times of 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 similar to Favara and Giannetti (2017), who show that banks with a higher market share are less likely to trigger foreclosures. However, our paper highlights the *negative* effects of keeping zombie firms alive. Our findings add to the large 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 the ex-post decision of a bank to either liquidate a firm or to extend zombie credit to it.

This paper also contributes to the literature on zombie loans, made even more relevant with the ongoing crisis. In their seminal paper, Caballero et al. (2008) show that the presence of zombie loans can make industries unproductive as it prevents the process of creative destruction. The literature on the causes of zombie lending has shown that, in the presence of limited liability, undercapitalized banks have an 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 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 that have access to more redeployable collateral receive larger loans with longer maturity and at lower interest rates (Benmelech et al., 2005). Chaney et al. (2012) show that real estate is a major source of collateral for firms and that increasing collateral value increases investments. Cvijanovic (2014), on the other hand, shows that increasing real estate prices lead to an increase in firm leverage. Our paper shows that higher levels of real estate assets can help firm secure loans, but for very different reasons. Liquidating firms with larger 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 where 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.

1 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 are a continuum of atomistic identical firms, each owns C units of real estate (or land) which can be used a collateral and has a positive NPV project which requires one unit of investment. There are 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 (N) and adverse (A). The probability of success is denoted by $q \in \{\alpha, \beta\}$, where α (β) is the probability of success in 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 section 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 which has very low probability of success in the future. The total cost to the bank of giving a zombie loan to a firm and keeping it alive is L. We will assume that L is small positive number very close to zero.[1]

If a firm's project succeeds, then it pays F to its bank. The *successful* firm is then endowed with another project which is financed by the same bank, and the process can repeat in future. The continuation value of each firm to the bank 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 monopoly power or information rent from relationship lending.

[1]This assumption is not necessary but considerably simplifies the proof of proposition 1. The results will still hold as long as L is small enough.

As discussed above, if a firm fails at $t = 1$, then the bank can liquidate it and sell the collateral at market price denoted by p. We assume that the intrinsic or fair value of one unit land is given by Z which is independent of the aggregate state.[2] 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 price is determined as following. We assume that at $t = 1$, there are outside investors who are ready to buy the land. These outside investors have a total wealth of W.[3] The investors can be interpreted as experts who understand the local economy and the real estate markets. Their wealth characterizes the demand for the real estate assets.

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 α is high enough (hence supply is low enough) such that even if banks liquidate all their loans ($\lambda = 0$), land is sold at fair price Z.

Assumption 1. $W > Z(1 - \alpha)C$.

As the readers might have guessed, we will assume that in the adverse state if all banks liquidate with probability one, then land will not be sold at fair price and there will be cash-in-the-market pricing.

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

If all banks liquidate with probability $1 - \lambda$ in the adverse state then the price is given by

[2] 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.

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

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

This price is weakly decreasing in $1 - \lambda$, or equivalently weakly increasing in the number of zombie loans.

We assume that the continuation value of the successful firms to the bank, V, will be a function price. There are many justifications for this assumption. First, the profitability of a firm or the probability of its success depends on how number and scale of other firms functioning in the economy. 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 increases 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 make zombie loans which also keeps the prices higher. Further, as pointed out by Benmelch and Bergman (2011), higher price of collateral due to prevention of bankruptcy can reduce the cost of capital and increase investment by neighboring firms. The larger scale of operation will hive higher positive spillover effect of firms in the locality. Finally, as the price of real estate falls, it will reduce the home equity value of the residents in the area, who may in turn reduce their consumption (Mian et al. (2015)). We capture these ideas in a reduced form by assuming 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

$$q(F + V(p(\lambda))) + (1-q)(1-\lambda)Cp(\lambda) - (1-q)\lambda L; \quad q \in \{\alpha, \beta\}. \tag{2}$$

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 assumed so far.

1.1 Equilibrium with atomistic banks

If all the banks are atomistic, they all take price as given and will choose their λ to maximize their utility. It is clear that irrespective of the state, banks will choose $\lambda = 1$. So by assumptions 1 and 2, in good state the price will be equal to the fair value and in the bad 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 bad state the price is given by $W/(1-\beta)C$.

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

1.2 Equilibrium when banks are not atomistic

Now let us assume that one of the banks ("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. But in the bad 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 bad state since they will take price as given. We assume that in the bad state the price is below fair value.

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

Assumption $2'$ is stronger than assumption 2. It implies that even if the large bank gives zombie loans to all failed firms, i.e. chooses $\lambda = 1$, the supply in the adverse state is high enough that land will not be sold at fair price. Now if the large bank chooses the probability zombie loan as λ, then the price, $p(\lambda)$, 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

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

This 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^*.

As discussed above, there are two benefits of giving the zombie loan. First, it increases the price of collateral. Second, the increased price increases the value of V. The large bank will internalize these effects and give zombie loans with positive probability ($\lambda > 0$). More interestingly, it can be shown that as the market share increases, it gives zombie loans to higher fraction of failed firms.

Proposition 1. If assumptions 1 and $2'$ hold true and

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

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

Proof: See appendix.

The intuition for the result is simple. More liquidation results in 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 higher probability. Condition (5) simply gives the boundary conditions required for 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. But 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.

1.3 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 remaining half firms have low collateral denoted by $C_L < C_H$. Average size of the collateral is still C.[4] The other characteristics of the firm, V and L, remain the same.[5] As before there is a large bank with market share f and atomistic banks with a combined market share of $(1 - f)$. Each banks' portfolio is equally distributed between the two types of firms and the face value of loans remain the same.[6]

In the normal state, by assumption 1, all banks will continue to liquidate all firms. In

[4]This assumption is not necessary, and merely reduces the effort of refining assumptions 1 and 2′

[5]It may seem unreasonable to assume the other characteristics of a firm do not change with the size of the collateral. But 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 is same, but some firms have more real estate assets than the 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 modelling the market for not real estate assets of the firm when it is liquidated.

[6]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 pay off, the face value is irrelevant to our calculations.

the adverse state, when a firm goes bankrupt, the larger bank chooses to give a zombie loan to high (low) collateral firm with probability λ_H (λ_L). The total collateral liquidated by large firms is denoted by τ and is given by

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

where τ. 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.

The price in the adverse state is given by

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

Utility function of the large bank is given by

$$\beta(F + V(p(\lambda_H, \lambda_L))) + \tau p(\lambda_H, \lambda_L) - \frac{1-\beta}{2}(\lambda_H + \lambda_L)L. \tag{8}$$

Given this set up, it can be shown that the high collateral firms are more likely to get a zombie loan than the low collateral firms.

Proposition 2. Given assumption 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 $\lambda_L^* = 1$ and $\lambda_H^* = \frac{\tau^* - C_L f(1-\beta)/2}{C_H f(1-\beta)/2}$.

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. 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 and the remaining collateral will come from the high collateral firms.

The intuition is as following. The cost of giving a zombie loan, L, is fixed and is independent of the collateral level. So, 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.

2 Data

To test our hypotheses, we need information on the value of collateral available to firms and their borrowings. We also need information on the exposure of various lenders to these firms. We use accounting data for listed US firms from Standard & Poor's COMPUSTAT database. Details on syndicated loans are from the Thompson Reuters Dealscan database. We access the House Price Index from the Office of the Federal Housing Enterprise Oversight and the Consumer Price Index from the Bureau of Labour Statistics.

2.1 Firm Data

We use firms with non-missing real estate assets, headquartered in the United States. We then exclude firms operating in finance, insurance, real-estate, construction, and mining. We restrict our sample period from 1993 to 2015 and to firms that have data for at least three years in this period. This leaves us with 6,804 firms and 73,126 firm-year observations.

2.1.1 Real Estate Assets:

We classify real estate as total *Buildings, Land, and 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 real estate, we need to calculate the average age of assets. The ratio of accumulated depreciation in 1993 to the gross book value of the real estate measures the proportion of the cost claimed as depreciation. Assuming a depreciable life of 40 years and straight-line depreciation, we calculate the average age of a firm's real estate. We inflate real estate assets using state-level and MSA-level real estate inflation. For real estate purchased before 1975, we use CPI to inflate its value.

Real Estate Prices: We get the House Price Index (HPI) from the Office of the Federal Housing Enterprise Oversight. The HPI is available at the state and MSA levels. We match each firm's ZIP and FIPS code to the respective MSA code. The HPI is then normalized to 1 in 2006. Previous work by Gyourko (2009) has shown that residential and commercial real estate prices are highly correlated so we assume that residential real estate price change reflects all real estate prices changes in an area. Since we don't know the exact location of all real estate holding of a firm, we assume that a firm's real estate is at the same location as its headquarters.

We restrict our sample to firms active in 1993 as accumulated depreciation is not available in COMPUSTAT after 1993. Our final sample has 3,430 firms and 36,831 firm-year observations. Chaney, Thesmar and Sraer (2012) show that for the median land-holding firm in COMPUSTAT, the market value of real estate is a sizable fraction of tangible assets of the firm and so is a good proxy for the collateral available to a firm. We define *RealEstate* as the market value of real estate standardized by lagged PPE.

2.1.2 Dependent Variables

We aim to explain a channel of subsidized lending so our main variable of interest is the probability of zombie lending. The other variables of interest are *long-term debt, debt issuance, investment, productivity, return-on-assets, and interest coverage ratio*. Debt variables are normalized by lagged *PPE*.

We define the *Investment rate* as the ratio of capital expenditures (*Capex*) to the previous year's *PPE*. The *Interest Coverage Ratio* is the ratio of a firm's earnings before interest and taxes (*EBIT*) and its *interest expense* while *Return-On-Assets* is calculated as the ratio of operating income minus depreciation and amortization to assets. We also calculate the *operating return on assets* as the ratio of operating cash-flows to assets. And finally, *leverage* is the ratio of a firm's total debt to assets.

We calculate a firm f's productivity A at the two-digit SIC code (sector) level i using a Cobb-Douglas production function. We estimate the function $Y_{f,t} = A_{f,t}K_{f,t-1}^{\alpha_i}L_{f,t}^{\beta_i}$, where Y is the value-added, K is fixed assets and L is the employment.

2.1.3 Controls

For our analysis, we need to control for factors that affect a firm's borrowing decision. We use *Tobin's-q* to proxy for investment opportunities and the *Kaplan-Zingales Index* (KZ) (Kaplan and Zingales, 1997) and firm *age* to proxy for financing constraints. We cut-off firm age (in 1993) at 33 so that no firm's birth year is before 1960. *Tobin's q* (market-to-book ratio) is calculated as the ratio of a firm's market value to its book value. The *KZ-Index* is calculated as

$$\begin{aligned}KZ\text{-}Index = &-1.002*(ib-dp)/at_{t-1} - 39.368*(dvc-dvp)/at_{t-1} - 1.315*che/at_{t-1}\\&+3.139*(dltt+dlc)/(dltt+dlc+seq)+0.283*q\end{aligned}$$

where *ib* is the income before extraordinary items, *dp* is depreciation and amortization, *at* is the book value of a firms assets, *dvc* and *dvp* are the common and preferred dividends, *che* is the cash and short-term investment, *dltt* and *dlc* are the long-term and short-term debt, and *seq* is the shareholders' equity.

To ensure that our results are robust, we winsorize all ratio variables at the 1% and 99% levels.

2.2 Zombie Lending using Accounting Data

Zombie firms are companies that are unprofitable and can go bankrupt in the future. To identify zombie lending, we follow the approach of Caballero, Hoshi and Kashyap (2008) and Acharya, Eisert, Eufinger and Hirsch (2019). The classification of a firm as a zombie hinges on the firm receiving subsidized credit from banks. A firm receives subsidized credit if, its interest rate on borrowing is lower than the rate paid by the most creditworthy firms in the economy. We calculate this 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 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). The interest coverage ratio is a good proxy for the S&P rating of a firm and thus of the highest rated firms.

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}),

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

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.

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

Given x_{it}, a firm is classified as a zombie if it meets the following criteria: (i) x_{it} is negative *i.e.* the excess interest paid by the firm is negative which implies that its interest cost is less than that of the most creditworthy firms (ii) it is in the bottom tercile of firms when classified by the 3-year average interest coverage ratio. For small firms (<\$5bn in market cap), $ICR = 3$ corresponds to a rating of BB while for larger firms, $ICR = 2$ is equivalent to a BB rating (Damodaran). When using the bottom tercile of ICR as a proxy for S&P rating, only 1 datapoint has an ICR above 3 and 1.2% of the data points have an ICR greater than 2. Hence, selecting the bottom tercile is a good proxy for a firm's credit rating.

2.3 Loan Level Data

To test our hypothesis, we need to calculate the market share of lenders in each location. Thompson Reuter's Dealscan database contains detailed information on syndicated lending facilities to a firm. We merge Dealscan with COMPUSTAT using the link table provided by Chava and Roberts (2008). We can match 13,185 facilities (loans) to firms in our dataset, 36,549 observations of a loan from a bank to a firm and a total of 244,763 bank-firm-year data-points. Using this merged dataset, we can calculate the outstanding loans of a bank to a firm in each year. Assuming that the majority of a firm's real estate is in the same MSA as its headquarter, we can calculate the outstanding loans of each lender in each MSA. With the exact interest rate of each loan, we can identify specific loans as zombie loans. With the COMPUSTAT data, we classified an entire firm as a zombie.

2.3.1 Zombie Lending using Lending Data

To identify zombie firms from the COMPUSTAT data, we relied on an average rate of interest paid by a firm. Dealscan allows us to identify the specific loans which are "subsidized". The variable *"AllInDrawn"* is a composite way of reporting the pricing of facilities. We can thus compare the rate across facilities regardless of the underlying fee and spread structure. The *AllInDrawn* rates are quoted as a spread over LIBOR. The spread is not calculated for fixed-rate loans, letters of credit, or subordinated debt. We ignore these. Since secured loans are cheaper than unsecured loans, we divide facilities into secured and unsecured. As before, we classify loans as zombie if the interest rate on the loan is lower than that of the highest-rated firm.

2.3.2 Bank Market Shares

Syndicated loans are only a fraction of banks' total lending. However, they consist of the largest loans to the largest firms and thus account for a sizeable portion of total lending. Previous studies (Giannetti and Saidi, 2019; Chodorow-Reich, 2014) have used syndicated loans to evaluate bank lending policies. In our setting, negative spillover effects are larger for large borrowers whose loans have good coverage in Dealscan.

We consider the bank holding company as the ultimate provider of credit and aggregate all loans accordingly. 30% of the loans in our sample have only one lender. For the remaining loans, we ascribe a loan to a lender if its role is either *Lead Arranger, Agent, Bookrunner, Manager, Underwriter or Sole Lender*. Though both the arranger and the participant commit capital, the average lead arranger share is four times as large as the average participant share. Participants in a syndicated loan are more likely to sell their loans in the secondary market (Irani, Iyer, Meisenzahl and Peydro, 2018). For these reasons, the lead arranger is considered the "lender" in literature (Ivashina and Scharfstein, 2010).

If the arranger share data is missing, we attribute the median allocation of arrangers in our sample to the arranger. In the case of more than one arranger, we assign each arranger an equal fraction of the lead arranger's total share. We assume that a bank that arranges a loan retains it on its balance sheet. So, to calculate the loans retained by a bank, we add all loans that have not matured. In our setting, lenders with a large market share in a location have stronger incentives to avoid price-default spirals. This is because their decision to liquidate loans has a larger price impact. We assume that all creditors have the same seniority.

To evaluate this mechanism, we identify loans that are still outstanding. We define *MarketShare* as the dollar amount of loans arranged by a bank that have not matured, divided by the dollar amount of all loans issued in an MSA. Large banks have a more geographically diversified portfolio while most small banks tend to lend locally. Thus for small banks, loans to firms in an MSA is large compared to their total lending. Our model shows that liquidation by smaller banks does not have a price externality. So, a large portfolio share of loans to an MSA will not lead to zombie lending incentives. We define *PortfolioShare* as the total outstanding loans of a bank in an MSA divided by the total outstanding loans of a bank. Finally, *CollateralShare* is the share of collateral in an MSA that a bank has access to divided by the total collateral available in an MSA. To calculate *CollateralShare*, we ascribe the collateral of a firm to a bank in proportion to the bank's share of outstanding loans to the firm.

3 Empirical Strategy

We conduct our empirical analysis in three stages. We first document the effect of collateral value on firms' borrowing, investment, and productivity during positive and negative shocks to real estate collateral value. Second, we link this to the probability of receiving zombie loans during real estate downturns.Third, we exploit heterogeneity across bank-exposures to local real estate markets to establish the mechanisms driving the zombie lending.

3.1 Motivating specifications: Firm borrowing and real estate collateral

We motivate our empirical analysis by separating the effect of collateral value on debt during positive and negative real estate price shocks. We use a specification similar to Chaney et al. (2012), who relate increases in real estate collateral value to firm investment.

We use the specification:

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

for firm i, in year t. The outcome variable, $y_{i,t}$ is the change in debt from t-1 to t. α_i and δ_t are the firm and year fixed effects and control for the time-invariant firm-level factors and the macroeconomic shocks affecting all firms, respectively. Real Estate$_{i,t}$ is the market value of real estate held by a firm normalized by lagged plant, property and equipment. It is calculated by multiplying the change in the Housing Price Index (HPI) by the real estate holding of each firm in 1993. Negative Shock$_{MSA,t}$ is 1 if real estate price growth in an MSA is negative in year t. Control variables included are Tobin's q, KZ index, age and age squared. These variables control for firms' investment opportunity, financial constraints, and age. Standard errors are clustered at the firm level. β_1 measures the sensitivity of $y_{i,t}$ to real estate prices. The coefficient of interest, β_3 measures the differential effect on sensitivity to real estate prices during real estate price declines. $\beta_1 + \beta_3$, measures the sensitivity to real estate prices during real estate price declines. β_2 controls for the overall decline in the outcome variable.

If β_3 equals zero, this would imply that there are no differential effects on collateral-based lending during real estate price declines. If β_3 is greater than zero, this would imply that sensitivity to real estate collateral increases during downturns, say if, lender risk aversion increases during periods of stress and lenders switch to more secured lending (that is, lending secured by real estate as collateral). If β_3 is less than zero, this would imply that sensitivity to real estate collateral declines during real estate price declines. Sensitivity may decline if banks continue lending to borrowers whose real estate collateral values decline (due to the real estate price declines).[7]

[7] Another reason for the decline in sensitivity could be, if say, firms switch to borrowing from other sources of financing and start relying less on real estate collateral-based borrowing.

One reason for such continued support during real estate prices declines is if lenders believe that the shock is temporary and firms are likely to recover in the future. We examine whether debt issuance is driven by the healthier firms relative to the distressed firms using the specification:

$$
\begin{aligned}
y_{i,t} = &\beta_1 * \text{Low ICR}_{i,t} + \beta_2 * \text{Negative Shock}_{MSA,t} \\
&+ \beta_3 * \text{Low ICR}_{i,t} * \text{Negative Shock}_{MSA,t} \\
&+ \text{Controls}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}
\end{aligned} \tag{10}
$$

for firm i in time t. α_i and δ_t are the firm and year fixed effects. $y_{i,t}$ is the debt issuance in year t. Low $\text{ICR}_{i,t}$ is 1 for firms in the bottom tercile of firms the 3-year moving average of the interest coverage ratio (ICR). ICR is the ratio of profit to interest expenses and measures a firm's ability to service its debt. Low $\text{ICR}_{i,t}$ captures the relatively distressed or low quality borrowers in the economy. Control variables included are Tobin's q, KZ index, age and age squared. These variables control for firms' investment opportunity, financial constraints, and age. Standard errors are clustered at the firm level. The coefficient of interest, β_3, estimates the change in debt issuance for the low-quality firms relative to the high-quality firms during downturns. A positive β_3 would indicate that the increase in lending is higher for the low-quality firms. A negative β_3 would indicate a decline in lending to distressed borrowers consistent with say if banks become risk-averse during downturns and continue lending to only the safer borrowers.

3.2 Main specification: Zombie lending and real estate collateral

To estimate the probability of zombie lending to high collateral vs low collateral firms, we run a logit regression as below.

$$\begin{aligned}\text{Zombie}_{i,t} =&\beta_1 * \text{High Real Estate}_{i,t} + \beta_2 * \text{Negative Shock}_{MSA,t} \\ &+ \beta_3 * \text{High Real Estate}_{i,t} * \text{Negative Shock}_{MSA,t} \\ &+ \text{Controls}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}\end{aligned} \tag{11}$$

for firm i in year t. High Real Estate$_{i,t}$ is an indicator for firms with above-median real estate value, measured as the market value of real estate held by a firm normalized by lagged plant, property and equipment. Negative Shock$_{MSA,t}$ is an indicator for an MSA-year with negative real estate price change as measured by the house price index. α_i and δ_t are the firm and year fixed effects and control for the time-invariant firm-level unobservable factors and the annual shocks affecting all firms uniformly. Control variables included are Tobin's q, KZ index, age and age squared. These variables control for firms' investment opportunity, financial constraints, and age. Tobin's Q and the KZ-Index to control for the demand and supply of credit respectively. The coefficient of interest, β_3, estimates the probability of a high collateral firm receiving a zombie loan compared to a low collateral firm during a negative shock. β_1 estimates the probability of receiving a zombie loan for high real estate firms during normal times.

3.3 Specifications to examine underlying mechanisms

If the existence of zombie firms has negative spillover effects on an industry (Caballero, Hoshi and Kashyap, 2008), banks should be wary of lending to zombie firms. ideally, they would force these firms to restructure and help the creative destruction process. Banks may, on the other hand, continue lending to these firms if they believe that fire sale of assets can depresses the value of other firms, which can then negatively affects the bank's assets. Our model (proposition 3) predicts that banks with a large market share of loans bear a proportionate cost of the fire sale of land, depressing prices, and would likely trade-off the cost of zombie lending with zombie spillover on their own balance sheets. To see if this mechanism is in play, we test if banks with large market shares in an MSA are more likely to engage in zombie lending to firms with high real estate collateral.

??? We estimate a bank k's propensity to provide a zombie loan to a firm with high real estate holdings (because these firms would have a larger impact on real estate prices in case of a fire sale) following a shock to the MSA depends on its market share in an MSA. Our specification is as follows:

$$\begin{aligned}\text{Zombie Reln}_{i,k,t} = & \beta_1 * \text{High Real Estate}_{i,t} + \beta_2 * \text{Negative Shock}_{MSA,t} + \beta_3 * \text{Lender Share}_{k,t-1} \\ & + \beta_4 * \text{High Real Estate}_{i,t} * \text{Negative Shock}_{MSA,t} * \text{Lender Share}_{k,t-1} \\ & + \alpha_k + \delta_t + \epsilon_{i,k,t}\end{aligned} \tag{12}$$

here, the outcome Zombie Reln$_{i,k,t}$ is a subsidized loans by lender k to a firm i in an MSA. *NegShock* is an indicator variable indicating declining real estate prices in the MSA. *High-RealEstate* indicates firms with above-median real estate holdings and *Lendershare* is the market share of the lender. *LenderShare* can be defined in two ways. *MarketShare* is the share of loans outstanding held by the bank in an MSA and *CollateralShare* is the share of collateral in an MSA that a bank has claims on divided by the total available collateral in an MSA. δ_t and α_k are year and lender fixed-effects respectively. This allows us to exclude possible alternative explanations that weakly capitalized banks may want to lend to their clients so that they don't have to recognize bad loans and hence raise more equity capital (Caballero, Hoshi and Kashyap, 2008 and Acharya, Eisert, Eufinger and Hirsch, 2019). We cluster standard errors at the lender level to allow for bank policies to be correlated across time and MSAs.

The coefficient of interest, β_4 if positive will indicate that during distress, banks with higher market share are more likely to provide a subsidized loan to firms with large real estate holdings.

3.4 Identification

Endogeneity in our estimation can arise if decline in real estate prices across MSAs are correlated and a fall in real estate prices led to lax monetary policy and subsequent increase in lending by banks. Our identification strategy thus exploits the variation across MSAs in the size and timing of the housing bust in the 2000s. Different MSAs in the United States had different house price appreciation during the boom. MSAs differ in the size of changes in local housing demand (Davidoff, 2016 and Ferreira and Gyourko, 2012) and in local housing supply elasticity (Mian and Sufi, 2011). There is a consensus that the variation in housing prices during the the boom and bust of the 2000's was not the result of changes in traditional fundamentals like productivity, income, or population, but rather was the result of factors specific to the housing market. These explanations include irrational exuberance, the introduction of products like interest-only-mortgages, and changes in lending standards.

We use the size and timing of structural breaks in housing prices as an event study which allows us to assess whether sharp changes in local housing demand lead to a change in trend in zombie lending or borrowing by firms. We interpret the estimate as the reduced-form effect of a structural break in local house prices, which is valid whether the break is caused by speculative forces or from a combination of these forces and other economic shocks.

To create our event, we search for sharp changes in housing prices between 2001 and 2010. We rely on the assumption that underlying economic fundamentals do not change abruptly and that sharp breaks from the trend in a market's housing price reflects variation due to exogenous or housing-related shocks and not due to abrupt changes in bank lending. Figure 1 shows the housing price index from 2001 to 2010 for three MSAs which illustrate the identification and timing of the structural break. Using quarterly house prices for each MSA between 2001 and 2010, we estimate an OLS regression (Bai and Perron, 1998) with a single structural break and search for a break that maximizes the fit of the equation

$$HPI_{MSA,t} = \alpha_{msa} + \tau_{msa} * t + \lambda_{msa}(t - t^*_{msa})\mathbb{1}[t > t^*] + \epsilon_{MSA,t} \tag{13}$$

here, *HPI* is the log house price index in an *MSA* in quarter-year t, and t^* is the time of the structural break. τ is the MSA's linear price trend before the break and λ is the size of the structural break. This estimation is similar to Ferreira and Gyourko (2012) and Charles, Hurst and Notowidigdo (2018).

Finally, we estimate the event study regression

$$y_{i,t} = \beta_1 * break_{t-1} + \beta_2 * HighRealEstate_i + \beta_3 * break_{t-1} * HighRealEstate_i + \epsilon_{i,t} \tag{14}$$

here, $break$ is an indicator for the year which maximizes the R^2 of equation (**??**), and $HighRealEstate$ is an indicator for high real estate holding firms. β_3 is the coefficient of interest that allows us to assess the instantaneous impact of a structural break in prices on lending and probability of zombie lending ($y_{i,t}$).

3.5 Spillover

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. Our regression follows Caballero, Hoshi and Kashyap (2008)

$$\begin{aligned} y_{i,t} =& \beta_1 * NonZombie_{i,t} + \beta_2 * IndZombiePct_{j,t} + \beta_3 * NonZombie_{i,t} * IndZombiePct_{j,t} \\ &+ \alpha_{i/j} + \delta_t + \epsilon_{i,t} \end{aligned} \tag{15}$$

where *NonZombie* is an indicator for firms not classified as zombie in the year. *IndZombiePct* is the percentage of zombie firms in an industry. The unit of observation is the firm-year where i denotes the firm and t denotes the year. $\alpha_{i/j}$ is either the firm or industry fixed effect accounting for either firm-specific or industry-specific shocks. δ_t is the year fixed effect controlling for the annual shocks affecting all firms uniformly.

The dependent variables are investment, profit, productivity, change in employment, and return on assets. We expect the existence of zombie firms in an industry to depress all the above variables for healthy firms.

4 Results

We now present the results of our analysis. First we identify the effect of collateral value on borrowing during and adverse shocks. We then test to see if lending during adverse shocks is dominated by high-quality borrowers or is some of it misallocated. Next, we estimate the probability of zombie loans for borrowers with high collateral and banks with larger market shares. We conclude by documenting the spillover effects of zombie lending on healthy firms.

4.1 Sensitivity of Debt to Real Estate Value

Increases in collateral values provides firms access to more and cheaper credit for longer maturities (Benmelech, Garmaise and Moskowitz, 2005; Benmelech and Bergman, 2009). This is the collateral channel of lending. We begin by separating the sensitivity of debt to collateral during normal and adverse times. Table 2 estimates (9) where the dependent variable is the change in long-term debt. During normal times, the as real estate values rise, firms are able to raise more debt. A 1% increase in real estate value results in an increase in debt by 0.046%. During adverse periods the elasticity of debt issuance to collateral value decreases to 0.017. That is, the deleveraging during a downturn slower than the leveraging during good times.

4.2 Inefficient Lending

A possible explanation of firms increasing their borrowing and investment during negative shocks is that interest rates fall during a recession which makes it a good time to borrow cheaply for firms that have profitable investment opportunities and are not financially constrained.

Firms that have a low interest coverage ratio have a lower ability to cover their interest expense from their operating income, are more susceptible to downturns, and are therefore considered riskier. Generally, we expect banks to lend less to firms with a low interest coverage ratio or lend at a higher interest rate. We divide firms into terciles by interest coverage ratio. A comparison of our sorting with S&P ratings shows that the bottom terciles of firms by interest coverage ration corresponds to firms with ratings of BB or lower as discussed previously. These firms should in general receive less credit than other firms.

We test this intuition via (10) in Table 3. We regress debt issuance on an indicator for the lowest moving average interest coverage ratio tercile and negative shock. Our results (Table 3, Row 1) indicate that low interest coverage ratio firms indeed issue 12.5% less debt than other firms during normal times. During a negative shock (Table 3, Row 3), we find that low ICR firms surprisingly issue 45% more debt than firms with higher interest coverage ratios. These results are robust to controls of firm demand for credit as well as financial constraints as measured by Tobin's Q and the KZ-Index respectively.

This is not a clear indication of inefficient lending. If these firms borrow at a higher interest rate than more creditworthy firms, we would not classify these as zombie loans. Having established an asymmetric borrowing pattern where safe firms issue more debt during normal times while riskier firms issue more debt during negative shocks, we proceed to identify instances of zombie lending, *i.e.* we want to check if the additional borrowing by risky firms during negative shocks is at market rates or at subsidized rates intended to keep them afloat.

4.3 Zombie Lending and the Collateral Channel

4.3.1 Estimating Zombie Lending

We follow the specification of Caballero, Hoshi and Kashyap (2008) and Acharya, Eisert, Eufinger and Hirsch (2019) to identify zombie firms. We then estimate (11) to verify our hypothesis that collateral is a channel for zombie lending. The results are presented in Table 4, Panel A. We successively add controls to the baseline specification and find that the coefficient of interest (β_3) is always significant. In our full specification (column 4), during a negative shock, firms with above-median real estate holdings (*High Real Estate*) are 2.3 times more likely to receive a subsidized loan compared to firms with below-median real estate holding. To control for variation between industries where certain sectors may get preferential treatment due to government policy intervention or any industry-specific news, we run the regression with industry fixed effects (Column 5) as well. In this case, firms with above-median real estate are 1.5 times more likely to receive zombie loans compared to firms with below-median real estate holdings. This is our main result and validates our hypothesis that collateral is an important channel for evergreening of loans viz. zombie lending.

4.3.2 Survivorship Bias and Robustness

Survivorship Bias: Our method to calculate the market value of real estate holdings of a firm requires that the sample firms exist in 1993 (the last year when accumulated depreciation is available in COMPUSTAT). This introduces a survivorship bias in our sample. To establish the robustness of our result, we assume that tangible assets *i.e.* property, plant, and equipment are a good proxy for collateral value and divide our sample into firms with above and below the median value of PPE in the first year of the appearance of the firm in the sample. We then re-estimate equation (11) in Table 4B. Here, high PPE firms are 1.48 times more likely than low PPE firms to receive zombie loans. The results are similar to those in Panel A which alleviates some concern about survivorship bias in our baseline result.

Robustness In Table 5, we reestimate (11) with an indicator for zombie loans identified from the dealscan on an indicator for firms with above-median collateral in 1993 (*High Real Estate*) and separately, firms with above-median book value of collateral in the year of their first appearance in the dataset (*High Real Estate1*) which controls for survivorship bias as above. We use lender and year fixed effects to control for heterogeneity arising out of lender characteristics and time-varying heterogeneity. The identification of zombie using dealscan data is cleaner because we have the exact borrowing cost and are able to identify specific loans as zombie loans. The results confirm our hypothesis that firms with above-median collateral value are more likely to receive zombie loans during negative shocks than firms with below-median collateral value.

These three results robustly confirm our findings and identify collateral as a channel for zombie lending.

4.4 Mechanism

Table 6 tests the main result of our model viz. the probability of zombie lending depends on the market share of the bank in an MSA. We explore whether high market-share banks are more likely to indulge in zombie lending during a downturn and if so, do they preferentially lend to high collateral firms. We estimate (12) by regressing bank market share and indicators for high real estate and negative shock on an indicator of zombie loans. Column 1 shows that *High Real Estate* firms are more likely to get a zombie loan from a bank if the bank has a higher share of loans in the MSA. A 1% increase in a bank's market share increases its probability of giving a zombie loan by 0.042%. This is the gist of proposition 3 that a bank which has a larger presence in an MSA internalizes the negative spillover of the bankruptcy of a firm with large real estate and does not recognize bad loans. Instead it provides the firm with subsidized loans hoping for a recovery in the future and preventing a spillover of a fire sale to its other assets.

More important to the fire sale mechanism is the share of collateral that a bank has liens to which it will need to liquidate in case of a default. Column 2 tests if banks with higher collateral share in an MSA are more likely to give zombie loans. We estimate that an increase of 1% in collateral share is associated with an increase of 0.047% increase in the probability of zombie lending to high real estate firms after a fall in real estate prices.

Along with an increase in zombie lending to specific firms, banks should increase their zombie lending in an MSA in order effectively prevent a collapse in real estate prices. Table 7 regresses measures of a bank's share of zombie loans in an MSA on the bank's market share and collateral share and finds that banks with a larger market (or collateral) share are likely to have a larger share of zombie loans during distress in the MSA. In Table 7, *BankNewZombie* is the ratio of the new zombie loans disbursed by a bank in an MSA to the total outstanding loans of a bank. An increase in this measure would indicates a bank subsidizing its borrowers either in a specific MSA. It could also indicate a bank systematically giving out cheap loans to everyone. *MSANewZombie* is the ratio of new zombie loans disbursed by a bank in an MSA to the total loans disbursed by the bank in the MSA. *MSANewZombie* specifically measures if a bank is giving out more zombie loans in the MSA compared to other banks.

During normal times, an increase in market (or collateral) share of a bank reduces the zombie-proportion of the new loans it originates (Row 1). In column 1 (& 2) we see that a 1% increase in market share during a shock leads to an increase in the proportion of new zombie loans disbursed by the bank by 0.027% (0.022%) while it increases the new zombie share of loans by 0.063% (0.053%). The results indicate that high market (collateral) share banks originate a higher number of new zombie loans in an MSA during a downturn.

4.5 Identification

We use the variation between MSAs in the timing and size of structural breaks in house prices during the 2007-2009 financial crisis as our identification strategy. Figure 2 shows the distribution of the structural breaks in different MSAs by year. There is sufficient variation in the year of the structural break to infer that the increase in lending and zombie lending during a negative shocks as in Table 2 and Table 4 are not due to global factors affecting lending. Moreover, most of the structural breaks are concentrated in 2005 and 2006 which were years before the Fed reduced interest rates so that any additional lending was not firms taking advantage of low rates. Furthermore, since the shocks would have begun in the MSAs identified, we can be certain that the additional lending is not because of increased collateral value either.

The structural breaks are used to get the instantaneous effect of a change in the value of collateral to changes in debt and the probability of zombie lending. We estimate (14) in Table 8. *Break 1* indicates a negative structural break between 2001 and 2010 while *Break 2* is a negative and significant structural break. We regress the zombie firms and Δ *Debt* on *HighRealEstate1* and the structural break indicator to create an event study for our results in Table 2 and Table 4 & Table 5. We find that the probability of zombie lending is approximately 50% higher (Columns 1 & 2) for high real estate firms post a structural break compared to low real estate firm. The magnitude of the estimate is very similar to the magnitude estimated in Table 4. The two indicators of structural break are increasingly significant as is expected from their construction. The result confirms our initial results that during a negative shock, firms with high collateral are more likely to receive zombie loans and any loans in general as well. Columns 3 & 4 also show that high real estate are more likely to raise additional debt post a structural break (as in Table 2).

4.6 Spillover Effects of Zombie Firms

Finally, we explore the spillover effects of zombies on non-zombie firms in an industry. Non-zombie firms in an industry can be affected by zombie firms through two channels. Evergreening of loans shifts the supply of credit to these zombie firms reducing the credit available to healthier firms. The effect of zombie firms on investment can go both ways. Healthy firms may know that other firms are unproductive increase their investments hoping to gain a greater share of the market. On the other hand, the presence of zombie firms may induce banks to reduce their exposure to the sector which would reduce investments by healthy firms.

The prevalence of zombies also distorts the competitive process in the industry Acharya, Crosignani, Eisert and Eufinger, 2020. 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 thereby profitability. But, subsidized credit keeps zombie firms artificially alive which congests the market. Zombie firms also bear lower interest rates than non-zombie firms and so have lower costs. This reduces product market prices and correspondingly mark-ups and increases wages in the industry.

Following Caballero, Hoshi and Kashyap (2008), equation (15) allows us to estimate the effect of the presence of zombie firms in an industry on healthy firms. Table 9 presents results which show that non-zombie firms have lower investments and return-on-assets when ($\beta_3 < 0$) they operate in industries with many zombie firms compared to firms in industries with lower zombie percentage. The estimates imply that a 1% rise in zombie percentage leads to non-zombie firms reducing their investment by 1.16% and their ROA is reduced by 0.95%.

5 Conclusion

Theory predicts a positive relationship between debt and collateral. We show that firms with collateral can raise more debt during a shock than firms with less collateral. Some of this lending results from increased risk aversion and move towards safer lending by banks. But, we observe that some is directed to low-quality firms.

We next show that firms with high collateral have a higher probability of receiving zombie loans. This identifies collateral as a channel for zombie lending. Previous work by Peek and Rosengren (2005) and Acharya, Eisert, Eufinger and Hirsch (2019) show that weak banks (banks close to their regulatory capital requirements) are responsible for zombie lending. Since equity capital is expensive, banks close to regulatory capital requirements prefer to evergreen their loans. This allows a bank to not recognize non-performing assets (or defaults) which would force the bank to set aside capital buffers for the impending default.

Our model and empirical tests show that banks behave rationally in evergreening some of these loans. Banks with large market share are aware that since they hold a lien on a large proportion of real estate in an area, a fire sale will hurt their portfolio. By evergreening some loans, they minimize the spillover on their balance sheet.

However, zombie lending has negative spillovers on healthy firms in an economy. The credit misallocation reduces return-on-assets and employment of healthy firms in industries dominated by zombie firms. Firms in an industry dominated by zombies face a congested market, have lower mark-ups, and higher labour costs. This reduces future investment as well.

The presence of collateral can lead banks into believing that some loans are safe while ignoring the underlying financials of a firm. Banks are averse to calling in collateral during recessions because of possible contagion effects of selling collateral in a bad economy. Zombie lending in some sense subverts regulatory oversight by dressing up the bank's and firm's balance sheets. Besides it also has negative spillover effects on healthy firms. Regulators would, thus, need to be especially wary of it.

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Table 1: Summary Statistics in 1993

	Mean	SD	Min	Max
Real Estate	0.861	1.726	0.000	22.686
Leverage	0.289	0.377	0.000	3.852
Investment	0.440	0.768	0.000	5.605
Tobin's Q	2.334	2.778	0.534	62.878
KZ Index	0.743	2.741	-18.260	22.764
Age	11.433	10.876	0.000	34.000
ROA	-0.028	0.442	-6.187	0.369
Interest Coverage Ratio	5.532	107.767	-701.667	598.400
Land Supply Elasticity	1.440	0.866	0.595	6.396
Firms	6803			

Table 1 reports the summary statistics of the firms in the sample in 1993. Real estate value is calculated by estimating average age and historical cost of the real estate holdings of a firm in 1993. The real estate index which is normalized to 1 in 2006 is used to inflate real estate holdings to market value which is then normalized by lagged PPE. Tobin's Q, KZ-Index, Age, Age^2 and interest coverage ratio are used as controls for credit demand and/or supply. Tobin's Q is calculated as the ratio of enterprise value of a firm to its book value following Almeida and Campello (2007). The Kaplan-Zingales Index is calculated based on the 5-factor model of Lamont, Polk and Saa-Requejo (2001)). Interest coverage ratio is the ratio of a firms' EBIT to interest expense. Firm age is calculated using the first appearance of a firm in the COMPUSTAT dataset with a cut-off at 1960. Leverage is the ratio of total debt to assets. Return on assets is calculated as the ratio of operating income minus depreciation and amortization to assets. Investment is measured as capex normalized by lagged fixed assets.

Table 2: Sensitivity of Debt to Real Estate Value

	(1)	(2)	(3)	(4)	(5)
	Δ Long-Term Debt				
Real Estate	0.066***	0.059***	0.061***	0.051***	0.046***
	(0.014)	(0.015)	(0.015)	(0.012)	(0.014)
Negative Shock	0.061	0.067	0.067	0.060	0.059
	(0.050)	(0.052)	(0.053)	(0.054)	(0.056)
Negative Shock × Real Estate	-0.040***	-0.040***	-0.038***	-0.030**	-0.029**
	(0.013)	(0.014)	(0.014)	(0.012)	(0.014)
Tobin's Q		0.022**			0.031***
		(0.009)			(0.010)
KZ Index			-0.001		-0.009
			(0.009)		(0.011)
Age				0.005	0.012
				(0.008)	(0.008)
Age^2				-0.000	-0.000
				(0.000)	(0.000)
Observations	35035	31503	31308	31634	29039
R^2	0.11	0.12	0.12	0.12	0.14
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2 estimates the sensitivity of debt to collateral value by regressing change in debt on change in value of real estate holdings from 1994 to 2014. The sensitivity of debt to real estate holdings is positive during periods of rising real estate prices indicating that as the value of real estate holding increases, long term borrowing increases. However, this sensitivity is lower during periods of falling real estate prices indicating that firms do not reduce their borrowings when the value of their collateral falls. Real estate value is calculated by estimating average age and historical cost of the real estate holdings of a firm in 1993. The real estate index which is normalized to 1 in 2006 is used to inflate real estate holdings to market value which is then normalized by lagged PPE. *NegShock* is an indicator for years which saw a fall in the Residential Price Index in a MSA. Tobin's Q, KZ-Index, Age and Age^2 are used as controls for credit demand and/or supply. Tobin's Q is calculated as the ratio of enterprise value of a firm to its book value following Almeida and Campello (2007). The Kaplan-Zingales Index is calculated based on the 5-factor model of Lamont, Polk and Saa-Requejo (2001)). Firm age is calculated using the first appearance of a firm in the COMPUSTAT dataset with a cut-off at 1960. Standard errors are clustered at the firm-level

Table 3: Debt Issuance and Interest Coverage Ratio

	(1)	(2)	(3)	(4)	(5)
	Debt Issuance				
Low ICR	-0.111	-0.111	-0.146	-0.152	-0.125
	(0.092)	(0.093)	(0.096)	(0.099)	(0.098)
Negative Shock	-0.142*	-0.092	-0.150	-0.109	-0.061
	(0.085)	(0.091)	(0.095)	(0.085)	(0.092)
Low ICR × Negative Shock	0.309*	0.412**	0.453**	0.326*	0.454**
	(0.182)	(0.189)	(0.201)	(0.188)	(0.197)
Tobin's Q		0.198***			0.199***
		(0.028)			(0.028)
KZ Index			0.014		-0.030
			(0.023)		(0.021)
Age				0.057***	0.063***
				(0.018)	(0.020)
Age^2				-0.000*	-0.000
				(0.000)	(0.000)
Observations	53707	46436	46237	49679	42872
R^2	0.40	0.42	0.40	0.40	0.42
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3 explores lending to low interest coverage ratio firms to high ICR firsm during normal times and during a shock. The results indicate that during normal times, low ICR firms are less likely to get debt whereas during a shock, low ICR firms are able to issue more debt compared to high ICR firms. The interest coverage ratio is measured as the EBIT by the interest expense and we define low ICR firms as the bottom tercile of firms by moving average ICR. *NegShock* is an indicator for years which saw a fall in the Residential Price Index in a MSA. Tobin's Q, KZ-Index, Age and Age^2 are used as controls for credit demand and/or supply. Tobin's Q is calculated as the ratio of enterprise value of a firm to its book value following Almeida and Campello (2007). The Kaplan-Zingales Index is calculated based on the 5-factor model of Lamont, Polk and Saa-Requejo (2001). Firm age is calculated using the first appearance of a firm in the COMPUSTAT dataset with a cut-off at 1960. Standard errors are clustered at the firm-level

Table 4: Probability of Zombie Lending

Panel A: High Real Estate Firms

	(1)	(2)	(3)	(4)
	Zombie			
High Real Estate	-0.456	-0.392	-0.379	-0.380
	(0.280)	(0.300)	(0.281)	(0.262)
Negative Shock	-0.277**	-0.243*	-0.241	-0.242*
	(0.124)	(0.135)	(0.150)	(0.137)
High Real Estate $\times$ Negative Shock	0.837***	0.864***	0.834***	0.835***
	(0.238)	(0.226)	(0.281)	(0.189)
Tobin's Q		-0.005		-0.002
		(0.008)		(0.008)
KZ Index			-0.014	-0.014
			(0.009)	(0.009)
Observations	9658	8519	8416	8416
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Panel B: High PPE Firms

	(1)	(2)	(3)	(4)
	Zombie			
Negative Shock	0.179*	0.028	0.023	0.025
	(0.096)	(0.095)	(0.082)	(0.091)
High PPE $\times$ Negative Shock	0.320**	0.403**	0.398**	0.397***
	(0.158)	(0.179)	(0.182)	(0.135)
Tobin's Q		0.002		0.006*
		(0.003)		(0.003)
KZ Index			-0.008	-0.010**
			(0.005)	(0.005)
Observations	26473	22002	21455	21455
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 estimates the probability of zombie lending from 1994 to 2014 by estimating a logit model on an indicator for zombie firms on firms with above median real estate holdings and negative real estate shocks. Following Caballero, Hoshi and Kashyap (2008), a firms is defined to have received a zombie loan if its interest expense is lower than the highest rated firms in the year and it is rated BB or lower. Tobin's Q and KZ-Index are used as controls for credit demand and/or supply. Tobin's Q is calculated as the ratio of enterprise value of a firm to its book value following Almeida and Campello (2007). The Kaplan-Zingales Index is calculated based on the 5-factor model of Lamont, Polk and Saa-Requejo (2001). Panel B uses an unbalanced dataset and proxies for firms with high collateral using firms with above median PPE. Standard errors are clustered at the firm-level

Table 5: Probability of Zombie Lending - Dealscan Data

	(1)	(2)	(3)	(4)
	Zombie Dealscan			
High Real Estate 1	-0.022***	-0.026***	-0.028***	-0.027***
	(0.005)	(0.005)	(0.006)	(0.005)
Negative Shock	-0.016**	-0.011	-0.010	-0.010
	(0.007)	(0.008)	(0.008)	(0.008)
High Real Estate 1 $\times$ NegShock	0.024***	0.028***	0.027***	0.027***
	(0.007)	(0.008)	(0.008)	(0.008)
Tobin's Q		0.002		0.002
		(0.002)		(0.002)
KZ Index			0.003***	0.003***
			(0.001)	(0.001)
Observations	40062	34969	40063	34969
Year FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 replicates the result from Table 4 using the dealscan dataset. It estimates the probability of zombie lending from 1994 to 2014 by estimating a linear probability model on an indicator for zombie firms on firms with above median real estate holdings and negative real estate shocks. High Real Estate1 are firms with above median real estate holding in 1993. Following Caballero, Hoshi and Kashyap (2008), a firms is defined to have received a zombie loan if its interest expense is lower than the highest rated firms in the year and it is rated BB or lower. Tobin's Q and KZ-Index are used as controls for credit demand and/or supply. Tobin's Q is calculated as the ratio of enterprise value of a firm to its book value following Almeida and Campello (2007). The Kaplan-Zingales Index is calculated based on the 5-factor model of Lamont, Polk and Saa-Requejo (2001).Standard errors are clustered at the firm-level

Table 6: Probability of Zombie Lending - Bank Market Share

	(1)	(2)	(3)
	Zombie Dealscan		
High Real Estate	0.005***	0.005***	0.008***
	(0.001)	(0.002)	(0.003)
High Real Estate × Negative Shock	-0.006***	-0.007***	-0.009***
	(0.003)	(0.002)	(0.003)
High Real Estate × Market Share	-0.009		-0.046***
	(0.007)		(0.017)
Negative Shock × Market Share	-0.001		-0.010*
	(0.007)		(0.005)
High Real Estate × Negative Shock × Market Share	0.042*		0.049***
	(0.025)		(0.014)
High Real Estate × Collateral Share		-0.014*	
		(0.008)	
Negative Shock × Collateral Share		-0.007	
		(0.009)	
High Real Estate × Negative Shock × Collateral Share		0.047***	
		(0.022)	
High Real Estate × High Capital			-0.011***
			(0.004)
High Real Estate × Negative Shock × High Capital			0.010***
			(0.003)
High Real Estate × Negative Shock × High Capital × Market Share			-0.076**
			(0.031)
Observations	13323	13258	8615
Year FE	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 estimates a linear probability model to estimate how the probability of zombie lending depends on bank market share. The dependent variable is an indicator for zombie lending to a firm by a specific lender in a year. The independent variables include indicators for above median real estate firms, a negative real estate shock and an estimate of a bank's market share. *Market Share* is the percentage of outstanding loans in an MSA arranged by a bank. *Portfolio Share* is the percentage of outstanding loans arranged by a bank in an MSA divided by the total outstanding loans arranged by the bank. *Collateral Share* is the share of collateral in an MSA that a bank has access to which is calculated as the share of outstanding loans arranged for a firm multiplied by the value of collateral of the firm divided by the total collateral available in an MSA. *High Capital* is an indicator variable for banks in the top tercile by Tier 1 capital in a year. Standard errors are clustered at the firm-level

Table 7: New Zombie Loans in MSA

	(1)	(2)	(3)	(4)
	BankNewZombie		MSANewZombie	
Market Share	-0.008***		-0.018***	
	(0.003)		(0.005)	
Collateral Share		-0.007**		-0.016***
		(0.003)		(0.006)
Negative Shock	-0.004*	-0.003*	-0.012***	-0.011***
	(0.002)	(0.002)	(0.004)	(0.004)
Negative Shock $\times$ Market Share	0.027**		0.063**	
	(0.013)		(0.031)	
Negative Shock $\times$ Collateral Share		0.022*		0.053*
		(0.012)		(0.029)
Observations	8865	8802	8865	8802
Year FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 tests whether high market share banks internalize the cost of spillover in their lending decisions. The independent variable is the market share of a lender in an MSA in a year. The dependent variables are the *BankNewZombie* which is the ratio of new zombie loans of a bank in an MSA to the total loans of the bank. *MSANewZombie* is the ratio of the new zombie loans disbursed by a bank in an MSA to the total value of new loans disbursed by the bank in the MSA. *Negative Shock* is an indicator for negative real estate shock. The results indicate that high market share banks originated a higher fraction of zombie loans in an MSA by number and dollar amount thus confirming our hypothesis. Standard errors are clustered at the firm-level

Table 8: Structural Break - Probability of Zombie Lending

	(1)	(2)	(3)	(4)
	Zombie		Δ Long-Term Debt	
Break 1	0.129		-0.322***	
	(0.374)		(0.119)	
High Real Estate1 × Break 1	0.487*		0.268***	
	(0.252)		(0.078)	
Break 2		0.331		-0.293**
		(0.365)		(0.118)
High Real Estate1 × Break 2		0.517**		0.286***
		(0.253)		(0.079)
Observations	5157	5157	19753	19753
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8 uses a structural break in real estate prices to create an instrument for local negative real estate shocks following Charles, Hurst and Notowidigdo (2018). We regress and indicator for zombie lending and change in debt on the structural break IV and an indicator for above median real estate holding to estimates the probability of zombie lending. Following Caballero, Hoshi and Kashyap (2008), a firms is defined to have received a zombie loan if its interest expense is lower than the highest rated firms in the year and it is rated BB or lower. Break1 indicates when the structural break is negative and break2 is an indicator for a significant negative break. Columns 1-2 estimate the probability of zombie lending following a negative structural break while columns 3-4 estimate the change in debt following a negative structural break which tie in with the results of Table 4,5 and 2 respectively. Standard errors are clustered at the firm-level

Table 9: Spillover Effects of Zombie Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Investment	ROA	Productivity	Δ Emp	Investment	ROA	Productivity	Δ Emp
Non Zombie	0.019	0.079***	0.530***	-0.017**	-0.063*	0.304***	0.869***	-0.004
	(0.030)	(0.025)	(0.044)	(0.007)	(0.033)	(0.031)	(0.050)	(0.008)
IndustryZombiePct	1.045**	0.592*	-0.296	-0.039	0.906	1.761**	0.864*	-0.147
	(0.463)	(0.328)	(0.480)	(0.105)	(0.624)	(0.661)	(0.461)	(0.144)
Non Zombie × IndustryZombiePct	-1.165**	-0.953***	0.419	0.057	-0.838	-2.086***	-0.296	-0.056
	(0.473)	(0.345)	(0.503)	(0.107)	(0.613)	(0.599)	(0.478)	(0.134)
Observations	107400	117029	76159	95448	107400	117029	76159	125300
R^2	0.33	0.65	0.54	0.18	0.06	0.05	0.02	0.02
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	No	No	No	No
Industry FE	No	No	No	No	Yes	Yes	Yes	Yes

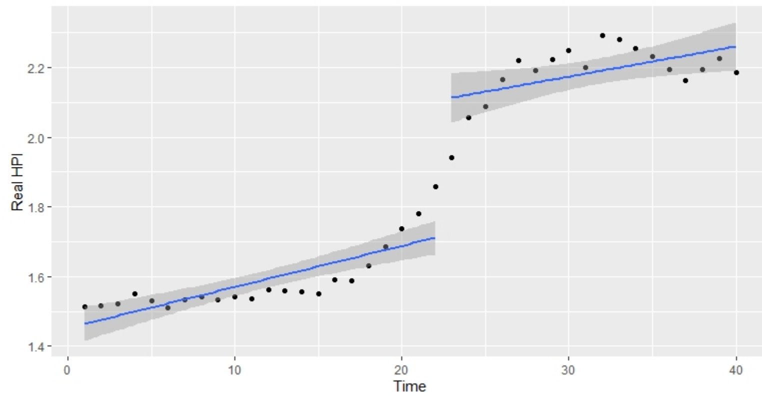
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

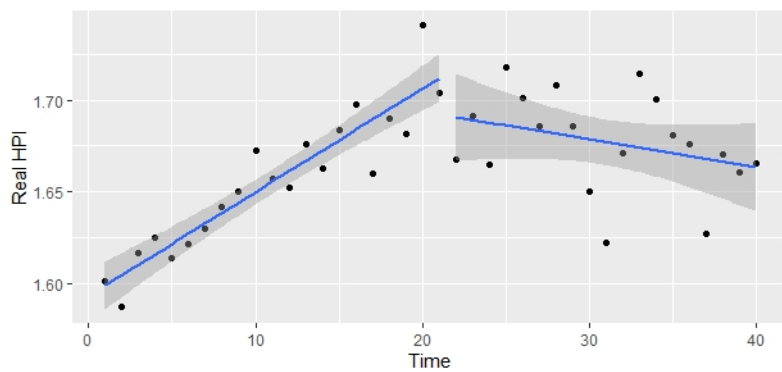
Table 9 explores the spillover effects of zombie lending from 1994 to 2014. The specification follows Caballero, Hoshi and Kashyap (2008). The regressors are an indicator for non-zombie firms, the percentage of zombie firms in an industry and an interaction term. Our variables of interest are investment, return on assets, productivity and employment growth. The results show that a greater percentage of zombie firms in an industry depresses investment and returns on assets of non-zombie firms in the industry. Investment is measured as capex normalized by the lagged PPE, and return on asset as EBIT by lagged assets. Productivity is calculated using a Cobb-Douglas function for firms with the capital-labour ratio determined at the 2-digit SIC level. We control for year and firm fixed effects in the first four columns and industry and year fixed effects in the last four.Standard errors are clustered at the firm-level

Figure 1: Structural Breaks

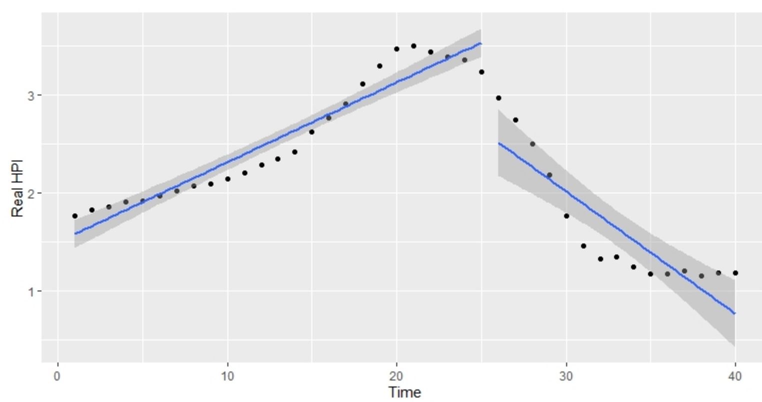
(A) **Positive Structural Break - Midland,TX**



(B) **Non-Significant Structural Break - Waco,TX**

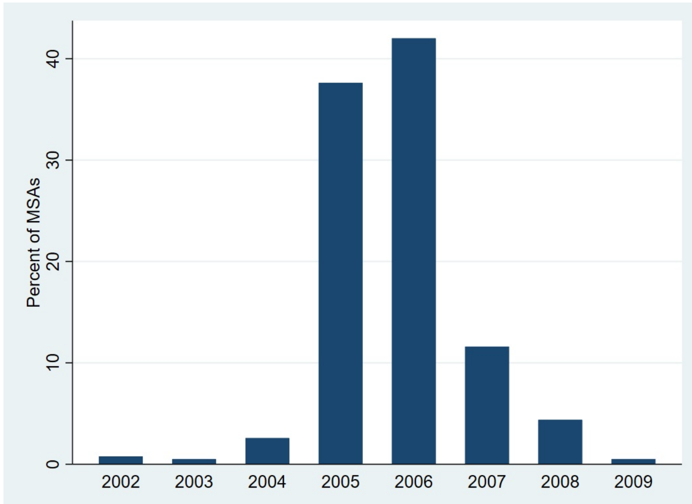


(C) **Negative Structural Break - Merced,CA**



Note: Figure 1 This figure shows graphs of quarterly house price data for three MSAs. The house price index for each city is normalized so that 2001:I = 100 . The dotted lines report the house price series, while the solid lines reports the estimated house price and also the structural breaks. Figure 1A shows a positive and significant structural break while Figure 1C shows a negative and significant structural break.

Figure 2: Distribution of Structural Breaks



Note: Figure 2 shows the percentage of MSA's that have a structural break in a year. Equation 13 identifies the year between 2001 and 2010 in which a structural break in housing prices occurs in an MSA. The heterogeneity in the timing of this structural break is used as an instrument for our identification strategy in equation 14.

Appendix A: Proofs

A.1 Proof of Proposition 1

Taking the first order condition for equation 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 analyse 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 (8) 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.

Table B1: Sensitivity of Debt to Instrumented Real Estate Value

	(1)	(2)	(3)	(4)	(5)
	Δ Long-Term Debt				
Real Estate I	0.068***	0.061***	0.064***	0.053***	0.049***
	(0.014)	(0.015)	(0.015)	(0.012)	(0.014)
Negative Shock	0.079	0.070	0.073	0.068	0.063
	(0.052)	(0.054)	(0.054)	(0.056)	(0.058)
Negative Shock $\times$ Real Estate I	-0.047***	-0.047***	-0.046***	-0.037***	-0.037***
	(0.011)	(0.012)	(0.011)	(0.010)	(0.011)
Tobin's Q		0.021**			0.029***
		(0.010)			(0.011)
KZ Index			0.005		-0.002
			(0.010)		(0.012)
Age				0.009	0.014*
				(0.008)	(0.008)
Age^2				-0.000	-0.000
				(0.000)	(0.000)
Observations	30874	27982	27838	28007	25683
R^2	0.10	0.12	0.12	0.12	0.14
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B1 replicates the result from Table 2 using instrumented real estate values. We re-estimate the sensitivity of debt to collateral value. The sensitivity of debt to real estate holdings is positive during periods of rising real estate prices indicating that as the value of real estate holding increases, long term borrowing increases. However, this sensitivity is lower during periods of falling real estate prices indicating that firms do not reduce their borrowings when the value of their collateral falls. Local house price elasticities are from Saiz (2010). Real estate value is calculated by estimating average age and historical cost of the real estate holdings of a firm in 1993. *Negative Shock* is an indicator for years which saw a fall in the Residential Price Index in a MSA. Tobin's Q, KZ-Index, Age and Age^2 are used as controls for credit demand and/or supply. Tobin's Q is calculated as the ratio of enterprise value of a firm to its book value following Almeida and Campello (2007). The Kaplan-Zingales Index is calculated based on the 5-factor model of Lamont, Polk and Saa-Requejo (2001)). Firm age is calculated using the first appearance of a firm in the COMPUSTAT dataset with a cut-off at 1960. Standard errprs are clustered at the firm-level

Table B2: Probability of Zombie Lending Instrumented

	(1)	(2)	(3)	(4)
	Zombie			
High Real Estate I	0.281	0.312	0.306	0.305
	(0.250)	(0.262)	(0.262)	(0.262)
Negative Shock	-0.204	-0.196	-0.195	-0.194
	(0.137)	(0.148)	(0.148)	(0.148)
High Real Estate I × Negative Shock	0.560***	0.573***	0.556***	0.556***
	(0.185)	(0.194)	(0.196)	(0.196)
Tobin's Q		-0.003		0.001
		(0.008)		(0.008)
KZ Index			-0.018**	-0.018**
			(0.009)	(0.009)
Observations	8419	7461	7367	7367
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2 replicates the result of Table 4 using instrumented real estate prices. We estimate the probability of zombie lending from 1994 to 2014 by fitting a logit model on an indicator for zombie firms on firms with above median real estate holdings and negative real estate shocks. Following Caballero, Hoshi and Kashyap (2008), a firms is defined to have received a zombie loan if its interest expense is lower than the highest rated firms in the year and it is rated BB or lower. Tobin's Q and KZ-Index are used as controls for credit demand and/or supply. Tobin's Q is calculated as the ratio of enterprise value of a firm to its book value following Almeida and Campello (2007). The Kaplan-Zingales Index is calculated based on the 5-factor model of Lamont, Polk and Saa-Requejo (2001). Panel B uses an unbalanced dataset and proxies for firms with high collateral using firms with above median PPE. Standard errprs are clustered at the firm-level

Table B3: Alternate Zombie Definitions

	(1)	(2)	(3)	(4)
	Zombie	Zombie 1	Zombie 2	Zombie 3
HighRealEstate	-0.380	-0.504**	0.230	-0.347
	(0.270)	(0.212)	(0.222)	(0.232)
Neg Shock	-0.242	-0.176	0.032	-0.137
	(0.175)	(0.153)	(0.118)	(0.145)
High Real Estate × Neg Shock	0.835***	0.720***	0.341*	0.522**
	(0.210)	(0.268)	(0.184)	(0.252)
Tobin's Q	-0.002	-0.002	-0.010	-0.954***
	(0.007)	(0.010)	(0.008)	(0.183)
KZ Index	-0.014	-0.013	0.063***	0.026
	(0.010)	(0.010)	(0.010)	(0.021)
Observations	8416	8174	14555	8442
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B3 replicates the result of Table 4 using alternate definitions of zombie firms. instrumented real estate prices. *Zombie* is the same definition of subsidized lending used in the main text following Caballero et al. (2008). *Zombie 1* is a similar definition of zombie firms which identifies them as firms with $excessinterest < 0$, $3yrMovAvgICR < 1$ and the firm issuing debt in the year. *Zombie 2* follows from the definition used in Banerjee and Hofmann (2018) where firms have $3yrMovAvgICR < 1$ and $age >= 10$. Lastly, *Zombie3* is a firm in the bottom tercile of ICR and $Tobin'sQ <= 1$. We estimate the probability of zombie lending from 1994 to 2014 by fitting a logit model on an indicator for zombie firms on firms with above median real estate holdings and negative real estate shocks. Tobin's Q and KZ-Index are used as controls for credit demand and/or supply. Tobin's Q is calculated as the ratio of enterprise value of a firm to its book value following Almeida and Campello (2007). The Kaplan-Zingales Index is calculated based on the 5-factor model of Lamont, Polk and Saa-Requejo (2001). Standard errprs are clustered at the firm-level