DEMAND-DRIVEN PROPAGATION OF JOB LOSSES: EVIDENCE FROM THE GREAT RECESSION

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ABSTRACT

This paper presents evidence for the demand-driven propagation of job losses, in the context of the U.S. during the Great Recession. Using county-level tradable job losses driven by aggregate shocks as an instrument, it shows that retail and restaurant employment fell by 0.37 percent for every 1 percent of job loss in the rest of the county's economy. The finding is not driven by the house price decline or by credit supply problems. Moreover, the spillover is more severe for retail and restaurant sectors that are most affected by consumer demand shocks during the Great Recession, which strengthens the argument for the demand-driven propagation of job losses.

JEL code: E24, E62

Keyword: Demand-driven propagation, recession, job losses

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1. **INTRODUCTION**

Economists and policymakers have been concerned about downward demand spirals in recessions. That is, initial job losses would lead to further cuts in consumer spending, which will lead to cutbacks in business investment plans. A weakening economy will lead to more job cuts, provoking a further cycle of contraction.

In this paper, in the context of the Great Recession, we examine how the demand channel propagates job losses across sectors during the 2007-2010 period in US counties. We find that in a U.S. county, job losses in retail and restaurants (referred to as RR) are caused by job losses in the rest of the county's economy, which comprises of tradable, construction and other services (TCS). On average, a 1% decrease in TCS employment causes a 0.28 to 0.37 percent decrease in RR employment between 2007 and 2010. The propagation is not likely driven by the collapse in house prices or by credit supply problems. Instead, the evidence points to a demand channel.

The finding, drawn from the context of the Great Recession, provides important lessons and policy implications regarding the responses to the economic downturns. Our findings suggest a role for demand-stabilizing policies to mitigate demand-driven propagation associated with initial job losses. Without such policies in place to assist hardest hit population and sectors, initial negative shocks could spread through other healthier sectors of the economy and worsen the scale and scope of a recession.

There has been little empirical evidence for the propagation of job losses because it is difficult to separate different rounds of job losses in the data. For example, laid-off automobile workers could postpone purchasing new TV sets, and cut back their restaurant meals. Restaurant workers would then lose their jobs and would no longer be able to afford new cars, which could affect the jobs of automobile workers. The impacts of job losses are intertwined, occur at the same time, and are difficult to separate (Figure 1.1).

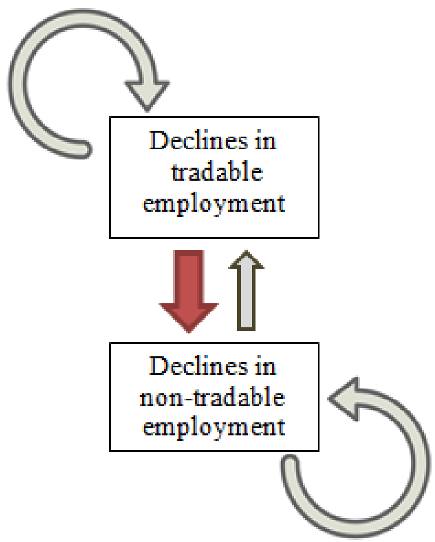

Figure 1.1: Intertwined feedback loops of job losses

We address the endogeneity issue by focusing on only one direction of the job loss propagation, namely, from tradable job losses to non-tradable job losses (the large red arrow in Figure 1.1). The exogenous source of tradable job losses is from *the tradable job losses that are only driven by aggregate shocks in the rest of the U.S.* (in the spirit of Bartik, 1991). For brevity, we refer to these job losses as Bartik tradable job losses. A county's Bartik tradable job losses in the Great Recession are determined by how exposed the county was to tradable industries and how those tradable industries' national employment fell during the Great Recession. Bartik tradable job losses are then used to instrument for job losses in tradable, construction, and other services (TCS). Note that TCS and retail and restaurants (RR) cover the whole county's private economy. Hence by instrumenting for TCS job losses, we could estimate the full spill-over impact to RR from the rest of the county's private economy.

We estimate the impact of the *instrumented* TCS job losses on RR job losses and argue that the estimated impact reflects demand-driven propagation. Retail and restaurant job growth is chosen as the outcome variable because these sectors represent *final consumption*, hence their job losses are easier to attribute to a decline in demand. We find that negative spillover from TCS job losses is stronger for more income-elastic RR industries than for less income-elastic ones. This finding strengthens the argument for a demand-driven channel.

Attention is paid to competing channels. We argue that the propagation of job losses is not driven by a collapse in house prices, a prominent factor in the Great Recession. Additionally, the relationship is not driven by the credit channel, i.e., the possibility that the spillover from TCS job losses to RR job losses is due to credit supply issues. We show econometrically that this is not the case.

The paper is organized as follows: section 2 reviews the literature; section 3 discusses the data; section 4 presents a model and the identification strategy in detail; section 5 reports the main results; section 6 examines alternative propagation mechanisms; finally, section 7 concludes.

2. LITERATURE REVIEW

The literature has discussed the role of demand in the Great Recession. On the empirical front, a series of papers by Atif Mian, Amir Sufi and other co-authors show that in counties that have higher pre-crisis household leverage, consumption cuts and employment losses during the crisis are higher (Mian and Sufi, 2010; Mian, Sufi and Rao, 2013; Mian and Sufi 2014; Mian, Sufi and Trebbi, 2015). This is because when house price slumps, deleveraging households must cut consumption, causing job losses. This paper takes the demand channel one step further. While Mian and Sufi's papers discuss the job losses due to deleveraging households cutting consumption, this paper focuses instead on the spillover of job losses and presents this as evidence for the demand-led propagation in the Great Recession.

This paper is also related to a large, and hotly debated, literature on fiscal multipliers. Estimated fiscal multipliers vary widely (see Ramney, 2011 for a literature review). Many have found the multipliers smaller than one, and potentially close to zero, while others have found substantially larger multipliers.[2] Our findings lend support to demand-stabilizing fiscal policies.

The literature has also provided some theoretical foundation for demand-driven propagation. Early sticky-price models emphasize the role of aggregate demand as a key driver of the business cycle (see, e.g., Christiano, Eichenbaum and Evans, 2005; Gali, 2010; Woodford, 2003). Recent theoretical papers, motivated by the Great Recession, discuss the aggregate demand effects. Eggertsson and Krugman (2012) build a simple new Keynesian model of debt-driven slumps, in which deleveraging agents depress aggregate demand. The paradox of thrift, a job multiplier and demand propagation emerge naturally from their model. Heathcote and Perri (2018) focus on self-fulfilling unemployment. In their model, since households expect high unemployment, they have strong pre-cautionary incentives to cut spending, making the expectation of high unemployment a reality.

Our paper is also related to Moretti (2010). He uses three years of data (1980, 1990 and 2000) and a Bartik-typed instrument to estimate the *long-term* employment across U.S. cities. Note that Moretti's focus is different to ours. With three waves of data (10 years apart), Moretti examines on the long-run "geography of jobs". Using two years of data, 2007 and 2010, we are interested in estimating the propagation of job losses during the Great Recession. Note that over the short-run, local labor market conditions such as wages, reallocation of labor across sectors and emigration are much less likely to adjust compared to those over the long-run. Hence, the propagation of job losses could be more severe, especially if facing with large shocks like those during the Great Recession or during Covid-19 crisis.

[2] For the U.S., Barro and Redlick (2011) find that the multiplier for temporary defense spending is 0.4-0.5 contemporaneously and 0.6-0.7 over two years. Ramey (2011) uses a narrative approach to construct U.S. government spending news variables, and obtains the multipliers in the range from 0.6 to 1.2. Nakamura and Steinsson (2014) exploit regional variations in military buildups to estimate the multiplier of military procurement in the range of 1.4-1.9. In Serrato and Wingender (2014) and Shoah (2015), the estimated multipliers are as high as 1.88 and 2.12.

3. DATA

Three major sources of data are used in the paper. The first source is the Census Bureau. County employment data by industry are from the County Business Patterns (CBP) dataset. CBP data are recorded in March each year. Employment data in 2007 and 2010 are chosen, because March of 2007 and March of 2010 are closest to the bottom and peak of the nation's unemployment rate. CBP data at the four-digit industry level are used.[3] We place each of the four-digit industries into one of four categories: retail and restaurants, tradable, construction and other services, following Mian and Sufi (2014)'s categorization. The full list of *retail and restaurants* are shown in table 3.1. They are all local stores. In 2007, they constitute 19.6% of national total employment. Their demand is generally income elastic (with many retailers of durable goods and restaurants), which makes them ideal candidates for analyses on demand.

A 4-digit NAICS industry is defined as *tradable* if it has tangible imports plus exports at least $10,000 per worker, or if total exports plus imports exceed $500M. They consist of mostly oil, gas, mining and manufacturing. Table 3.2 indicates that tradable industries account for about 15% of a county's total employment. *Construction* industries are those that are related to construction, real estate, or land development. The remaining industries are classified as *other services*. They consist of wholesales, transportation, finance, schools, hospitals, government etc. They account for about 52 percent of a county's workforce in 2007. All in all, tradable, construction and other services (TCS) account for 79 percent, and retail and restaurants (RR) account for about 21 percent of a county's employment.

The second source of data is from the Bureau of Labor Statistics (BLS). The BLS' Quarterly Census of Employment and Wages provides average weekly wages within a quarter for every 4-digit to 6-digit NAICS industry, across U.S. counties. For the analysis on wage rigidity, average weekly nominal wages for *Manufacturing* (NAICS code 31-33), *Retail* (NAICS code 44-45) and *Full Service Restaurants* (NAICS code 7221) are chosen. To be consistent with the timing of employment data, average weekly wages during quarter I-2007 and during quarter I-2010 are chosen.

The third major source of data is from the work of Atif Mian, Amir Sufi and other co-authors. Data for pre-crisis household leverage are borrowed from Mian, Rao and Sufi (2013). It is calculated as households' debt to income ratio in 2006. Data for the change in housing net worth between 2006 and 2009 are from Mian and Sufi (2014). The two proxies are strongly correlated. Other pre-crisis county-level control variables are also from Mian and Sufi (2014): fraction of white population, median household income, fraction of homes that are owner-occupied, fraction of population with less than high school diploma, fraction of population with only a high school diploma, unemployment rate, poverty rate, and fraction of urban population.

Table 3.2 presents the summary statistics of the variables used in the paper. Most of the variables have full coverage, except wages and the leverage proxies. Between 2007 and 2010, on average, TCS industries lost about 8 percent of their jobs. Among them, tradable industries lost 19 percent of their jobs and construction lost 17.7 percent. The job losses in RR industries are more modest, about 4.4 percent on average. Nominal retail and restaurant weekly wages increased 2.3 percent and 9.3 percent, respectively. Note that federal minimum wage increased 40 percent (from $5.15 to $7.25 an hour) during the same period, which could explain the increases in retail and restaurant wages.

Finally, house prices over time by counties are provided by Zillow Research. We use the house prices in March 2010 and March 2007, to match with the timing of the employment data. Due to the limitations of house price data, there are only 989 counties with house prices.

[3] County data at the four-digit industry level are sometimes suppressed for confidentiality reasons. However, the Census Bureau provides a range within which the employment number lies. As in Mian and Sufi (2014), we take the mean of this range as a proxy for the missing employment number in such cases.

4. IDENTIFICATION STRATEGY

4.1 A model

To provide insights to the empirical estimates, consider a small open economy (e.g., a county) that exports a monopolistically competitive good E (exported good), produces a non-tradable good N, and imports a composite good I (imported good). Production function of good N takes the form $y^N = b^N l^N$, where b^N is productivity and l^N is employment of sector N. Production function of good E takes the form $y^E = b^E (l^E)^\alpha (f^E)^{1-\alpha}$, where b^E is productivity, l^E is employment, and f^E is a local fix factor of sector E. Assume that all factors' income stays in the county and consumers spend all their income every period.

Consumers have Cobb-Douglas preferences over the non-tradable good N and imported good I, with the shares of expenditure θ^N and θ^I on goods N and I respectively. Therefore:

$$P^N b^N l^N = \theta^N [P^N b^N l^N + P^E b^E (l^E)^\alpha (f^E)^{1-\alpha}] \qquad (1)$$

where P^N and P^E are prices of good N and E. Assume that the export sector's output is driven by nominal external demand D:

$$P^E b^E (l^E)^\alpha (f^E)^{1-\alpha} = D \qquad (2)$$

Total labor supply is normalized to 1 (i.e, in a county, labor supply is fixed in the short run):

$$l^N + l^E = 1 \qquad (3)$$

4.1.1 Period 0

In period 0, the wages of the export (E) and non-tradable sectors (N) are equalized:

$$P_0^N b^N = \alpha P_0^E b^E (l_0^E)^{\alpha-1} (f^E)^{1-\alpha} \qquad (4)$$

Combining (4) and (1), we obtain the relationship between l_0^N and l_0^E as follows: $l_0^N = \frac{1}{\alpha}\frac{\theta^N}{1-\theta^N} l_0^E$. This and (3) allow us to solve for l_0^N and l_0^E. We then solve for prices P_0^E and P_0^N as functions of l_0^N and l_0^E:

$$P_0^E = \frac{D_0}{b^E (l_0^E)^\alpha (f^E)^{1-\alpha}} \quad \text{and} \quad P_0^N = \frac{\theta^N}{1-\theta^N}\frac{D_0}{b^N l_0^N} \qquad (5)$$

4.1.2 A decline in nominal demand for exports

Consider a decline of external nominal demand: $D_1 = \delta D_0$, where $\delta < 1$.

a. P^E and P^N are flexible

If prices are flexible, a decline in nominal demand would cause adjustments in prices and no change in employment of both sectors. The new prices are $P_1^E = \frac{\delta D_0}{b^E (l_0^E)^\alpha (f^E)^{1-\alpha}}$ and $P_1^N = \frac{\theta^N}{1-\theta^N}\frac{\delta D_0}{b^N l_0^N}$. In other words, prices fall in proportion to the fall in export demand. The county maintains full employment in both sectors.

b. P^E and P^N are rigid

If prices are rigid, a decline in export demand would cause job losses in the export sector *E*, which transmit to the non-tradable sector N. We will distinguish the direct demand channel of transmission (i.e., coming from laid-off workers in the export sector *E* cutting consumption of good N) from the indirect demand channel (i.e. changes in aggregate demand).

Since prices are completely rigid, we obtain $P_1^E = P_0^E$ and $P_1^N = P_0^N$ as derived in (5). Since $P_0^E b^E (l_1^E)^\alpha (f^E)^{1-\alpha} = \delta D_0$, new employment in the export sector *E* is:

$$l_1^E = \left[\frac{\delta D_0}{P_0^E b^E (f^E)^{1-\alpha}}\right]^{\frac{1}{\alpha}} \qquad (6)$$

From (5) and (6), log change in employment of the export sector E is:

$$\Delta \log(l^E) = \log(l_1^E) - \log(l_0^E) = \frac{1}{\alpha}\log(\delta) < 0 \qquad (7)$$

Rewrite (1) and replace $P_0^E b^E (l_1^E)^\alpha (f^E)^{1-\alpha} = \delta D_0$, we obtain new employment in the non-tradable sector, l_1^N

$$P_0^N b^N l_1^N = \theta^N (P_0^N b^N l_1^N + \delta D_0) \qquad (8)$$

As (8) reveals, there are two channels that cause job losses in the non-tradable sector N. The first is the direct channel that comes from the reduction in the export sector E's income (i.e., from D_0 to δD_0). The second is the indirect (i.e. aggregate demand) channel that comes from the induced reduction of income in the non-tradable sector (i.e. from $P_0^N b^N l_0^N$ to $P_0^N b^N l_1^N$). Both channels cause a decline in the non-tradable sector's employment. If both channels take place, from (8), we obtain:

$$l_1^N = \frac{\theta^N}{1-\theta^N} \frac{\delta D_0}{P_0^N b^N} \quad (9)$$

Log change in employment of the non-tradable sector is:

$$\Delta \log(l^N) = \log(l_1^N) - \log(l_0^N) = \log(\delta) \qquad (10)$$

From equations (7) and (10), the relationship between log change of the export sector's employment and log change of the non-tradable sector's employment is:

$$\Delta \log(l^N) = \alpha \, \Delta \log(l^E) \quad (11)$$

(11) gives the prediction of the causal effect of the export sector's job losses on the non-tradable sector's job losses if both the direct and the aggregate demand channels operate. In other words, counties with larger job losses in the export sector are expected to see larger declines in the non-tradable sector's employment.

If one thinks of the TCS sector as the export sector in the model above, and the RR sector as the non-tradable sector, one can generally posit a family of *local* equilibrium models to examine the impact of TCS job losses on RR job losses in a county *j*:

$$\Delta L_{RR,j} = f\left(\Delta L_{TCS,j}, \Delta X_j, Z_j, \varphi\right) \qquad (13)$$

where ΔX_j captures changes in local *endogenous* variables that may affect employment, such as local house prices or credit conditions (see Figure 4.1 for a visual illustration). Z_j is a vector of *pre-existing* local characteristics such as education, current income or housing supply elasticity that could affect the extent of the job loss spillover. Finally, φ is a set of structural parameters. Examples of φ are the relative income elasticity of the RR sector, the complementarity of RR goods with others, the structure of production such as the degree of local decreasing or increasing returns, and the degree of price and wage stickiness

As Figure 4.1 shows, the spillover of TCS job losses on RR job losses works via the demand-led channel (which includes the direct and the aggregate demand channels) and via other potential equilibrium changes in the *local* economy. In other words, the estimated effect is the LATE (*local average treatment effect)* of exogenous TCS job losses. The estimate is of interest because it captures the full general equilibrium effect of TCS job losses on RR job losses. In section 6, we examine potentially important transmission mechanisms and argue that the evidence points to demand-led propagation.

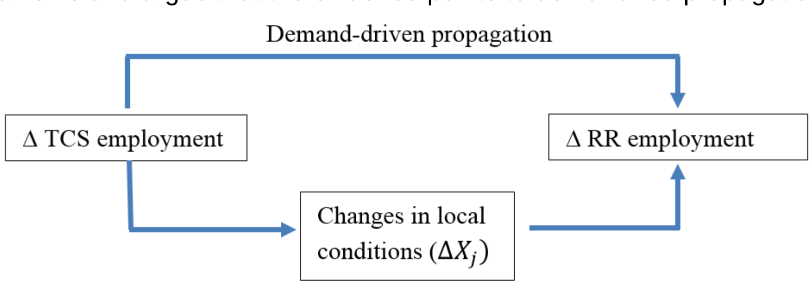

Figure 4.1: Potential transmission mechanisms of job losses

Since RR and TCS job losses are generally endogenous, i.e., we do not know if one type of job losses causes or is caused by the other type of job losses, or both are driven by common factors. To overcome this challenge, we use Bartik tradable job losses to instrument for TCS job losses.

4.2 Bartik tradable job losses

To see the relationship between TCS job losses and Bartik tradable job losses (or Bartik for short), consider TCS job losses of county *j*:

$$\Delta\log\left(l_j^{TCS}\right) \approx \frac{l_{j,2010}^{TCS} - l_{j,2007}^{TCS}}{l_{j,2007}^{TCS}} = \sum_{i\in TCS}\left(\frac{l_{j,2007}^{i}}{l_{j,2007}^{TCS}} \times \frac{l_{j,2010}^{i} - l_{j,2007}^{i}}{l_{j,2007}^{i}}\right)$$

where $l_{j,t}^{TCS}$ is TCS employment in county *j* at time *t*; $l_{j,t}^{i}$ is industry *i*'s employment in county *j* at time *t*. We split the job losses to those in tradable industries (T), and those in construction and service industries (CS):

$$\Delta\log\left(l_j^{TCS}\right) \approx \sum_{i\in T}\left(\frac{l_{j,2007}^{i}}{l_{j,2007}^{TCS}} \times \Delta\log l_j^i\right) + \sum_{i\in CS}\left(\frac{l_{j,2007}^{i}}{l_{j,2007}^{TCS}} \times \Delta\log l_j^i\right) \quad (14)$$

where $\sum_{i\in T}\left(\frac{l_{j,2007}^{i}}{l_{j,2007}^{TCS}} \times \Delta\log l_j^i\right)$ are job losses in all tradable industries in county *j* as a fraction of TCS employment. Tradable job losses might not be exogenous to a county's fundamentals. For example, labor supply issues (such as a raise in local minimum wages) could affect tradable employment in that county. To instrument for TCS job losses in a certain county, Bartik tradable job losses, which captures only tradable job losses driven by aggregate shocks in the rest of the country are used (i.e., leave-one-out Bartik). To see this, rewrite tradable job losses $\sum_{i\in T}\left(\frac{l_{j,2007}^{i}}{l_{j,2007}^{TCS}} \times \Delta\log l_j^i\right)$ as $\sum_{i\in T}\left(\frac{l_{j,2007}^{i}}{l_{j,2007}^{TCS}} \times \Delta\log l_{US-j}^i\right)$ $+ \sum_{i\in T}\left(\frac{l_{j,2007}^{i}}{l_{j,2007}^{TCS}} \times (\Delta\log l_j^i - \Delta\log l_{US-j}^i)\right)$.

The first term, $\sum_{i\in T}\left(\frac{l_{j,2007}^{i}}{l_{j,2007}^{TCS}} \times \Delta\log l_{US-j}^i\right)$, represents Bartik tradable job losses. It is the sum of Bartik job losses for all tradable industries. For each industry *i*, it is the county's pre-existing employment exposure to the industry, $\frac{l_{j,2007}^{i}}{l_{j,2007}^{TCS}}$, multiplied by change in industry employment *in the rest* of the country, $\Delta\log l_{US-j}^i$, where $\Delta\log l_{US-j}^i = \log\left(l_{US,2010}^i - l_{j,2010}^i\right) - \log\left(l_{US,2007}^i - l_{j,2007}^i\right)$. This is to mitigate the concern that an industry could be overly concentrated in a county and therefore change in the industry's national employment could be driven by the county's fundamentals. We interpret $\Delta\log l_{US-j}^i$ as an aggregate shock to industry *i's* employment in the rest of the U.S. The second term, $\sum_i^T\left(\frac{l_{j,2007}^{i}}{l_{j,2007}^{TCS}} \times (\Delta\log l_j^i - \Delta\log l_{US-j}^i)\right)$, could be interpreted as tradable job losses driven by county *j*-specific issues. Goldsmith-Pinkham et. al. (2020) examine the situations in which the identification assumptions of Bartik instruments might be invalid. We discuss them in section 5.2.

Hence, we can write TCS job losses as follows:

$$\Delta\log\left(l_j^{TCS}\right) = Bartik_j + \sum_i^T\left(\frac{l_{j,2007}^{i}}{l_{j,2007}^{TCS}} \times \left(\Delta\log l_j^i - \Delta\log l_{US}^i\right)\right) + \sum_i^{CS}\left(\frac{l_{j,2007}^{i}}{l_{j,2007}^{TCS}} \times \Delta\log l_j^i\right) \quad (15)$$

where the Bartik tradable job losses will be used to instrument for $\Delta\log\left(l_j^{TCS}\right)$.

The IV regression is:

$$\Delta\boldsymbol{\log}\left(\boldsymbol{l_j^{RR}}\right) = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\Delta\widehat{\boldsymbol{\log}\left(\boldsymbol{l_j^{TCS}}\right)} + \boldsymbol{\beta_2 lev_j} + \boldsymbol{controls_j} + \boldsymbol{\varepsilon_j} \qquad \textbf{(14)}$$

where $\Delta\widehat{\boldsymbol{\log}\left(\boldsymbol{l_j^{TCS}}\right)}$ represents TCS job losses instrumented by Bartik tradable job losses. $\Delta\log\left(l_j^{RR}\right) = \log\left(l_{j,2010}^{RR}\right) - \log\left(l_{j,2007}^{RR}\right)$ is log change in retail and restaurant employment; $\Delta\log\left(l_j^{TCS}\right)$ is log change in tradable, construction and services employment in county *j* . Note that all standard errors are robust and clustered at the state level. They are also weighted by number of households.

Lev_j are important control variables. They capture household leverage and changes in housing net worth. Mian, Rao and Sufi (2013) and Mian and Sufi (2014) show that pre-crisis household leverage (and similarly, changes in housing net worth during the Recession) explain the demand collapse during the Great

Recession. When house price slumps, highly leveraged households must deleverage, leading to a sharp reduction in consumption. Mian and Sufi (2014) find that in counties with higher pre-crisis household leverage (and larger declines in housing net worth during the Recession), retail and restaurant employment drop more. Equation (2) therefore examines two sources of demand shocks to retail and restaurant industries: the first one is from deleveraging households, the second one is from laid-off TCS workers.

5. MAIN EMPIRICAL RESULTS

5.1 OLS

Before proceeding to the main regressions, we would like to examine the simple OLS relationship between TCS job losses and RR job losses. We gradually add pre-crisis household leverage, changes in housing net worth and other control variables to the regressions. Column [5] of table 5.1 reveals that TCS job losses are significantly associated with RR job losses. Every 1 percent job loss in TCS is associated with 0.191 percent job losses in retail and restaurants. The coefficients are of course biased. They do not capture the causal effects of TCS job losses on RR job losses. Many sources of bias could take place. To identify a causal impact, we need to use Bartik tradable job losses as an instrument.

5.2 Bartik tradable job losses

Two components of Bartik tradable job losses are exposure to tradable employment and declines in aggregate employment of tradable industries. Regarding the second component, the Great Recession is associated with a massive collapse in employment, particularly of tradable industries. At the national level, some industries lost as much as 47% of their employment. Hardest hit industries are apparel manufacturing, motor vehicle manufacturing, furniture, electronics, construction-related, and oil and gas extraction (Table 5.2a). Understandably, if a county is exposed to tradable industries, and worse, to the hardest hit industries, the county's Bartik will be negative with a large magnitude. Table 5.2b lists ten large U.S counties with the largest and smallest Bartik. For example, in Howard County, Indiana, tradable job losses driven by aggregate shocks accounts for 20.71% of TCS employment in 2007.

Table 5.2c presents the summary statistics of Bartik tradable job losses. The mean value of Bartik is -0.0308. This implies on average, tradable job losses driven by aggregate shocks account for 3.08% of TCS employment in 2007.

How are Bartik tradable job losses related with a county's characteristics? Besides historical and idiosyncratic reasons, it is reasonable to predict that how much a county is exposed to tradable production could be driven by some of the county's characteristics, such as its abundance of land, its location next to key transportation hubs, education of the workforce etc.

An identification worry, as discussed in Goldsmith-Pinkham et. al. (2020) is that the Bartik instrument could be driven primarily by a selected number of industries whose employment shares predict RR employment growth through other channels other than TCS employment growth. For example, the high employment share of "Apparel Knitting Mills" could be correlated with urbanization, which in turn can cause RR employment growth. Goldsmith-Pinkham et. al. (2020) propose a measure of each industry's weight in the Bartik instrument (which is known as the Rotemberg weight). We compute the Rotemberg weight for the 82 4-digit NAICS tradable industries that are used to construct the Bartik instrument. The ten industries with the highest weights are listed in Table 5.2d. They constitute only about 17 percent of the total variation in the Bartik instrument. For example, the industry with the highest Rotemberg weight - Apparel Knitting Mills - only accounts for 2 percent of the total Bartik instrument. The finding suggests our Bartik instrument is not driven by any particular industry. A large number of industries with small Rotemberg weights in our analysis helps mitigate the endogeneity concerns (Borusyak, Hull, and Jaravel, 2022).

5.3 First stage relationship

Table 5.3 presents the results for the relationship between Bartik and the log change in TCS employment. Note that the sample is matched to that of the second stage. F-statistics are consistently high and larger than 10, implying a strong relationship between the instrument and the instrumented variable. Every tradable job lost due to aggregate shocks leads to 1.025 jobs lost in TCS (column [5]).

5.4 Baseline results

Tables 5.4a presents the reduced form relationship between Bartik tradable job losses and log changes in retail and restaurant. Column [1] does not include the proxies for household leverage, while columns [2] to [5] do. After the inclusion of the leverage proxies as control variables, the relationship between Bartik and log change in RR employment growth becomes positive and highly significant. Overall, column [4] implies that a 1% Bartik tradable job losses cause a 0.3% decline in retail and restaurant employment between 2007 and 2010. After including change in housing net worth as a control variable (column [5]), the effect of Bartik on RR employment has a larger magnitude. Figure 5.4 shows the scatter plot depicting the correlation between the Bartik and RR job growth, after controlling for household leverage (i.e., column [2] in Table 5.4a).

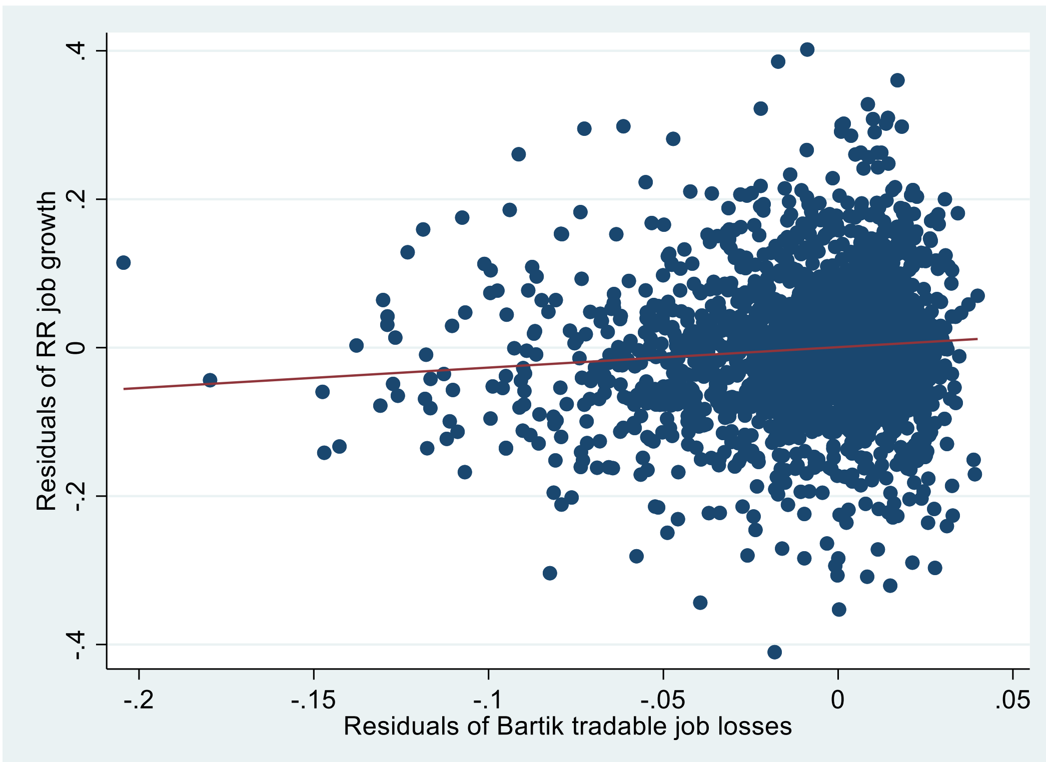

Figure 5.4: Scatterplot between the Bartik residuals and RR employment growth residuals (column [2], table 5.4a)

It is interesting to note that after including pre-crisis household leverage, Bartik tradable job losses have a significant effect on RR job losses. This is because Bartik tradable job losses and pre-crisis household leverage are highly correlated. The pairwise correlation between the two variables is 0.204 and is highly significant. This implies that in counties with lower pre-crisis household leverage, the number of Bartik tradable job losses during the Great Recession is larger (see Figure A1 in the Appendix for the scatter plot between the two variables). Similarly, Bartik and changes in housing net worth is significantly and negatively correlated. This result is consistent with that in table 5.2d. Counties more exposed to manufacturing are also those with high housing supply elasticity, perhaps because they have abundant land. Therefore, the house price run up during the boom time and the house price decline during the Great Recession are less severe in those counties.

Table 5.4b shows the IV regressions between TCS job losses and retail and restaurant job losses. They serve as the baseline results of the paper. Columns [4] and [5], with leverage proxies and other control variables, suggest that across counties, a 1% decrease in TCS job losses causes a 0.31% to 0.37% decrease in RR job losses. This is *above and beyond* the direct effect of households' deleveraging on retail and restaurant sectors, as documented by Mian and Sufi (2014). The relationship is robust to a series of county characteristics.

The causal relationship, which is 0.371 (column [5] of table 5.4b), is stronger than the simple correlation relationship, which is 0.191 (column [5] of table 5.1). This is possible, as the IV regressions estimate the local average treatment effect (TCS job losses driven by Bartik tradable job losses) whereas the OLS regressions estimate the average association over the entire population (all TCS job losses).

5.5 On wage rigidity

Local nominal wage rigidity matters for demand driven propagation of job losses. If wages were completely flexible, we could still obtain full employment even with a negative demand shock, because wages would adjust to absorb additional labor. If local wages are sticky, the only way retail and restaurant firms adjust to the demand shock is to shed labor and scale down their businesses.

We find some evidence for a drop of nominal wages in manufacturing, but not for those in retail and restaurant sectors[4] Table 5.5 shows that nominal wages for manufacturing decline more in counties with more negative Bartik or with larger drops of TCS employment. On the other hand, Bartik and TCS job losses do not seem to cause stronger declines in retail and restaurant wages.

The findings imply that while manufacturing wages go down, cross-sectoral reallocation of labor, from TCS to retail and restaurants, does not likely occur during the Great Recession. If there were hiring of unemployed TCS workers from restaurants, we would expect to see either hourly wages drop, or less hours worked per worker (if minimum wages are binding), both of which would result in lower average weekly wage. The swift and dramatic demand collapse during the Great Recession might have prevented local labor markets from adjusting. Mian and Sufi (2014) also find that there is little evidence of wage adjustment within or emigration out of the hardest hit counties.

5.6 Selection bias

We examine the possible degree of omitted variable bias by using Oster's (2019) approach. Oster (2019) proposes an approach to estimate the degree of omitted variable bias under the assumption that the selection of the observed controls is proportional to the selection of the unobserved controls. The approach computes a value δ of selection from omitted variables that are required to eliminate the effect of the Bartik instrument on RR employment growth. A larger value of δ in absolute value would indicate a larger omitted variable issue. We obtain $\delta = 0.1875$, using Oster's (2019) approach, which is small according to her proposed benchmark. This indicates that the concern of omitted variable bias in our regression specification is small.

6. ON THE TRANSMISSION MECHANISMS

Even in the case that a decline in retail and restaurant employment accompanies a decline in tradable employment, it still does not mean the transmission operates through the demand channel. In this section, we examine in detail two prominent competing hypotheses, namely, exposure to the house price collapse and credit supply problems. We argue that none of the competing hypotheses square well with the data. Moreover, we find that the job spillover is stronger for income-elastic retail and restaurant industries than the income-inelastic ones. This suggests demand effect is at play.

6.1 Housing

The house price collapse is one of the most dramatic characteristics of the Great Recession. House prices on average fell 11.2% between March 2007 and March 2010, across 945 counties where Zillow has data. Given such a change, a reasonable possibility is that housing could be a channel to transmit TCS job losses to RR job losses. TCS job losses could depress house prices in a county, which then would reduce

[4] Wages are measured as the average weekly wage during the first quarter of 2007, and that during the first quarter of 2010, for *Manufacturing* (NAISC code: 31-33) *Retail* (NAICS code 44-45) and *Full Service Restaurants* sector (NAICS code 7221).

the net worth of locals. Bearing a negative wealth effect, they must cut consumption, hurting the retail and restaurant sectors.

However, data do not seem to support the housing channel. Table 6.1 presents the impacts of Bartik and the instrumented TCS job losses on log change in house prices between 2007 and 2010, with housing supply elasticity as a key control. Housing supply elasticity (Saiz, 2010) measures how abundantly land for development is available. It has been shown, by Mian and Sufi (2014) and others, to be powerful in explaining the run up in house prices before Great Recession, and the collapse of house prices during the Recession. There is no evidence that TCS job losses cause the decline in house prices between 2007 and 2010, after housing supply elasticity is included.

6.2 Credit

The most prominent competing hypothesis is credit-led spillover. That is, the spillover from the TCS sector to the retail and restaurant sectors could take place via the credit market. For example, under-water tradable firms are late in their loan repayments, which weakens local banks' balance sheet. This in turn affects local lending to retail and restaurant firms. A decline in retail and restaurant employment therefore could be due to local credit problems, not local demand problems.

Table 6.2, however, shows this is not likely the case. We organize the regressions in two blocks. The first block, which consists of columns [1] to [3], shows log changes in the number of retail and restaurant firms between 2007 and 2010, by size (1 to 19 workers, 20 to 99 workers, and more than 100 workers). If the credit channel were the problem, smaller retail and restaurant firms should get hit more in counties with larger TCS job losses, because smaller firms should have more difficult access to credit. This is not the case here, as the coefficients become more positive for larger establishments. That is, instrumented job losses in TCS hurts larger RR firms more than they do smaller ones.

A concern is that the result could be driven by numbers of smaller firms being inflated, due to larger firms cutting jobs and becoming smaller firms. This is a possibility. We try to mitigate this possibility by using few numbers of bins (only three bins covering three groups of firm size as opposed to six available in the data). With fewer number of bins, the chance of firms moving to a different group is smaller.

The second block, which consists of columns [4] and [5], splits the counties into two groups, one with more national banks (National=1), and one with more local banks (Local=1) (as in Mian and Sufi, 2014). If credit were to play a key role in the transmission, retail and restaurant job losses would be more sensitive to TCS job losses in counties with more local banks, as local banks would be less likely to get help from outside their respective counties. We do not observe this case in columns [4] and [5]. Instead, high TCS job losses reduce retail and restaurant employment more in counties dominated by national banks.

6.3: Demand-elastic versus demand-inelastic retail and restaurant sectors

To further isolate the role of demand-driven job losses during the Great Recession, we identify industries within the retail and restaurant sectors that were most impacted by consumer demand shocks during the Great Recession based on the categorization by Giroud and Mueller (2017)[5] in Table 6.3a. The hypothesis we seek to test is as follows: if the effect of the tradable demand shock on retail and restaurant industries is operating through the local demand channel, we would anticipate a greater impact of the tradable demand shock on industries in the retail and restaurant sector where the sharp drop in consumer demand during the Great Recession had the most significant effect as identified by Giroud and Mueller (2017). Conversely, if the mechanism does not involve the role of local demand, then we would expect a smaller effect of the tradable demand shock on the retail and restaurant sectors within this subset of industries.

Table 6.3b displays the (i) baseline IV results for all retail and restaurant industries (column 1) and (ii) the results for retail and restaurant industries that are most impacted by consumer demand

[5] Using the confidential micro-level Longitudinal Business Database (LBD) data from the U.S. Census Bureau, Giroud and Mueller (2017) identify the top retail and restaurant industries whose establishment-level employment was most affected by the sharp drop in consumer demand during the Great Recession (see Table 6.3a for the list of industries).

shocks during the Great Recession (column 2) , and (iii) the results for retail and restaurant industries that are less affected by consumer demand shocks (column 3, i.e., industries that are not listed in Table 6.3a). We observe that the effect of tradable demand shock on the employment of retail and restaurants is larger and more significant among industries that are most affected by consumer demand shocks (column 2) than those that are less affected by consumer demand shocks during the Great Recession (column 3). We also conducted a separate regression analysis to examine the impact of TCS job losses on each R&R industry based on the R&R industry's demand elasticity using the interaction term in column 4. We can similarly observe that R&R industries most impacted by consumer demand shocks during the Great Recession saw an additional decline of 0.355 percent in their employment for every 1 percent decline in TCS employment within the county, compared to the rest of the R&R industries.

Although these results could not completely rule out the role of local labor supply, they do suggest that local demand plays a large and significant role in explaining the negative effect of a tradable demand shock on the employment of retail and restaurant sector during the Great Recession.

In addition to the regression results above, it has been well documented in several seminal works that the collapse in house prices during the Great Recession primarily induced a significant decrease in consumer demand by households, subsequently resulting in employment declines across U.S. counties (Mian and Sufi, 2010; Mian, Sufi and Rao, 2013; Mian and Sufi 2014). These studies, combined with our findings, lend support to the role of the demand-driven propagation of job losses during the Great Recession.

7. CONCLUSION

It is important to understand how shocks transmit across economic sectors and geographic areas, especially in recessionary periods. The Great Recession provides a good natural experience to study this. Utilizing a Bartik-typed instrument, our paper provides empirical evidence for local demand-driven propagation of job losses. It finds that larger job losses in tradable, construction, and services caused larger retail and restaurant job losses during the Great Recession. Retail and restaurant employment fell by 0.37 percent for every 1 percent job loss in the rest of the county’s economy. The result is statistically very significant and robust, suggesting a significant role of demand. The finding is not driven by the collapse in house prices or by credit supply problems. Moreover, the propagation is stronger in retail and restaurant sectors that are most affected by consumer demand shocks, which strengthens the argument for a demand-led spillover. Given the massive tradable employment losses, where some industries lost 30 to 40 percent of their workforce in such a short time, it is not very surprising that counties could not absorb or respond to such massive shocks.

The paper provides important policy implications regarding responses to economic downturn, such as the economic impact of the new corona virus (Covid-19). First, demand-driven mechanisms matter. The finding suggests a role for demand stabilizing policies to contain demand-driven transmissions of negative shocks. Without such policies in place to assist hardest-hit population and sectors, negative shocks could spread through other healthier sectors of the economy and worsen the scale and scope of a recession.

References

Autor, David H., David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review*, 103(6): 2121-68.

Barro, Robert J., and Charles J. Redlick. (2011) "Macroeconomic Effects from Government Purchases and Taxes." *Quarterly Journal of Economics 126 (1): 51–102*

Bartik, Timothy J. (1991) *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, MI: W.E. Upjohn Institute for Employment Research

Bils, Mark & Peter J. Klenow & Benjamin A. Malin, (2013) "Testing for Keynesian Labor Demand," *NBER Macroeconomics Annual*, University of Chicago Press, vol. 27(1), pages 311 - 349.

Borusyak, Kirill, Peter Hull, Xavier Jaravel. (2022) "Quasi-Experimental Shift-Share Research Designs". *The Review of Economic Studies*, Volume 89, (1), Pages 181–213,

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans (2005) "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy**"** *Journal of Political Economy*, 113 (1), 1–45

Daly, Mary, Bart Hobijn, and Timothy Ni (2013) "The path of wage growth and unemployment" *FEBSF Economic Letter*, 2013-20

Eggertsson Gauti & Paul Krugman, (2012) "Debt, Deleveraging, and the Liquidity Trap: A Fisher-Minsky-Koo Approach," *The Quarterly Journal of Economics*, vol. 127(3), pages 1469-1513.

Ilzetzki Ethan & Enrique G. Mendoza & Carlos A. Végh (2013) "How Big (Small?) are Fiscal Multipliers?" *Journal of Monetary Economics* 60:2, pp. 239-254

Gali, Jordi (2010) "Monetary Policy and Unemployment," in Benjamin M. Friedman and Michael Woodford, eds., *Handbook of Monetary Economics*, Vol. 3, chapter 10, pp. 487–546

Giroud, Xavier, Holger M. Mueller (2017) "Firm Leverage, Consumer Demand, and Employment Losses During the Great Recession" *Quarterly Journal of Economics*, 132(1): 271-316.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift (2020) "Bartik instruments: What, when, why, and how." *American Economic Review* 110.8: 2586-2624.

Heathcote, Jonathan and Fabrizio Perri (2018) "Wealth and Volatility," *The Review of Economic Studies,* 85(4), pp 2173-2213

Keynes Maynard John (1936), "The General Theory of Employment, Interest and Money"

Mian Atif and Amir Sufi (2010), "Household Leverage And The Recession Of 2007 To 2009" *IMF Economic Review*, 58, 74–117

Mian Atif and Amir Sufi (2014), "What Explains the 2007-2009 Drop in Employment?", *Econometrica*, Vol. 82, No. 6, 2197-2223

Mian Atif, Amir Sufi and Kamalesh Rao, (2013) "Household Balance Sheets, Consumption, and the Economic Slump" *Quarterly Journal of Economics*, 128 (4): 1687-1726

Mian Atif, Amir Sufi and Francesco Trebbi, (2015) "Foreclosures, House Prices, and the Real Economy", *Journal of Finance*, (70) pp 2587–2634

Moretti, Enrico (2010) "Local Multipliers" *American Economic Review: Papers & Proceedings* 100: 1–7

Nakamura, Emi, and Jon Steinsson. (2014) "Fiscal Stimulus in a Monetary Union: Evidence from US Regions." *American Economic Review* 104 (3): 753–92.

Nguyen, Ha and Shawheen Rezaei (2016) "The great recession and job loss spillovers: impact of tradable employment shocks on supporting services" *World Bank Policy Working Paper 7453*

Oyster, Emily (2019) "Unobservable Selection and Coefficient Stability: Theory and Evidence" *Journal of Business & Economic Statistics*, vol. 37 (2), 187-204

Ramey, Valerie A. (2011). “Identifying Government Spending Shocks: It’s All in the Timing.” *Quarterly Journal of Economics* 126 (1): 1–50.

Ramey, Valerie A. (2011) "Can Government Purchases Stimulate the Economy?" *Journal of Economic Literature*, vol. 49(3), pages 673-85, September.

Saiz Albert, (2010) "The Geographic Determinants of Housing Supply," *The Quarterly Journal of Economics*, MIT Press, vol. 125(3), pages 1253-1296, August.

Serrato, Juan C. S., and Philippe Wingender. (2014) “Estimating Local Fiscal Multipliers.” *Mimeo*

Shoag, Daniel (2015). “The Impact of Government Spending Shocks: Evidence on the Multiplier from State Pension Plan Returns.” *Mimeo*

Woodford, Michael, (2003) Interest and Prices, Princeton, NJ: Princeton University Press

NAICS	Industry name	Percentage of total employment, 2007
4411	Automobile dealers	1.05
4412	Other motor vehicle dealers	0.15
4413	Automotive parts accessories and tire stores	0.41
4421	Furniture stores	0.23
4422	Home furnishing stores	0.27
4431	Electronics and appliance stores	0.42
4451	Grocery stores	2.13
4452	Specialty food stores	0.15
4453	Beer wine and liquor stores	0.13
4461	Health and personal care stores	0.89
4471	Gasoline stations	0.73
4481	Clothing stores	1.06
4482	Shoe stores	0.18
4483	Jewelry luggage and leather goods stores	0.14
4511	Sporting goods hobby and musical instrument stores	0.38
4512	Book periodical and music stores	0.16
4521	Department stores	1.36
4529	Other general merchandise stores	1.12
4531	Florists	0.09
4532	Office supplies stationery and gift stores	0.27
4533	Used merchandise stores	0.12
4539	Other misc store retailers	0.23
7221	Full-service restaurants	3.76
7222	Limited-service eating places	3.4
7223	Special food services	0.49
7224	Drinking places (alcoholic beverages)	0.31
	Total	19.63

Table 3.1: The list of retail and restaurants industries

	N	mean	SD	10th	90th
Retail and restaurant employment/Employment, 2007	3132	0.210	0.058	0.144	0.277
TCS employment/Employment, 2007	3084	0.791	0.055	0.724	0.856
Tradable employment/Employment, 2007	3085	0.146	0.107	0.031	0.288
Construction employment/Employment, 2007	3131	0.130	0.065	0.067	0.210
Other services employment/employment 2007	3134	0.516	0.104	0.386	0.647
Δ log of RT employment, 2007-2010	3132	-0.044	0.151	-0.183	0.111
Δ log of TCS employment, 2007-2010	3084	-0.080	0.128	-0.222	0.053
Δ log of tradable employment, 2007-2010	3048	-0.190	0.407	-0.609	0.133
Δ log of construction employment, 2007-2010	3126	-0.177	0.269	-0.484	0.122
Δ log of other services employment, 2007-2010	3134	-0.030	0.135	-0.173	0.110
Δ log of retail wage, 2007-2010	3099	0.029	0.101	-0.064	0.145
Δ log of restaurant wage, 2007-2010	2223	0.093	0.134	-0.030	0.248
Household leverage (debt/income), 2006	2219	1.573	0.584	0.971	2.366
Δ housing net worth, 2006-2009	944	-0.065	0.085	-0.172	0.003
Number of households, 2007	3135	36939	110855	2420	72622
fraction white, 2007	3135	0.870	0.150	0.658	0.988
Median Household Income ($), 2007	3135	35597	9147	26312	46608
fraction homes owner occupied, 2007	3135	0.741	0.075	0.643	0.818
fraction with less than a highschool diploma, 2007	3135	0.226	0.087	0.126	0.350
fraction with only a highschool diploma, 2007	3135	0.347	6.571	26.398	42.903
Unemployment rate, 2007	3135	0.058	0.058	0.058	0.058
Poverty rate, 2007	3135	0.142	0.065	0.073	0.226
fraction urban, 2007	3135	0.393	0.309	0.000	0.846

Table 3.2 Summary statistics of important variables. The unit of observation is a U.S. county.

VARIABLES	Δlog(retail and restaurant employment)				
	[1]	[2]	[3]	[4]	[5]
Δlog(TCS employment)	0.232***	0.174***	0.228***	0.150***	0.191***
	[0.058]	[0.053]	[0.084]	[0.045]	[0.067]
leverage 2006		-0.028***	-0.025***	-0.026***	-0.017*
		[0.003]	[0.007]	[0.006]	[0.010]
Δ housing net worth			0.036		0.067
			[0.050]		[0.062]
fraction white				0.016	-0.001
				[0.021]	[0.026]
median household income				0.000	0.000**
				[0.000]	[0.000]
fraction owner-occupied				-0.106	-0.089
				[0.063]	[0.070]
fraction less than highschool				-0.012	0.043
				[0.060]	[0.090]
fraction highschool				0.046	0.143
				[0.115]	[0.140]
unemployment rate				-0.239	-0.432
				[0.183]	[0.258]
poverty rate				0.158	0.340*
				[0.123]	[0.175]
fraction urban				-0.026***	-0.038**
				[0.010]	[0.018]
Constant	-0.035***	0.014	0.016	0.046	-0.021
	[0.010]	[0.013]	[0.020]	[0.034]	[0.054]
Observations	3,129	2,217	938	2,217	938
R-squared	0.052	0.129	0.186	0.144	0.217

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 5.1: Simple OLS relationship between TCS and RR job losses.

NAICS	Industry	log(emp 2010)-log(emp 2007)
3152	Cut and sew apparel manufacturing	-0.476
3362	Motor vehicle body and trailer manufacturing	-0.464
3363	Motor vehicle parts manufacturing	-0.397
3361	Motor vehicle manufacturing	-0.383
3315	Foundries	-0.334
3342	Communications equipment manufacturing	-0.327
3372	Office furniture (including fixtures) manufacturing	-0.316
3341	Computer and peripheral equipment manufacturing	-0.313
3332	Industrial machinery manufacturing	-0.310
3344	Semiconductor and other electronic component manufacturing	-0.287
3399	Other miscellaneous manufacturing	-0.281
3334	Ventilation heating air -conditioning and commercial refrigeration	-0.265
2111	Oil and gas extraction	-0.254
3335	Metalworking machinery manufacturing	-0.252
3261	Plastics product manufacturing	-0.249
3333	Commercial and service industry machinery manufacturing	-0.248
3366	Ship and boat building	-0.229
2123	Nonmetallic mineral mining and quarrying	-0.227
3231	Printing and related support activities	-0.225
3353	Electrical equipment manufacturing	-0.223

Table 5.2a: Hardest hit tradable industries in the Great Recession.

Note: The last column shows log change of employment between 2007 and 2010. Negative numbers imply job losses (note: only large industries with more than 50,000 workers in 2007 are included).

County name	State	Bartik
Howard County	IN	-0.2071
Elkhart County	IN	-0.1704
DeKalb County	AL	-0.1667
Hawkins County	TN	-0.1549
Walker County	GA	-0.1546
Eagle County	CO	-0.0011
Vernon Parish	LA	-0.0008
District of Columbia	DC	-0.0006
Arlington County	VA	-0.0004
Kings County	CA	-0.0001

Table 5.2b: Counties most and least exposed to tradable

(only large counties with more than 20,000 households are included)

	N	Mean	SD	10th	90th
All tradable job losses*	3084	-0.0278	0.0630	-0.0935	0.0162
Bartik*	3037	-0.0308	0.0303	-0.0705	-0.0035
County-specific tradable job losses*	3036	0.0031	0.0575	-0.0464	0.0519

*as fractions of TCS employment in 2007

Table 5.2c: Bartik and county-specific tradable job losses as fractions of 2007 TCS employment

NAICS	Name	Rotemberg weights
3151	Apparel Knitting Mills	0.0210
2122	Metal Ore Mining	0.0185
3362	Motor Vehicle Body and Trailer Manufacturing	0.0185
3361	Motor Vehicle Manufacturing	0.0184
3369	Other Transportation Equipment Manufacturing	0.0173
1141	Fishing	0.0164
3346	Manufacturing and Reproducing Magnetic and Optical Media	0.0158
3366	Ship and Boat Building	0.0153
3311	Iron and Steel Mills and Ferroalloy Manufacturing	0.0151
2111	Oil and Gas Extraction	0.0148
	Sum	**0.1711**

Table 5.2d: Ten industries with the largest Rotemberg weights

VARIABLES	Δlog(TCS employment)				
	[1]	[2]	[3]	[4]	[5]
Bartik	0.807***	1.139***	1.191***	0.984***	1.025***
	[0.157]	[0.108]	[0.157]	[0.127]	[0.163]
leverage 2006		-0.041***	-0.027***	-0.042***	-0.021***
		[0.006]	[0.009]	[0.006]	[0.008]
Δ housing net worth			0.130***		0.176***
			[0.040]		[0.041]
fraction white				0.041*	0.028
				[0.024]	[0.028]
median household income				0.000***	0.000***
				[0.000]	[0.000]
fraction owner-occupied				-0.127**	-0.107**
				[0.049]	[0.046]
fraction less than highschool				-0.062	0.022
				[0.060]	[0.063]
fraction highschool				0.006	0.041
				[0.091]	[0.093]
unemployment rate				0.175	0.375**
				[0.177]	[0.153]
poverty rate				0.147	0.162
				[0.105]	[0.134]
fraction urban				-0.036***	-0.044***
				[0.013]	[0.017]
Constant	-0.060***	0.024**	0.009	0.033	-0.047
	[0.010]	[0.012]	[0.017]	[0.048]	[0.050]
Observations	3,035	2,217	938	2,217	938
R-squared	0.052	0.199	0.266	0.231	0.326
F-stat	26.49	117.17	57.36	59.92	39.54

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3: First stage relationship between Bartik tradable job losses and TCS job losses

VARIABLES	Δlog(retail and restaurant employment)				
	[1]	[2]	[3]	[4]	[5]
Bartik	0.021	0.323***	0.336**	0.303***	0.380***
	[0.119]	[0.097]	[0.161]	[0.057]	[0.127]
leverage 2006		-0.037***	-0.032***	-0.033***	-0.022**
		[0.005]	[0.010]	[0.007]	[0.011]
Δ housing net worth			0.065		0.099
			[0.051]		[0.064]
fraction white				0.023	0.005
				[0.022]	[0.027]
median household income				0.000	0.000***
				[0.000]	[0.000]
fraction owner-occupied				-0.126**	-0.111
				[0.062]	[0.068]
fraction less than highschool				-0.003	0.067
				[0.057]	[0.084]
fraction highschool				0.054	0.156
				[0.124]	[0.151]
unemployment rate				-0.232	-0.381
				[0.201]	[0.279]
poverty rate				0.156	0.347**
				[0.127]	[0.172]
fraction urban				-0.034***	-0.051***
				[0.009]	[0.018]
Constant	-0.053***	0.023	0.020	0.058*	-0.020
	[0.011]	[0.016]	[0.024]	[0.033]	[0.051]
Observations	3,035	2,217	938	2,217	938
R-squared	0.000	0.110	0.154	0.131	0.200

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 5.4a: Reduced-form relationship between log change of RR employment and Bartik tradable job losses

VARIABLES	Δlog(retail and restaurant employment)				
	[1]	[2]	[3]	[4]	[5]
Δlog(TCS employment)	0.027	0.284***	0.283**	0.308***	0.371***
	[0.141]	[0.074]	[0.123]	[0.069]	[0.138]
leverage 2006		-0.025***	-0.024***	-0.020***	-0.014
		[0.003]	[0.007]	[0.007]	[0.010]
Δ housing net worth			0.028		0.033
			[0.052]		[0.069]
fraction white				0.011	-0.005
				[0.019]	[0.026]
median household income				0.000	0.000
				[0.000]	[0.000]
fraction owner-occupied				-0.087	-0.072
				[0.062]	[0.068]
fraction less than highschool				0.016	0.058
				[0.059]	[0.090]
fraction highschool				0.052	0.141
				[0.102]	[0.122]
unemployment rate				-0.286	-0.520*
				[0.188]	[0.290]
poverty rate				0.111	0.287
				[0.124]	[0.177]
fraction urban				-0.022**	-0.035*
				[0.010]	[0.019]
Constant	-0.051***	0.016	0.017	0.048	-0.003
	[0.018]	[0.012]	[0.019]	[0.037]	[0.054]
Observations	3,035	2,217	938	2,217	938
R-squared	0.011	0.118	0.184	0.124	0.196

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 5.4b: Baseline IV results where log change of TCS employment is instrumented by Bartik tradable job losses

VARIABLES	Δlog(retail wage)		Δlog(restaurant wage)		Δlog(manufacturing wage)	
Bartik	-0.047		-0.103		0.639**	
	[0.070]		[0.124]		[0.306]	
Instrumented Δlog(TCS jobs)		-0.047		-0.099		0.648**
		[0.069]		[0.123]		[0.280]
leverage 2006	-0.019***	-0.021***	-0.012***	-0.016**	0.014*	0.041***
	[0.004]	[0.005]	[0.004]	[0.008]	[0.008]	[0.014]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.060	-0.059	0.177*	0.181*	-0.040	-0.060
	[0.049]	[0.048]	[0.094]	[0.095]	[0.090]	[0.073]
Observations	2,191	2,191	1,802	1,802	2,176	2,176
R-squared	0.209	0.201	0.176	0.159	0.053	-0.050

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 5.5: The effects of TCS job losses on nominal wages in RR and manufacturing sectors

VARIABLES	Δlog(house price)	
bartik	-1.426	
	[1.427]	
Instrumented Δlog(TCS jobs		-1.410
		[1.686]
housing supply elasticity	0.056***	0.066**
	[0.020]	[0.031]
Controls	Yes	Yes
Constant	0.190	0.188
	[0.364]	[0.445]
Observations	530	530
R-squared	0.436	0.083

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 6.1: The effect of TCS job losses on house price

	Δlog(RR firms)			Δlog(RR jobs)	
VARIABLES	1 to 19	20 to 99	100+	National	Local
	[1]	[2]	[3]	[4]	[5]
Instrumented Δlog(TCS jobs)	0.202*	0.308**	0.875**	0.336***	0.247**
	[0.114]	[0.137]	[0.404]	[0.108]	[0.102]
leverage 2006	-0.002	-0.014*	-0.023	-0.020***	-0.020*
	[0.007]	[0.008]	[0.020]	[0.006]	[0.012]
Controls	Yes	Yes	Yes	Yes	Yes
Constant	-0.027	0.065	-0.094	-0.016	0.166***
	[0.037]	[0.058]	[0.123]	[0.055]	[0.054]
Observations	2,217	2,216	1,849	1,181	1,036
R-squared	0.167	0.045	-0.006	0.179	0.063

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 6.2: The credit channel.

Note: The first three columns show the effect of TCS job losses on the number of RR firms by firm size (1 to 19 workers; 20 to 99 workers; 100+ workers). The last two columns show the effect of TCS job losses on RR job losses in counties dominated by national banks and in those dominated by local banks.

4-digit NAICS	NAICS description	Sector
7221	Full-Service Restaurants	Non-Tradable
4461	Health and Personal Care Stores	Non-Tradable
4539	Other Miscellaneous Store Retailers	Non-Tradable
4431	Electronics and Appliances Stores	Non-Tradable
4413	Automotive Parts, Accessories and Tire Stores	Non-Tradable
4411	Automobile Dealers	Non-Tradable
4482	Shoe Stores	Non-Tradable

Table 6.3a: Retail & Restaurant Industries in Which Consumer Demand Shocks have the Biggest Impact during Great Recession.

Source: Giroud and Mueller (2017)

VARIABLES	(1) All R&R Industries	(2) Demand-elastic R&R Industries	(3) Other R&R Industries	(4) R&R Industries
Δlog(TCS employment)	0.371***	0.477**	0.262*	0.063
	[0.138]	[0.226]	[0.150]	[0.119]
Δlog(TCS employment)*Demand-Elastic RR industry dummy				0.355*
				[0.204]
Demand-Elastic RR industry dummy				0.03
				[0.025]
Control	Yes	Yes	Yes	Yes
Observations	938	938	938	50,077
R-squared	0.196	0.108	0.201	0.001

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 6.3b: Impact on demand elastic vs demand-inelastic industries

Notes: the effect of TCS job losses on job losses of all retail and restaurant industries (column (1)); retail and restaurant industries in which consumer demand shocks have the biggest impact during the Great Recession based on the categorization by Giroud and Mueller (2017) (column (2), which we refer to as “demand-elastic” RR industries); and the rest of the retail and restaurant industries (column (3)). Column (4) shows the differential impact of TCS job losses on job losses of each R&R industry by the industry’s demand elasticity (the demand elastic dummy variable=1 if the industry is most impacted by consumer demand shock as shown in Table 6.3a, =0 otherwise).

Appendix

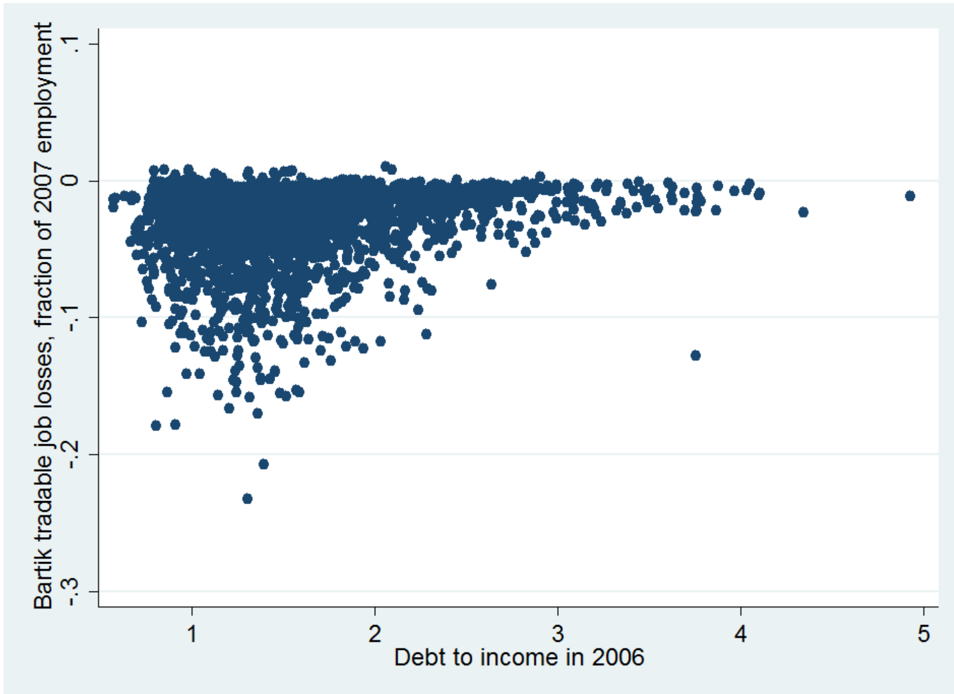

Figure A1: Scatterplot of pre-crisis household leverage and Bartik tradable job losses.