THE EFFECT OF NATIONAL INDUSTRY SHOCKS ON LOCAL EMPLOYMENT: IMPACTS ON GEOGRAPHICAL INEQUALITY AND INEFFICIENCY

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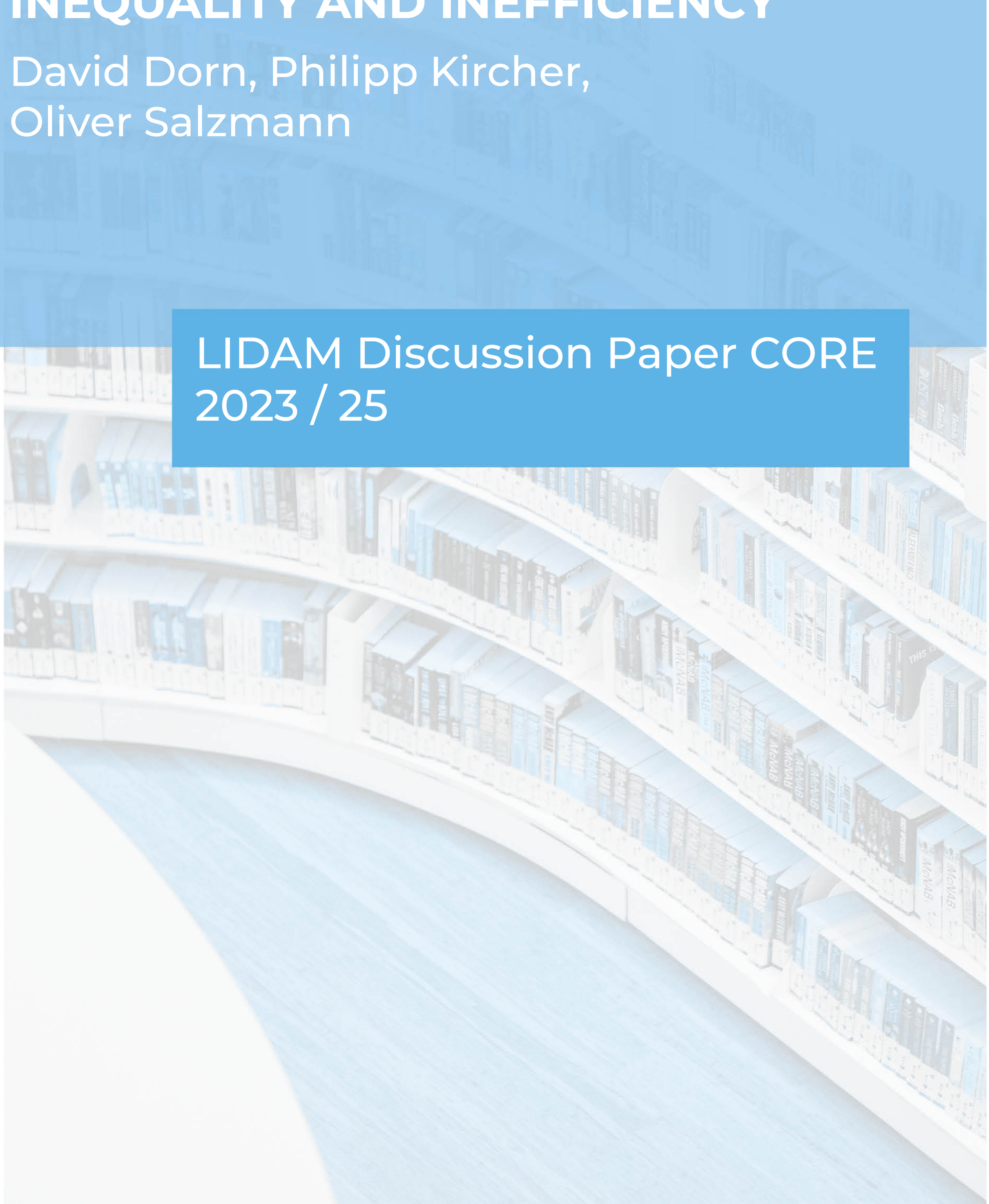

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The effect of national industry shocks on local employment: impacts on geographical inequality and inefficiency

By David Dorn, Philipp Kircher and Oliver Salzmann*

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Abstract

We analyse the effect of national industry shocks on local employment. By providing a novel structural view on the Bartik framework, we show that the difference in national and regional employment growth trends can be attributed to within-region spillovers. These spillovers can be quantified in a simple regression of regional employment change predictions versus actual regional employment changes, where regional employment change predictions are based on national shocks. We find consistent evidence that a predicted change in employment by 1% is associated with a 1.3% change in actual employment in a region. We hypothesize that agglomeration plays a key role in explaining the difference between the predicted and the actual employment growth. When we allow for non-linearities in a variety of setups, we find that the main driver of agglomeration effects are regions with particularly strong growth in employment which outperform their predictions. Taking the employment weighted mean as inflection point, regions with below mean predicted employment growth show a roughly 1:1 translation of predicted job creation to actual job creation. For regions with above mean predictions this ratio increases to 1:1.7.

1. Introduction

Whenever an industry experiences a change in production, be it due to demand or supply side shocks, any subsequent employment changes are distributed over the locations in which the industry resides (Adao et al., 2019; Caliendo et al., 2018). Agglomeration is known to create productivity spillovers within an industry and for its supply chains and related industries (Ellison et al., 2010; Greenstone et al., 2010; Delgado et al., 2014).[1] These two facts combined imply that shocks to employment will have spatially differentiated impacts based on which industries are affected, the impetus of these industries to concentrate, and the overall industry mix in each

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[1] See Puga (2010) for an overview on the possible causes of agglomeration.

region. In an effort to estimate this process we first provide a novel structural view on the Bartik framework which is commonly used to link national and local employment changes. We show that spillovers can be quantified in a simple regression of regional employment change predictions versus actual regional employment changes, where regional employment change predictions are based on national shocks. As such the predictions depict an homogeneous world in which each region mirrors the nation. The difference in predictions and outcomes captures the agglomeration effect of regional specialization and allows us to quantify how much employment inequality is induced by spatial concentration. Furthermore, we show how the framework is applicable to any shock that is identifiable on a national industry level under a small set of assumptions, making it easy to use and general in nature. As far as we are aware, a similar approach has so far only been employed by Notowidigdo (2020), though the focus of his paper is on population dynamics in large cities. We discuss the role of population in our analysis and a number of other key difference in our approaches in section 5 below.

Across the 722 mainland US commuting zones (CZs) for five 5-year periods starting in 1982-1987 and ending in 2002-2007, we find consistent evidence that a predicted change in employment by 1% is associated with a 1.3% change in actual employment in a region. We hypothesize that agglomeration plays a key role in explaining the difference between the predicted and the actual employment growth. Agglomeration creates larger employment pools and stronger intra-industry links through which a shock can travel, leading to larger actual changes in employment than predicted by national trends. Our results are largely driven by the manufacturing sector. This is not surprising, as non-manufacturing mainly consists of services that are required in all locations with less agglomeration potential. 1 predicted new job in manufacturing can be decomposed to yield between 0.7-1 actual new jobs in non-manufacturing and 1-1.4 actual new jobs change in manufacturing. This is in line with Moretti (2010), who finds that new manufacturing jobs create further jobs in local services, though he estimates a slightly larger impact, ranging from 1-2.5 new jobs in non-manufacturing, depending on the skill content of the manufacturing job.[2]

This suggests substantial inequality effects - but not per se distributional effects - as some regions are even more left behind than just their industry mix would suggest whereas other regions grow even more. The former in particular is usually what comes to mind with places like Detroit, which are surrounded by the narrative of general industrial collapse which bled into the regional economy at large. However when we allow for non-linearities in a variety of setups, we find that the main driver of agglomeration effects are regions with particularly strong growth in

[2]Moretti estimates the impact of a change in manufacturing jobs on the change in non-manufacturing jobs directly, using national variation as instrument for plausibly exogenous variation. He attributes his results to a) increased demand due to the new worker and b) increases in the equilibrium wage which together increase the demand for local goods and services. There is large variance as to which manufacturing sectors yield the most non-manufacturing jobs with the high tech sector generating the largest spillovers (4.9 non-manufacturing jobs). However, there are no discernible spillovers within manufacturing. Splitting manufacturing into random industry subsets A and B, no additional increases in jobs are found in B if an exogenous shock occurs in A.

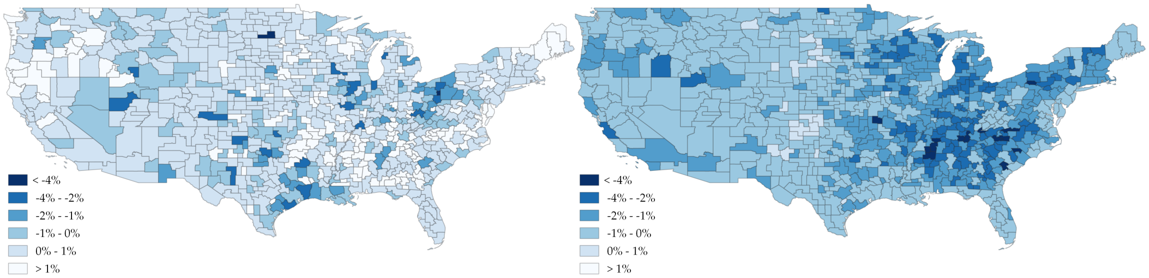
employment. Taking the employment weighted mean as inflection point, regions with below mean predictions show a roughly 1:1 translation of predicted job creation to actual job creation. For regions with above mean predictions this ratio increases to 1:1.7. Our evidence suggests that agglomeration induced inequality is amplified by exceptional employment growth in regions that were already predicted to experience strong growth performance based on national trends. This asymmetry in responses of employment is similar to the asymmetry in population responses found by Glaeser and Gyourko (2005), who contribute muted population responses for cities in decline to durable housing stocks and house price changes. Using a dynamic spatial equilibrium model in which the standard trade-off of city-specific wages, amenities and housing costs is enriched by durable housing, population growth is shown to be more elastic during expansion as more housing will be constructed. During downturns housing costs play a larger role as the housing stock is mainly affected by depreciation. This leads to drops in wages being off-set by lower housing costs and hence a smaller population impact.

Our results are driven by a multitude of medium to large commuting zones which beat predictions, whereas very large regions typically underperform compared to their prediction. This is in line with a growing strand of urban economics arguing that the largest and most productive cities are hampered by planning and zoning regulations leading to large potential losses in aggregate growth (Albouy et al., 2019; Duranton and Puga, 2019; Hsieh and Moretti, 2019) and with evidence that smaller cities have benefited from new technologies that allow firms to scale up production and enter new markets (Hsieh and Rossi-Hansberg, 2021).[3] Using a simple counter-factual calculation in which we assign all regions the average predicted employment growth rate, we find that aggregate growth is reduced by 1.3% over five years or 9.6% over the 25 year period we observe. As agglomeration spillovers are focussed in fast growing regions, focussing on equity instead of efficiency - by for example making the industry mix homogeneous across the nation - would reduce aggregate growth rate significantly in the long run. Furthermore, we perform a indicative exercise which shows that our results are largely driven by changes in population, with only weak evidence that employment changes are driven by non-employment changes.

To estimate our results we construct employment predictions using three types of variation which we commonly refer to as shocks. The simple shift-share setup or Bartik shock, changes to steel, coal and oil prices or Price shocks and changes in Chinese import competition in the US or China Trade shocks. The latter two are applied to the whole economy by applying input-output weights to construct downstream and upstream effects to other industries, making them IO Price and IO China Trade shocks respectively. These shocks were chosen for a variety of reasons. The

[3] Notably the focus in Hsieh and Rossi-Hansberg (2021) is on new technologies in non-manufacturing that allows firms like Walmart to expand across the nation. They show that industry concentration in smaller regions has actually fallen between 1977 and 2013 following the expansion of non-manufacturing firms. This is a complementary dynamic to the agglomeration effects we find, driven by the manufacturing sector.

Figure 1: *Predicted Mfg. employment change* $\mathbb{P}\hat{E}_{ct}^{S,mfg}$ *by commuting zone*



(a) *IO Price shock predictions, 1982-1987* **(b)** *IO China Trade shock predictions, 2002-2007*

Bartik setup captures all shocks to employment directly, though it does not allow for explicit interpretation of what generated the changes. The coal and steel industry are historically highly spatially concentrated, both due to resource constraints but also due to strong economies of scale. Glaeser et al. (2015) make the case that such specialization led to larger firms and reduced local entrepreneurship, which had long-running effects of reduced employment growth. The rise in Chinese import competition as identified in Autor et al. (2013) in contrast affected virtually every manufacturing industry, yet it too was particularly significant in a few regions.

Figure 1 shows the change in predicted manufacturing employment relative to total employment. Regions with strong negative predictions from the IO Price shocks in the 80s are clustered around natural coal deposits, where coal and steel industries agglomerated. For the IO China Trade shock in the 2000s most regional predictions are negative, however the rust belt and the Appalachians can be identified as the core of the predicted manufacturing decline. These maps highlight the vast difference in growth experience regions may be predicted to have based on just national trends. It is likely that future shocks such as automation will again have diverse effects for different industries (Acemoglu and Restrepo, 2020). As such, it is of particular relevance to understand the role of industrial agglomerations and spatial concentration when it comes to the employment impact of labor market shocks, both for inequality (whether changes to national industries break down more or less than 1:1 to the regional level) and for efficiency (whether employment growth would be different if the regional industry composition would be different).

The paper proceeds as follows. Section 2 gives a structural view on capturing labor demand shocks via the Bartik framework. We detail the data and construction of our employment predictions in section 3. Section 4 goes into the empirical strategy and results. In section 5 we perform an indicative exercise to test whether our results are driven by population or non-employment dynamics. We perform a variety of robustness checks in section 6, before concluding in section 7.

2. A model of Bartik labor demand shocks

There are many industries i that operate in many commuting zones (or regions) c. In each period t, industry i in region c is subject to a labor demand shock S'_{cit} which is drawn from some distribution $D'(.)$ with mean μ'_{it} and standard deviation σ'_{it},

$$S'_{cit} \sim D'(\mu'_{it}, \sigma'_{it}) \tag{1}$$

A realization of this shock for industry i in region c is

$$S'_{cit} = \mu'_{it} + s'_{cit} \tag{2}$$

The mean μ'_{it} represents a national demand shock that affects industry i in all regions of the country, while s'_{cit} (with $E[s'_{cit} = 0]$) is a local deviation from the national shock. The shock S'_{cit} is scaled as a percentage change of labor demand in an industry and region, and is thus not mechanically related to the size of the industry or region. The parameters of the distribution $D'(.)$, μ'_{it} and σ'_{it}, can vary across industries and time periods. If μ'_{it} is large in absolute value and σ'_{it} is small, then there is a strong and geographically fairly uniform demand shock for the industry. Conversely, if μ'_{it} is small in absolute value and σ'_{it} is large, then the demand shocks for industry i display little spatial correlation.

Demand shocks can create spillover effects across industries, and across and within regions. Therefore, the (observed) change of employment in industry i in region c, $\hat{E}_{cit}$ with $\hat{X}_t = \frac{X_{t+1}-X_t}{X_t}$, can be a function of the (usually unobserved) demand shocks to any industry and region,

$$\hat{E}_{cit} = g(\mu'_{it}, \mu'_{jt}, s'_{cit}, s'_{cjt}, s'_{rit}, s'_{rjt}) \tag{3}$$

where j and r respectively denote industries and regions other than i and c. One example for a spillover would be a demand shock μ'_{jt} to industry j that changes the demand for the outputs of j's supplier industry i and thus affects $\hat{E}_{cit}$. Note that this classification of shocks treats μ'_{it} as a gross or direct industry demand shock (for instance due to a change in import competition in industry i), but allows that industry i experiences additional industry-level demands shocks due to spillovers (for instance due to a change in import competition in i's customer industry j).

Instead of working with gross demand shocks S'_{cit}, we can define net demand shocks S_{cit} that include all spillover effects. Let the net labor demand shock faced by industry i in region c have a distribution $D(.)$ with mean μ_{it} and standard deviation σ_{it}

$$S_{cit} \sim D(\mu_{it}, \sigma_{it}) \tag{4}$$

where a realization of this shock for industry i in region c is

$$S_{cit} = \mu_{it} + s_{cit} \tag{5}$$

with $E[s_{cit} = 0]$. By definition of this net shock, the employment change in industry i of region c depends only on S_{cit}, which is inclusive of all spillovers from other industries and/or regions,

$$\hat{E}_{cit} = f(S_{cit}) = f(\mu_{it} + s_{cit}) \tag{6}$$

If we assume that $f(.)$ is a linear function (with $f(0) = 0$), then this becomes

$$\hat{E}_{cit} = f(\mu_{it}) + f(s_{cit}) \tag{7}$$

and we can characterize the national employment change in industry i as

$$\hat{E}_{it} = f(\mu_{it}) + \sum_c \frac{E_{cit}}{E_{it}} f(s_{cit}) \tag{8}$$

where E_{cit}/E_{it} is the share of region c in industry i's national start-of-period employment. Note that since $E[s_{cit} = 0]$ and $f(0) = 0$, it holds that $E[\sum_c E_{cit}/E_{it} f(s_{cit})] = 0$, and thus

$$\hat{E}_{it} \approx f(\mu_{it}) \tag{9}$$

The total employment change in region c can be written as

$$\hat{E}_{ct} = \sum_i \frac{E_{cit}}{E_{ct}} f(\mu_{it}) + \sum_i \frac{E_{cit}}{E_{ct}} f(s_{cit}) \tag{10}$$

where $\frac{E_{cit}}{E_{ct}}$ is the share of industry i in region c's total start-of-period employment. If we define the average demand shock across all national industries as $\bar{\mu}_t \equiv \sum_i \frac{E_{it}}{E_t} \mu_{it}$, then this expression can be further decomposed as

$$\hat{E}_{ct} = f(\bar{\mu}_t) + \sum_i \frac{E_{cit}}{E_{ct}} f(\mu_{it} - \bar{\mu}_t) + \sum_i \frac{E_{cit}}{E_{ct}} f(s_{cit}) \tag{11}$$

The first term in this equation represents the employment effect of a national average demand shock that is the same across all regions; the second is a deviation from that average that is due to region c's specialization in industries that experience above or below average demand shocks; and the third is a demand shock that is idiosyncratic to region c.

The Bartik shift share setup combines national employment changes by industry with initial industry employment shares of a region in order to create an instrument for regional employment growth. A simple regression of $\hat{E}_{ct}$ on an industry-weighted average of $\hat{E}_{it}$ is however problematic because the region-specific shock component s_{cit} contributes both to the measurement of $\hat{E}_{ct}$ and of $\hat{E}_{it}$. To break this mechanical correlation, we can instead compute the leave-out Bartik instrument whose industry components $\hat{E}_{-cit}$ capture observed industry employment growth in all regions other than c,

$$\hat{E}_{-cit} = f(\mu_{it}) + \sum_{c'} 1[c' \neq c] \frac{E_{c'it}}{E_{it} - E_{cit}} f(s_{c'it}) \tag{12}$$

where the summation $\sum_{c'}$ includes all regions inclusive of c, but the indicator function $1[c' \neq c]$ sets the summation element for region c to zero. The Bartik shift share variable is then defined as

$$\sum_i \frac{E_{cit}}{E_{ct}} \hat{E}_{-cit} \tag{13}$$

With the approximation (9), this becomes

$$E[\sum_i \frac{E_{cit}}{E_{ct}} \hat{E}_{-cit}] \approx \sum_i \frac{E_{cit}}{E_{ct}} f(\mu_{it}) = f(\bar{\mu}_t) + \sum_i \frac{E_{cit}}{E_{ct}} f(\mu_{it} - \bar{\mu}_t) \tag{14}$$

The classical Bartik setup then regresses (11) on the Bartik variable (13)

$$\hat{E}_{ct} = \alpha_t + \beta_t [\sum_i \frac{E_{cit}}{E_{ct}} \hat{E}_{-cit}] + \epsilon_{ct} \tag{15}$$

It is instructive to compare (15) to equation (11). The regression coefficient α_t will capture

$$\alpha_t = f(\bar{\mu}_t) \tag{16}$$

which is the employment effect of an economy-wide average labor demand shock. The regression coefficient β_t will capture

$$\beta_t = E[(\sum_i \frac{E_{cit}}{E_{ct}} f(\mu_{it} - \bar{\mu}_t) + \sum_i \frac{E_{cit}}{E_{ct}} f(s_{cit})) | \sum_i \frac{E_{cit}}{E_{ct}} f(\mu_{it} - \bar{\mu}_t)] \tag{17}$$

which is the relation between the de-meaned outcome variable and the de-meaned regressor. This expression simplifies to

$$\beta_t = 1 + E[\sum_i \frac{E_{cit}}{E_{ct}} f(s_{cit})) | \sum_i \frac{E_{cit}}{E_{ct}} f(\mu_{it} - \bar{\mu}_t)] \tag{18}$$

If the average local demand shock for region c is orthogonal to the average national industry demand shock faced by the region's industries, then $\beta_t = 1$. In this case, regional employment growth is exactly as large as predicted by national industry demand shocks. If instead local demand shocks are more positive in regions that are exposed to greater positive national industry shocks, then $\beta_t > 1$. One plausible interpretation for $\beta_t > 1$ is that national industry shocks create local spillovers, for instance, a boom of local manufacturing industries may create a positive demand shock for local restaurants.

Note that this interpretation of $\beta_t > 1$ as capturing local spillovers does not violate the notion that the net demand shocks S_{cit} already include all spillover effects. Key to the interpretation of S_{cit} is its decomposition into national and local components, $S_{cit} = \mu_{it} + s_{cit}$. If for instance the decline of a national industry j creates a uniform negative national spillover for its supplier industry i, then this demand effect is captured by μ_{it}, and does not affect the estimate of (18). If instead the decline of industry j affects primarily the establishments of industry i that are located in the same region as the industry j establishments, then this local spillover will manifest in terms of negative values of s_{cit} for the regions where industries i and j collocate (and positive values of s_{cit} in regions where industries i and j don't collocate, so that on average $E[s_{cit} = 0]$).

Finally, it is worthwhile to observe that we need to assume linearity only for the function $f(.)$ which captures the effect of an (unobserved) unit demand shock on employment, but we don't need to assume linearity in the Bartik regression (15). A non-linear version of (15) would allow that the conditional expectation in (18) is non-linear, which would for instance be the case if regions exposed to positive national industry shocks have systematically more positive local shocks, while regions exposed to negative industry shocks do not have proportionately more negative local shocks (or vice versa).

2.I. Demand versus supply shocks

The Bartik shocks can in principle be interpreted either as demand shocks, supply shocks, or a combination of both. An example for a national industry supply shock would be an immigration wave that leads to increased employment in industries that heavily rely on immigrant labor. The reason why Bartik shocks are usually interpreted as demand rather than supply shocks is empirical rather than conceptual. A regression of changes in regional wages on the Bartik variable 13 tends to generate a positive coefficient, i.e., wages tend to grow faster in regions whose industries experience greater national employment growth. This result suggests that the Bartik variable primarily captures demand rather than supply shocks. Since industries are by definition differentiated by their outputs, but to a lesser degree differentiated by their inputs, it seems plausible that differential employment growth across national industries often reflects the impact of demand forces, while supply shocks may be more uniform across industries or more specific to regions.

2.II. Specific industry demand shocks

The Bartik setup assumes that the demand shocks S_{cit} are unobserved. However, we are able to observe and measure certain national industry demand shocks, such as import competition from China or plausibly exogenous changes in world market prices for the outputs of commodity-producing industries. Let us reformulate the total demand shock to industry i in region c as

$$S'_{cit} = \zeta'_{it} + \mu'_{it} + s'_{cit} \tag{19}$$

where ζ'_{it} is an observed gross national industry demand shock, μ'_{it} is an unobserved gross national industry shock, and s'_{cit} is an unobserved local shock. The observed national employment change for industry i can be expressed as

$$\hat{E}_{it} = h(\zeta'_{it}, \zeta'_{jt}, \mu'_{it}, \mu'_{jt}, s'_{cit}, s'_{cjt}) \tag{20}$$

where function $h(.)$ recognizes that outcomes in industry i can be affected by spillovers from other industries j (as well as shocks to any region c). We put additional structure on function $h(.)$ by assuming that (i) since $E[s'_{cit}] = E[s'_{cjt}] = 0$, employment changes at the level of national industries are only affected by the national shocks ζ' and μ', (ii) the unobserved national industry shocks μ' are not systematically correlated with the observed shocks ζ', (iii) the spillover effect of ζ'_{jt} on $\hat{E}_{it}$ operates through national input-output linkages as conceptualized by Acemoglu et al. (2016), and (iv) the effect of a unit labor demand shock on employment is constant across periods. We then estimate

$$\hat{E}_{-cit} = \kappa_{-ct} + \gamma_{-c1}\zeta'_{it} + \gamma_{-c2}\sum_j \omega^D_{ijt}\zeta'_{jt} + \gamma_{-c3}\sum_j \omega^U_{jit}\zeta'_{jt} + \epsilon_{-cit} \tag{21}$$

where the weights ω^D_{ijt} and ω^U_{jit} capture the extent to which industry i is exposed to shocks in industry j through downstream and upstream linkages.[4] The predicted values from this regression, which we denote by $\mathbb{P}\hat{E}_{-cit}$, capture two components. The first is a national average employment growth effect κ_{-ct} that is shared across industries, and can result from any observed or unobserved shock. The second component, which is responsible for the entire variation of $\mathbb{P}\hat{E}_{-cit}$ across industries, is due to industries' differential direct and indirect exposure to the observed shocks ζ'_{it} and ζ'_{jt}. Any cross-industry variation in unobserved industry shocks μ'_{it} is instead absorbed into the error term of regression (21), and does hence not affect $\mathbb{P}\hat{E}_{-cit}$.

We finally run the regression

$$\hat{E}_{ct} = \alpha_t + \beta_t[\sum_i \frac{E_{cit}}{E_{ct}}\mathbb{P}\hat{E}_{-cit}] + \epsilon_{ct} \tag{22}$$

[4]We give a more detailed definition for the construction of the input-output linkages below.

As in the Bartik case, we would expect a coefficient estimate of $\beta_t = 1$ if (net) local shocks are orthogonal to a region's industry composition, but $\beta_t > 1$ if regions that are specialized in industries with positive direct or indirect observed industry demand shocks tend to have more positive local shocks.

The key difference between (22) and (15) is that here we are predicting variation in employment growth across regions based on a specific, observed type of demand shock (e.g., import competition from China, exposure to world market prices for commodities) while the above Bartik setup captures any national demand (or supply) shock. The conditions (i)-(iv) are relevant in order to correctly isolate and measure the differential impact of this observed industry shocks across regions. A violation for instance of condition (ii) would imply that spatial variation in $\mathbb{P}\hat{E}_{-cit}$ is not solely due observed industry shocks, but also partly due to unobserved industry shocks, which would bring this setup closer to that of the Bartik shock whether the source of industry demand changes is not specified.

A second difference between the two setups is that while we assume a linear mapping $f(.)$ between unobserved national industry demand shocks and their employment effects in the Bartik case, the specific-shock setup would allow us test for such linearity by exploring a non-linear version of regression (21).

3. Construction of employment predictions

Before detailing the construction of the employment predictions and the data we employ, let us first briefly unify the notation. Equations (22) and (15) both regress employment change outcomes on employment change predictions, with the difference being the source of the employment change predictions. From now on we more generally refer to regional employment change predictions from any source as $\mathbb{P}\hat{E}_{ct}$. From equation (13) it follows that

$$\mathbb{P}\hat{E}_{ct} = \sum_i \frac{E_{cit}}{E_{ct}} \hat{E}_{-cit} \tag{23}$$

if we use the Bartik shift-share as source of variation. Equivalently we define the regional employment change predictions as

$$\mathbb{P}\hat{E}_{ct} = \sum_i \frac{E_{cit}}{E_{ct}} \mathbb{P}\hat{E}_{cit} \tag{24}$$

where $\mathbb{P}\hat{E}_{cit}$ is generated from (21) if we look at specific industry demand shocks. Which source is used at which point is made explicit in the results section below. By restricting the set of industries used on the RHS of (23) and (24) we can also create regional sector predictions. Particularly pertinent is the distinction between manufacturing and non-manufacturing, as most non-manufacturing industries occur in most regions by necessity, whereas manufacturing industries tend to form more clusters.[5] For example, restricting the industry set in (24) yields

$$\mathbb{P}\hat{E}_{ct}^{S,mfg} = \sum_i \frac{E_{cit}}{E_{ct}} \mathbb{P}\hat{E}_{cit},\ i \in Manufacturing \tag{25}$$

$$\mathbb{P}\hat{E}_{ct}^{S,non-mfg} = \sum_i \frac{E_{cit}}{E_{ct}} \mathbb{P}\hat{E}_{cit},\ i \in Non-Manufacturing \tag{26}$$

Note that employment shares are still relative to total regional employment E_{ct}. We identify variables rescaled in this way additionally by superscript S. The advantage of this rescaling method is that predictions are now additive in nature, i.e.

$$\mathbb{P}\hat{E}_{ct} = \mathbb{P}\hat{E}_{ct}^{S} = \mathbb{P}\hat{E}_{ct}^{S,mfg} + \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \tag{27}$$

which later on allows us to interpret sectoral results as elasticities and to decompose the overall employment impact of sectoral predictions into changes in manufacturing and non-manufacturing employment respectively.

For our sample we observe all 722 mainland commuting zones c for five 5-year periods starting with 1982-1987 and ending with 2002-2007. These 5 year periods are chosen as they closely match the release cycle of the BEA IO tables which we use in the computation of specific industry demand shocks.[6] Employment data comes from the County Business Patterns (CBP) data. CBP records employment by county-industry cell on a yearly basis. Some cells are encoded only with size class information if there are competition or national security concerns. For these we employ the fixed point algorithm as in Autor et al. (2013) to elicit an explicit employment figure.

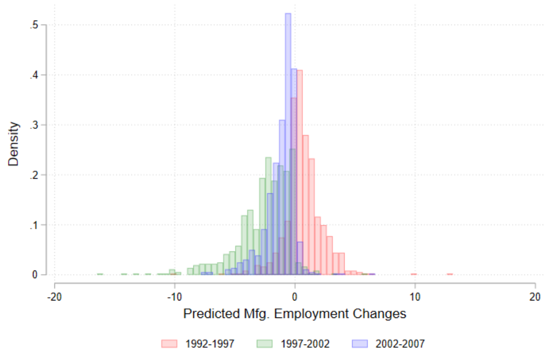
The industry classification system used in CBP was overhauled and replaced several times throughout the years. The biggest changes were the introduction of the 1987 SIC classification and the switch to NAICS in 1997. We construct a crosswalk between the different SIC and NAICS classifications used in CBP between 1974 and 2007, using a mix of manual concordance and previous work by Autor et al. (2013), Acemoglu et al. (2016) and Fort et al. (2016). The final data is available using a partially aggregated version of the 4-digit SIC87 classification with 735 industries.[7] Since recordings at this very detailed industry level are more susceptible to measurement error we further aggregate employment to the 3-digit SIC87 level, leaving us with

[5]An alternative approach would be to split sectors into tradable and non-tradable following Mian and Sufi (2014). They designate industries to be non-tradable based on geographic ubiquity. Certain service industries such as amusement parks are tradable under this definition, though for our purposes the tendency of manufacturing industries to agglomerate is more relevant.

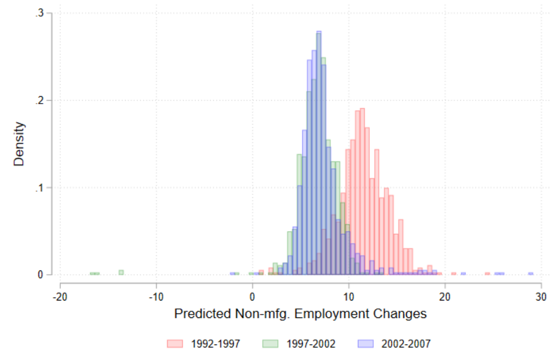
[6]Additionally the Report of Organization, one of the main sources for the County Business Patterns data, is conducted in years ending on 2 and 7, fitting our 5-year structure as well.

[7]For a more detailed breakdown on how we construct a unified industry classification across the sample, see the technical appendix E.

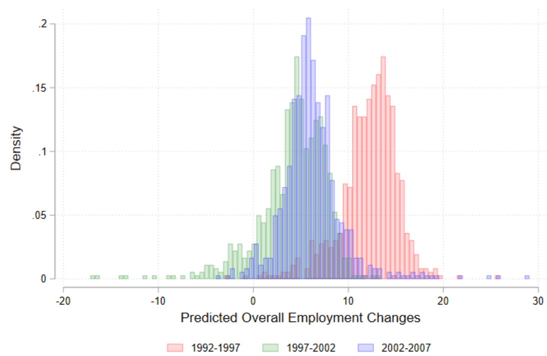
Figure 2: *Employment Change Predictions using Bartik Shocks*



(a) *Manufacturing*



(b) *Non-Manufacturing*



(c) *Overall*

338 industries which form the basis for the Bartik Shocks.[8] The use of IO data to generate the IO Price and IO China shocks introduces a final set of industry aggregations, leaving us with 141 to 176 aggregate industries, depending on which year of IO data is used.[9] All county level data is aggregated to the CZ level following the 1990 IPUMS commuting zone definition.

3.I. Bartik Shocks

We have reviewed the construction of the simple Bartik shock above, with regional employment change predictions defined in (23). Figure 2 shows the distribution of predicted employment changes across commuting zones, broken down by sectors for the last three of our five year periods.[10] Table 13 in appendix I.1 lists descriptive statistics for the Bartik predictions and for

[8] Industry classifications are generally more detailed for the manufacturing sector, which make up the vast amount of 4-digit SIC87 industries. Going to the 3-digit level we are left with 136 manufacturing industries and 202 non-manufacturing industries.

[9] For details on how we match the IO data to the rest of our datasets, see the technical appendix E.

[10] Graphs for the remaining three periods can be found in the general appendix A. We restrict our exposition on the last three periods here since the IO China Trade Shock is not available in the first three periods and for visual clarity.

actual employment outcomes. Overall we see that growth slowed in the 2000s and 90s compared to the late 70s and 80s, though the early periods exhibit a higher variation in predicted growth, driven by a larger range in non-manufacturing. Keeping in mind that the Bartik setup tracks the actual national industry employment trends, regional variation is created only by the difference in industry mix in each region. Accordingly, manufacturing predictions are almost exclusively negative in the 2000s, in which US manufacturing suffered from increase import competition from China and a transition to the service sector. While the 90s still show some regions with positive manufacturing growth, the highest mass of regions is at or around zero growth. In the late 70s and the 80s most manufacturing industries were still growing, with a few notable exceptions, such as the coal and steel industries.

3.II. IO Price Shocks

The second type of shock we observe are percentage changes of commodity prices in selected industries. In particular, we focus on the steel, coal and oil industries. The late 70s saw a final boom in coal, followed by a strong and persistent decline from the early 80s until today. Similarly, steel industries suffered from a collapse in shipments and employment in the early 80s from which they never recovered. These busts are well documented in the literature and represent some of the most vivid employment shocks in recent history (Alder et al., 2014; Black et al., 2003; Collard-Wexler and De Loecker, 2015). The main alternative to coal for energy production in the 80s was oil. The correlation of these industries informs our usage of oil as third commodity to include. To construct the shock, we use purchaser price indeces (PPI) from the BLS for industries using the 4-digit SIC87 classification where possible. For industries where the BLS industry series does not cover the whole time frame, they are completed using commodity price indeces (CPI) instead. We manually track which commodities are produced by which industries to get industry based prices series where necessary. Ultimately we collect price data for six 4-digit steel industries, three 4-digit coal industries and two 4-digit petrol industries, which are aggregated to the 3-digit level by taking the simple mean.[11]

To account for the propagation of price changes to the whole economy we further construct input-output weights from BEA IO data tables. The full exposure of a change in commodity prices of industry j is then captured by downstream, upstream and direct exposure in the supply chain.

[11] For a more detailed breakdown on which industries were used and how the price series were collected, see the technical appendix E.

II.1 Downstream Exposure

For industry i, let ω^D_{ijt} be the usage weight with respect to inputs from industry j, calculated as

$$\omega^D_{ijt} = \frac{q_{ijt}p_{jt}}{\sum_{k\in I} q_{ikt}p_{kt}} \tag{28}$$

That is ω^D_{ij} is inputs purchased from industry j, q_{ij}, at industry j producer prices p_j, relative to total purchases in industry i.
For any industry j which we presume has faced a shock between t and t+1, we can then compute the downstream exposure of industry i of that shock, by multiplying the price change $\hat{p}_{jt} = \frac{p_{jt+1}-p_{jt}}{p_{jt}}$ with the usage weight in time t, ω^D_{ijt}. Let DE^j_{it} be a measure of the effect on i by a shock in j.

$$DE^j_{it} = \omega^D_{ijt}\hat{p}_{jt} \tag{29}$$

The cumulative downstream exposure to several industries $j \in J$ is then simply the sum of the individual exposures

$$DE^J_{it} = \sum_{j\in J} \omega^D_{ijt}\hat{p}_{jt} \tag{30}$$

II.2 Upstream Exposure

Upstream exposure can be constructed similarly to downstream exposure, though the usage weight now refers the suppliers of the shocked industry j instead of its users. I.e. let ω^U_{jit} be the upstream usage weight, given by

$$\omega^U_{jit} = \frac{q_{jit}p_{it}}{\sum_{k\in I} q_{kit}p_{it}} \tag{31}$$

Upstream exposure is then given by

$$UE^j_{it} = \omega^U_{jit}\hat{p}_{jt} \tag{32}$$

or cumulatively,

$$UE^J_{it} = \sum_{j\in J} \omega^U_{jit}\hat{p}_{jt} \tag{33}$$

II.3 Direct Exposure

Direct exposure is simply given by the shock in the industry itself, i.e.

$$LE_t^j = \hat{p}_{jt} = \frac{p_{jt+1} - p_{jt}}{p_{jt}} \tag{34}$$

or cumulatively for several industries

$$LE_t^J = \sum_{j \in J} \hat{p}_{jt} \tag{35}$$

We use the three different exposures variables to generate employment change predictions by running a version of the regression in (21). We additionally include a dummy for manufacturing and interact it with the exposure variables as manufacturing and non-manufacturing experienced vastly different time trends and exposure to commodity price changes was much higher on average in manufacturing. The adjusted prediction regression looks as follows

$$\begin{aligned} \hat{E}_{-cit} =& \kappa_{-ct1} + \kappa_{-ct2} x \mathbb{1}^{i \in Mfg} \\ & + \gamma_{-c11} DE_{it}^J x (1 - \mathbb{1}^{i \in Mfg}) + \gamma_{-c12} DE_{it}^J x \mathbb{1}^{i \in Mfg} \\ & + \gamma_{-c21} UE_{it}^J x (1 - \mathbb{1}^{i \in Mfg}) + \gamma_{-c22} UE_{it}^J x \mathbb{1}^{i \in Mfg} \\ & + \gamma_{-c31} LE_{it}^J x (1 - \mathbb{1}^{i \in Mfg}) + \gamma_{-c32} LE_{it}^J x \mathbb{1}^{i \in Mfg} \\ & + \epsilon_{-cit} \end{aligned} \tag{36}$$

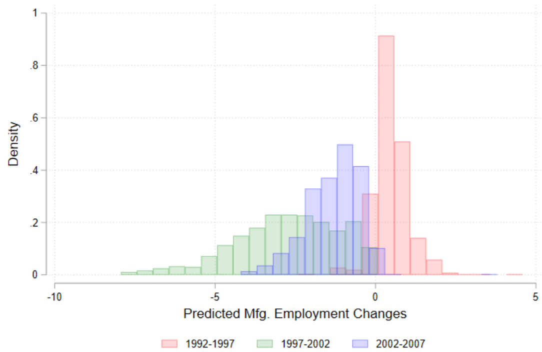
Applying (36) to the steel, coal and oil industries, we construct the exposure variables for each commodity. Due to further aggregation when joining the IO data, we are left with two aggregate steel industries for the exposure to steel price changes, one aggregate coal industry for coal and one aggregate petrol industries for oil.[12] The predicted values of (36) then form our IO Price Shock industry-region employment change predictions, $\mathbb{P}\hat{E}_{cit}$, from which we derive the regional and region-sector predictions as described above.[13]

Figure 3 shows the same distribution histograms as for the Bartik Shocks above, now based on the regional IO price shock predictions. Due to aggregation when matching the IO weights to the employment data the distributions are coarser, however the overall trends in both sets of graphs are very similar. The distributions of overall and non-manufacturing employment change predictions shift to the left after 1997. The standard deviation is somewhat smaller

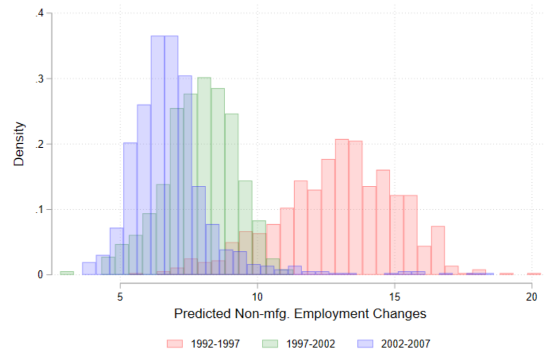
[12] Descriptive statistics for the IO exposure of the price shocks, the IO Price Shock predictions, their sectoral breakdown as well as graphs showing the PPI series are reported in appendices II.1 and II.2.

[13] The prediction regression in (36) is weighted by the initial industry employment level E_{-cit}, which accounts for the fact that shocks to large industries should have a higher weight when accounting for employment dynamics. Robust HAC standard errors are used.

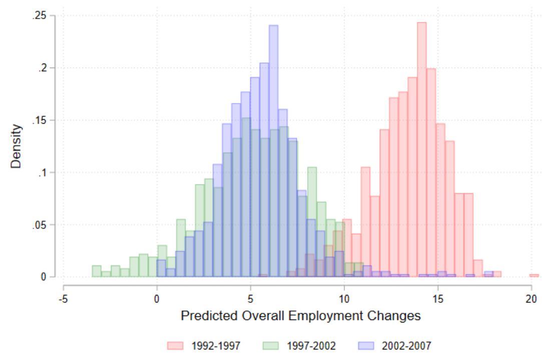
Figure 3: *Employment Change Predictions using IO Price Shocks*



(a) *Manufacturing*



(b) *Non-Manufacturing*



(c) *Overall*

for the IO price shock predictions, as can be seen in the descriptive statistics in table 17 in appendix II.1. This is particularly visible in manufacturing where the brunt of the IO price shock happened. Manufacturing predictions are somewhat more skewed towards zero with fewer outlier regions.

3.III. China Trade Shocks

The third shock we observe is the IO China Trade Shock. Our construction of the shock mirrors Acemoglu et al. (2016). As such we use the same data on imports, exports and total shipments by industry which are based on the UN Comtrade database.[14] Let ΔIP_{it} be the import penetration ratio of China in the US in industry i, between t and t+1.

$$\Delta IP_{it} = \frac{\Delta M_{it}^{UC}}{Y_{i91} + M_{i91} - EX_{i91}} \tag{37}$$

[14]We aggregate this SIC coded industry data in the same fashion as for the IO Price data to fit the IO structure.

ΔM_{it}^{UC} is the change in Chinese Imports to the US in industry i. The denominator is the initial absorption in industry i in 1991, given by total industry production Y_{i91} plus industry imports M_{i91} minus industry exports EX_{i91}. We construct exposure variables to a change in the import penetration ratio in a similar fashion to the IO price shocks.[15] I.e. the cumulative direct exposure as well as the downstream and upstream exposure in industry i to a change in the import penetration ratio in a set of industries J is given by

$$CDE_{it}^{J} = \sum_{j \in J} \omega_{ijt}^{D} \Delta IP_{jt} \qquad \text{downstream exposure} \tag{38}$$

$$CUE_{it}^{J} = \sum_{j \in J} \omega_{jit}^{U} \Delta IP_{jt} \qquad \text{upstream exposure} \tag{39}$$

$$CLE_{t}^{J} = \sum_{j \in J} \Delta IP_{jt} \qquad \text{direct exposure} \tag{40}$$

There may be unidentified demand shocks which affect both the import penetration ratio and employment outcomes. We apply the same instrumentation strategy as Acemoglu et al. (2016) to account for this. The instrumental exposure variables are constructed equivalently as above, with the instrumental import penetration ratio ΔIPO_{it} now relating to Chinese imports to a set of developed countries other than the US.

$$\Delta IPO_{it} = \frac{\Delta M_{it}^{OC}}{Y_{i88} + M_{i88} - EX_{i88}} \tag{41}$$

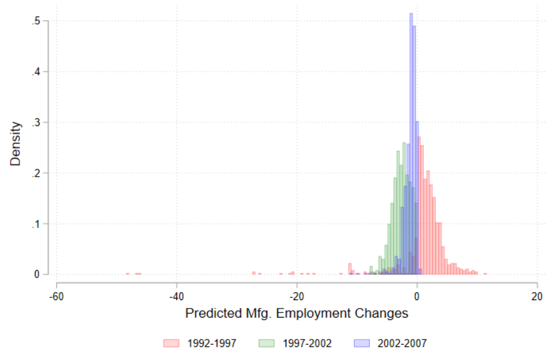
To construct employment predictions, we run a regression as in (36) where the exposure variables are now relating to the Chinese Trade Shock and using a two-stage instrumental variable approach.

The descriptive statistics for the IO China Shock predictions can be found in table 24 in appendix III.1. Due to a lack of the underlying trade data, we cannot generate predictions prior to 1990. This restricts us to a maximum of three 5-year periods when using the China Trade Shock as source for our employment change predictions.[16] Since China only ascended to the WTO in 2001, this is not too big of a concern, as before 1990 there was no Chinese Import Shock to speak of. Figure 4 shows the distribution histograms. The trade shock based predictions show more variation for manufacturing, with a handful of outliers especially in the 90s. These translate into the overall predictions as well, which are generally more dominated by the non-manufacturing sector. The general shape and relative positioning of the 5-year periods still conforms well with the other two shocks however.

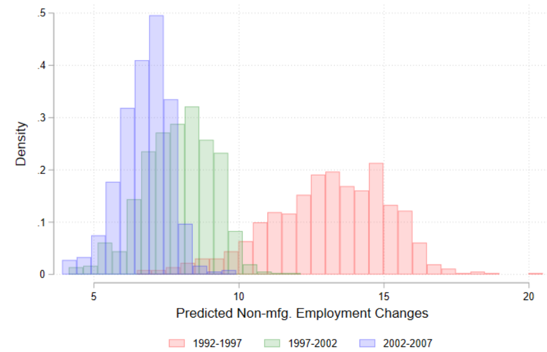
[15] Descriptive statistics for the IO exposure to the China Trade Shock can be found in the appendix section III.2.

[16] For our baseline specifications we further restrict ourselves to the last two five year periods, as the first five year period is used to construct a population control as detailed below.

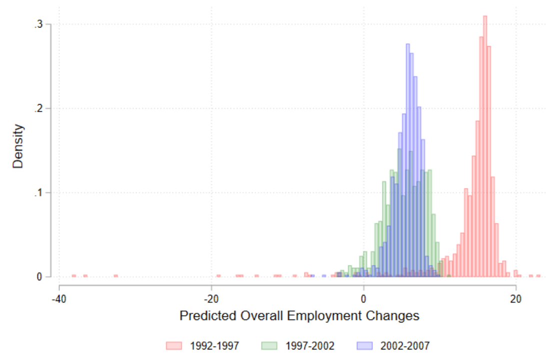
Figure 4: *Employment Change Predictions using IO China Shocks*



(a) *Manufacturing*



(b) *Non-Manufacturing*



(c) *Overall*

4. Empirical strategy and results

Now that we have established how we construct predicted employment changes we can start estimating the impact of local agglomeration as detailed in our framework in specifications (15) and (22). Generally our setup has a structural interpretation following our exposition in section 2 with all factors that may further impact employment such as wages being implicitly included in the employment change predictions. As such the inclusion of further control variables is not necessarily warranted. One issue that could still confound the results regardless is population and migration dynamics. Previous literature established that city population growth partly relies on factors outside of industry or employment conditions. For instance, the trend of US population moving towards regions with more sunshine hours (Glaeser et al., 2014), or immigrants often settling in cities that already house immigrants of the same nationality (Card, 2001). Hence we may expect that cities with certain traits (good climate, Mexican diaspora) have a persistently elevated growth rate of population, where this inflow of population also raises employment. To account for this, we compute and control for the component of lagged city population growth that is not explained by past shocks to the city's industries, $popres_{ct-1}$, by taking residuals from

$$\hat{Pop}_{ct-1} = \alpha_{t-1} + \beta_{t-1}\mathbb{P}\hat{E}^S_{ct-1} + \epsilon_{ct-1} \tag{42}$$

The residuals from (42), $popres_{ct-1}$, represent regional employment growth that is perpendicular to the employment predictions in t-1.[17] We then include this residual lagged population growth control in our baseline regression

$$\hat{E}^S_{ct} = \alpha_t + \beta\mathbb{P}\hat{E}^S_{ct} + \theta popres_{ct-1} + \epsilon_{ct} \tag{43}$$

We run specification (43), pooled for five 5-year periods with the Bartik and IO Price Shock, and for two 5-year periods for the IO China Shock, where we replace overall regional employment predictions by the sector-region predictions in some set-ups.[18][19][20] Table 1 shows the results.

For each shock the first column separates the predictions by sector, whereas the second column shows the overall prediction. We are particularly interested to find out whether our coefficients are larger than 1, as that would be an indication of agglomeration effects following our exposition above. We include p-values of one sided t-tests for the H_0 of the coefficients being smaller or equal to one in the bottom rows of the table. The null can be rejected for the manufacturing estimates as well as for the overall estimates of all shocks. For the overall predictions we find coefficients of around 1.2-1.4. Regions that we predict to grow by 1% in reality grow by 1.2-1.4% on average. Our coefficients also translate directly into jobs. 1 predicted new job yields 1.2-1.4 actual new jobs and conversely we would interpret 1 predicted job loss resulting in 1-2-1.4 actual layoffs.[21] The effect is even stronger for manufacturing. Since we rescaled our variables by overall employment in (27), the sector coefficients are elasticities. The manufacturing coefficient in the first column for each shock can then be read as 1 predicted new manufacturing job yielding 2-2.7 new overall jobs. The employment rescaling also allows us to translate in which sector the new jobs are created. Tables 8 and 9 in appendix B show the results for manufacturing and non-manufacturing outcomes respectively. For the Bartik shock we find 1.1 new manufacturing jobs and 1 new non-manufacturing job following one new predicted manufacturing job. For the IO Price shock the split is 1.5 manufacturing jobs and 1.2 non-manufacturing jobs. For the IO China

[17]Population data is collected using the Population and Housing Unit Estimates data.

[18]A sixth period, 1977-1982, is available to compute the lagged residual population growth control for the Bartik and IO Price shocks. For the IO China Trade shocks the third period, 1992-1997 is used.

[19]We weight regressions in (43) by initial commuting zone employment E_{ct}. Robust standard errors are clustered at the state level. Results by period are reported in full in appendix C.

[20]Running the specification without any controls or with several alternative population controls does not significantly alter our results, as we detail in section 6 below.

[21]Whether the effect is symmetrical for negative shocks is still a topic of discussion. Overall employment grew for most regions in basically all periods, making our current analysis functionally specific to employment gains. In the next section we explore non-linear specifications to take first steps to uncover whether there are differential impacts even within positive growth distributions.

Table 1: *Linear specification*

Dependent Variable: Rescaled employment change in all industries $\hat{E}_{ct}^{S}$						
	Bartik Shock Pooled		IO Price Shock pooled		IO China Shock Pooled	
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	1.067***		1.087***		0.269	
	(0.211)		(0.289)		(0.520)	
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	2.066***		2.694***		2.049***	
	(0.439)		(0.565)		(0.340)	
$\mathbb{P}\hat{E}_{ct}^{S}$		1.325***		1.393***		1.234***
		(0.175)		(0.225)		(0.156)
$popres_{ct-1}$	0.427***	0.413***	0.444***	0.449***	0.603***	0.603***
	(0.116)	(0.117)	(0.100)	(0.101)	(0.051)	(0.052)
Time FE	✓	✓	✓	✓	✓	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	0.377	-	0.383	-	0.917	-
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.010	-	0.002	-	0.002	-
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S} \leq 1$	-	0.035	-	0.044	-	0.069
R^2	0.427	0.702	0.387	0.681	0.376	0.665
Observations	3,610	3,610	3,610	3,610	1,444	1,444

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

Shock non-manufacturing gains were somewhat smaller at 0.7 new jobs, with 1.4 new jobs in manufacturing. This is in line with Moretti (2010), who finds that one new manufacturing job leads to the creation of 1.6 jobs in non-manufacturing. We note here that while pooled results are rather strong, by-period results show a large range of variation, with e.g. the 1992-1997 and 1997-2002 periods having only small gains in non-manufacturing jobs following a new manufacturing job. This is visible in the full results breakdown by period in appendix C particularly in Panel A of tables 12, 16 and 23. Within manufacturing results as presented in Panel B of the same tables are considerably more stable as our way of constructing employment predictions from national trends is more suited to the manufacturing sector.

The non-manufacturing estimates for the Bartik and IO Price Shock are of similar size at around 1, with the IO China Shock coefficient being close to zero. Looking at the effects of a predicted new job in non-manufacturing, we find little to no impact in the manufacturing sector, implying that non-manufacturing spillovers tend to be concentrated in the non-manufacturing sector itself.

A possible reason for the smaller coefficient using the IO China Trade Shock maybe the restricted look at two periods which are likely not enough to establish a structural pattern for non-manufacturing in which industries follow less of a national trend.[22] Additionally, small coefficients in our setup could be caused by attenuation bias. Though we aggregated our data first to the 3-digit SIC87 level and then again to fit the IO structure, some level of measurement error may remains. If that is the case, our predictions are mismeasured as well. As the measurement error is uncorrelated with actual employment changes, this would bias our results towards zero. The lagged residual population growth is significant and of similar size in all specifications implying that persistent population growth is indeed correlated with employment growth even when accounting for the previous periods employment predictions explicitly.

4.I. Distributional Effects

The linear specification in (43) does not allow us to make statements about distributional effects of shocks. Overall the economy may be better of by redistributing labor across regions, so that all regions become more uniform in their industry mix and the spatial distribution of employment growth becomes more equalized, or by concentrating labor so that only a few fast growing regions emerge. We explore the possibility of distributional effects by running two non-linear versions of (43), a quadratic and a spline. We focus on overall predictions and outcomes, as the interpretation of sectoral coefficients gets more convoluted once we go beyond the linear case.[23]

We start by splitting the linear specification in two parts via a spline regression. Regional growth patterns may differ for expansions and recessions, or more aptly in our case for low and high growth regions/periods as we have very few observations of actual employment contractions given that we observe 5-year windows. A reduction in demand in one industry may have knock-on effects to local services leading to a further weakening in demand. A similar pattern may not occur when jobs are created. In such an example neither a linear nor a simple quadratic specification would be suitable to reveal the full picture. Using a spline we allow for the predictor to have differing effects above and below a cut-off. In particular, we spline predictions at the their pooled employment weighted means $\mu_{\mathbb{P}\hat{E}^S_{ct}}$. We then add $(\mathbb{P}\hat{E}^S_{ct} - \mu_{\mathbb{P}\hat{E}^S_{ct}})\mathbb{1}[\mathbb{P}\hat{E}^S_{ct} \geq \mu_{\mathbb{P}\hat{E}^S_{ct}}]$ as second predictor in the regression, which allows for a different slope for predictions above the mean, without introducing a discontinuity in the regression.

$$\hat{E}^S_{ct} = \alpha_t + \beta_1 \mathbb{P}\hat{E}^S_{ct} + \beta_2(\mathbb{P}\hat{E}^S_{ct} - \mu_{\mathbb{P}\hat{E}^S_{ct}})\mathbb{1}[\mathbb{P}\hat{E}^S_{ct} \geq \mu_{\mathbb{P}\hat{E}^S_{ct}}] + \theta popres_{ct-1} + \epsilon_{ct} \tag{44}$$

The slope of the spline below the average prediction is then given by β_1, whereas the slope above the mean is given by $\beta_1 + \beta_2$.

[22] Looking at the by-period results in appendix III in table 23, Panel A. and C., we can see non-manufacturing coefficients closer to 1 for the IO China Shock, though they are very imprecisely measured.

[23] We briefly explore sectoral results in the appendix I, including an examination of sub-sectors within non-manufacturing. More generally results that include sectoral breakdowns are also included in full in appendix D.

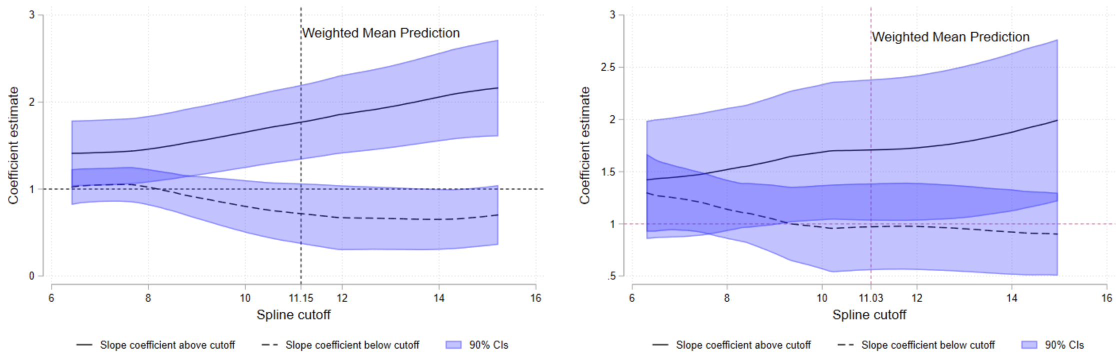
Table 2: *Spline Specification*

Dependent Variable: Rescaled employment change in all industries $\hat{E}^S_{ct}$	Bartik Shock Pooled	IO Price Shock Pooled	IO China Shock Pooled
$\mathbb{P}\hat{E}^S_{ct}$	0.718***	0.972***	1.500***
	(0.207)	(0.248)	(0.235)
$(\mathbb{P}\hat{E}^S_{ct} - \mu_{\mathbb{P}\hat{E}^S_{ct}})\mathbb{1}[\mathbb{P}\hat{E}^S_{ct} \geq \mu_{\mathbb{P}\hat{E}^S_{ct}}]$	1.051***	0.736	−0.727
	(0.350)	(0.535)	(0.646)
$popres_{ct-1}$	0.392***	0.451***	0.609***
	(0.118)	(0.100)	(0.052)
Time FE	✓	✓	✓
$\beta_1 + \beta_2$	1.769***	1.708***	0.774
	(0.256)	(0.403)	(0.480)
P-value $H_0 : \mathbb{P}\hat{E}^S_{ct} \leq 1$	0.798	0.536	0.140
P-value $H_0 : \beta_1 + \beta_2 \leq 1$	0.102	0.165	0.640
P-value $H_0 : \beta_1 = \beta_1 + \beta_2$	0.004	0.176	0.267
R^2	0.710	0.683	0.667
Observations	3,610	3,610	1,444

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

We report the sum of coefficients explicitly in the results in table 2. We once again add p-values for one-sided t-tests whether coefficients are larger than 1 and additionally whether the two slopes are equal to each other. For the IO Price and Bartik shocks the above mean slope is large at around 1.7-1.8 compared to the below mean slope at 0.7-1.0. We can reject the H_0 that both slopes are equal for the Bartik Shock, indicating that the effect we find in the linear specification is focussed in regions that are predicted to grow more than the average, with regions growing at or below the average having a roughly 1:1 predicted new jobs to actual new jobs ratio. The Bartik shock is generally the most precisely measured, as the employment change prediction step does not involve a regression fit. Hence the similar sized IO Price Shock coefficients should be seen as encouraging evidence of a potential break in the pattern around the mean even if coefficients are not estimated precisely enough to differentiate the slopes based on the t-test. For the IO China Shock the slope below the mean appears to be larger, with a coefficient of 1.5 compared to 0.8 above the mean. However we cannot reject that these coefficients are in fact equal, as the above mean slope is estimated rather imprecisely. The two periods available for the IO China Trade shock, 1997-2002 and 2002-2007 are the periods with the lowest average growth rates in our

Figure 5: *Spline estimates at variable cut-offs*



(a) *Bartik shock predictions* **(b)** *IO Price shock predictions*

sample, with the predicted period averages of 6.0% and 5.8% being well below the overall average prediction in either the Bartik or the IO Price Shock at around 11%. The lack of evidence with the IO China Trade shock thus potentially just reflects the fact few regions grew quickly enough to generate sufficient agglomeration spillovers to detect distributional effects in these periods.

The location of the inflection point in the spline might matter. For example the commuting zone Detroit-Flint, the region which features the prime example of a city in decline had an employment weighted average growth rate of 8.3% over our sample - bolstered still by strong growth in the mid 80s and 90s - and an employment weighted average predicted growth rate of 11.3%.[24] The weighted mean prediction for the Bartik shocks is 11.15%, indicating that over all periods Detroit was predicted to grow more than the average. In order to test for the sensitivity of the threshold choice, figure 5 plots β_1 as below cut-off coefficient and $\beta_1 + \beta_2$ as above cut-off coefficient, where we let the cut-off vary from the 25$^{\text{th}}$ percentile to the 75$^{\text{th}}$ percentile of weighted predictions. Increasing the cut-off increases the coefficient estimate even further, indicating that the regions with the highest predicted employment growth had actual employment growth that goes even beyond the ratio of 1:1.7. It is also interesting to note that the 90% confidence intervals are relatively stable, meaning that the precision of our estimations does not change drastically throughout the sample. When reducing the cut-off, the above cut-off coefficient is consistently larger than 1, though we would not be able to reject the equality of both coefficients once we reach around 9% of predicted employment growth. Nevertheless this is sufficient evidence that our results are not biased by the exact location of a few large regions within the distributions of predicted vs actual employment growth. The IO Price shock graph shows a similar dynamic though the below mean coefficient stays somewhat larger and the above mean coefficient somewhat smaller

[24]The somewhat large positive growth here is also driven by the fact that we do not observe cities but commuting zones even if we colloquially equate the two on occasion. The story of Detroit is also a story of urban flight, increasing employment in the surrounding sub-urbs. The commuting zone Detroit-Flint is made up of 10 counties in total.

when compared to the Bartik shock spline. At no cut-off can we reject the H_0 of the coefficients being different from each other as indicated by the overlapping confidence intervals.[25] A possible explanation for the dichotomy in responses found for the Bartik and IO Price Shock is the housing channel. Whereas the housing supply is highly elastic in growing cities, cities in decline often have a persistent durable housing stock which means adjustments happen via the house price dimension instead. As housing becomes cheaper, the population loss induced by the decline is partly offset (Glaeser and Gyourko, 2005).

A second way to test for non-linearities is to run a simple quadratic regression such as

$$\hat{E}^S_{ct} = \alpha_t + \beta_{1t}\mathbb{P}\hat{E}^S_{ct} + \beta_{2t}\left(\mathbb{P}\hat{E}^S_{ct}\right)^2 + \theta_t popres_{ct-1} + \epsilon_{ct} \tag{45}$$

which allows us to test whether average ratio between predicted an actual employment growth differs along the distribution of predictions. The growth performance of industries for example may be an indicator of agglomeration effects as particularly well performing industries are able to outcompete adjacent industries for highly productive employees. Such a dynamic would imply that the more growth we predict, the more actual growth we should observe.

Table 3 shows the results. The square coefficient is significant only for the Bartik Shocks. The IO Price Shocks have a coefficient of similar magnitude but not enough precision to be significant whereas the IO China Trade Shock produces an imprecisely estimated negative square term. There is no clear consistent picture emerging on first glance, though as with the spline results the IO Price Shocks seems to mirror the Bartik shock with less precision, and the IO China Trade shock is again less comparable with the other two predictions due to the different time frames.

To get a sense of how different the spline and the quadratic specifications perform, we plot them against each other in figure 6. The graphs show the functional form of each specification as implied by the coefficient estimates, where the constant term is the average of the time fixed effects. We restrict the functions to be within the 10^{th} and 90^{th} percentile of the distribution of predictions. For both the Bartik and the IO Price shock it is evident that the spline and quadratic fit are relatively similar, with the largest difference to the linear fit occurring around the mean prediction. For the IO Price shock the differences in fits seem to be somewhat smaller, which is in line with our results above.[26]

The spline showed that our results are largely driven by regions with high predicted growth, particularly so for the Bartik shock. The graphical comparison confirms that this notion is generally supported by the quadratic specification. However, a benefit to the quadratic over the spline is

[25] The spline cut-off graph for the IO China Trade shock is shown in figure 9 in the general appendix A. The below cut-off coefficient is very stable between the 25^{th} percentile to the 75^{th} percentile of the distribution, with the above mean cut-off going towards zero but with constantly increasing confidence intervals. We cannot reject the H_0 that the coefficients are in fact equal at any point.

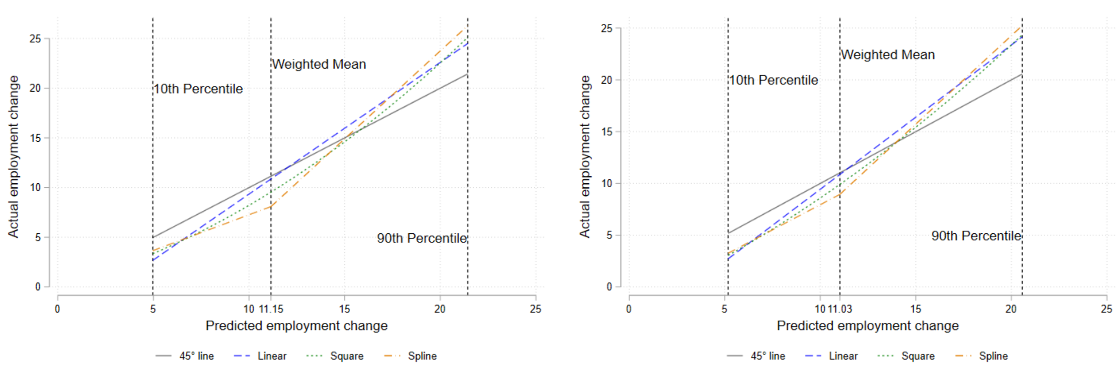
[26] Figure 10 in the appendix shows the graph for the IO China Trade shock. The quadratic fit looks very close to linear. The difference in spline and linear fit are generally not large either.

Table 3: *Square specification*

Dependent Variable: Rescaled employment change in all industries $\hat{E}^S_{ct}$	Bartik Shock pooled	IO Price Shock pooled	IO China Shock pooled
$\mathbb{P}\hat{E}^S_{ct}$	0.503*	0.817*	1.644***
	(0.284)	(0.415)	(0.415)
$(\mathbb{P}\hat{E}^S_{ct})^2$	0.031***	0.022	-0.042
	(0.011)	(0.020)	(0.047)
$popres_{ct-1}$	0.398***	0.449***	0.608***
	(0.115)	(0.099)	(0.052)
Time FE	✓	✓	✓
P-value $H_0 : \mathbb{P}\hat{E}^S_{ct} \leq 1$	0.957	0.670	0.064
R^2	0.709	0.683	0.666
Observations	3,610	3,610	1,444

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

Figure 6: *Comparison of linear, spline and quadratic regression results with average time fixed effect*



(a) *Bartik shock predictions* **(b)** *IO Price shock predictions*

that we can use it to investigate the equity-efficiency trade-off in fostering regional growth that is implied by these results.

4.II. Efficiency vs. Equity

When looking at which regions drive our results, there is significant variation across periods. Yet generally our results are informative in spite - not because - of the largest US regions in terms of employment levels.[27] We already gave the example of Detroit above with a ratio of predicted to actual growth of 1:0.74. Looking at another very large commuting zone that is typically regarded to have grown rapidly, San Francisco-Oakland, we find a five year predicted average employment growth of 13.8%, with the actual average five year growth amounting to 9.1%. This yields a ratio of 1:0.66, somewhat smaller even than the ratio of Detroit even though the actual growth was quite a bit stronger. This is in line with findings in the urban economics literature that large cities have been hampered by restrictive planning and zoning laws, leading to growth below the optimum (Albouy et al., 2019; Duranton and Puga, 2019; Hsieh and Moretti, 2019). There are 17 commuting zones in our sample that had mean employment above 1 million over the periods that we observe. Only six of these have a ratio above 1:1, with the strongest performer being Atlanta with a ratio of 1:1.56.[28] This lack in agglomeration effects in very large commuting zone in turn implies that our results are driven by a multitude of medium to large commuting zones which beat their predictions substantially.[29][30] Restricting our sample to commuting zones above 100.000 mean employment, Atlanta only has the 23rd highest ratio.

Interpreting our results within the efficiency-equity trade-off, a social planner should take into account both the predicted growth performance and the geographic concentration of industries. In periods of low growth, geographic concentration of industries is not very relevant, as regions losing out due to their industry mix do not fare worse than predicted according to our results. However for a strong positive shock in a set of industries, the efficient outcome would be to have these industries be geographically concentrated in order to take advantage of the increasing gains of agglomeration. While distributing a positive shock asymmetrically over all regions would increase efficiency, it would also increase inequality in outcomes. In order to gauge the benefits of the spatial distribution of industries and regions in our sample, we explore a simple counter-factual calculation in which we assign all regions the average predicted growth rate. Taking the coefficients from the quadratic specification of table 3, we get a counter-factual average national growth rate of 9.5% if all regions had an industry mix that yields the average prediction of employment growth. Looking at the actual average over our predicted outcomes instead, we find a five year national growth rate of employment of 10.8%. Given that agglomeration spillovers are focussed in fast growing regions, reducing the growth rate of these regions by e.g. making the

[27] The numbers we showcase in this section are based on the Bartik shock results. The numbers for the IO Price Shock are sufficiently similar. Dynamics change somewhat for the IO China Trade shock which is based on two periods with relatively low growth.

[28] Atlanta had a mean predicted change of 12.1% and a mean actual change of 18.9%

[29] As we weight all our regressions by initial share of national employment within periods, small regions will barely affect the outcomes, even if they had rapid growth.

[30] Coincidentally, the largest ratio for commuting zones with mean employment above 100,000 is found for the second Atlanta commuting zone which indicates the same city of Atlanta, Georgia (commuting zone code 06600 compared to the previous Atlanta commuting zone 09100). Here we predict a five year growth rate of only 3.5% on average, with the actual growth rate being 11.7%, a ratio of 1:3.4. Whereas our overall results are still driven by a majority of "independent" medium to large commuting zones, the story of the two Atlantas shows that there is also a sub-dynamic of cities growing beyond the geographic boundaries that is a commuting zone.

industry mix homogenous across the nation would reduce aggregate growth by 1.3% over five years or 9.6% over the 25 year period.

5. Non-employment and population channels

While our results so far show strong effects of job creation in fast growing regions we have yet to discuss whether these jobs are sourced from increased in-migration into a region or the unemployment/non-employment pool within a region. We perform an indicative exercise to gauge the importance of each of these channels by creating both non-employment growth predictions and working-age population growth predictions out of our employment growth predictions. In particular, we first run our baseline regression without any controls

$$\hat{E}^S_{ct} = \alpha_t + \beta \mathbb{P}\hat{E}^S_{ct} + \epsilon_{ct} \tag{46}$$

and then construct

$$\mathbb{P}\hat{NE}_{ct} = \left(\alpha^{est}_t + \beta^{est}\mathbb{P}\hat{E}^S_{ct}\right) \frac{E_{ct}}{WPop_{ct} - Ect}(-1) \tag{47}$$

and

$$\mathbb{P}W\hat{P}op_{ct} = \left(\alpha^{est}_t + \beta^{est}\mathbb{P}\hat{E}^S_{ct}\right) \frac{E_{ct}}{WPop_{ct}} \tag{48}$$

where α^{est}_t are the time fixed effects estimates and β^{est} is the coefficient estimate on the employment change predictions from (46). $\mathbb{P}\hat{NE}_{ct}$ and $\mathbb{P}W\hat{P}op_{ct}$ correspond to non-employment change predictions and working-age population change predictions in commuting zone c at time t respectively.[31] The benefit of first running (46) and rescaling the predicted outcomes instead of rescaling the employment change predictions directly is that we capture how our employment predictions translate into employment outcomes. If for example our predictions do not correlate well with the employment outcomes, there is no reason to believe that they correlate well with non-employment or population outcomes. Instead, when we now regress non-employment and working-age population changes on their respective predictions in a similar fashion to our employment baseline, i.e.

$$\hat{NE}_{ct} = a^{NE}_t + b^{NE}\mathbb{P}\hat{NE}_{ct} + c^{NE} popres_{ct-1} + e^{NE}_{ct} \tag{49}$$

[31]Descriptive statistics for non-employment and working-age population predictions and outcomes are located in appendix C.

Table 4: *Linear specification*

Dependent Variable: Non-employment change in all industries $\hat{NE}_{ct}$			
	Bartik Shock pooled	IO Price Shock pooled	IO China Shock pooled
$\mathbb{P}\hat{NE}_{ct}$	0.081**	0.022	−0.189
	(0.031)	(0.045)	(0.122)
$popres_{ct-1}$	0.945***	0.923***	1.034***
	(0.077)	(0.064)	(0.121)
Time FE	✓	✓	✓
P-value $H_0 : \mathbb{P}\hat{NE}_{ct} = 1$	0.000	0.000	0.000
R^2	0.577	0.557	0.652
Observations	3,610	3,610	1,444
Dependent Variable: Working Age Population Change $W\hat{P}op_{ct}$			
	Bartik Shock pooled	IO Price Shock pooled	IO China Shock pooled
$\mathbb{P}W\hat{P}op_{ct}$	0.643***	0.681***	0.501***
	(0.060)	(0.090)	(0.126)
$popres_{ct-1}$	0.651***	0.656***	0.760***
	(0.042)	(0.044)	(0.038)
Time FE	✓	✓	✓
P-value $H_0 : \mathbb{P}W\hat{P}op_{ct} = 1$	0.000	0.001	0.000
R^2	0.767	0.762	0.879
Observations	3,610	3,610	1,444

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

and

$$W\hat{P}op_{ct} = a_t^{WPop} + b^{WPop}\mathbb{P}W\hat{P}op_{ct} + c^{WPOP} popres_{ct-1} + e_{ct}^{WPop} \tag{50}$$

we would expect $b^{NE} = 1$ under the assumption that employment changes fully work through non-employment changes and population is constant. Similarly, under the assumption that employment changes fully work through working-age population changes, we would expect $b^{WPop} = 1$.

Table 4 shows the results for both non-employment and working-age population. Whereas before we added p-values for coefficients being smaller or equal to 1, under our assumptions we now additionally test whether the coefficients equal 1. We reject that hypothesis for all coefficients both for non-employment and working-age population. This is not surprising as the assumptions of employment changes working exclusively through non-employment or through working-age population changes are not particularly realistic. Nevertheless, we find some evidence for non-employment being a significant albeit weaker channel for the Bartik Shocks. A possible reason the non-employment results are weaker is that it does not account for movements from out of the labor force into unemployment and vice versa. Population on the other hand seems to be a strong consistent channel across all shocks with rather stable coefficients of around 0.5-0.7. We note that while we could interpret the coefficient size similarly to the employment coefficients above, this assumption based set-up is not meant to find the true effect size of the non-employment and working-age population channel. Instead we prefer to interpret this exercise as indication that our employment results seem to be driven largely by changes in population.

Population effects from employment change predictions is also the topic of interest in Notowidigdo (2020). He finds that population responds to employment change predictions mainly for above average predictions, with little to no response for predictions below the average. There are two key differences between the analysis in Notowidigdo (2020) and ours. Firstly, the overall focus of Notowidigdo is on the population growth of large cities, for which he analyzes MSAs with time-variant boundaries than can capture the spatial expansion (or contraction) of metropolitan areas.[32] Since spatial changes of MSAs occur stepwise rather than gradual (i.e., by adding or subtracting entire counties or CONSPUMAs), they tend to induce sizable jumps in population and employment numbers. Our focus instead is on the distribution of national employment shocks across a complete set of local labor markets in the US. Since we hold the boundaries of these local labor markets constant over time, we do not conflate within-location and across-location changes. Secondly, we are interested in assessing whether the actual employment growth of a local labor market is larger, equal or smaller than the growth which would be predicted based on national industry employment trends and local labor market composition. Notowidigdo instead does not derive predictions for local growth rates of employment, but seeks to predict changes in employment-to-population ratios, which depend both on employment and population trends.

The analysis in this section has shown that the job creation process we describe mainly works through changes in population, with only small and more tentative evidence for the non-employment channel. We now turn to testing the sensitivity of our employment results.

[32] Notowidigdo (2020) also performs his analysis on employment outcomes with similar results, though these are not the main focus of the paper. The key differences between the two papers are just as relevant when talking about employment changes.

Table 5: *Linear specification robustness checks using the Bartik Shock predictions*

Dependent Variable: Rescaled employment change in all industries $\hat{E}^S_{ct}$	Baseline	No $popres_{ct-1}$	Lagged Pop. Growth	Lagged Predictions	Log Population	Census Division FE
$\mathbb{P}\hat{E}^S_{ct}$	1.325***	1.357***	1.256***	1.784***	1.535***	1.361***
	(0.175)	(0.227)	(0.177)	(0.213)	(0.163)	(0.159)
$popres_{ct-1}$	0.427***			0.451***	0.411***	0.194*
	(0.116)			(0.099)	(0.109)	(0.107)
$\hat{Pop}_{ct-1}$			0.317***			
			(0.038)			
$\mathbb{P}\hat{E}^S_{ct-1}$				−0.679***		
				(0.193)		
$log(Pop_{ct})$					−0.861***	
					(0.314)	
Time FE	✓	✓	✓	✓	✓	✓
Census Division FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}^S_{ct} \leq 1$	0.035	0.061	0.078	0.000	0.001	0.014
R^2	0.702	0.356	0.430	0.448	0.433	0.463
Observations	3,610	4,332	4,332	3,610	3,610	3,600

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

6. Robustness

We perform several robustness checks to test whether our result of coefficients larger than 1 in the linear specification is stable. The robustness checks are mostly concerned with the role of population, as there is a legitimate concern that our results are driven by regions that experienced persistent population growth, for example due to attractive amenities, making the employment growth a by-product of migration patterns. We have seen that the population channel is the more important driver of the agglomeration effects we find and this line of logic also informed the inclusion of our lagged residual population growth control.

Table 5 shows several robustness checks run for the Bartik shock predictions, with the first column showing the baseline specification results. In column 2, we exclude any and all controls. The coefficient estimate remains rather stable, though the R^2 drops significantly, indicating that population growth is important in explaining employment growth patterns. Column 3 replaces the lagged residual population growth variable with the simple lagged population growth instead.

Our reason for not using the simple version are concerns that our employment change predictions could also be highly persistent, implying that the simple lagged population growth control may pick-up some of the employment variation through that channel. The coefficient in column 3 is marginally smaller than in our baseline and the R^2 drops somewhat. Of note is that columns 2 and 3 include an additional period, 1977-1982, in the regression, which we otherwise use to compute $popres_{ct-1}$. Overall the results remain stable also with the simple version if somewhat smaller, which could also be driven by the fact that the US was facing a recession in the late 70s/early 80s which is now included in the sample.

In column 4 we control for the possible persistency of our predictions directly by including $\mathbb{P}\hat{E}^S_{ct-1}$ in the regression. Interestingly we find a sizeable and significant negative coefficient for the previous periods predictions. As we work with 5-year time spans, this might just be cyclical variation in employment growth as the economy goes through a business cycle. The inclusion of lagged predictions does increase the coefficient estimate of the current periods predictions by around 0.36 while also dropping the R^2. Column 5 includes initial log population levels in the regression. Region size can affect regional growth, as Gibrat's Law is often violated in the short run (Glaeser et al., 2014). The overall results are somewhat stronger than before with the coefficient of initial log population indicating that large regions did grow less in terms of employment which is again in tune with urban planning restrictions.[33]

Finally we added census division fixed effects in the the last robustness check in column 6. Structural migration patterns between larger regions, e.g. towards the coastal areas on the West and East coast could explain stronger employment growth that we don't account for by just including regional population growth controls. While the inclusion of census division fixed effects does decrease the size and significance of the population control, the coefficient on our predictions is again stable.

Tables 10 and 11 in appendix B show the same robustness checks for the other two sources of variation for our predictions. The IO Price Shock coefficients become somewhat stronger in most of the specifications. For the IO China Trade shock coefficients, we see a sizeable reduction in columns 2 and 3. These are the specifications that include the initial 1992-1997 period, which shows very little correlation between our predictions and actual employment outcomes for any of the shocks, driving down the overall coefficient estimate. Yet the results also show in general

[33]A size control seems to be particularly relevant for the periods of 1987-1992 and 1992-1997. When looking at our by-period results, e.g. in table 12 in appendix C, we note that our prediction approach performs markedly worse for these periods, with overall predicted employment change coefficients being small and insignificant. In order to investigate this breakdown in the 90s we ran a multitude of unreported tests using sub-samples and additional controls, by for example excluding specific sectors such as construction or computer services. Ultimately the only way to "discipline" the results was to include a size control, such as initial log population, hinting at the violation of Gibrat's Law particularly in the early and mid 90s. The inclusion of a size control increased coefficients to be around 1, though not larger than 1 as in most other periods. We decided against the inclusion of this control in our standard specification as our results are already strong even with the outlier periods included. However we encourage further research into the particularities of employment dynamics during this decade.

that the IO China Trade shock is more sensitive to other specifications. The below average growth performance in the latter periods of our sample being the likely cause of this.

7. Conclusion

We analyse the effect of national industry shocks on local employment. By providing a novel structural view on the Bartik framework, we show that the difference in national and regional employment growth trends can be attributed to within-region spillovers. We hypothesize that agglomeration plays a key role in creating these spillovers, as agglomeration leads to the creation of larger employment pools and stronger intra-industry links through which a shock can travel. Using three different sources of variation to construct employment predictions we find consistent evidence that a predicted change in employment by 1% is associated with a 1.3% change in actual employment in a region. Our results are largely driven by the manufacturing sector. 1 predicted new job in manufacturing can be decomposed to yield between 0.7-1 actual new jobs in non-manufacturing and 1-1.4 actual new jobs change in manufacturing.

This suggests substantial inequality effects - but not per se an impact on aggregate employment - as some regions are even more left behind than just their industry mix would suggest whereas other regions grow even more. However, when we allow for non-linearities in a variety of setups, we find that the main driver of agglomeration effects are regions with particularly strong growth in employment. Taking the employment weighted mean as inflection point, regions with below mean predictions show a roughly 1:1 translation of predicted job creation to actual job creation. For regions with above mean predictions this ratio increases to 1:1.7. Using a simple counter-factual calculation in which we assign all regions the average predicted employment growth rate, we find that aggregate growth is reduced by 1.3% over five years or 9.6% over the 25 year period we observe. Furthermore, we perform an indicative exercise which shows that our results are largely driven by changes in population, with only weak evidence that employment changes are driven by non-employment changes.

The discourse around the equity-efficiency nexus is usually focussed on the trade-off of diverting resources from the average region towards regions in decline. Our results show no aggregate implications for such a policy. Instead, as we find agglomeration spillovers to be concentrated in fast growing regions, the more pertinent trade-off is between the average region and fast growing regions. A focus on equity instead of efficiency - by for example making the industry mix homogeneous across the nation - would reduce aggregate growth rate significantly in the long run.

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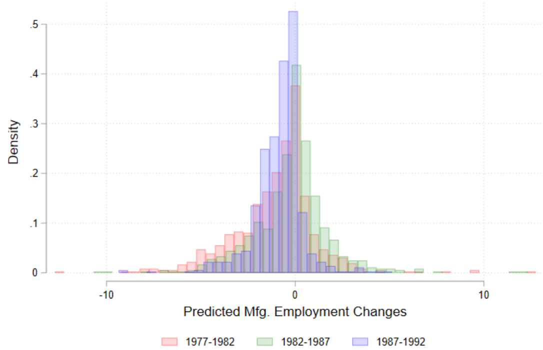
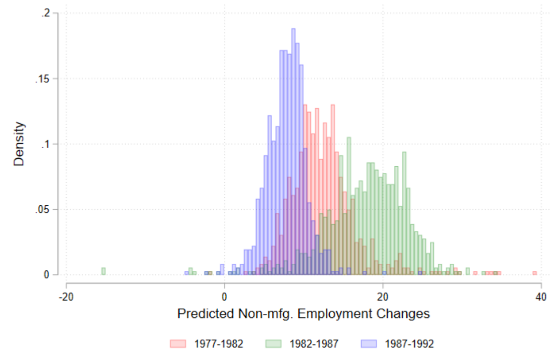
A. General Appendix

Figure 7: *Employment Change Predictions using Bartik Shocks*



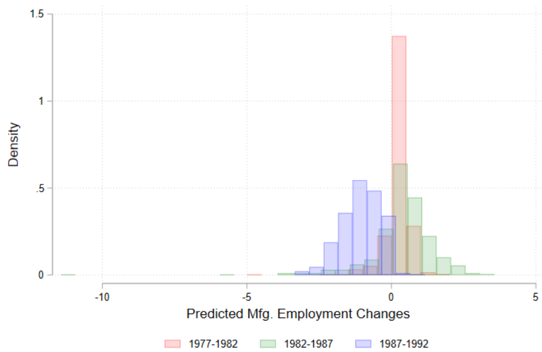
(a) *Manufacturing*



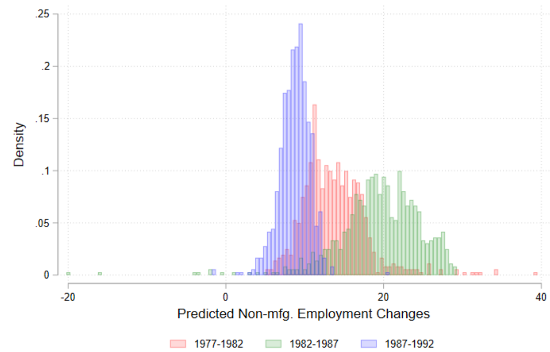
(b) *Non-Manufacturing*

(c) *Overall*

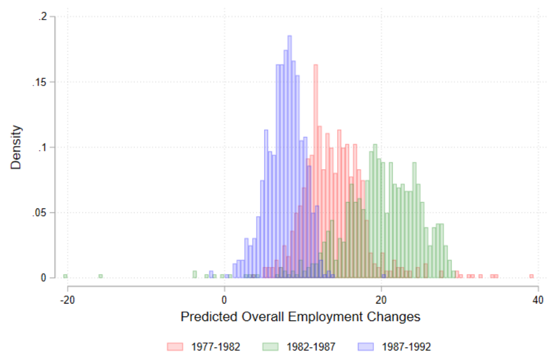
Figure 8: *Employment Change Predictions using IO Price Shocks*



(a) *Manufacturing*



(b) *Non-Manufacturing*



(c) *Overall*

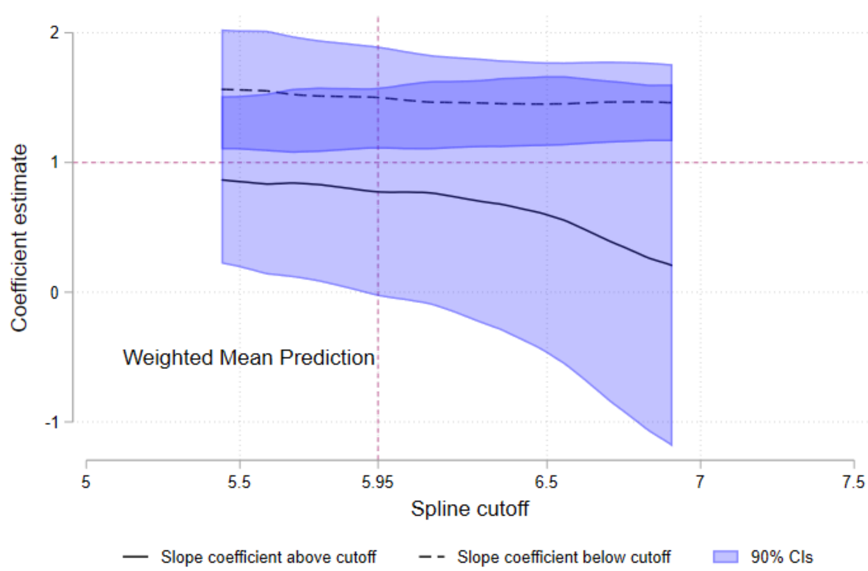


Figure 9: *Spline estimates at variable cut-offs - IO China Trade shock predictions*

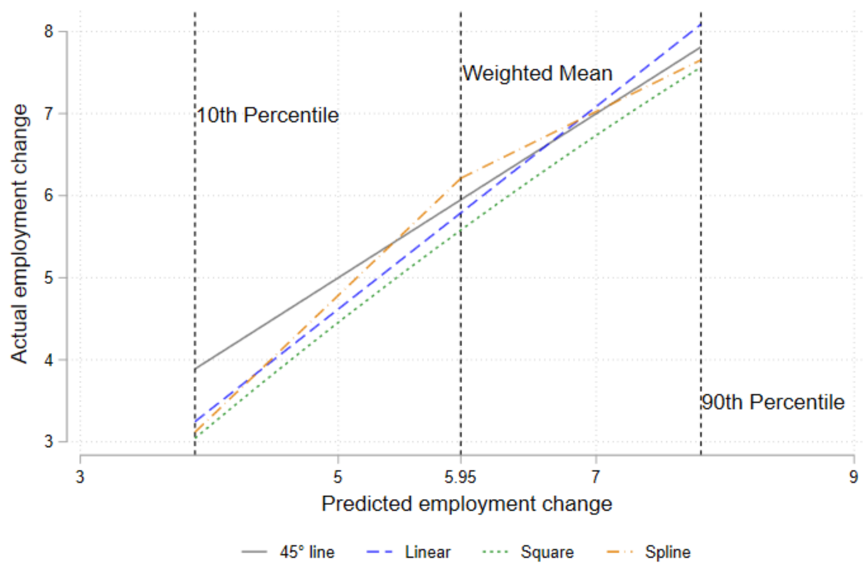


Figure 10: *Comparison of IO China Trade shock specifications with average time fixed effect*

A.I. Distributional Effects within Sectors

Table 6 provides a breakdown of the spline specification in (44) where we split overall employment predictions into manufacturing and non-manufacturing once more. While the coefficient estimates are not as straightforward to interpret due to the inclusion of a full set of sectoral predictions, we can nevertheless identify some general trends on how the larger than 1 coefficients from the linear specification translates into the sectors, dependent on whether a region is predicted to grow more than the average or not. Specifically we find that the large manufacturing coefficient in the linear case seems to be driven by large spillovers from new manufacturing jobs into both new non-manufacturing and new manufacturing jobs within regions with stronger-than-average employment growth predictions. 1 new predicted job in such a region generates 3.6/2.0 (IO Prices Shocks/Bartik Shocks) new jobs in non-manufacturing and 1.7/1.2 new jobs in manufacturing, combining to 5.3/3.2 new jobs in the overall economy. Additionally we find evidence of spillovers also from non-manufacturing into non-manufacturing in these regions, with a predicted new job generating 1.5/1.7 new jobs. Here no effect on manufacturing is found which means that the total gain in employment is similarly 1.5 and 1.7 depending on the shock used to identify our variation. For regions with below-than-average growth predictions we still find some combined spillovers stemming from 1 new manufacturing job generating up to 2.7/1.4 new jobs in the overall economy, but they are generally less pronounced. There are no spillovers from non-manufacturing in these regions. Looking at the population response in columns 4 and 8, we see that the response is again highest in manufacturing for larger-than-average growth regions. This implies that the large gains here go hand in hand with larger gains in the working-age population.

Table 6: *Spline Specification*

	Rescaled employment change overall and within sectors							
	IO Price Shock Pooled				Bartik Shock Pooled			
Outcome Variable:	$\hat{E}_{ct}^{S,non-mfg}$	$\hat{E}_{ct}^{S,mfg}$	$\hat{E}_{ct}^{S}$	$W\hat{P}OP_{ct}$	$\hat{E}_{ct}^{S,non-mfg}$	$\hat{E}_{ct}^{S,mfg}$	$\hat{E}_{ct}^{S}$	$W\hat{P}OP_{ct}$
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} < \mu_{\mathbb{P}\hat{E}_{ct}^{S}}]$	0.235	−0.417**	−0.182	0.513**	0.816***	−0.063	0.753***	0.637***
	(0.512)	(0.166)	(0.653)	(0.214)	(0.205)	(0.056)	(0.241)	(0.130)
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S}}]$	1.526***	−0.008	1.517***	0.819***	1.746***	−0.041	1.705***	0.660***
	(0.363)	(0.086)	(0.407)	(0.129)	(0.230)	(0.075)	(0.270)	(0.095)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} < \mu_{\mathbb{P}\hat{E}_{ct}^{S}}]$	1.043**	1.631***	2.674***	0.936***	0.414**	1.020***	1.434***	0.525***
	(0.388)	(0.220)	(0.538)	(0.166)	(0.186)	(0.085)	(0.215)	(0.140)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S}}]$	3.642***	1.730***	5.372***	1.516***	2.040***	1.157***	3.197***	1.064***
	(1.080)	(0.370)	(1.134)	(0.280)	(0.595)	(0.197)	(0.728)	(0.272)
$\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S}}]$	−13.139*	−3.962**	−17.101*	−4.474	−16.489***	−1.281	−17.770***	−2.933
	(7.532)	(1.963)	(8.829)	(0.043)	(4.915)	(0.968)	(5.462)	(0.041)
$popres_{ct-1}$	0.376***	0.071***	0.446***	0.659***	0.310***	0.086***	0.397***	0.645***
	(0.085)	(0.024)	(0.096)	(0.043)	(0.099)	(0.027)	(0.114)	(0.041)
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} < \mu_{\mathbb{P}\hat{E}_{ct}^{S}}] \leq 1$	0.812	0.963	0.839	0.868	0.732	0.983	0.754	0.891
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S}}] \leq 1$	0.192	0.973	0.212	0.802	0.095	0.977	0.117	0.913
P-value Non-Mfg: $H_0 : \beta_1 = \beta_2$	0.058	0.032	0.038	0.279	0.003	0.773	0.007	0.887
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} < \mu_{\mathbb{P}\hat{E}_{ct}^{S}}] \leq 1$	0.465	0.107	0.099	0.618	0.902	0.426	0.146	0.909
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S}}] \leq 1$	0.123	0.149	0.081	0.158	0.165	0.285	0.102	0.427
P-value Mfg: $H_0 : \beta_1 = \beta_2$	0.006	0.799	0.006	0.071	0.005	0.506	0.010	0.072
R^2	0.397	0.265	0.405	0.547	0.455	0.318	0.461	0.560
Observations	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

In table 7 we now additionally zoom into more detailed non-manufacturing sectors in order to establish which non-manufacturing sectors benefit the most from spillovers from manufacturing. The ratios in the table show whether the coefficient estimate is large with respect to the intial average employment share in each region. For example, the ratio of 1.108 for agriculture in above average growth regions implies that the spillover from manufacturing accounts for a roughly proportionate increase in employment in agriculture as the initial employment share of agriculture would suggest. Contrary to that, we see that mining, financial services and real estate benefit a lot more from a new job in manufacturing, up to 3 times as much in the case of mining compared to the initial employment share. We generally find the largest ratios in mining, which may be due to its strong employment adjustment while being simultaneously concentrated in few regions, leading to a small average initial employment share. More generally spillovers from manufacturing are focussed on construction, retail, financial services, real estate and computer and business services, with some variation in whether we are in a fast or slower growing region. Spillovers from non-manufacturing in fast growing regions are similarly situated. This supports our hypothesis of consumption spillovers leading to increased demand in retail and services, while the real estate and construction channel may indicate further adjustments via housing.

Table 7: *Spline Specification*

	Bartik Shock Pooled: Rescaled employment change overall and within sectors											
Outcome Variable:	$\hat{E}_{ct}^{S,non-mfg}$	$\hat{E}_{ct}^{S,agri}$	$\hat{E}_{ct}^{S,mining}$	$\hat{E}_{ct}^{S,construct}$	$\hat{E}_{ct}^{S,whole}$	$\hat{E}_{ct}^{S,retail}$	$\hat{E}_{ct}^{S,finserv}$	$\hat{E}_{ct}^{S,real}$	$\hat{E}_{ct}^{S,cobuserv}$	$\hat{E}_{ct}^{S,healthedu}$	$\hat{E}_{ct}^{S,trans}$	$\hat{E}_{ct}^{S,resid}$
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} < \mu_{\mathbb{P}\hat{E}_{ct}^{S}}]$	0.816***	0.017***	0.234***	0.108***	0.038	0.107*	0.075***	0.000	0.062*	0.001	0.032	0.204***
	(0.205)	(0.006)	(0.058)	(0.030)	(0.026)	(0.056)	(0.019)	(0.003)	(0.036)	(0.027)	(0.027)	(0.065)
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S}}]$	1.746***	0.011***	0.131***	0.154***	0.120***	0.209***	0.272**	0.024**	0.251***	0.116**	0.117***	0.582***
	(0.230)	(0.003)	(0.033)	(0.043)	(0.024)	(0.051)	(0.116)	(0.011)	(0.030)	(0.047)	(0.023)	(0.067)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} < \mu_{\mathbb{P}\hat{E}_{ct}^{S}}]$	0.414**	0.012**	−0.149***	0.126***	−0.036*	0.209***	0.069**	0.006	0.040	0.044	−0.019	0.152*
	(0.186)	(0.005)	(0.038)	(0.028)	(0.018)	(0.042)	(0.031)	(0.005)	(0.049)	(0.047)	(0.019)	(0.085)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S}}]$	2.040***	0.017**	0.056*	0.148**	0.195***	0.600***	0.364***	0.043***	0.140**	0.168	0.147***	0.291***
	(0.595)	(0.008)	(0.030)	(0.072)	(0.043)	(0.214)	(0.129)	(0.013)	(0.064)	(0.126)	(0.042)	(0.097)
$\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S}}]$	−16.489***	−0.011***	1.409**	−1.275	−1.294**	−2.51***	−3.215	−0.415	−2.694***	−1.672	−1.254***	−6.099***
	(4.915)	(0.075)	(0.567)	(0.716)	(0.385)	(0.627)	(2.111)	(0.177)	(0.849)	(0.666)	(0.470)	(1.346)
$popres_{ct-1}$	0.310***	0.008***	−0.014**	0.019	0.024**	0.120***	0.000	−0.002	0.049***	−0.001	0.020***	0.136***
	(0.099)	(0.002)	(0.007)	(0.021)	(0.009)	(0.023)	(0.024)	(0.003)	(0.012)	(0.014)	(0.007)	(0.037)
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Avg. Initial Emp. Share	0.798	0.006	0.007	0.054	0.068	0.208	0.076	0.007	0.061	0.116	0.060	0.194
Ratio Non-Mfg Below	1	2.771	32.691	1.956	0.546	0.503	0.965	0.000	0.994	0.008	0.522	1.028
Ratio Non-Mfg Above	1	0.838	8.553	1.303	0.807	0.459	1.636	1.567	1.881	0.457	0.891	1.371
Ratio Mfg Below	1	3.855	−41.029	4.498	−1.02	1.937	1.750	1.652	1.264	0.731	−0.610	1.510
Ratio Mfg Above	1	1.108	3.129	1.072	1.122	1.128	1.874	2.403	0.898	0.567	0.958	0.587
Demeaning Method	O.P.	O.P.	O.P.	O.P.	O.P.	O.P.	O.P.	O.P.	O.P.	O.P.	O.P.	O.P.
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} < \mu_{\mathbb{P}\hat{E}_{ct}^{S}}] \leq 1$	0.732	0.998	0.976	0.989	0.991	0.980	0.993	0.999	0.988	0.991	0.991	0.974
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S}}] \leq 1$	0.095	0.999	0.988	0.984	0.991	0.980	0.950	0.996	0.987	0.983	0.992	0.950
P-value Non-Mfg: $H_0 : \beta_1 = \beta_2$	0.003	0.393	0.025	0.403	0.003	0.093	0.123	0.046	0.000	0.021	0.010	0.000
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} < \mu_{\mathbb{P}\hat{E}_{ct}^{S}}] \leq 1$	0.902	0.998	0.990	0.990	0.995	0.983	0.989	0.998	0.984	0.985	0.994	0.968
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg}\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S}}] \leq 1$	0.165	0.998	0.990	0.973	0.983	0.843	0.936	0.996	0.976	0.952	0.984	0.957
P-value Mfg: $H_0 : \beta_1 = \beta_2$	0.005	0.603	0.000	0.768	0.000	0.068	0.044	0.012	0.213	0.255	0.001	0.250
R^2	0.455	0.053	0.212	0.255	0.255	0.454	0.390	0.188	0.373	0.267	0.142	0.422
Observations	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.
Demeaning Methods: O.P. - The mean used in the regression is the overall means.
Ratio Formula: (Sub-Sector Coefficient / Non-Mfg Coefficient) / (Sub-Sector Emp. Share / Non-Mfg Emp. Share)
agri - agriculture, fishing and forestry
mining - mining
construct - construction
whole - wholesale trade
retail - retail trade
finserv - financial services
real - real estate
cobuserv - computer and business services
healthedu - health and education
trans - transport and public utilities
resid - residual non-manufacturing services (including cobuserv)

B. Appendix - Additional results

Table 8: *Linear Specification: Manufacturing*

Dependent Variable: Rescaled employment change in manufacturing industries $\hat{E}_{ct}^{S,mfg}$	Bartik Shock Pooled	IO Price Shock Pooled	IO China Shock Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	-0.093	-0.088	-0.038
	(0.060)	(0.062)	(0.214)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	1.068***	1.456***	1.388***
	(0.110)	(0.179)	(0.175)
$popres_{ct-1}$	0.089***	0.072***	0.053***
	(0.027)	(0.025)	(0.016)
Time FE	✓	✓	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	1	1	1
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.268	0.007	0.016
R^2	0.313	0.258	0.442
Observations	3,610	3,610	1,444

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

Table 9: *Linear Specification: Non-Manufacturing*

Dependent Variable: Rescaled employment change in non-manufacturing industries $\hat{E}_{ct}^{S,non-mfg}$			
	Bartik Shock Pooled	IO Price Shock Pooled	IO China Shock Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	1.160***	1.175***	0.307
	(0.164)	(0.252)	(0.443)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	0.998***	1.238**	0.661**
	(0.361)	(0.469)	(0.283)
$popres_{ct-1}$	0.338***	0.372***	0.550***
	(0.100)	(0.088)	(0.044)
Time FE	✓	✓	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	0.167	0.245	0.938
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.502	0.307	0.881
R^2	0.417	0.378	0.326
Observations	3,610	3,610	1,444

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

Table 10: *Linear specification robustness checks using the IO Price Shock predictions*

Dependent Variable:
Rescaled employment change in all industries $\hat{E}^S_{ct}$

	Baseline	No $popres_{ct-1}$	Lagged Pop. Growth	Lagged Predictions	Log Population	Census Division FE
$\mathbb{P}\hat{E}^S_{ct}$	1.393***	1.808***	1.508***	1.935***	1.509***	1.385***
	(0.225)	(0.289)	(0.256)	(0.403)	(0.272)	(0.240)
$popres_{ct-1}$	0.444***			0.450***	0.443***	0.252**
	(0.100)			(0.099)	(0.095)	(0.096)
$\hat{Pop}_{ct-1}$			0.282***			
			(0.039)			
$\mathbb{P}\hat{E}^S_{ct-1}$				−0.810**		
				(0.378)		
$log(Pop_{ct})$					−0.485	
					(0.323)	
Time FE	✓	✓	✓	✓	✓	✓
Census Division FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}^S_{ct} \leq 1$	0.044	0.004	0.027	0.012	0.034	0.058
R^2	0.681	0.330	0.386	0.396	0.382	0.414
Observations	3,610	4,332	4,332	3,610	3,610	3,600

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

Table 11: *Linear specification robustness checks using the IO China Trade Shock predictions*

Dependent Variable: Rescaled employment change in all industries $\hat{E}^S_{ct}$	Baseline	No $popres_{ct-1}$	Lagged Pop. Growth	Lagged Predictions	Log Population	Census Division FE
$\mathbb{P}\hat{E}^S_{ct}$	1.234***	0.551***	0.304***	1.059***	1.353***	1.006***
	(0.156)	(0.135)	(0.075)	(0.179)	(0.168)	(0.163)
$popres_{ct-1}$	0.603***			0.581***	0.602***	0.463***
	(0.051)			(0.048)	(0.050)	(0.058)
$\hat{Pop}_{ct-1}$			0.659***			
			(0.105)			
$\mathbb{P}\hat{E}^S_{ct-1}$				0.202		
				(0.121)		
$log(Pop_{ct})$					-0.318	
					(0.332)	
Time FE	✓	✓	✓	✓	✓	✓
Census Division FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}^S_{ct} \leq 1$	0.069	0.999	1	0.372	0.021	0.486
R^2	0.665	0.259	0.449	0.376	0.378	0.436
Observations	1,444	2,166	2,166	1,444	1,444	1,440

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

C. Appendix - Full linear results

C.I. Bartik Shocks

Table 12: *Linear Specification by period, Bartik shock predictions.*

Panel A. Dependent Variable: Rescaled employment change in non-manufacturing $\hat{E}_{ct}^{S,non-mfg}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	1.670***	−0.959**	0.112	1.171***	2.066***	1.160***
	(0.177)	(0.472)	(0.205)	(0.234)	(0.281)	(0.164)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	1.860***	1.611***	0.487	−0.102	0.015	0.998***
	(0.614)	(0.423)	(0.518)	(0.163)	(0.345)	(0.361)
$popres_{ct-1}$	−0.049	0.269**	0.618***	0.462***	0.721***	0.338***
	(0.223)	(0.100)	(0.205)	(0.056)	(0.092)	(0.100)
Time FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	0.000	1	1	0.234	0.000	0.167
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.084	0.077	0.837	1	0.997	0.502
R^2	0.338	0.133	0.237	0.410	0.517	0.417
Observations	722	722	722	722	722	3,610

Panel B. Dependent Variable: Rescaled employment change in manufacturing $\hat{E}_{ct}^{S,mfg}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	−0.059	−0.631***	−0.172**	0.103	0.132*	−0.093
	(0.070)	(0.119)	(0.072)	(0.085)	(0.077)	(0.060)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	1.061***	0.643***	0.903***	1.197***	1.079***	1.068***
	(0.281)	(0.236)	(0.103)	(0.073)	(0.112)	(0.110)
$popres_{ct-1}$	0.097	0.019	0.142***	0.050**	0.061***	0.089***
	(0.076)	(0.030)	(0.033)	(0.022)	(0.014)	(0.027)
Time FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	1	1	1	1	1	1
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.414	0.931	0.823	0.005	0.242	0.268
R^2	0.189	0.143	0.255	0.549	0.326	0.313
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

cont

Panel C. Dependent Variable: Overall rescaled employment change $\hat{E}^S_{ct}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}^{S,non-mfg}_{ct}$	1.611***	−1.589***	−0.059	1.274***	2.198***	1.067***
	(0.227)	(0.571)	(0.233)	(0.292)	(0.307)	(0.211)
$\mathbb{P}\hat{E}^{S,mfg}_{ct}$	2.921***	2.255***	1.390**	1.095***	1.094***	2.066***
	(0.822)	(0.601)	(0.561)	(0.186)	(0.362)	(0.439)
$popres_{ct-1}$	0.048	0.288**	0.760***	0.512***	0.782***	0.427***
	(0.279)	(0.123)	(0.221)	(0.061)	(0.097)	(0.116)
Time FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}^{S,non-mfg}_{ct} \leq 1$	0.005	1	1	0.176	0.000	0.377
P-value $H_0 : \mathbb{P}\hat{E}^{S,mfg}_{ct} \leq 1$	0.012	0.021	0.245	0.306	0.398	0.010
R^2	0.328	0.155	0.250	0.513	0.524	0.427
Observations	722	722	722	722	722	3,610

Panel D. Dependent Variable: Overall rescaled employment change $\hat{E}^S_{ct}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}^{S}_{ct}$	1.899***	−0.719	0.205	1.199***	1.759***	1.325***
	(0.247)	(0.451)	(0.243)	(0.138)	(0.176)	(0.175)
$popres_{ct-1}$	0.053	0.253*	0.660**	0.509***	0.799***	0.413***
	(0.279)	(0.140)	(0.255)	(0.063)	(0.096)	(0.117)
Time FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}^{S}_{ct} \leq 1$	0.000	1	0.999	0.078	0.000	0.035
R^2	0.317	0.080	0.218	0.512	0.517	0.702
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

cont

	Panel F. Dependent Variable: Population Change $\hat{Pop}^S_{ct}$					
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}^S_{ct}$	0.735***	0.660***	0.067	0.592***	0.484***	0.600***
	(0.062)	(0.157)	(0.115)	(0.078)	(0.150)	(0.059)
$popres_{ct-1}$	0.519***	0.779***	0.682***	0.749***	0.944***	0.683***
	(0.057)	(0.088)	(0.132)	(0.042)	(0.052)	(0.038)
Time FE	-	-	-	-	-	✓
R^2	0.613	0.543	0.528	0.794	0.737	0.607
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

I.1 Descriptive statistics

Table 13: *Employment Descriptive Statistics: Bartik shock predictions*

	N	mean	sd	median	25^{th} ptile	75^{th} ptile	min	max
				Period 1977-1982				
E_{ct}	722	85,799	250,800	20,354	6,855	61,484	127	3,124,053
$\hat{E}^{S}_{ct}$	722	13.238	12.549	11.331	5.546	19.174	−47.547	141.586
$\mathbb{P}\hat{E}^{S}_{ct}$	722	13.386	4.391	14.037	11.021	16.187	−4.716	39.549
E^{mfg}_{ct}	722	25,884	75,072	5,955	1,272	18,761	0	923,338
$\hat{E}^{S,mfg}_{ct}$	722	0.177	4.292	0.250	−2.55	3.011	−45.771	17.408
$\mathbb{P}\hat{E}^{S,mfg}_{ct}$	722	0.238	2.036	0.544	−0.928	1.272	−12.748	12.557
$E^{non-mfg}_{ct}$	722	59,916	179,114	12,890	5,188	41,284	127	2,392,668
$\hat{E}^{S,non-mfg}_{ct}$	722	13.061	9.613	11.095	7.640	15.483	−17.999	141.608
$\mathbb{P}\hat{E}^{S,non-mfg}_{ct}$	722	13.149	3.106	13.314	11.366	14.812	−2.10	39.359
				Period 1982-1987				
E_{ct}	722	97,157	280,966	21,920	7,914	69,776	124	3,579,479
$\hat{E}^{S}_{ct}$	722	20.833	15.776	20.711	12.629	32.237	−44.315	87.316
$\mathbb{P}\hat{E}^{S}_{ct}$	722	20.769	4.681	21.428	18.663	23.901	−15.775	34.302
E^{mfg}_{ct}	722	26,035	76,576	6,047	1,244	19,440	0	1,090,304
$\hat{E}^{S,mfg}_{ct}$	722	0.247	4.133	−0.365	−2.091	2.418	−24.490	55.423
$\mathbb{P}\hat{E}^{S,mfg}_{ct}$	722	0.285	1.621	0.397	−0.321	1.261	−10.691	11.824
$E^{non-mfg}_{ct}$	722	71,122	207,727	14,474	5,828	47,394	120	2,632,436
$\hat{E}^{S,non-mfg}_{ct}$	722	20.586	13.799	20.164	13.241	29.120	−47.438	76.349
$\mathbb{P}\hat{E}^{S,non-mfg}_{ct}$	722	20.483	3.861	20.827	18.941	22.826	−15.558	34.196
				Period 1987-1992				
E_{ct}	722	117,398	370,359	24,630	7,430	76,644	125	5,306,806
$\hat{E}^{S}_{ct}$	722	7.956	8.411	7.594	3.189	12.800	−40.719	108.830
$\mathbb{P}\hat{E}^{S}_{ct}$	722	8.349	2.112	8.693	7.463	9.416	−5.42	24.533
E^{mfg}_{ct}	722	26,532	79,829	6,341	1,213	19,526	2	1,275,639
$\hat{E}^{S,mfg}_{ct}$	722	−1.007	2.812	−1.052	−3.118	0.400	−41.584	23.129
$\mathbb{P}\hat{E}^{S,mfg}_{ct}$	722	−0.934	0.778	−0.790	−1.351	−0.482	−9.366	4.849
$E^{non-mfg}_{ct}$	722	90,867	294,348	16,487	5,935	57,057	118	4,031,167
$\hat{E}^{S,non-mfg}_{ct}$	722	8.963	6.461	8.745	5.422	12.228	−40.443	112.240
$\mathbb{P}\hat{E}^{S,non-mfg}_{ct}$	722	9.283	1.724	9.461	8.630	10.068	−5.075	24.618

Variables weighted by commuting zone employment; except for employment level variables.

cont.

	N	mean	sd	median	25$^{\text{th}}$ ptile	75$^{\text{th}}$ ptile	min	max
				Period 1992-1997				
E_{ct}	722	126,739	379,854	27,051	8,756	84,757	189	5,476,064
$\hat{E}^{S}_{ct}$	722	14.296	8.315	13.286	8.201	18.475	-24.990	94.535
$\mathbb{P}\hat{E}^{S}_{ct}$	722	14.449	2.210	14.687	13.546	15.884	-3.089	25.413
E^{mfg}_{ct}	722	25,105	69,263	6,494	1,244	20,740	1	1,096,407
$\hat{E}^{S,mfg}_{ct}$	722	0.520	2.346	0.299	-0.937	1.620	-38.278	36.236
$\mathbb{P}\hat{E}^{S,mfg}_{ct}$	722	0.566	1.138	0.440	0.015	1.059	-10.364	12.990
$E^{non-mfg}_{ct}$	722	101,633	314,221	19,249	6,793	65,641	177	4,379,657
$\hat{E}^{S,non-mfg}_{ct}$	722	13.776	7.184	12.534	8.824	16.701	-19.520	96.009
$\mathbb{P}\hat{E}^{S,non-mfg}_{ct}$	722	13.883	2.219	14.189	12.511	15.169	0.646	24.615
				Period 1997-2002				
E_{ct}	722	144,857	416,405	31,445	10,020	97,216	183	5,743,296
$\hat{E}^{S}_{ct}$	722	6.018	5.987	5.673	2.095	10.386	-34.213	79.047
$\mathbb{P}\hat{E}^{S}_{ct}$	722	6.245	2.797	6.857	4.870	7.726	-17.171	13.068
E^{mfg}_{ct}	722	25,764	67,918	7,150	1,575	21,921	1	1,045,100
$\hat{E}^{S,mfg}_{ct}$	722	-2.44	2.437	-1.927	-3.46	-0.908	-25.485	11.650
$\mathbb{P}\hat{E}^{S,mfg}_{ct}$	722	-2.409	1.397	-2.093	-3.051	-1.536	-16.473	5.677
$E^{non-mfg}_{ct}$	722	119,093	352,891	24,016	8,004	77,779	140	4,698,196
$\hat{E}^{S,non-mfg}_{ct}$	722	8.458	4.835	8.256	5.831	11.137	-36.953	79.023
$\mathbb{P}\hat{E}^{S,non-mfg}_{ct}$	722	8.654	1.797	8.886	7.532	9.551	-16.908	13.100
				Period 2002-2007				
E_{ct}	722	153,576	447,038	32,058	10,407	100,593	132	6,345,220
$\hat{E}^{S}_{ct}$	722	5.850	6.686	4.516	1.460	9.518	-57.557	126.757
$\mathbb{P}\hat{E}^{S}_{ct}$	722	5.942	1.620	5.738	5.324	6.639	-3.953	28.661
E^{mfg}_{ct}	722	22,230	57,487	6,545	1,427	19,292	0	934,928
$\hat{E}^{S,mfg}_{ct}$	722	-1.089	1.716	-0.955	-1.838	-0.250	-16.989	19.635
$\mathbb{P}\hat{E}^{S,mfg}_{ct}$	722	-1.069	0.815	-0.889	-1.40	-0.601	-7.828	6.517
$E^{non-mfg}_{ct}$	722	131,345	392,805	24,611	8,565	84,996	122	5,410,292
$\hat{E}^{S,non-mfg}_{ct}$	722	6.939	5.945	5.718	3.117	9.996	-58.401	118.502
$\mathbb{P}\hat{E}^{S,non-mfg}_{ct}$	722	7.012	1.099	6.917	6.330	7.382	-2.356	28.776

Variables weighted by commuting zone employment; except for employment level variables.

Table 14: *Non-Employment Descriptive Statistics: Bartik Shock*

	N	mean	sd	median	25^{th} ptile	75^{th} ptile	min	max
				Period 1977-1982				
NE_{ct}	722	973,884	1,226,815	425,766	157,759	1,387,466	7540	4,280,390
$\hat{NE}^S_{ct}$	722	2.237	7.619	1.782	-3.381	7.216	-31.537	48.163
$\mathbb{P}\hat{NE}^S_{ct}$	722	-11.344	6.552	-11.866	-15.614	-6.731	-48.169	15.382
				Period 1982-1987				
NE_{ct}	722	972,407	1,243,861	436,907	163,350	1,211,185	5850	4,629,436
$\hat{NE}^S_{ct}$	722	-9.698	11.271	-11.196	-17.157	-4.383	-41.374	73.765
$\mathbb{P}\hat{NE}^S_{ct}$	722	-20.166	10.883	-18.877	-26.251	-13.403	-86.490	24.043
				Period 1987-1992				
NE_{ct}	722	884,551	1,063,434	477,736	172,703	1,129,972	6400	3,938,249
$\hat{NE}^S_{ct}$	722	1.412	9.254	0.598	-5.931	8.157	-39.942	59.173
$\mathbb{P}\hat{NE}^S_{ct}$	722	-10.274	4.317	-9.606	-12.357	-7.202	-42.978	6.221
				Period 1992-1997				
NE_{ct}	722	895,921	1,164,552	450,110	159,392	1,045,198	5030	4,512,884
$\hat{NE}^S_{ct}$	722	-3.806	7.441	-3.812	-8.261	0.957	-24.932	52.968
$\mathbb{P}\hat{NE}^S_{ct}$	722	-19.983	7.341	-20.002	-25.182	-15.139	-66.814	-1.017
				Period 1997-2002				
NE_{ct}	722	833,950	1,126,368	389,761	153,971	1,109,976	5120	4,488,788
$\hat{NE}^S_{ct}$	722	9.117	9.181	7.831	3.443	13.181	-30.893	62.717
$\mathbb{P}\hat{NE}^S_{ct}$	722	-10.459	7.010	-10.193	-14.573	-5.717	-62.184	25.391
				Period 2002-2007				
NE_{ct}	722	911,764	1,218,000	437,800	177,727	1,184,798	4170	4,877,240
$\hat{NE}^S_{ct}$	722	6.590	8.916	5.666	1.169	11.380	-78.571	42.590
$\mathbb{P}\hat{NE}^S_{ct}$	722	-9.209	4.773	-9.425	-11.873	-6.962	-51.289	13.991

Variables weighted by commuting zone employment

Table 15: *Population Descriptive Statistics: Bartik Shock*

	N	mean	sd	median	25th ptile	75th ptile	min	max
					Period 1977-1982			
Pop_{ct}	722	302,607	828,928	93,531	37,374	243,409	1,638	10,901,224
$WPop_{ct}$	722	197,220	549,984	58,154	22,658	154,928	9430	7,283,973
$\hat{\text{Pop}}_{ct}$	722	5.249	7.170	3.059	0.080	9.671	-14.442	51.943
$\hat{\text{Pop}}_{ct-1}$	722	11.892	15.083	8.405	1.559	18.021	-18.133	116.248
$\text{W}\hat{\text{P}}\text{op}_{ct}$	722	7.059	7.359	4.478	1.719	11.990	-16.867	53.003
$\mathbb{P}W\hat{P}op_{ct}^{S}$	722	5.986	3.058	6.633	3.911	7.911	-5.868	22.577
					Period 1982-1987			
Pop_{ct}	722	318,867	860,571	96,120	38,261	258,159	1,418	12,074,781
$WPop_{ct}$	722	211,287	582,413	61,821	23,677	170,767	8590	8,208,915
$\hat{\text{Pop}}_{ct}$	722	4.699	6.376	3.091	0.869	7.519	-19.691	29.116
$\hat{\text{Pop}}_{ct-1}$	722	12.945	15.834	9.455	2.393	20.306	-18.133	116.248
$popres_{ct-1}$	722	0.514	7.116	-0.918	-5.487	4.534	-19.142	37.846
$\text{W}\hat{\text{P}}\text{op}_{ct}$	722	4.800	6.589	3.315	1.250	7.849	-21.091	27.971
$\mathbb{P}W\hat{P}op_{ct}^{S}$	722	10.018	4.571	10.602	7.348	13.242	-16.075	23.351
					Period 1987-1992			
Pop_{ct}	722	333,355	914,209	96,975	37,104	265,200	1,433	13,603,160
$WPop_{ct}$	722	221,207	620,657	61,043	22,781	172,859	8590	9,245,054
$\hat{\text{Pop}}_{ct}$	722	5.993	5.485	5.011	1.935	9.287	-16.718	42.141
$\hat{\text{Pop}}_{ct-1}$	722	5.239	6.460	3.331	1.252	8.534	-19.691	29.116
$popres_{ct-1}$	722	0.294	5.527	-1.189	-3.429	4.099	-22.641	21.560
$\text{W}\hat{\text{P}}\text{op}_{ct}$	722	4.456	5.316	3.766	-0.001	7.971	-18.040	41.698
$\mathbb{P}W\hat{P}op_{ct}^{S}$	722	4.325	1.165	4.308	3.651	4.765	-3.373	12.505

Variables weighted by commuting zone employment; except for level variables.

cont.

	N	mean	sd	median	25^{th} ptile	75^{th} ptile	min	max
				Period 1992-1997				
Pop_{ct}	722	352,863	972,104	100,044	37,306	277,854	1,272	15,072,590
$WPop_{ct}$	722	230,991	647,381	63,815	22,654	180,817	7500	9,988,948
$\hat{\text{Pop}}_{ct}$	722	6.366	5.362	4.981	3.031	8.324	-12.083	40.091
$\hat{\text{Pop}}_{ct-1}$	722	6.200	5.645	5.299	1.942	9.784	-16.718	42.141
$popres_{ct-1}$	722	0.205	5.646	-0.797	-4.012	3.890	-22.602	36.794
$\hat{\text{WPop}}_{ct}$	722	6.670	5.855	5.307	2.464	9.260	-13.371	47.991
$\mathbb{P}W\hat{Pop}^S_{ct}$	722	8.111	1.667	8.349	7.119	9.357	0.723	12.746
				Period 1997-2002				
Pop_{ct}	722	375,100	1,021,585	105,946	38,853	293,154	1,265	15,697,571
$WPop_{ct}$	722	246,447	675,878	68,500	24,788	191,321	7670	10,232,084
$\hat{\text{Pop}}_{ct}$	722	5.672	4.885	4.518	2.913	7.752	-17.782	27.896
$\hat{\text{Pop}}_{ct-1}$	722	6.678	5.616	5.347	3.367	8.887	-12.083	40.091
$popres_{ct-1}$	722	0.294	5.443	-1.642	-3.27	2.915	-16.891	33.219
$\hat{\text{WPop}}_{ct}$	722	6.993	4.900	5.724	4.026	9.679	-18.974	27.971
$\mathbb{P}W\hat{Pop}^S_{ct}$	722	3.702	2.074	4.151	2.476	4.935	-11.603	9.629
				Period 2002-2007				
Pop_{ct}	722	395,766	1,084,719	106,972	40,142	306,024	1,113	16,900,049
$WPop_{ct}$	722	263,521	727,064	70,082	25,872	199,402	6890	11,222,460
$\hat{\text{Pop}}_{ct}$	722	4.714	5.314	3.668	1.063	7.432	-18.305	29.156
$\hat{\text{Pop}}_{ct-1}$	722	5.867	4.973	4.872	3.190	7.866	-17.782	27.896
$popres_{ct-1}$	722	0.149	4.732	-0.359	-3.548	1.928	-18.552	21.918
$\hat{\text{WPop}}_{ct}$	722	5.802	5.037	5.242	2.131	7.861	-16.666	29.014
$\mathbb{P}W\hat{Pop}^S_{ct}$	722	3.457	1.607	3.572	2.961	4.341	-5.87	19.208

Variables weighted by commuting zone employment; except for level variables.

C.II. IO Price Shocks

Table 16: *Linear Specification by period, IO Price shock predictions.*

Panel A. Dependent Variable: Rescaled employment change in non-manufacturing $\hat{E}_{ct}^{S,non-mfg}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	1.587***	−0.797	−0.130	1.738***	1.516**	1.175***
	(0.290)	(0.860)	(0.468)	(0.608)	(0.574)	(0.252)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	4.414***	2.311**	−3.462**	−0.277	0.243	1.238**
	(1.154)	(1.120)	(1.282)	(0.394)	(0.712)	(0.469)
$popres_{ct-1}$	0.158	0.182	0.581***	0.423***	0.735***	0.372***
	(0.274)	(0.120)	(0.211)	(0.064)	(0.115)	(0.088)
Time FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	0.024	0.979	0.990	0.116	0.187	0.245
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.002	0.124	0.999	0.999	0.853	0.307
R^2	0.228	0.039	0.246	0.324	0.378	0.378
Observations	722	722	722	722	722	3,610

Panel B. Dependent Variable: Rescaled employment change in manufacturing $\hat{E}_{ct}^{S,mfg}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	0.011	−0.768***	−0.202*	−0.440**	−0.023	−0.088
	(0.063)	(0.262)	(0.120)	(0.169)	(0.138)	(0.062)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	1.681***	1.501**	1.146**	1.843***	1.361***	1.456***
	(0.477)	(0.603)	(0.428)	(0.181)	(0.432)	(0.179)
$popres_{ct-1}$	0.141*	−0.006	0.110***	0.029	0.047**	0.072***
	(0.079)	(0.043)	(0.034)	(0.020)	(0.020)	(0.025)
Time FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	1	1	1	1	1	1
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.080	0.205	0.367	0.000	0.204	0.007
R^2	0.171	0.043	0.129	0.466	0.176	0.258
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

cont

Panel C. Dependent Variable: Overall rescaled employment change $\hat{E}^S_{ct}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}^{S,non-mfg}_{ct}$	1.599***	-1.565	-0.332	1.297*	1.493**	1.087***
	(0.326)	(1.097)	(0.518)	(0.703)	(0.650)	(0.289)
$\mathbb{P}\hat{E}^{S,mfg}_{ct}$	6.095***	3.812**	-2.316	1.566***	1.603*	2.694***
	(1.414)	(1.608)	(1.576)	(0.498)	(0.925)	(0.565)
$popres_{ct-1}$	0.299	0.176	0.690***	0.452***	0.782***	0.444***
	(0.330)	(0.158)	(0.235)	(0.072)	(0.124)	(0.100)
Time FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}^{S,non-mfg}_{ct} \leq 1$	0.036	0.988	0.993	0.337	0.226	0.383
P-value $H_0 : \mathbb{P}\hat{E}^{S,mfg}_{ct} \leq 1$	0.000	0.043	0.980	0.130	0.259	0.002
R^2	0.242	0.037	0.222	0.439	0.379	0.387
Observations	722	722	722	722	722	3,610

Panel D. Dependent Variable: Overall rescaled employment change $\hat{E}^S_{ct}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}^{S}_{ct}$	1.965***	-0.226	-0.185	1.442***	1.536***	1.393***
	(0.334)	(0.628)	(0.469)	(0.188)	(0.246)	(0.225)
$popres_{ct-1}$	0.313	0.186	0.708***	0.454***	0.782***	0.449***
	(0.360)	(0.163)	(0.232)	(0.071)	(0.124)	(0.101)
Time FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}^{S}_{ct} \leq 1$	0.003	0.972	0.993	0.011	0.017	0.044
R^2	0.190	0.018	0.214	0.439	0.379	0.681
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

cont

	Panel F. Dependent Variable: Population Change $\hat{Pop}_{ct}^{S}$					
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S}$	0.902***	0.935***	0.324	0.575***	0.683***	0.778***
	(0.078)	(0.255)	(0.248)	(0.071)	(0.161)	(0.062)
$popres_{ct-1}$	0.576***	0.668***	0.693***	0.732***	0.930***	0.693***
	(0.072)	(0.075)	(0.127)	(0.047)	(0.051)	(0.039)
Time FE	-	-	-	-	-	✓
R^2	0.568	0.551	0.509	0.786	0.703	0.601
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

II.1 Descriptive statistics - General

Table 17: *Employment Descriptive Statistics: IO Price shock predictions*

	N	mean	sd	median	25th ptile	75th ptile	min	max
				Period 1977-1982				
E_{ct}	722	85,799	250,800	20,354	6,855	61,484	127	3,124,053
$\hat{E}^{S}_{ct}$	722	13.238	12.549	11.331	5.546	19.174	−47.547	141.586
$\mathbb{P}\hat{E}^{S}_{ct}$	722	13.242	2.607	13.120	11.816	14.850	3.370	39.221
E^{mfg}_{ct}	722	25,884	75,072	5,955	1,272	18,761	0	923,338
$\hat{E}^{S,mfg}_{ct}$	722	0.177	4.292	0.250	−2.55	3.011	−45.771	17.408
$\mathbb{P}\hat{E}^{S,mfg}_{ct}$	722	0.182	0.379	0.235	0.117	0.338	−4.985	1.753
$E^{non-mfg}_{ct}$	722	59,916	179,114	12,890	5,188	41,284	127	2,392,668
$\hat{E}^{S,non-mfg}_{ct}$	722	13.061	9.613	11.095	7.640	15.483	−17.999	141.608
$\mathbb{P}\hat{E}^{S,non-mfg}_{ct}$	722	13.059	2.555	12.884	11.447	14.539	5.004	39.132
				Period 1982-1987				
E_{ct}	722	97,157	280,966	21,920	7,914	69,776	124	3,579,479
$\hat{E}^{S}_{ct}$	722	20.833	15.776	20.711	12.629	32.237	−44.315	87.316
$\mathbb{P}\hat{E}^{S}_{ct}$	722	20.564	3.369	20.567	19.120	22.809	−20.556	29.285
E^{mfg}_{ct}	722	26,035	76,576	6,047	1,244	19,440	0	1,090,304
$\hat{E}^{S,mfg}_{ct}$	722	0.247	4.133	−0.365	−2.091	2.418	−24.490	55.423
$\mathbb{P}\hat{E}^{S,mfg}_{ct}$	722	0.252	0.844	0.365	0.031	0.723	−11.437	3.170
$E^{non-mfg}_{ct}$	722	71,122	207,727	14,474	5,828	47,394	120	2,632,436
$\hat{E}^{S,non-mfg}_{ct}$	722	20.586	13.799	20.164	13.241	29.120	−47.438	76.349
$\mathbb{P}\hat{E}^{S,non-mfg}_{ct}$	722	20.312	3.196	20.398	18.990	22.014	−20.221	29.260
				Period 1987-1992				
E_{ct}	722	117,398	370,359	24,630	7,430	76,644	125	5,306,806
$\hat{E}^{S}_{ct}$	722	7.956	8.411	7.594	3.189	12.800	−40.719	108.830
$\mathbb{P}\hat{E}^{S}_{ct}$	722	8.255	1.539	8.339	7.452	9.287	−1.959	20.499
E^{mfg}_{ct}	722	26,532	79,829	6,341	1,213	19,526	2	1,275,639
$\hat{E}^{S,mfg}_{ct}$	722	−1.007	2.812	−1.052	−3.118	0.400	−41.584	23.129
$\mathbb{P}\hat{E}^{S,mfg}_{ct}$	722	−0.981	0.441	−0.945	−1.175	−0.716	−3.343	0.735
$E^{non-mfg}_{ct}$	722	90,867	294,348	16,487	5,935	57,057	118	4,031,167
$\hat{E}^{S,non-mfg}_{ct}$	722	8.963	6.461	8.745	5.422	12.228	−40.443	112.240
$\mathbb{P}\hat{E}^{S,non-mfg}_{ct}$	722	9.236	1.176	9.326	8.687	10.071	−1.775	20.597

Variables weighted by commuting zone employment; except for employment level variables.

cont.

	N	mean	sd	median	25^{th} ptile	75^{th} ptile	min	max
				Period 1992-1997				
E_{ct}	722	126,739	379,854	27,051	8,756	84,757	189	5,476,064
$\hat{E}_{ct}^{S}$	722	14.296	8.315	13.286	8.201	18.475	-24.990	94.535
$\mathbb{P}\hat{E}_{ct}^{S}$	722	14.395	1.442	14.676	13.890	15.202	5.387	20.229
E_{ct}^{mfg}	722	25,105	69,263	6,494	1,244	20,740	1	1,096,407
$\hat{E}_{ct}^{S,mfg}$	722	0.520	2.346	0.299	-0.937	1.620	-38.278	36.236
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	722	0.535	0.399	0.498	0.308	0.698	-2.416	4.297
$E_{ct}^{non-mfg}$	722	101,633	314,221	19,249	6,793	65,641	177	4,379,657
$\hat{E}_{ct}^{S,non-mfg}$	722	13.776	7.184	12.534	8.824	16.701	-19.520	96.009
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	722	13.860	1.598	14.201	12.950	14.703	5.326	20.125
				Period 1997-2002				
E_{ct}	722	144,857	416,405	31,445	10,020	97,216	183	5,743,296
$\hat{E}_{ct}^{S}$	722	6.018	5.987	5.673	2.095	10.386	-34.213	79.047
$\mathbb{P}\hat{E}_{ct}^{S}$	722	6.026	1.959	6.102	5.113	7.206	-3.471	10.859
E_{ct}^{mfg}	722	25,764	67,918	7,150	1,575	21,921	1	1,045,100
$\hat{E}_{ct}^{S,mfg}$	722	-2.44	2.437	-1.927	-3.46	-0.908	-25.485	11.650
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	722	-2.435	1.081	-2.351	-2.897	-1.611	-7.939	-0.018
$E_{ct}^{non-mfg}$	722	119,093	352,891	24,016	8,004	77,779	140	4,698,196
$\hat{E}_{ct}^{S,non-mfg}$	722	8.458	4.835	8.256	5.831	11.137	-36.953	79.023
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	722	8.460	0.924	8.515	8.064	9.043	2.808	11.076
				Period 2002-2007				
E_{ct}	722	153,576	447,038	32,058	10,407	100,593	132	6,345,220
$\hat{E}_{ct}^{S}$	722	5.850	6.686	4.516	1.460	9.518	-57.557	126.757
$\mathbb{P}\hat{E}_{ct}^{S}$	722	5.893	1.233	6.032	5.499	6.577	-0.029	17.799
E_{ct}^{mfg}	722	22,230	57,487	6,545	1,427	19,292	0	934,928
$\hat{E}_{ct}^{S,mfg}$	722	-1.089	1.716	-0.955	-1.838	-0.250	-16.989	19.635
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	722	-1.083	0.514	-0.982	-1.207	-0.770	-4.20	3.624
$E_{ct}^{non-mfg}$	722	131,345	392,805	24,611	8,565	84,996	122	5,410,292
$\hat{E}_{ct}^{S,non-mfg}$	722	6.939	5.945	5.718	3.117	9.996	-58.401	118.502
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	722	6.975	0.772	7.015	6.680	7.392	3.612	18.274

Variables weighted by commuting zone employment; except for employment level variables.

Table 18: *Non-Employment Descriptive Statistics: IO Price Shock*

	N	mean	sd	median	25^{th} ptile	75^{th} ptile	min	max
				Period 1977-1982				
NE_{ct}	722	973,884	1,226,815	425,766	157,759	1,387,466	7540	4,280,390
$\hat{NE}^S_{ct}$	722	2.237	7.619	1.782	-3.381	7.216	-31.537	48.163
$\mathbb{P}\hat{NE}^S_{ct}$	722	-10.910	7.064	-10.063	-14.031	-6.811	-78.737	20.054
				Period 1982-1987				
NE_{ct}	722	972,407	1,243,861	436,907	163,350	1,211,185	5850	4,629,436
$\hat{NE}^S_{ct}$	722	-9.698	11.271	-11.196	-17.157	-4.383	-41.374	73.765
$\mathbb{P}\hat{NE}^S_{ct}$	722	-19.856	8.846	-19.522	-25.366	-14.127	-84.432	29.404
				Period 1987-1992				
NE_{ct}	722	884,551	1,063,434	477,736	172,703	1,129,972	6400	3,938,249
$\hat{NE}^S_{ct}$	722	1.412	9.254	0.598	-5.931	8.157	-39.942	59.173
$\mathbb{P}\hat{NE}^S_{ct}$	722	-10.459	3.746	-10.413	-12.359	-7.807	-24.049	-0.589
				Period 1992-1997				
NE_{ct}	722	895,921	1,164,552	450,110	159,392	1,045,198	5030	4,512,884
$\hat{NE}^S_{ct}$	722	-3.806	7.441	-3.812	-8.261	0.957	-24.932	52.968
$\mathbb{P}\hat{NE}^S_{ct}$	722	-19.788	6.639	-18.734	-24.676	-15.408	-63.614	-2.731
				Period 1997-2002				
NE_{ct}	722	833,950	1,126,368	389,761	153,971	1,109,976	5120	4,488,788
$\hat{NE}^S_{ct}$	722	9.117	9.181	7.831	3.443	13.181	-30.893	62.717
$\mathbb{P}\hat{NE}^S_{ct}$	722	-10.222	6.541	-9.999	-13.897	-6.329	-65.496	20.888
				Period 2002-2007				
NE_{ct}	722	911,764	1,218,000	437,800	177,727	1,184,798	4170	4,877,240
$\hat{NE}^S_{ct}$	722	6.590	8.916	5.666	1.169	11.380	-78.571	42.590
$\mathbb{P}\hat{NE}^S_{ct}$	722	-9.651	4.657	-9.386	-12.409	-6.518	-39.173	10.440

Variables weighted by commuting zone employment

Table 19: *Population Descriptive Statistics: IO Price Shock*

	N	mean	sd	median	25^{th} ptile	75^{th} ptile	min	max
Period 1977-1982								
Pop_{ct}	722	302,607	828,928	93,531	37,374	243,409	1,638	10,901,224
$WPop_{ct}$	722	197,220	549,984	58,154	22,658	154,928	9430	7,283,973
$\hat{\text{Pop}}_{ct}$	722	5.249	7.170	3.059	0.080	9.671	−14.442	51.943
$\hat{\text{Pop}}_{ct-1}$	722	11.892	15.083	8.405	1.559	18.021	−18.133	116.248
$\text{W}\hat{\text{P}}\text{op}_{ct}$	722	7.059	7.359	4.478	1.719	11.990	−16.867	53.003
$\mathbb{P}W\hat{P}op^S_{ct}$	722	5.845	3.505	5.574	3.977	7.916	−7.824	36.905
Period 1982-1987								
Pop_{ct}	722	318,867	860,571	96,120	38,261	258,159	1,418	12,074,781
$WPop_{ct}$	722	211,287	582,413	61,821	23,677	170,767	8590	8,208,915
$\hat{\text{Pop}}_{ct}$	722	4.699	6.376	3.091	0.869	7.519	−19.691	29.116
$\hat{\text{Pop}}_{ct-1}$	722	12.945	15.834	9.455	2.393	20.306	−18.133	116.248
$popres_{ct-1}$	722	0.403	6.598	−1.178	−4.663	5.400	−25.194	30.521
$\text{W}\hat{\text{P}}\text{op}_{ct}$	722	4.800	6.589	3.315	1.250	7.849	−21.091	27.971
$\mathbb{P}W\hat{P}op^S_{ct}$	722	9.922	3.459	10.121	7.967	11.958	−19.659	22.931
Period 1987-1992								
Pop_{ct}	722	333,355	914,209	96,975	37,104	265,200	1,433	13,603,160
$WPop_{ct}$	722	221,207	620,657	61,043	22,781	172,859	8590	9,245,054
$\hat{\text{Pop}}_{ct}$	722	5.993	5.485	5.011	1.935	9.287	−16.718	42.141
$\hat{\text{Pop}}_{ct-1}$	722	5.239	6.460	3.331	1.252	8.534	−19.691	29.116
$popres_{ct-1}$	722	0.381	5.762	−1.152	−3.14	3.353	−23.387	25.302
$\text{W}\hat{\text{P}}\text{op}_{ct}$	722	4.456	5.316	3.766	−0.001	7.971	−18.040	41.698
$\mathbb{P}W\hat{P}op^S_{ct}$	722	4.371	0.747	4.508	4.005	4.917	0.545	6.997

Variables weighted by commuting zone employment; except for level variables.

cont.

	N	mean	sd	median	25th ptile	75th ptile	min	max
				Period 1992-1997				
Pop_{ct}	722	352,863	972,104	100,044	37,306	277,854	1,272	15,072,590
$WPop_{ct}$	722	230,991	647,381	63,815	22,654	180,817	7500	9,988,948
$\hat{\mathrm{Pop}}_{ct}$	722	6.366	5.362	4.981	3.031	8.324	-12.083	40.091
$\hat{\mathrm{Pop}}_{ct-1}$	722	6.200	5.645	5.299	1.942	9.784	-16.718	42.141
$popres_{ct-1}$	722	0.211	5.444	-0.429	-3.963	3.878	-25.023	37.141
$\mathrm{W}\hat{\mathrm{P}}\mathrm{op}_{ct}$	722	6.670	5.855	5.307	2.464	9.260	-13.371	47.991
$\mathbb{P}W\hat{P}op^{S}_{ct}$	722	8.067	1.232	8.095	7.427	9.046	2.289	11.604
				Period 1997-2002				
Pop_{ct}	722	375,100	1,021,585	105,946	38,853	293,154	1,265	15,697,571
$WPop_{ct}$	722	246,447	675,878	68,500	24,788	191,321	7670	10,232,084
$\hat{\mathrm{Pop}}_{ct}$	722	5.672	4.885	4.518	2.913	7.752	-17.782	27.896
$\hat{\mathrm{Pop}}_{ct-1}$	722	6.678	5.616	5.347	3.367	8.887	-12.083	40.091
$popres_{ct-1}$	722	0.312	5.566	-1.127	-3.414	2.680	-18.007	33.263
$\mathrm{W}\hat{\mathrm{P}}\mathrm{op}_{ct}$	722	6.993	4.900	5.724	4.026	9.679	-18.974	27.971
$\mathbb{P}W\hat{P}op^{S}_{ct}$	722	3.662	1.929	3.924	2.653	4.950	-6.169	10.141
				Period 2002-2007				
Pop_{ct}	722	395,766	1,084,719	106,972	40,142	306,024	1,113	16,900,049
$WPop_{ct}$	722	263,521	727,064	70,082	25,872	199,402	6890	11,222,460
$\hat{\mathrm{Pop}}_{ct}$	722	4.714	5.314	3.668	1.063	7.432	-18.305	29.156
$\hat{\mathrm{Pop}}_{ct-1}$	722	5.867	4.973	4.872	3.190	7.866	-17.782	27.896
$popres_{ct-1}$	722	0.152	4.725	-0.585	-3.177	2.160	-26.886	19.987
$\mathrm{W}\hat{\mathrm{P}}\mathrm{op}_{ct}$	722	5.802	5.037	5.242	2.131	7.861	-16.666	29.014
$\mathbb{P}W\hat{P}op^{S}_{ct}$	722	3.525	1.194	3.767	2.917	4.409	-2.201	13.680

Variables weighted by commuting zone employment; except for level variables.

II.2 Descriptive statistics - Price IO exposure

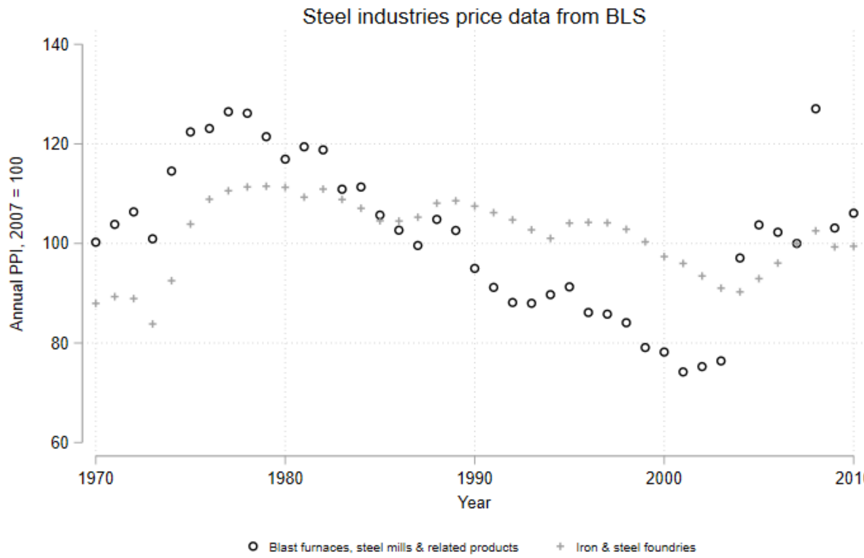


Table 20: *Descriptive Statistics steel price shock using IO 1977, IO 1987 and IO 1992 tables respectively*

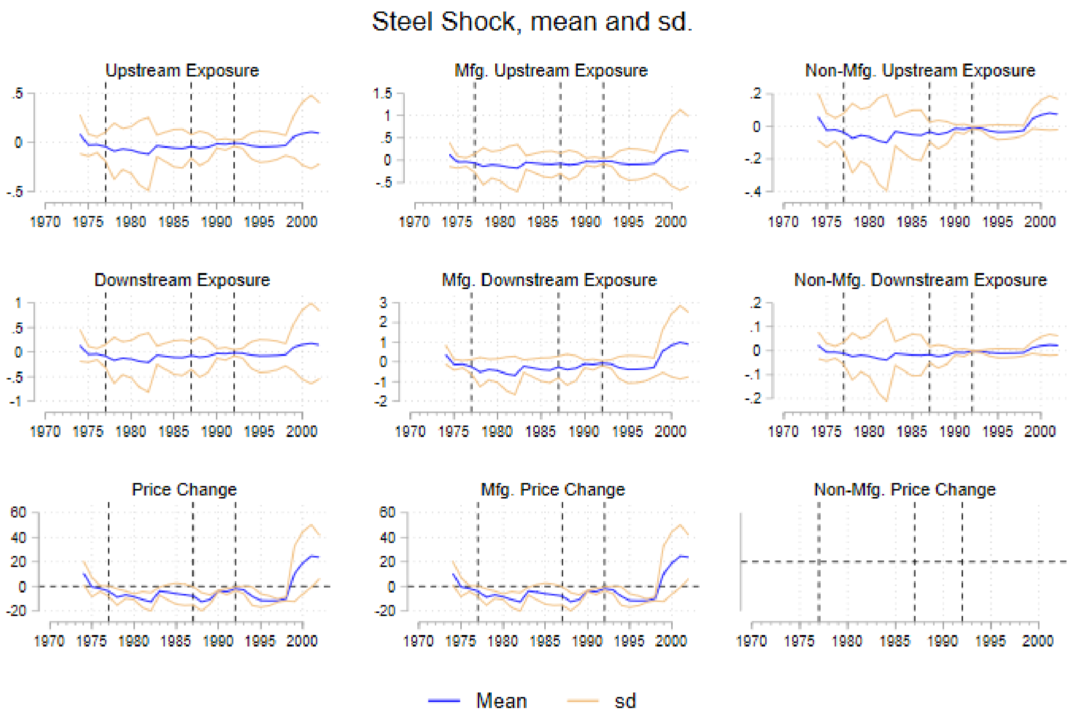
	N	mean	sd	median	25th ptile	75th ptile	min	max
				Overall				
$DE^{Steel}_{i,1977-1982}$	140	−0.083	0.235	−0.001	−0.036	0.000	−1.755	0.000
$DE^{Steel}_{i,1982-1987}$	140	−0.213	0.598	−0.002	−0.109	−0.001	−4.684	0.000
$DE^{Steel}_{i,1987-1992}$	165	−0.072	0.282	−0.001	−0.059	0.000	−2.935	0.000
$DE^{Steel}_{i,1992-1997}$	174	−0.016	0.068	0.000	0.000	0.000	−0.621	0.000
$DE^{Steel}_{i,1997-2002}$	174	−0.078	0.322	−0.001	−0.002	−0.001	−2.898	0.000
$DE^{Steel}_{i,2002-2007}$	174	0.162	0.767	0.003	0.002	0.005	0.000	7.694
$UE^{Steel}_{i,1977-1982}$	140	−0.045	0.149	−0.015	−0.032	−0.005	−1.378	0.000
$UE^{Steel}_{i,1982-1987}$	140	−0.120	0.371	−0.044	−0.092	−0.016	−3.683	0.000
$UE^{Steel}_{i,1987-1992}$	165	−0.042	0.120	−0.013	−0.041	−0.007	−1.828	0.000
$UE^{Steel}_{i,1992-1997}$	174	−0.010	0.033	−0.004	−0.012	0.000	−0.543	0.000
$UE^{Steel}_{i,1997-2002}$	174	−0.047	0.148	−0.026	−0.058	−0.001	−2.559	0.000
$UE^{Steel}_{i,2002-2007}$	174	0.107	0.343	0.058	0.001	0.142	0.000	6.728
$LE^{Steel}_{i,1977-1982}$	2	−3.926	4.245	−6.059	−6.059	0.299	−6.059	0.299
$LE^{Steel}_{i,1982-1987}$	2	−12.528	7.360	−16.169	−16.169	−5.09	−16.169	−5.09
$LE^{Steel}_{i,1987-1992}$	2	−7.784	7.358	−11.499	−11.499	−0.497	−11.499	−0.497
$LE^{Steel}_{i,1992-1997}$	2	−1.958	1.391	−2.655	−2.655	−0.569	−2.655	−0.569
$LE^{Steel}_{i,1997-2002}$	2	−11.528	1.384	−12.284	−12.284	−10.261	−12.284	−10.261
$LE^{Steel}_{i,2002-2007}$	2	23.815	17.456	32.874	6.996	32.874	6.996	32.874

Weighted by industry employment.

cont.

	N	mean	sd	median	25^{th} ptile	75^{th} ptile	min	max
				Manufacturing				
$DE^{Steel}_{i,1977-1982}$	89	−0.250	0.371	−0.136	−0.307	−0.006	−1.755	0.000
$DE^{Steel}_{i,1982-1987}$	89	−0.688	0.972	−0.364	−0.893	−0.018	−4.684	0.000
$DE^{Steel}_{i,1987-1992}$	117	−0.263	0.548	−0.043	−0.218	−0.002	−2.935	0.000
$DE^{Steel}_{i,1992-1997}$	119	−0.066	0.127	−0.007	−0.063	0.000	−0.621	0.000
$DE^{Steel}_{i,1997-2002}$	119	−0.351	0.620	−0.057	−0.305	−0.001	−2.898	0.000
$DE^{Steel}_{i,2002-2007}$	119	0.881	1.631	0.126	0.002	0.775	0.000	7.694
$UE^{Steel}_{i,1977-1982}$	89	−0.064	0.205	−0.010	−0.053	−0.003	−1.322	0.000
$UE^{Steel}_{i,1982-1987}$	89	−0.173	0.523	−0.031	−0.174	−0.011	−3.643	0.000
$UE^{Steel}_{i,1987-1992}$	117	−0.070	0.224	−0.008	−0.039	−0.002	−1.828	0.000
$UE^{Steel}_{i,1992-1997}$	119	−0.017	0.066	−0.001	−0.004	0.000	−0.543	0.000
$UE^{Steel}_{i,1997-2002}$	119	−0.084	0.305	−0.008	−0.021	−0.001	−2.559	0.000
$UE^{Steel}_{i,2002-2007}$	119	0.200	0.776	0.021	0.004	0.050	0.000	6.728
$LE^{Steel}_{i,1977-1982}$	2	−3.926	4.245	−6.059	−6.059	0.299	−6.059	0.299
$LE^{Steel}_{i,1982-1987}$	2	−12.528	7.360	−16.169	−16.169	−5.09	−16.169	−5.09
$LE^{Steel}_{i,1987-1992}$	2	−7.784	7.358	−11.499	−11.499	−0.497	−11.499	−0.497
$LE^{Steel}_{i,1992-1997}$	2	−1.958	1.391	−2.655	−2.655	−0.569	−2.655	−0.569
$LE^{Steel}_{i,1997-2002}$	2	−11.528	1.384	−12.284	−12.284	−10.261	−12.284	−10.261
$LE^{Steel}_{i,2002-2007}$	2	23.815	17.456	32.874	6.996	32.874	6.996	32.874
				Non-Manufacturing				
$DE^{Steel}_{i,1977-1982}$	51	−0.011	0.047	0.000	−0.005	0.000	−0.793	0.000
$DE^{Steel}_{i,1982-1987}$	51	−0.039	0.172	−0.001	−0.021	−0.001	−2.117	0.000
$DE^{Steel}_{i,1987-1992}$	48	−0.016	0.033	−0.001	−0.010	0.000	−0.275	0.000
$DE^{Steel}_{i,1992-1997}$	55	−0.001	0.003	0.000	0.000	0.000	−0.073	0.000
$DE^{Steel}_{i,1997-2002}$	55	−0.002	0.012	−0.001	−0.002	−0.001	−0.337	0.000
$DE^{Steel}_{i,2002-2007}$	55	0.006	0.028	0.003	0.002	0.005	0.000	0.901
$UE^{Steel}_{i,1977-1982}$	51	−0.037	0.117	−0.032	−0.032	−0.015	−1.378	0.000
$UE^{Steel}_{i,1982-1987}$	51	−0.100	0.296	−0.092	−0.092	−0.044	−3.683	0.000
$UE^{Steel}_{i,1987-1992}$	48	−0.034	0.060	−0.013	−0.041	−0.009	−0.848	0.000
$UE^{Steel}_{i,1992-1997}$	55	−0.008	0.009	−0.007	−0.012	0.000	−0.079	0.000
$UE^{Steel}_{i,1997-2002}$	55	−0.037	0.042	−0.035	−0.058	0.000	−0.383	0.000
$UE^{Steel}_{i,2002-2007}$	55	0.087	0.101	0.081	0.000	0.142	0.000	0.979
$LE^{Steel}_{i,1977-1982}$	0	–	–	–	–	–	–	–
$LE^{Steel}_{i,1982-1987}$	0	–	–	–	–	–	–	–
$LE^{Steel}_{i,1987-1992}$	0	–	–	–	–	–	–	–
$LE^{Steel}_{i,1992-1997}$	0	–	–	–	–	–	–	–
$LE^{Steel}_{i,1997-2002}$	0	–	–	–	–	–	–	–
$LE^{Steel}_{i,2002-2007}$	0	–	–	–	–	–	–	–

Weighted by industry employment.



Steel Shock, mean and sd.
Upstream Exposure
Mfg. Upstream Exposure
Non-Mfg. Upstream Exposure
Downstream Exposure
Mfg. Downstream Exposure
Non-Mfg. Downstream Exposure
Price Change
Mfg. Price Change
Non-Mfg. Price Change
1970 1975 1980 1985 1990 1995 2000
Mean
sd

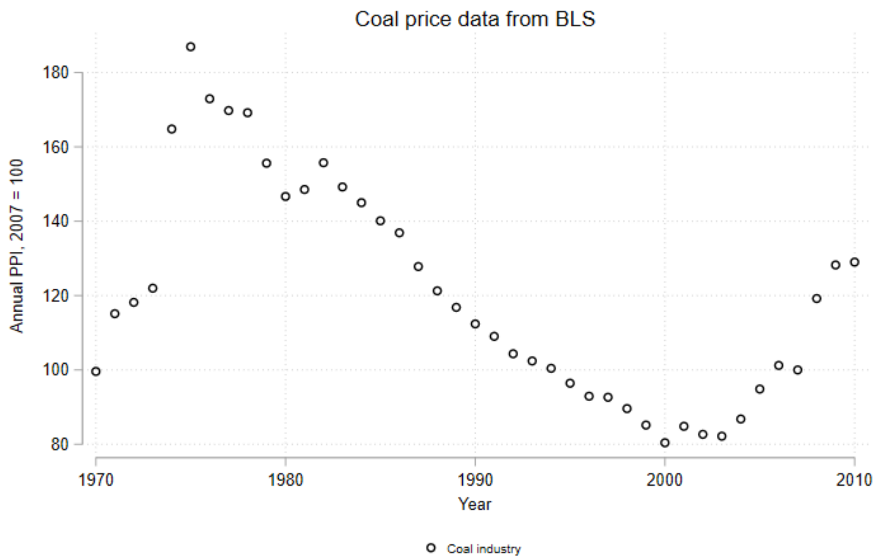


Table 21: *Descriptive Statistics coal price shock using IO 1977, IO 1987 and IO 1992 tables respectively*

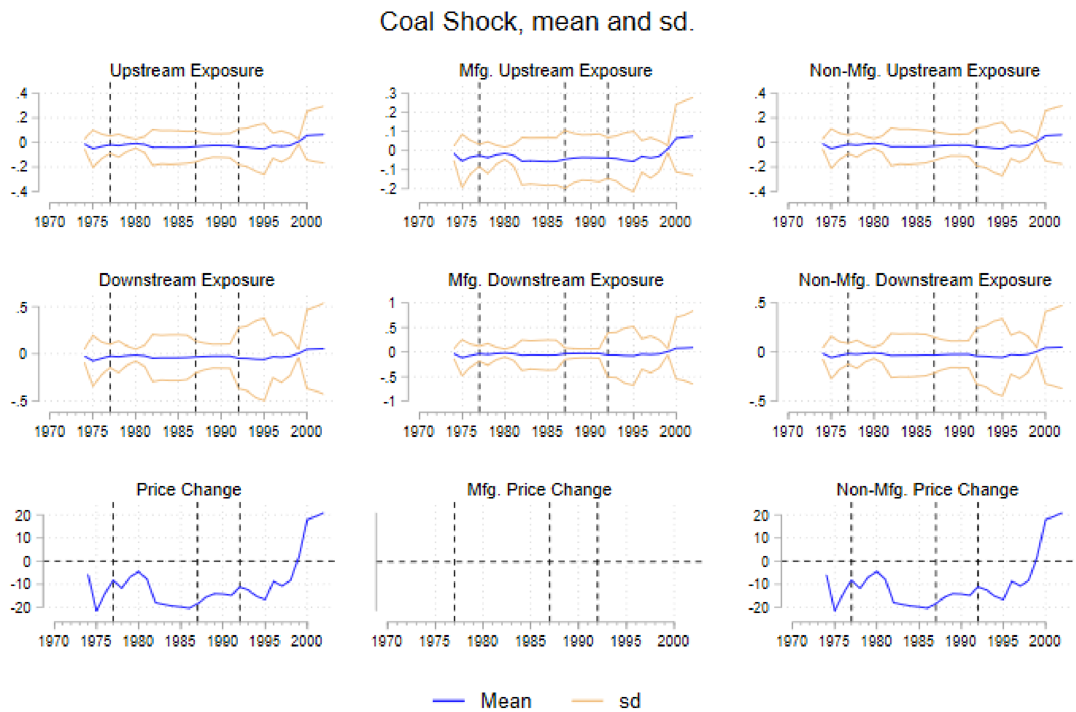
	N	mean	sd	median	25th ptile	75th ptile	min	max
				Overall				
$DE^{Coal}_{i,1977-1982}$	140	−0.022	0.123	0.000	−0.002	0.000	−1.005	0.000
$DE^{Coal}_{i,1982-1987}$	140	−0.043	0.249	0.000	−0.003	0.000	−2.181	0.000
$DE^{Coal}_{i,1987-1992}$	165	−0.031	0.168	−0.001	−0.002	0.000	−1.518	0.000
$DE^{Coal}_{i,1992-1997}$	174	−0.053	0.352	−0.004	−0.004	−0.001	−6.355	0.000
$DE^{Coal}_{i,1997-2002}$	174	−0.041	0.293	−0.003	−0.004	−0.001	−6.094	0.000
$DE^{Coal}_{i,2002-2007}$	174	0.070	0.536	0.006	0.002	0.007	0.000	11.872
$UE^{Coal}_{i,1977-1982}$	140	−0.020	0.070	−0.011	−0.011	−0.006	−0.906	0.000
$UE^{Coal}_{i,1982-1987}$	140	−0.042	0.146	−0.025	−0.025	−0.014	−1.965	0.000
$UE^{Coal}_{i,1987-1992}$	165	−0.034	0.126	−0.012	−0.021	−0.002	−1.542	0.000
$UE^{Coal}_{i,1992-1997}$	174	−0.040	0.159	−0.018	−0.026	0.000	−1.942	0.000
$UE^{Coal}_{i,1997-2002}$	174	−0.035	0.139	−0.018	−0.025	0.000	−1.862	0.000
$UE^{Coal}_{i,2002-2007}$	174	0.065	0.257	0.034	0.001	0.049	0.000	3.628
$LE^{Coal}_{i,1977-1982}$	1	−8.264	–	−8.264	−8.264	−8.264	−8.264	−8.264
$LE^{Coal}_{i,1982-1987}$	1	−17.932	–	−17.932	−17.932	−17.932	−17.932	−17.932
$LE^{Coal}_{i,1987-1992}$	1	−18.358	–	−18.358	−18.358	−18.358	−18.358	−18.358
$LE^{Coal}_{i,1992-1997}$	1	−11.216	–	−11.216	−11.216	−11.216	−11.216	−11.216
$LE^{Coal}_{i,1997-2002}$	1	−10.757	–	−10.757	−10.757	−10.757	−10.757	−10.757
$LE^{Coal}_{i,2002-2007}$	1	20.954	–	20.954	20.954	20.954	20.954	20.954

Weighted by industry employment.

cont.

	N	mean	sd	median	25^{th} ptile	75^{th} ptile	min	max
				Manufacturing				
$DE^{Coal}_{i,1977-1982}$	89	−0.034	0.155	−0.003	−0.005	−0.001	−1.005	0.000
$DE^{Coal}_{i,1982-1987}$	89	−0.065	0.311	−0.006	−0.011	−0.003	−2.181	0.000
$DE^{Coal}_{i,1987-1992}$	117	−0.031	0.118	−0.003	−0.008	−0.001	−1.518	0.000
$DE^{Coal}_{i,1992-1997}$	119	−0.059	0.446	−0.004	−0.010	−0.002	−6.355	0.000
$DE^{Coal}_{i,1997-2002}$	119	−0.047	0.373	−0.004	−0.009	−0.002	−6.094	0.000
$DE^{Coal}_{i,2002-2007}$	119	0.095	0.749	0.007	0.005	0.018	0.000	11.872
$UE^{Coal}_{i,1977-1982}$	89	−0.026	0.058	−0.007	−0.027	−0.002	−0.384	0.000
$UE^{Coal}_{i,1982-1987}$	89	−0.056	0.124	−0.015	−0.059	−0.005	−0.833	0.000
$UE^{Coal}_{i,1987-1992}$	117	−0.046	0.152	−0.004	−0.012	−0.001	−1.272	0.000
$UE^{Coal}_{i,1992-1997}$	119	−0.038	0.106	−0.005	−0.014	0.000	−0.876	0.000
$UE^{Coal}_{i,1997-2002}$	119	−0.038	0.105	−0.005	−0.020	0.000	−0.840	0.000
$UE^{Coal}_{i,2002-2007}$	119	0.075	0.204	0.010	0.001	0.038	0.000	1.637
$LE^{Coal}_{i,1977-1982}$	0	–	–	–	–	–	–	–
$LE^{Coal}_{i,1982-1987}$	0	–	–	–	–	–	–	–
$LE^{Coal}_{i,1987-1992}$	0	–	–	–	–	–	–	–
$LE^{Coal}_{i,1992-1997}$	0	–	–	–	–	–	–	–
$LE^{Coal}_{i,1997-2002}$	0	–	–	–	–	–	–	–
$LE^{Coal}_{i,2002-2007}$	0	–	–	–	–	–	–	–
				Non-Manufacturing				
$DE^{Coal}_{i,1977-1982}$	51	−0.017	0.106	0.000	0.000	0.000	−0.999	0.000
$DE^{Coal}_{i,1982-1987}$	51	−0.035	0.223	0.000	0.000	0.000	−2.168	0.000
$DE^{Coal}_{i,1987-1992}$	48	−0.031	0.181	−0.001	−0.002	0.000	−1.216	0.000
$DE^{Coal}_{i,1992-1997}$	55	−0.051	0.319	−0.003	−0.004	−0.001	−2.317	0.000
$DE^{Coal}_{i,1997-2002}$	55	−0.039	0.269	−0.003	−0.003	−0.001	−2.223	0.000
$DE^{Coal}_{i,2002-2007}$	55	0.065	0.480	0.005	0.002	0.007	0.000	4.329
$UE^{Coal}_{i,1977-1982}$	51	−0.017	0.075	−0.011	−0.011	−0.011	−0.906	0.000
$UE^{Coal}_{i,1982-1987}$	51	−0.036	0.154	−0.025	−0.025	−0.024	−1.965	0.000
$UE^{Coal}_{i,1987-1992}$	48	−0.031	0.118	−0.012	−0.021	−0.004	−1.542	0.000
$UE^{Coal}_{i,1992-1997}$	55	−0.040	0.173	−0.019	−0.026	0.000	−1.942	0.000
$UE^{Coal}_{i,1997-2002}$	55	−0.035	0.148	−0.019	−0.025	0.000	−1.862	0.000
$UE^{Coal}_{i,2002-2007}$	55	0.063	0.268	0.036	0.000	0.049	0.000	3.628
$LE^{Coal}_{i,1977-1982}$	1	−8.264	–	−8.264	−8.264	−8.264	−8.264	−8.264
$LE^{Coal}_{i,1982-1987}$	1	−17.932	–	−17.932	−17.932	−17.932	−17.932	−17.932
$LE^{Coal}_{i,1987-1992}$	1	−18.358	–	−18.358	−18.358	−18.358	−18.358	−18.358
$LE^{Coal}_{i,1992-1997}$	1	−11.216	–	−11.216	−11.216	−11.216	−11.216	−11.216
$LE^{Coal}_{i,1997-2002}$	1	−10.757	–	−10.757	−10.757	−10.757	−10.757	−10.757
$LE^{Coal}_{i,2002-2007}$	1	20.954	–	20.954	20.954	20.954	20.954	20.954

Weighted by industry employment.


Coal Shock, mean and sd.
Upstream Exposure
Mfg. Upstream Exposure
Non-Mfg. Upstream Exposure
Downstream Exposure
Mfg. Downstream Exposure
Non-Mfg. Downstream Exposure
Price Change
Mfg. Price Change
Non-Mfg. Price Change
Mean
sd

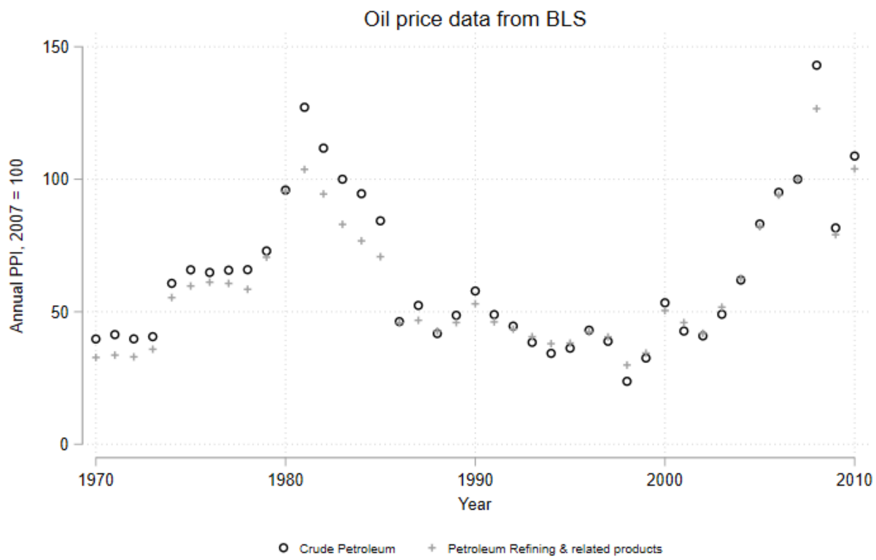


Table 22: *Descriptive Statistics oil price shock using IO 1977, IO 1987 and IO 1992 tables respectively*

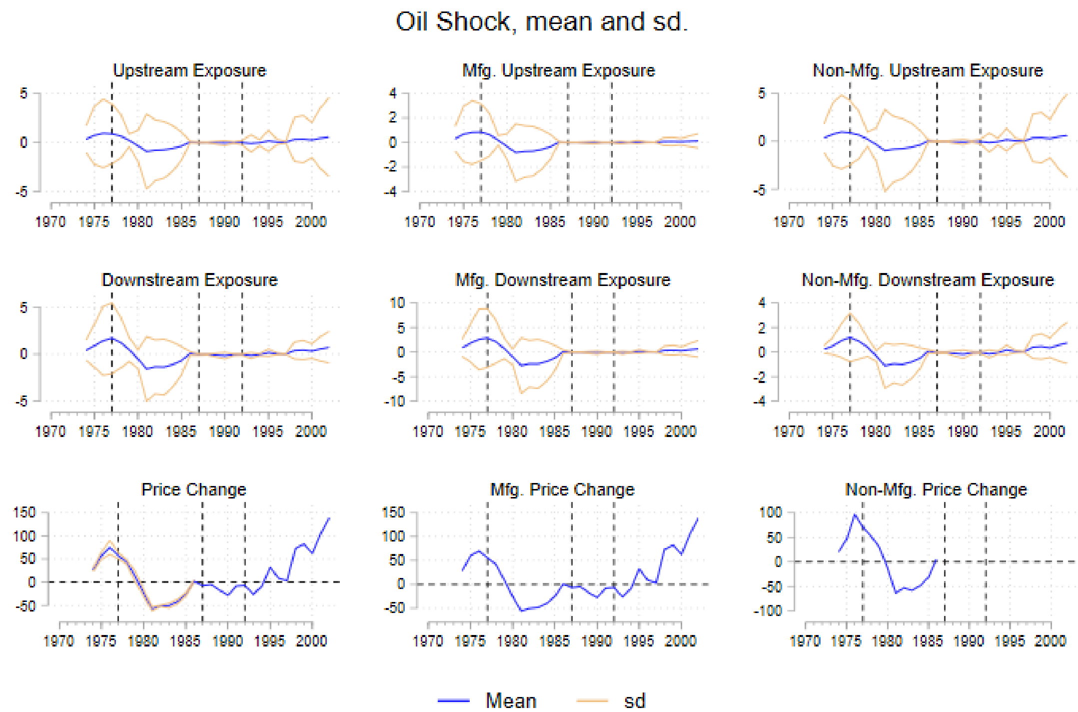
	N	mean	sd	median	25th ptile	75th ptile	min	max
				Overall				
$DE^{Oil}_{i,1977-1982}$	140	1.702	3.751	0.756	0.640	1.254	0.087	37.640
$DE^{Oil}_{i,1982-1987}$	140	−1.34	2.870	−0.613	−1.108	−0.516	−29.552	−0.072
$DE^{Oil}_{i,1987-1992}$	165	−0.040	0.087	−0.025	−0.035	−0.012	−1.81	−0.001
$DE^{Oil}_{i,1992-1997}$	174	−0.040	0.087	−0.020	−0.034	−0.013	−1.874	0.000
$DE^{Oil}_{i,1997-2002}$	174	0.021	0.045	0.010	0.007	0.017	0.000	0.940
$DE^{Oil}_{i,2002-2007}$	174	0.852	1.859	0.408	0.277	0.705	0.000	39.172
$UE^{Oil}_{i,1977-1982}$	140	0.859	3.045	0.504	0.215	0.841	0.000	76.648
$UE^{Oil}_{i,1982-1987}$	140	−0.802	3.094	−0.444	−0.731	−0.290	−69.057	0.000
$UE^{Oil}_{i,1987-1992}$	165	−0.018	0.066	−0.013	−0.037	−0.001	−4.965	0.000
$UE^{Oil}_{i,1992-1997}$	174	−0.036	0.252	−0.005	−0.031	0.000	−4.03	0.000
$UE^{Oil}_{i,1997-2002}$	174	0.015	0.113	0.003	0.000	0.016	0.000	2.022
$UE^{Oil}_{i,2002-2007}$	174	0.610	4.472	0.109	0.001	0.647	0.000	84.268
$LE^{Oil}_{i,1977-1982}$	2	57.329	6.752	55.548	55.548	55.548	55.548	70.126
$LE^{Oil}_{i,1982-1987}$	2	−50.957	1.470	−50.454	−50.454	−50.454	−53.104	−50.454
$LE^{Oil}_{i,1987-1992}$	1	−7.176	–	−7.176	−7.176	−7.176	−7.176	−7.176
$LE^{Oil}_{i,1992-1997}$	1	−6.634	–	−6.634	−6.634	−6.634	−6.634	−6.634
$LE^{Oil}_{i,1997-2002}$	1	3.329	–	3.329	3.329	3.329	3.329	3.329
$LE^{Oil}_{i,2002-2007}$	1	138.708	–	138.708	138.708	138.708	138.708	138.708

Weighted by industry employment.

cont.

	N	mean	sd	median	25^{th} ptile	75^{th} ptile	min	max
				Manufacturing				
$DE^{Oil}_{i,1977-1982}$	89	2.868	5.977	1.254	0.597	2.334	0.141	37.640
$DE^{Oil}_{i,1982-1987}$	89	−2.385	4.769	−1.108	−2.048	−0.515	−29.552	−0.116
$DE^{Oil}_{i,1987-1992}$	117	−0.028	0.086	−0.012	−0.023	−0.010	−1.81	−0.001
$DE^{Oil}_{i,1992-1997}$	119	−0.032	0.080	−0.018	−0.029	−0.010	−1.874	0.000
$DE^{Oil}_{i,1997-2002}$	119	0.016	0.040	0.009	0.005	0.014	0.000	0.940
$DE^{Oil}_{i,2002-2007}$	119	0.665	1.697	0.374	0.218	0.604	0.000	39.172
$UE^{Oil}_{i,1977-1982}$	89	0.829	2.308	0.233	0.073	0.778	0.000	16.629
$UE^{Oil}_{i,1982-1987}$	89	−0.744	2.091	−0.405	−0.664	−0.066	−15.104	0.000
$UE^{Oil}_{i,1987-1992}$	117	−0.007	0.029	−0.001	−0.004	0.000	−0.374	0.000
$UE^{Oil}_{i,1992-1997}$	119	−0.006	0.031	0.000	−0.002	0.000	−0.410	0.000
$UE^{Oil}_{i,1997-2002}$	119	0.003	0.014	0.000	0.000	0.001	0.000	0.206
$UE^{Oil}_{i,2002-2007}$	119	0.117	0.589	0.007	0.002	0.052	0.000	8.573
$LE^{Oil}_{i,1977-1982}$	1	55.548	–	55.548	55.548	55.548	55.548	55.548
$LE^{Oil}_{i,1982-1987}$	1	−50.454	–	−50.454	−50.454	−50.454	−50.454	−50.454
$LE^{Oil}_{i,1987-1992}$	1	−7.176	–	−7.176	−7.176	−7.176	−7.176	−7.176
$LE^{Oil}_{i,1992-1997}$	1	−6.634	–	−6.634	−6.634	−6.634	−6.634	−6.634
$LE^{Oil}_{i,1997-2002}$	1	3.329	–	3.329	3.329	3.329	3.329	3.329
$LE^{Oil}_{i,2002-2007}$	1	138.708	–	138.708	138.708	138.708	138.708	138.708
				Non-Manufacturing				
$DE^{Oil}_{i,1977-1982}$	51	1.197	1.992	0.756	0.640	0.756	0.087	12.539
$DE^{Oil}_{i,1982-1987}$	51	−0.957	1.558	−0.613	−0.613	−0.516	−9.708	−0.072
$DE^{Oil}_{i,1987-1992}$	48	−0.044	0.088	−0.033	−0.035	−0.024	−0.816	−0.001
$DE^{Oil}_{i,1992-1997}$	55	−0.043	0.090	−0.028	−0.034	−0.014	−0.682	−0.002
$DE^{Oil}_{i,1997-2002}$	55	0.022	0.046	0.012	0.007	0.017	0.001	0.342
$DE^{Oil}_{i,2002-2007}$	55	0.893	1.902	0.412	0.277	0.705	0.034	14.254
$UE^{Oil}_{i,1977-1982}$	51	0.872	3.336	0.504	0.504	0.911	0.000	76.648
$UE^{Oil}_{i,1982-1987}$	51	−0.824	3.411	−0.444	−0.731	−0.444	−69.057	0.000
$UE^{Oil}_{i,1987-1992}$	48	−0.021	0.074	−0.013	−0.037	−0.002	−4.965	0.000
$UE^{Oil}_{i,1992-1997}$	55	−0.045	0.289	−0.009	−0.031	0.000	−4.03	0.000
$UE^{Oil}_{i,1997-2002}$	55	0.019	0.128	0.003	0.000	0.016	0.000	2.022
$UE^{Oil}_{i,2002-2007}$	55	0.717	4.952	0.129	0.001	0.647	0.000	84.268
$LE^{Oil}_{i,1977-1982}$	1	70.126	–	70.126	70.126	70.126	70.126	70.126
$LE^{Oil}_{i,1982-1987}$	1	−53.104	–	−53.104	−53.104	−53.104	−53.104	−53.104
$LE^{Oil}_{i,1987-1992}$	0	–	–	–	–	–	–	–
$LE^{Oil}_{i,1992-1997}$	0	–	–	–	–	–	–	–
$LE^{Oil}_{i,1997-2002}$	0	–	–	–	–	–	–	–
$LE^{Oil}_{i,2002-2007}$	0	–	–	–	–	–	–	–

Weighted by industry employment.



Oil Shock, mean and sd.
Upstream Exposure
Mfg. Upstream Exposure
Non-Mfg. Upstream Exposure
Downstream Exposure
Mfg. Downstream Exposure
Non-Mfg. Downstream Exposure
Price Change
Mfg. Price Change
Non-Mfg. Price Change
Mean
sd

C.III. China Trade Shock

Table 23: *Linear Specification by period, IO China Trade shock predictions.*

Panel A. Dependent Variable: Rescaled employment change in non-manufacturing $\hat{E}_{ct}^{S,non-mfg}$			
	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	0.935*	0.739	0.307
	(0.478)	(0.608)	(0.443)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	0.048	1.081*	0.661**
	(0.366)	(0.548)	(0.283)
$popres_{ct-1}$	0.417***	0.758***	0.550***
	(0.059)	(0.113)	(0.044)
Time FE	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	0.554	0.665	0.938
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.994	0.442	0.881
R^2	0.315	0.358	0.326
Observations	722	722	1,444

Panel B. Dependent Variable: Rescaled employment change in manufacturing $\hat{E}_{ct}^{S,mfg}$			
	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	-0.268	-0.007	-0.038
	(0.293)	(0.284)	(0.214)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	1.729***	1.088***	1.388***
	(0.247)	(0.185)	(0.175)
$popres_{ct-1}$	0.037*	0.065***	0.053***
	(0.021)	(0.017)	(0.016)
Time FE	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	1	1	1
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.002	0.318	0.016
R^2	0.476	0.230	0.442
Observations	722	722	1,444

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment.
Robust standard errors in parentheses are clustered on state.

cont

Panel C. Dependent Variable: Overall rescaled employment change $\hat{E}^{S}_{ct}$			
	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}^{S,non-mfg}_{ct}$	0.667	0.732	0.269
	(0.565)	(0.718)	(0.520)
$\mathbb{P}\hat{E}^{S,mfg}_{ct}$	1.777***	2.169***	2.049***
	(0.393)	(0.624)	(0.340)
$popres_{ct-1}$	0.454***	0.823***	0.603***
	(0.066)	(0.120)	(0.051)
Time FE	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}^{S,non-mfg}_{ct} \leq 1$	0.721	0.645	0.917
P-value $H_0 : \mathbb{P}\hat{E}^{S,mfg}_{ct} \leq 1$	0.027	0.034	0.002
R^2	0.432	0.369	0.376
Observations	722	722	1,444

Panel D. Dependent Variable: Overall rescaled employment change $\hat{E}^{S}_{ct}$			
	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}^{S}_{ct}$	1.255***	1.571***	1.234***
	(0.178)	(0.268)	(0.156)
$popres_{ct-1}$	0.451***	0.832***	0.603***
	(0.067)	(0.123)	(0.052)
Time FE	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}^{S}_{ct} \leq 1$	0.079	0.019	0.069
R^2	0.430	0.367	0.665
Observations	722	722	1,444

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

cont

Panel F. Dependent Variable: Population Change $\hat{Pop}^S_{ct}$			
	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}^S_{ct}$	0.368***	0.837***	0.435***
	(0.072)	(0.204)	(0.084)
$popres_{ct-1}$	0.737***	0.959***	0.819***
	(0.044)	(0.054)	(0.036)
Time FE	-	-	✓
R^2	0.795	0.700	0.730
Observations	722	722	1,444

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

III.1 Descriptive statistics

Table 24: *Employment Descriptive Statistics: IO China Trade shock predictions*

	N	mean	sd	median	25^{th} ptile	75^{th} ptile	min	max
				Period 1992-1997				
E_{ct}	722	126,739	379,854	27,051	8,756	84,757	189	5,476,064
$\hat{E}_{ct}^{S}$	722	14.296	8.315	13.286	8.201	18.475	-24.990	94.535
$\mathbb{P}\hat{E}_{ct}^{S}$	722	14.379	2.932	15.006	13.795	15.683	-38.320	22.993
E_{ct}^{mfg}	722	25,105	69,263	6,494	1,244	20,740	1	1,096,407
$\hat{E}_{ct}^{S,mfg}$	722	0.520	2.346	0.299	-0.937	1.620	-38.278	36.236
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	722	0.522	2.538	0.504	0.131	1.404	-48.443	11.222
$E_{ct}^{non-mfg}$	722	101,633	314,221	19,249	6,793	65,641	177	4,379,657
$\hat{E}_{ct}^{S,non-mfg}$	722	13.776	7.184	12.534	8.824	16.701	-19.520	96.009
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	722	13.856	1.638	14.110	13.028	14.909	6.479	20.264
				Period 1997-2002				
E_{ct}	722	144,857	416,405	31,445	10,020	97,216	183	5,743,296
$\hat{E}_{ct}^{S}$	722	6.018	5.987	5.673	2.095	10.386	-34.213	79.047
$\mathbb{P}\hat{E}_{ct}^{S}$	722	6.016	1.995	6.144	4.911	7.404	-3.586	11.214
E_{ct}^{mfg}	722	25,764	67,918	7,150	1,575	21,921	1	1,045,100
$\hat{E}_{ct}^{S,mfg}$	722	-2.44	2.437	-1.927	-3.46	-0.908	-25.485	11.650
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	722	-2.434	1.077	-2.294	-2.954	-1.659	-7.927	-0.014
$E_{ct}^{non-mfg}$	722	119,093	352,891	24,016	8,004	77,779	140	4,698,196
$\hat{E}_{ct}^{S,non-mfg}$	722	8.458	4.835	8.256	5.831	11.137	-36.953	79.023
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	722	8.450	0.966	8.521	8.041	9.149	4.128	11.838
				Period 2002-2007				
E_{ct}	722	153,576	447,038	32,058	10,407	100,593	132	6,345,220
$\hat{E}_{ct}^{S}$	722	5.850	6.686	4.516	1.460	9.518	-57.557	126.757
$\mathbb{P}\hat{E}_{ct}^{S}$	722	5.891	1.213	6.038	5.491	6.565	-6.975	9.845
E_{ct}^{mfg}	722	22,230	57,487	6,545	1,427	19,292	0	934,928
$\hat{E}_{ct}^{S,mfg}$	722	-1.089	1.716	-0.955	-1.838	-0.250	-16.989	19.635
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	722	-1.084	0.739	-0.947	-1.316	-0.650	-11.245	0.488
$E_{ct}^{non-mfg}$	722	131,345	392,805	24,611	8,565	84,996	122	5,410,292
$\hat{E}_{ct}^{S,non-mfg}$	722	6.939	5.945	5.718	3.117	9.996	-58.401	118.502
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	722	6.975	0.558	6.989	6.837	7.290	3.902	9.840

Variables weighted by commuting zone employment; except for employment level variables.

Table 25: *Non-Employment Descriptive Statistics: IO China Trade Shock*

	N	mean	sd	median	25^{th} ptile	75^{th} ptile	min	max
				Period 1992-1997				
NE_{ct}	722	895,921	1,164,552	450,110	159,392	1,045,198	5030	4,512,884
$\hat{NE}^{S}_{ct}$	722	−3.806	7.441	−3.812	−8.261	0.957	−24.932	52.968
$\mathbb{P}\hat{NE}^{S}_{ct}$	722	−19.792	6.644	−18.878	−24.700	−15.381	−64.170	−2.766
				Period 1997-2002				
NE_{ct}	722	833,950	1,126,368	389,761	153,971	1,109,976	5120	4,488,788
$\hat{NE}^{S}_{ct}$	722	9.117	9.181	7.831	3.443	13.181	−30.893	62.717
$\mathbb{P}\hat{NE}^{S}_{ct}$	722	−10.236	6.617	−10.682	−13.594	−6.001	−65.849	22.451
				Period 2002-2007				
NE_{ct}	722	911,764	1,218,000	437,800	177,727	1,184,798	4170	4,877,240
$\hat{NE}^{S}_{ct}$	722	6.590	8.916	5.666	1.169	11.380	−78.571	42.590
$\mathbb{P}\hat{NE}^{S}_{ct}$	722	−9.607	4.239	−9.248	−12.383	−6.813	−30.655	8.514

Variables weighted by commuting zone employment

Table 26: *Population Descriptive Statistics: IO China Trade Shock*

	N	mean	sd	median	25^{th} ptile	75^{th} ptile	min	max
				Period 1992-1997				
Pop_{ct}	722	352,863	972,104	100,044	37,306	277,854	1,272	15,072,590
$WPop_{ct}$	722	230,991	647,381	63,815	22,654	180,817	7500	9,988,948
$\hat{\text{Pop}}_{ct}$	722	6.366	5.362	4.981	3.031	8.324	−12.083	40.091
$\hat{\text{Pop}}_{ct-1}$	722	6.200	5.645	5.299	1.942	9.784	−16.718	42.141
$\text{W}\hat{\text{P}}\text{op}_{ct}$	722	6.670	5.855	5.307	2.464	9.260	−13.371	47.991
$\mathbb{P}W\hat{P}op^S_{ct}$	722	8.068	1.236	8.140	7.410	9.055	2.318	11.706
				Period 1997-2002				
Pop_{ct}	722	375,100	1,021,585	105,946	38,853	293,154	1,265	15,697,571
$WPop_{ct}$	722	246,447	675,878	68,500	24,788	191,321	7670	10,232,084
$\hat{\text{Pop}}_{ct}$	722	5.672	4.885	4.518	2.913	7.752	−17.782	27.896
$\hat{\text{Pop}}_{ct-1}$	722	6.678	5.616	5.347	3.367	8.887	−12.083	40.091
$popres_{ct-1}$	722	0.312	5.613	−0.877	−3.005	2.495	−18.492	33.662
$\text{W}\hat{\text{P}}\text{op}_{ct}$	722	6.993	4.900	5.724	4.026	9.679	−18.974	27.971
$\mathbb{P}W\hat{P}op^S_{ct}$	722	3.662	1.934	3.883	2.508	5.123	−6.036	10.196
				Period 2002-2007				
Pop_{ct}	722	395,766	1,084,719	106,972	40,142	306,024	1,113	16,900,049
$WPop_{ct}$	722	263,521	727,064	70,082	25,872	199,402	6890	11,222,460
$\hat{\text{Pop}}_{ct}$	722	4.714	5.314	3.668	1.063	7.432	−18.305	29.156
$\hat{\text{Pop}}_{ct-1}$	722	5.867	4.973	4.872	3.190	7.866	−17.782	27.896
$popres_{ct-1}$	722	0.149	4.687	−0.528	−3.09	2.338	−25.464	20.071
$\text{W}\hat{\text{P}}\text{op}_{ct}$	722	5.802	5.037	5.242	2.131	7.861	−16.666	29.014
$\mathbb{P}W\hat{P}op^S_{ct}$	722	3.517	0.949	3.694	3.071	4.290	−3.573	6.100

Variables weighted by commuting zone employment; except for level variables.

III.2 Descriptive statistics - China Trade IO exposure

Table 27: *Descriptive Statistics IO China Trade shock using IO 1992 tables*

	N	mean	sd	median	25^{th} ptile	75^{th} ptile	min	max
				Overall				
$CDE_{i,1992-1997}$	174	0.205	0.359	0.099	0.073	0.165	0.012	4.641
$CDE_{i,1997-2002}$	174	0.311	0.535	0.159	0.124	0.214	−0.177	7.719
$CDE_{i,2002-2007}$	174	0.634	0.926	0.318	0.264	0.605	0.022	12.143
$CUE_{i,1992-1997}$	174	0.277	1.005	0.222	0.033	0.277	−0.015	63.373
$CUE_{i,1997-2002}$	174	0.492	1.042	0.324	0.061	0.512	0.000	38.625
$CUE_{i,2002-2007}$	174	0.924	1.596	0.555	0.127	1.064	−0.227	32.627
$CLE_{i,1992-1997}$	116	3.445	11.033	0.433	0.029	2.048	−0.541	176.976
$CLE_{i,1997-2002}$	116	6.169	16.325	0.894	0.096	3.222	−15.710	109.183
$CLE_{i,2002-2007}$	116	9.149	20.700	2.341	0.404	10.364	−1.757	131.760
				Manufacturing				
$CDE_{i,1992-1997}$	118	0.511	0.612	0.313	0.167	0.631	0.021	4.641
$CDE_{i,1997-2002}$	118	0.817	0.933	0.419	0.225	1.075	−0.177	7.719
$CDE_{i,2002-2007}$	118	1.840	1.603	1.458	0.819	2.104	0.043	12.143
$CUE_{i,1992-1997}$	118	0.668	2.003	0.323	0.097	0.857	−0.015	63.373
$CUE_{i,1997-2002}$	118	1.284	2.006	0.704	0.145	1.850	0.000	38.625
$CUE_{i,2002-2007}$	118	2.551	3.161	1.275	0.219	4.177	−0.227	32.627
$CLE_{i,1992-1997}$	116	3.445	11.033	0.433	0.029	2.048	−0.541	176.976
$CLE_{i,1997-2002}$	116	6.169	16.325	0.894	0.096	3.222	−15.710	109.183
$CLE_{i,2002-2007}$	116	9.149	20.700	2.341	0.404	10.364	−1.757	131.760
				Non-Manufacturing				
$CDE_{i,1992-1997}$	55	0.110	0.120	0.099	0.073	0.099	0.012	2.240
$CDE_{i,1997-2002}$	55	0.170	0.185	0.159	0.114	0.159	0.019	3.111
$CDE_{i,2002-2007}$	55	0.371	0.316	0.318	0.228	0.318	0.022	2.745
$CUE_{i,1992-1997}$	55	0.155	0.133	0.144	0.028	0.277	0.000	0.886
$CUE_{i,1997-2002}$	55	0.274	0.233	0.226	0.058	0.512	0.000	1.324
$CUE_{i,2002-2007}$	55	0.570	0.483	0.459	0.124	1.064	0.000	5.793
$CLE_{i,1992-1997}$	0	–	–	–	–	–	–	–
$CLE_{i,1997-2002}$	0	–	–	–	–	–	–	–
$CLE_{i,2002-2007}$	0	–	–	–	–	–	–	–

Weighted by industry employment.

D. Appendix - Full non-linear results

D.I. Bartik Shocks

Table 28: *Square Specification by period, Bartik shock predictions.*

Panel A. Dependent Variable: Rescaled employment change in non-manufacturing $\hat{E}_{ct}^{S,non-mfg}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	1.682***	2.329	-1.625	1.571***	2.750***	0.038
	(0.548)	(1.847)	(1.088)	(0.222)	(0.728)	(0.492)
$\left(\mathbb{P}\hat{E}_{ct}^{S,non-mfg}\right)^2$	0.000	-0.190	0.065	-0.026	-0.038	0.038**
	(0.017)	(0.121)	(0.043)	(0.017)	(0.029)	(0.016)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	1.860***	1.472***	0.509	-0.077	-0.054	1.040***
	(0.626)	(0.431)	(0.522)	(0.180)	(0.354)	(0.347)
$popres_{ct-1}$	-0.049	0.247**	0.616***	0.461***	0.717***	0.330***
	(0.226)	(0.108)	(0.204)	(0.056)	(0.092)	(0.097)
Time FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	0.110	0.238	0.990	0.007	0.010	0.972
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.088	0.139	0.824	1.000	0.998	0.455
R^2	0.338	0.172	0.244	0.414	0.519	0.428
Observations	722	722	722	722	722	3,610

Panel B. Dependent Variable: Rescaled employment change in manufacturing $\hat{E}_{ct}^{S,mfg}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	-0.031	-0.602***	-0.154**	0.105	0.138*	-0.092
	(0.074)	(0.120)	(0.073)	(0.082)	(0.076)	(0.066)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	1.071***	1.130***	0.836***	1.082***	0.966***	1.076***
	(0.278)	(0.393)	(0.129)	(0.132)	(0.196)	(0.140)
$\left(\mathbb{P}\hat{E}_{ct}^{S,mfg}\right)^2$	0.089*	0.156*	0.033	-0.015	-0.027	0.003
	(0.047)	(0.084)	(0.024)	(0.018)	(0.039)	(0.021)
$popres_{ct-1}$	0.093	0.027	0.139***	0.053**	0.062***	0.089***
	(0.075)	(0.028)	(0.033)	(0.021)	(0.013)	(0.027)
Time FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	1.000	1.000	1.000	1.000	1.000	1.000
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.399	0.371	0.895	0.269	0.568	0.296
R^2	0.206	0.152	0.258	0.550	0.327	0.313
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

cont.

Panel C. Dependent Variable: Overall rescaled employment change $\hat{E}^S_{ct}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}^S_{ct}$	1.104	1.871	-1.616	1.403***	1.481***	0.503*
	(0.667)	(1.173)	(1.146)	(0.139)	(0.339)	(0.284)
$(\mathbb{P}\hat{E}^S_{ct})^2$	0.022	-0.182*	0.069	-0.022	0.022	0.031***
	(0.017)	(0.099)	(0.047)	(0.015)	(0.024)	(0.011)
$popres_{ct-1}$	0.039	0.207	0.653**	0.513***	0.796***	0.398***
	(0.279)	(0.147)	(0.254)	(0.064)	(0.097)	(0.115)
Time FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}^S_{ct} \leq 1$	0.439	0.231	0.986	0.003	0.081	0.957
R^2	0.320	0.120	0.226	0.516	0.518	0.709
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

Table 29: *Spline Specification by period, Bartik shock predictions.*

Panel A. Dependent Variable: Rescaled employment change in non-manufacturing $\hat{E}_{ct}^{S,non-mfg}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	1.796***	0.313	-0.323	1.615***	2.473***	0.275
	(0.336)	(0.332)	(0.274)	(0.237)	(0.544)	(0.321)
$(\mathbb{P}\hat{E}_{ct}^{S,non-mfg} - \mu_{\mathbb{P}\hat{E}_{ct}^{S,non-mfg}})\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S,non-mfg} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S,non-mfg}}]$	-0.313	-3.10***	1.054	-0.901*	-0.567	1.368***
	(0.920)	(1.038)	(0.658)	(0.479)	(0.692)	(0.431)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	1.844***	1.350***	0.524	-0.189	-0.048	1.131***
	(0.584)	(0.447)	(0.523)	(0.171)	(0.353)	(0.348)
$popres_{ct-1}$	-0.042	0.221*	0.609***	0.455***	0.723***	0.318***
	(0.236)	(0.110)	(0.206)	(0.057)	(0.093)	(0.098)
Constant	✓	✓	✓	✓	✓	-
Time FE	-	-	-	-	-	✓
$\beta_1 + \beta_2$	1.483**	-2.787***	0.731	0.714*	1.906***	1.643***
	(0.648)	(0.863)	(0.503)	(0.390)	(0.367)	(0.221)
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	0.127	0.857	0.935	0.117	0.113	0.867
P-value $H_0 : \beta_1 + \beta_2 \leq 1$	0.296	0.929	0.656	0.701	0.123	0.105
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.193	0.289	0.735	0.954	0.896	0.386
P-value $H_0 : \beta_1 = \beta_1 + \beta_2$	0.735	0.004	0.116	0.066	0.417	0.003
R^2	0.339	0.212	0.248	0.421	0.518	0.435
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

cont.

Panel B. Dependent Variable: Rescaled employment change in manufacturing $\hat{E}_{ct}^{S,mfg}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	-0.027	-0.599***	-0.133*	0.107	0.127	-0.085
	(0.079)	(0.122)	(0.072)	(0.088)	(0.079)	(0.066)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	0.695**	0.359	0.591**	1.098***	1.058***	0.988***
	(0.296)	(0.270)	(0.244)	(0.131)	(0.143)	(0.107)
$(\mathbb{P}\hat{E}_{ct}^{S,mfg} - \mu_{\mathbb{P}\hat{E}_{ct}^{S,mfg}})\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S,mfg} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S,mfg}}]$	0.827	0.829	0.546*	0.331	0.089	0.182
	(0.661)	(0.664)	(0.312)	(0.269)	(0.412)	(0.286)
$popres_{ct-1}^{centred}$	0.092	0.025	0.137***	0.044**	0.061***	0.089***
	(0.075)	(0.028)	(0.032)	(0.018)	(0.012)	(0.027)
Constant	✓	✓	✓	✓	✓	-
Time FE	-	-	-	-	-	✓
$\beta_1 + \beta_2$	1.521***	1.188**	1.136***	1.429***	1.148***	1.169***
	(0.550)	(0.562)	(0.118)	(0.179)	(0.345)	(0.242)
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	0.976	0.976	0.980	0.969	0.971	0.981
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.755	0.873	0.829	0.296	0.377	0.536
P-value $H_0 : \beta_1 + \beta_2 \leq 1$	0.259	0.397	0.227	0.126	0.371	0.305
P-value $H_0 : \beta_1 = \beta_1 + \beta_2$	0.217	0.218	0.087	0.225	0.829	0.529
R^2	0.200	0.148	0.262	0.552	0.326	0.314
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

cont.

	Panel C. Dependent Variable: Overall rescaled employment change $\hat{E}^S_{ct}$					
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}^S_{ct}$	1.745***	0.422	-0.463	1.384***	1.329***	0.718***
	(0.434)	(0.352)	(0.367)	(0.167)	(0.221)	(0.207)
$(\mathbb{P}\hat{E}^S_{ct} - \mu_{\mathbb{P}\hat{E}^S_{ct}})\mathbb{1}[\mathbb{P}\hat{E}^S_{ct} \geq \mu_{\mathbb{P}\hat{E}^S_{ct}}]$	0.413	-3.277***	1.802	-0.508	0.824	1.051***
	(0.888)	(1.193)	(1.113)	(0.400)	(0.491)	(0.350)
$popres^{centred}_{ct-1}$	0.038	0.168	0.651**	0.508***	0.782***	0.392***
	(0.288)	(0.152)	(0.245)	(0.062)	(0.098)	(0.118)
Constant	✓	✓	✓	✓	✓	-
Time FE	-	-	-	-	-	✓
$\beta_1 + \beta_2$	2.158***	-2.854***	1.339	0.876***	2.153***	1.769***
	(0.581)	(0.984)	(0.845)	(0.314)	(0.363)	(0.256)
P-value $H_0 : \mathbb{P}\hat{E}^S_{ct} \leq 1$	0.168	0.826	0.922	0.131	0.188	0.798
P-value $H_0 : \beta_1 + \beta_2 \leq 1$	0.148	0.920	0.379	0.620	0.097	0.102
P-value $H_0 : \beta_1 = \beta_1 + \beta_2$	0.644	0.009	0.112	0.210	0.100	0.004
R^2	0.318	0.151	0.242	0.517	0.523	0.710
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

D.II. IO Price Shocks

Table 30: *Square Specification by period, IO Price shock predictions.*

Panel A. Dependent Variable: Rescaled employment change in non-manufacturing $\hat{E}_{ct}^{S,non-mfg}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	2.008**	2.492	1.258	8.792**	-1.667	0.106
	(0.771)	(2.865)	(2.021)	(3.435)	(2.285)	(0.711)
$\left(\mathbb{P}\hat{E}_{ct}^{S,non-mfg}\right)^2$	-0.012	-0.196	-0.053	-0.426*	0.158	0.034
	(0.029)	(0.203)	(0.075)	(0.214)	(0.119)	(0.026)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	4.438***	2.611**	-3.543***	-0.448	1.557	1.530***
	(1.160)	(1.176)	(1.280)	(0.327)	(1.137)	(0.489)
$popres_{ct-1}$	0.161	0.187	0.583***	0.433***	0.733***	0.370***
	(0.278)	(0.124)	(0.212)	(0.060)	(0.114)	(0.085)
Time FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	0.099	0.302	0.449	0.014	0.875	0.892
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.002	0.089	1.000	1.000	0.313	0.142
R^2	0.229	0.048	0.247	0.341	0.381	0.383
Observations	722	722	722	722	722	3,610

Panel B. Dependent Variable: Rescaled employment change in manufacturing $\hat{E}_{ct}^{S,mfg}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	0.024	-0.667**	-0.169	-0.440**	-0.128	-0.078
	(0.066)	(0.299)	(0.119)	(0.172)	(0.126)	(0.066)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	1.931***	2.955**	0.662	1.973***	2.710***	1.603***
	(0.517)	(1.275)	(0.541)	(0.405)	(0.788)	(0.275)
$\left(\mathbb{P}\hat{E}_{ct}^{S,mfg}\right)^2$	0.127**	0.700	0.447	0.021	0.405	0.040
	(0.057)	(0.606)	(0.308)	(0.066)	(0.316)	(0.047)
$popres_{ct-1}$	0.140*	-0.007	0.112***	0.028	0.039**	0.072***
	(0.078)	(0.042)	(0.033)	(0.019)	(0.018)	(0.025)
Time FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	1.000	1.000	1.000	1.000	1.000	1.000
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.039	0.066	0.732	0.010	0.018	0.017
R^2	0.180	0.050	0.135	0.466	0.191	0.259
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

cont.

Panel C. Dependent Variable: Overall rescaled employment change $\hat{E}^S_{ct}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}^S_{ct}$	2.027**	0.820	4.359*	2.069***	0.660	0.817*
	(0.901)	(2.370)	(2.502)	(0.477)	(0.733)	(0.415)
$(\mathbb{P}\hat{E}^S_{ct})^2$	-0.002	-0.070	-0.168*	-0.063	0.076	0.022
	(0.032)	(0.189)	(0.093)	(0.052)	(0.066)	(0.020)
$popres_{ct-1}$	0.313	0.189	0.712***	0.466***	0.783***	0.449***
	(0.363)	(0.169)	(0.232)	(0.067)	(0.123)	(0.099)
Time FE	-	-	-	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}^S_{ct} \leq 1$	0.130	0.530	0.093	0.015	0.677	0.670
R^2	0.190	0.019	0.219	0.444	0.382	0.683
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

Table 31: *Spline Specification by period, IO Price shock predictions.*

Panel A. Dependent Variable: Rescaled employment change in non-manufacturing $\hat{E}_{ct}^{S,non-mfg}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	2.118***	-0.071	-0.086	3.209***	-1.684	-0.109
	(0.331)	(0.645)	(0.564)	(0.706)	(1.045)	(0.550)
$(\mathbb{P}\hat{E}_{ct}^{S,non-mfg} - \mu_{\mathbb{P}\hat{E}_{ct}^{S,non-mfg}})\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S,non-mfg} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S,non-mfg}}]$	-1.375	-1.852	-0.124	-2.783**	3.397***	1.706**
	(1.357)	(2.269)	(0.737)	(1.195)	(1.244)	(0.765)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	4.530***	2.312**	-3.48***	-0.612*	2.744***	2.061***
	(1.179)	(1.058)	(1.267)	(0.329)	(1.000)	(0.597)
$popres_{ct-1}^{centred}$	0.186	0.181	0.581***	0.432***	0.734***	0.367***
	(0.298)	(0.126)	(0.212)	(0.058)	(0.111)	(0.086)
Constant	✓	✓	✓	✓	✓	-
Time FE	-	-	-	-	-	✓
$\beta_1 + \beta_2$	0.743	-1.923	-0.210	0.426	1.713***	1.597***
	(1.089)	(2.030)	(0.622)	(0.770)	(0.610)	(0.373)
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	0.092	0.827	0.848	0.098	0.882	0.853
P-value $H_0 : \beta_1 + \beta_2 \leq 1$	0.574	0.807	0.849	0.704	0.225	0.178
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.103	0.216	0.912	0.936	0.166	0.163
P-value $H_0 : \beta_1 = \beta_1 + \beta_2$	0.316	0.418	0.868	0.024	0.009	0.030
R^2	0.239	0.051	0.246	0.354	0.392	0.390
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

cont.

Panel B. Dependent Variable: Rescaled employment change in manufacturing $\hat{E}_{ct}^{S,mfg}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	-0.012	-0.625**	-0.156	-0.436**	-0.129	-0.065
	(0.074)	(0.302)	(0.115)	(0.180)	(0.124)	(0.070)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	1.951***	0.105	0.042	1.726***	1.150**	1.286***
	(0.652)	(1.074)	(0.741)	(0.272)	(0.534)	(0.188)
$(\mathbb{P}\hat{E}_{ct}^{S,mfg} - \mu_{\mathbb{P}\hat{E}_{ct}^{S,mfg}})\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S,mfg} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S,mfg}}]$	-0.929	2.879*	2.117*	0.325	1.134	0.594
	(1.203)	(1.675)	(1.135)	(0.359)	(0.761)	(0.467)
$popres_{ct-1}^{centred}$	0.139*	-0.003	0.113***	0.026	0.042**	0.073***
	(0.078)	(0.040)	(0.033)	(0.019)	(0.018)	(0.024)
Constant	✓	✓	✓	✓	✓	-
Time FE	-	-	-	-	-	✓
$\beta_1 + \beta_2$	1.021	2.984***	2.159***	2.051***	2.283***	1.880***
	(0.893)	(0.919)	(0.608)	(0.221)	(0.477)	(0.417)
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	0.977	0.941	0.969	0.960	0.965	0.979
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.191	0.721	0.790	0.114	0.413	0.185
P-value $H_0 : \beta_1 + \beta_2 \leq 1$	0.492	0.138	0.154	0.066	0.113	0.141
P-value $H_0 : \beta_1 = \beta_1 + \beta_2$	0.444	0.092	0.068	0.370	0.143	0.210
R^2	0.174	0.062	0.144	0.468	0.186	0.260
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

cont.

Panel C. Dependent Variable: Overall rescaled employment change $\hat{E}^S_{ct}$						
	1982-1987	1987-1992	1992-1997	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}^S_{ct}$	2.452***	0.121	0.192	1.831***	0.903**	0.972***
	(0.445)	(0.547)	(0.537)	(0.290)	(0.335)	(0.248)
$(\mathbb{P}\hat{E}^S_{ct} - \mu_{\mathbb{P}\hat{E}^S_{ct}})\mathbb{1}[\mathbb{P}\hat{E}^S_{ct} \geq \mu_{\mathbb{P}\hat{E}^S_{ct}}]$	-1.262	-0.903	-1.098	-1.051	1.523*	0.736
	(1.589)	(2.215)	(0.888)	(0.702)	(0.822)	(0.535)
$popres^{centred}_{ct-1}$	0.330	0.186	0.711***	0.469***	0.782***	0.451***
	(0.383)	(0.167)	(0.232)	(0.064)	(0.121)	(0.100)
Constant	✓	✓	✓	✓	✓	-
Time FE	-	-	-	-	-	✓
$\beta_1 + \beta_2$	1.190	-0.782	-0.906	0.780	2.426***	1.708***
	(1.233)	(1.872)	(0.742)	(0.492)	(0.603)	(0.403)
P-value $H_0 : \mathbb{P}\hat{E}^S_{ct} \leq 1$	0.095	0.823	0.813	0.107	0.590	0.536
P-value $H_0 : \beta_1 + \beta_2 \leq 1$	0.451	0.742	0.882	0.634	0.127	0.165
P-value $H_0 : \beta_1 = \beta_1 + \beta_2$	0.431	0.685	0.223	0.141	0.070	0.176
R^2	0.197	0.021	0.217	0.451	0.389	0.683
Observations	722	722	722	722	722	3,610

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

D.III. China Trade Shocks

Table 32: *Square Specification by period, IO China Trade shock predictions.*

Panel A. Dependent Variable: Rescaled employment change in non-manufacturing $\hat{E}_{ct}^{S,non-mfg}$			
	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	6.090*	−2.77	4.361*
	(3.477)	(5.758)	(2.523)
$\left(\mathbb{P}\hat{E}_{ct}^{S,non-mfg}\right)^2$	−0.300	0.257	−0.252
	(0.218)	(0.446)	(0.171)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	−0.219	1.167**	0.520*
	(0.374)	(0.560)	(0.286)
$popres_{ct-1}$	0.426***	0.762***	0.563***
	(0.057)	(0.113)	(0.046)
Time FE	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	0.075	0.742	0.095
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.999	0.383	0.950
R^2	0.325	0.359	0.331
Observations	722	722	1,444

Panel B. Dependent Variable: Rescaled employment change in manufacturing $\hat{E}_{ct}^{S,mfg}$			
	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	−0.281	−0.154	−0.064
	(0.300)	(0.297)	(0.223)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	1.874***	1.490***	1.544***
	(0.553)	(0.273)	(0.302)
$\left(\mathbb{P}\hat{E}_{ct}^{S,mfg}\right)^2$	0.022	0.061**	0.024
	(0.086)	(0.025)	(0.041)
$popres_{ct-1}$	0.036*	0.063***	0.052***
	(0.019)	(0.017)	(0.015)
Time FE	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	1.000	1.000	1.000
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.060	0.040	0.039
R^2	0.476	0.236	0.442
Observations	722	722	1,444

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment.
Robust standard errors in parentheses are clustered on state.

cont.

Panel C. Dependent Variable: Overall rescaled employment change $\hat{E}^S_{ct}$			
	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}^S_{ct}$	2.042***	0.717*	1.644***
	(0.570)	(0.409)	(0.415)
$(\mathbb{P}\hat{E}^S_{ct})^2$	-0.077	0.099	-0.042
	(0.058)	(0.060)	(0.047)
$popres_{ct-1}$	0.465***	0.836***	0.608***
	(0.063)	(0.121)	(0.052)
Time FE	-	-	✓
P-value $H_0 : \mathbb{P}\hat{E}^S_{ct} \leq 1$	0.037	0.754	0.064
R^2	0.438	0.372	0.666
Observations	722	722	1,444

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

Table 33: *Spline Specification by period, IO China Trade shock predictions.*

Panel A. Dependent Variable: Rescaled employment change in non-manufacturing $\hat{E}_{ct}^{S,non-mfg}$	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	2.062***	-0.092	1.305**
	(0.604)	(0.662)	(0.529)
$(\mathbb{P}\hat{E}_{ct}^{S,non-mfg} - \mu_{\mathbb{P}\hat{E}_{ct}^{S,non-mfg}})\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S,non-mfg} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S,non-mfg}}]$	-2.005*	1.847	-1.733**
	(1.151)	(1.840)	(0.850)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	-0.239	1.247**	0.559*
	(0.375)	(0.549)	(0.290)
$popres_{ct-1}^{centred}$	0.427***	0.773***	0.573***
	(0.058)	(0.111)	(0.047)
Constant	✓	✓	-
Time FE	-	-	✓
$\beta_1 + \beta_2$	0.056	1.755	-0.428
	(0.928)	(1.526)	(0.689)
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	0.165	0.827	0.334
P-value $H_0 : \beta_1 + \beta_2 \leq 1$	0.753	0.354	0.857
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.906	0.366	0.815
P-value $H_0 : \beta_1 = \beta_1 + \beta_2$	0.088	0.320	0.047
R^2	0.331	0.362	0.334
Observations	722	722	1,444

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

cont.

Panel B. Dependent Variable: Rescaled employment change in manufacturing $\hat{E}_{ct}^{S,mfg}$			
	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}_{ct}^{S,non-mfg}$	-0.274	-0.101	-0.035
	(0.298)	(0.302)	(0.217)
$\mathbb{P}\hat{E}_{ct}^{S,mfg}$	1.709***	0.990***	1.411***
	(0.311)	(0.203)	(0.200)
$(\mathbb{P}\hat{E}_{ct}^{S,mfg} - \mu_{\mathbb{P}\hat{E}_{ct}^{S,mfg}})\mathbb{1}[\mathbb{P}\hat{E}_{ct}^{S,mfg} \geq \mu_{\mathbb{P}\hat{E}_{ct}^{S,mfg}}]$	0.066	0.671	-0.099
	(0.447)	(0.439)	(0.259)
$popres_{ct-1}^{centred}$	0.036*	0.063***	0.053***
	(0.019)	(0.017)	(0.016)
Constant	✓	✓	-
Time FE	-	-	✓
$\beta_1 + \beta_2$	1.775***	1.661***	1.312***
	(0.341)	(0.411)	(0.229)
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,non-mfg} \leq 1$	0.927	0.915	0.934
P-value $H_0 : \mathbb{P}\hat{E}_{ct}^{S,mfg} \leq 1$	0.131	0.516	0.144
P-value $H_0 : \beta_1 + \beta_2 \leq 1$	0.132	0.177	0.202
P-value $H_0 : \beta_1 = \beta_1 + \beta_2$	0.884	0.134	0.703
R^2	0.476	0.236	0.442
Observations	722	722	1,444

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment. Robust standard errors in parentheses are clustered on state.

cont.

Panel C. Dependent Variable: Overall rescaled employment change $\hat{E}^S_{ct}$			
	1997-2002	2002-2007	Pooled
$\mathbb{P}\hat{E}^S_{ct}$	1.689***	1.147***	1.500***
	(0.313)	(0.293)	(0.235)
$(\mathbb{P}\hat{E}^S_{ct} - \mu_{\mathbb{P}\hat{E}^S_{ct}})\mathbb{1}[\mathbb{P}\hat{E}^S_{ct} \geq \mu_{\mathbb{P}\hat{E}^S_{ct}}]$	-1.127	1.515	-0.727
	(0.744)	(1.196)	(0.646)
$popres^{centred}_{ct-1}$	0.466***	0.844***	0.609***
	(0.062)	(0.119)	(0.052)
Constant	✓	✓	-
Time FE	-	-	✓
$\beta_1 + \beta_2$	0.562	2.662**	0.774
	(0.510)	(1.033)	(0.480)
P-value $H_0 : \mathbb{P}\hat{E}^S_{ct} \leq 1$	0.136	0.352	0.140
P-value $H_0 : \beta_1 + \beta_2 \leq 1$	0.726	0.177	0.640
P-value $H_0 : \beta_1 = \beta_1 + \beta_2$	0.137	0.211	0.267
R^2	0.443	0.374	0.667
Observations	722	722	1,444

Notes: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Observations are weighted by initial CZ share of national employment.
Robust standard errors in parentheses are clustered on state.

E. Technical Appendix

E.I. Construction of a unified SIC87OS industry classification

We construct a crosswalk between the different SIC and NAICS classifications used in the CBP data between 1974 and 2007, using a mix of manual concordance and previous work by Autor et al. (2013), Acemoglu et al. (2016) and Fort et al. (2016). The final data is available using a partially aggregated version of the 4-digit SIC87 classification - which we label SIC87OS - with 735 industries.

For the SIC72 and SIC77 to SIC87 concordance, we employ the SIC77-SIC87 bridge by Fort et al. (2016) for non-manufacturing industries and the SIC72-SIC87 concordance provided in the NBER-CES Manufacturing Industry Database for manufacturing industries.[34] The latter provides shipment weights for splits and newly created industries, which allows a complete weighted match of industries within manufacturing. Wherever necessary we allocate variables according to these weights when moving from SIC72/SIC77 to SIC87, as for example is the case with all CBP employment in manufacturing industries before 1988.

For non-manufacturing such weights are not available. Instead, we resolve many-to-many matches by creating the SIC87OS coding, which assigns the numerically smallest SIC87 code to all SIC72/77-SIC87 pairs which are of the type many-to-many or one-to-many. For example, the SIC72 industry *5013 Automotive Parts and Supplies* got split into the two SIC87 industries *5013 Motor Vehicle Supplies and New Parts* and *5015 Motor Vehicle Parts, Used*. Additionally, the SIC72 industry *5931 Used Merchandise Stores* was split into the two SIC87 industries *5015 Motor Vehicle Parts, Used* and *5932 Used Merchandise Stores*. As we cannot untangle how much employment from the former SIC72 *5931 Used Merchandise Stores* and *5013 Automotive Parts and Supplies* industries went into the new *5015 Motor Vehicle Parts, Used* industry, we assign the lowest SIC87 code in the many-to-many match to capture all employment in these industries. That is we get the following concordance:

SIC72	SIC87	SIC87OS
5013	5013	5013
5013	5015	5013
5931	5015	5013
5931	5932	5013

This way of aggregation has the implication that not all SIC87OS codes will represent the industry described in the SIC87 manual and instead some will also include additional industries. Within

[34] Note that only 3 industries differ from SIC72 to SIC77, with none of the differences being relevant for the SIC72-SIC87 concordance.

non-manufacturing, we condense 444 SIC72/77 industries and 460 SIC87 industries to 370 SIC87OS industries. There is no cross-pollination of manufacturing and non-manufacturing using this approach. Within manufacturing we further use another set of aggregations, corresponding to the SIC87DD coding from Autor et al. (2013) and Acemoglu et al. (2016) which aggregates a few industries to fit the available trade data for the China Trade Shock.

After 1997 CBP started using the NAICS classification. We use the Acemoglu et al. (2016) NAICS97-NAICS02 and SIC87-NAICS97 concordances which include employment weights for each match to once again get data on the SIC87OS level. Two more manual changes are made in the process. We change SIC87 *1061 Ferroalloy Ores* to *1099 Metal Ores N.E.C*, as only *1099 Metal Ores N.E.C* is recognized in the NAICS crosswalk. Furthermore, we fix a minor mistake where the NAICS97 *813940 Political Organizations* were matched to the SIC87 *8660 Religious Organizations* instead of the correct *8650 Political Organizations* in the original crosswalk.

The exact handling of 4-digit SIC codes is often inconsistent across sources. In order to unify the varying crosswalks used here and for the price and IO data later on, we adopt the general pattern of assigning industries a trailing 0 if they are the only industry 4-digit industry in their 3-digit industry group. E.g. we change SIC87 *1011 Iron Ores* to SIC87OS *1010 Iron Ores*, as there is no other 101x industry besides Iron Ores.

E.II. Construction of Producer Price Index Data

We collect producer prices for three broad industries, steel, coal and oil. We follow the same collection and construction process for each broad industry. First, we identify the relevant 4-digit SIC87 codes related to each broad industry. Then we track the respective NAICS17 codes for each of the SIC87 codes in order to gather industry-level producer price indeces from the BLS that continue after the switch to the NAICS in 1997. For many industries the BLS industry PPI does not cover our whole timespan. In these cases, we further look for commodity price series. We identify which commodities are produced by each NAICS17 industry we observe and then gather the relevant BLS commodity price indeces. Once again the commodity price series does not always cover a greater timespan than the PPI. In these cases we complement the data with discontinued commodity price series, now based on the SIC87 commodity content. We then match the BLS PPI with either the BLS CPI or the discontinued BLS CPI as follows. If there are multiple commodities per industry, we normalize the different series to a base year that exists for all commodities and then take the mean of over all commodities to get a general industry CPI. We then merge the CPI and PPI. We note that in overlapping years the CPI and PPI have a correlation of at least 0.9 for all industries.[35] We then once more rebase the CPI and PPI series to a common year and take the

[35]For two industries, SIC87 3324 and 3325 the PPI and discontinued CPI have only a partial overlap in one year. Here we rescale on that single year. The fact that CPI and PPI are highly correlated in all other industries gives us confidence that

mean in the overlapping years to generate one long-running producer price series by industry. We further deflate all series by the general CPI to 2007 levels to keep relative changes comparable. Tables 34-36 show the industries and the respective commodity series we use for the construction. Some other industries were not included due to various reasons.

- *3313 Electrometallurgical products* does not include steel products.
- *1241 Coal Mining Services*, *1381 Drilling Oil and Gas Wells*, *1382 Oil and Gas Field Exploration Services* and *1389 Oil and Gas Field Services, nec* are coal and oil related service industries that don't necessarily follow the resource price trend immediately.
- *2992 Lubricating Oil and Greases* includes animal and vegetable materials besides oil.
- *2999 Products of Petroleum and Coal, nec* has no CPI (discontinued or not) or PPI data before 1985.

this approach does not introduce a significant error.

Table 34: *Steel PPI/CPI Concordance*

Name	Type	Code	Timespan
Steel Works, Blast Furnaces and Rolling Mills	SIC87/NAICS17	3312/331221	1967-
Steel Wiredrawing and Steel Nails and Spikes	SIC87/NAICS17	3315/331222	1983-
	Discontinued Commodities	WDU10880211	1947-1996
		WDU10880213	1963-1996
		WDU10880621	1947-1996
		WDU10880951	1947-1990
		WDU10890141	1955-1978
		WDU10890146	1955-1980
		WDU10130286	1947-1981
		WDU10130287	1954-1981
		WDU10130288	1954-1981
		WDU10130292	1963-1981
		WDU10130294	1947-1981
		WDU10130297	1978-1981
		WDU10170511	1947-1996
Cold-Rolled Steel Sheet, Stip, and Bars	SIC87/NAICS17	3316/331221	1967-
Steel Pipe and Tubes	SIC87/NAICS17	3317/331210	1967-
Steel Investment Foundries	SIC87/NAICS17	3324/331512	1981-
	Discontinued Commodities	WDU10150141	1947-1980/1981*
Steel Foundries, nec	SIC87/NAICS17	3325/331513	1981-
	Discontinued Commodities	WDU10150141	1947-1980/1981*

* 1981 average manually computed from months January-June

Table 35: *Coal PPI/CPI Concordance*

Name	Type	Code	Timespan
Bituminous Coal and Lignite Surface Mining	SIC87/NAICS17	1221/212111	2002-
	Commodities	0512	1926-
Bituminous Coal Underground Mining	SIC87/NAICS17	1222/212112	2002-
	Commodities	0512	1926-
Anthracite Mining	SIC87/NAICS17	1231/212113	1980-
	Commodities	0511	1926-

Table 36: *Oil PPI/CPI Concordance*

Name	Type	Code	Timespan
Crude Petroleum and Natural Gas	SIC87/NAICS17	1311/211111*	1986-
	Commodities	0561	1947-
Petroleum Refining	SIC87/NAICS17	2911/324110	1977-
	Commodities	057	1947-

The actual NAICS17 code is 211120, however at the time of data extraction the BLS was still using the older NAICS code 211111.

E.III. Concordance of Input-Output Tables with the SIC87OS classification.

The BEA IO data uses yet another industry classification system, which changes across the years. Fortunately crosswalks to SIC77 and SIC87 are provided. Currently we match IO tables from 1977, 1987 and 1992 to our SIC87OS classification based on the provided crosswalks. We switch from one IO table to the next with the years of their publication, i.e. we use the 1977 IO table until 1986, the 1987 IO table until 1991 and the 1992 IO table thereafter. In case a 5-year period overlaps a publication year the IO table for the base year is also used to compute employment weights at the end of the period to ensure a match in industries. For example, for 1982-1987 the 1977 IO table is used for both years, for 1987-1992 we use the 1987 IO table in both years and for 1992-1997 the 1992 IO table. This is necessary as the IO-SIC concordances change slightly between the years meaning that industry classifications are not consistent across time after we join the IO data. Additionally, matching the IO industry codes to the SIC codes requires frequent and large many-to-many match. In order to not lose any information we create a separate set of aggregate industries for each IO table, which encompasses all SIC and IO industry codes that are included in a given many-to-many match. Following the aggregate industry coding, we are left with 141 industries using the 1977 IO concordance, 161 industries using the 1987 IO concordance and 176 industries using the 1992 IO concordance. The price index data we collected on the SIC87OS level now match to two aggregate steel industries, one aggregate coal industry and one aggregate petrol industries, where we use the simple mean to aggregate multiple price series from the SIC87OS to the aggregate industry level. For oil price data we initially have two aggregate industries remaining using the 1977 IO concordances, but only one in the other two concordances.