Evaluating the Accuracy of Regional Economic Impact Estimates: Considering a 2013 Beef Plant Closure in Texas

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Abstract

Many studies rely on regional economic impact analysis to estimate the larger effects of an event on a community, such as a plant opening or closure. However, few conduct an ex post analysis to consider how close the estimates were to actual economic events that ensued. This study examines the accuracy of a previous impact analysis of the closure of a Texas beef packing plant. The challenges of validating economic impact studies are demonstrated and several suggestions are offered for improving ex ante and ex post modeling efforts to help future researchers maintain the credibility of economic impact studies.

1 Introduction

Many studies rely on economic impact, or input-output (I-O), analysis to estimate economy-wide effects of hosting an event, gaining a new business, or in some cases, losing a local business. Caution must be taken to avoid over-estimating economic impacts by closely examining expected changes. Failure to think critically about assumptions and methods leads to inaccurate results (Swenson, 2006; Kinnaman, 2011). Even when the highest level of care in model-building is taken, estimated results will rare match actual outcomes. The economic machine has many moving parts, and it can be very difficult for researchers to isolate effects attributable to a single change in the regional economy. It is understandable that economic events cannot be predicted exactly; however, researchers should attempt to validate their model in order to reduce error as much as possible.

Relatively few researchers conduct an ex post analysis of impact studies' accuracy. To do so is almost to invite reputational risk. Impact analysis estimates the economic changes expected from an isolated event in absence of any other shocks. This is, of course, an unrealistic scenario as economies experience constant local and global change. General upticks or downturns in the economy or the trajectory of an unrelated industry can exacerbate or obscure economy-wide impacts. Following a plant opening or closure, other businesses may languish or boom in response to clustering effects and the availability of or competition for specialized labor and capital. Static economic analysis tools do not account for such agglomeration effects.

Ex ante, analysts cannot anticipate unrelated economic shocks. While some clustering effects may be expected, they are often outside the scope of static I-O estimates, and the process of tracking these linkages across multiple value chains with overlapping industries can be complex. Ex post, researchers can expect their estimates to differ from official data on economic growth or decline simply because economies are realize multiple positive and negative internal and external shocks within any given period. This presents

an additional challenge in determining whether the difference in predicted and observed changes are due to modeling error or other shocks. Still, an understanding of the assumptions and methods that promote accuracy in impact estimates, including the accounting of economic activity beyond the original event, is essential to the improvement of future models and the continued credibility of impact analysis studies. Davis (2001) notes that ex post studies provide information to improve the design of future ex ante impact studies and a standard against which ex ante analyses can be measured.

This paper evaluates the accuracy of assumptions and methods used in modeling both the direct and further regional economic impacts of the 2013 closure of the Cargill beef packing plant in Plainview, TX. The paper begins with a brief explanation of I-O, its benefits and its criticisms as well as a review of previous efforts to measure model accuracy. An overview of the original results of the plant closure study follows, along with an explanation of this study's methods and results. Finally, the estimated impacts and actual economic changes are compared and discussed, leading to the identification of best practices and further concerns related to I-O modeling.

2 Literature Review

2.1 Input-output Modeling

Several papers detail the theory and construction of I-O models (Miernyk, 1965; Holland and Wyeth, 1993; Shaffer, 1999; Davis, 2001). Input-output models account for transactions between industries, households, other institutions, and the world outside the modeled economy (Shaffer, 1999). Critically, I-O models are limited in that production recipes are fixed; sector x always purchases the same value of sector y's product (Davis, 2001). It is possible to change or customize purchase coefficients for a particular project, but the coefficient will be constant throughout the project. There are no constraints on resource availability, which facilitates the assumption of fixed prices and production or cost functions. Increasing employment does not drive up wages. Thus businesses will not substitute capital for labor, chicken for beef, or imported beef for local beef. Growth (or conversely decline) is linear and unlimited. These characteristics suggest some obvious limitations in estimating changes to an economy that, in reality, experiences constant technological change, supply and price shocks, evolution of consumer preferences, and agglomeration effects. Furthermore, economies experience multiple, unrelated shocks within a given year.

Economic impact analysis is used to estimate the impacts of changing final demand sales within a study area. Closely related, contribution analysis studies show how ongoing activity interacts within the broader economy (Watson et al., 2007). Within agriculture and agribusiness, impact analysis is often used to estimate the expected economy-wide changes due to a new facility or industry either before or during the construction or start-up phase (De La Torre Ugarte et al., 2007; Kebede and Ngandu, 1999). Studies measuring the contribution of ongoing economic activity, such as agricultural production or farmers markets, are also common (Amosson et al., 2014, 2012, 2009; McCorkle et al., 2016, 2014, 2011; Guerrero et al., 2012; Hughes et al., 2008; Deller, 2014). The impacts of natural disasters (Rose et al., 1997), pest infestation (Zapata et al., 2018), and government programs and policies (Reimer et al., 2017) are other popular topics. Many of these studies are commissioned by trade associations and other groups hoping to encourage public support, favorable policies, and/or public funding for the business or industry (John Dunham and Associates, 2016; Williams et al., 2016; Kaiser, 2016).

IMpact analysis for PLANning (IMPLAN) is used for many economic impact and contribution analyses. Specifically within the meat industry, a study was conducted which identified economic contributions from U.S. meat processing, poultry processing, rendering, hide and skin production, and offal production (John Dunham and Associates, 2016). The study found the meat and poultry industry contributed $1.0T in total economic output to the national economy.

Thompson et al. (2012) found that Nebraska's non-poultry livestock slaughter facilities contributed 51,900 jobs and $3.3 billion to the state's gross domestic product (GDP). Also using IMPLAN, Brown et al. (2016) found that beef slaughter facilities contributed 5,700 jobs and $533 million to Missouri's GDP. Informa Economics (2011) estimated a $489.1 million annual impact on Illinois GDP and 5,500 jobs from the establishment of a new East Moline pork processing plant.

Appiah et al. (2015) ex ante analysis of a 260-worker beef plant closure in Windom, MN, estimated a loss of 409 jobs, $14.1 million in labor income, and $151.3 million in output across the county economy. While their model estimated a loss to the cattle ranching sector, they noted that farmers would probably find other buyers for their cattle. The authors also predicted a loss of 92 jobs and $6.4 million in labor income in seven neighboring counties.

Broadway and Stull (2006) described the loss of a 2,300-worker Garden City, KS beef processing plant to a Christmas 2000 fire. Four years later, the plant remained closed with ConAgra refusing to consider purchase offers. In 2001, the unemployment rate tripled from 2.9 percent to 9.6 percent but had almost returned to pre-fire levels by 2003. Although overall county employment had shrunk by 1,900 jobs, the situation was compounded by a national recession.

One reason impact studies receive negative attention is the common practice of using them as cost-benefit analyses and using indirect and induced effects in calculating benefits. Another source of negative publicity is the inflation of impacts (Swenson, 2006; Kinnaman, 2011). While input-output models are relatively inexpensive and easy to use, they are static, assuming fixed prices and production relationships and an economy at less than full employment of labor and other resources. These assumptions may be appropriate in measuring some short-term impacts, but tend to over-estimate long-term change by ignoring potential redeployment and flexible pricing of capital, labor, and other inputs. Researchers should make every effort to validate their work to minimize model error given the propensity for suspicion of impact analysis by the public (Shafer, 2017) and concern about potential misuse (Hall, 2004; Crompton, 2006; Swenson, 2006).

2.2 Ex Post Evaluation of I-O Estimates

Ex post validation is difficult for several reasons. First, many studies measure relatively small events within a larger economy, such as the opening of a new business or an annual tourist event, and the economic effects of this isolated business or event can be difficult to entangle from a broader and constantly changing economy. Second, several studies measure the contribution of a large industry or major crop, but fluctuations due to global prices and weather make it difficult to isolate effects in a single year. Economic analysts contracted outside the community are unlikely to stay abreast of business openings, expansions, contractions, or closures, especially those unrelated to the shock they originally studied. Sorting out the effects of all these other shocks, which may be individually small but cumulatively significant, is often time-consuming. Production technology is constantly changing, and neither technological change nor production efficiencies from clustering are readily reflected in static I-O models, although these changes can be accounted for with sufficient data. Many times, researchers who provide impact or contribution analyses have moved on to new projects by the time data is available to verify accuracy, often several years later.

Stynes (1999) noted that, even when ex post evaluation is not possible, I-O studies benefit from "the ability to compare impact estimates with the observed levels of economic activity in each sector" (p. 17) and from observing whether the outcome seems logical given the overall size and structure of the regional industry and economy. Several researchers have compared various regional economic impact models as a way to verify the reasonableness of estimates: IMPLAN and REMI (Rickman and Schwer, 1993); IMPLAN and GAMS (Cassey et al., 2011); ACDS and IMPLAN (Mulligan et al., 2013); and JEDI and IMPLAN (Bae and Dall'Erba, 2016). It is also fairly common to report reasons for adjustments to a model, social accounting matrix, or methodology relative to a default version (Schwarm et al., 2006; Seung, 2014; Watson et al., 2015).

Blalock and Montgomery (2008) compared 2001 and 2006 IMPLAN estimates and found wide variation in total value added, employee compensation, and especially proprietors income. They calculated 2006 IMPLAN results that vary from 56 percent (total employment) to 476 percent (total proprietors income) when compared to estimates using 2001 data. They posited that proprietors were hard-hit by the 2001 recession or that the IMPLAN data process may have become "more (or less) pure" (p. 2) between 2001 and 2006. The nature of contribution studies appears to have prevented them from comparing their estimates to official state data. Nevertheless, their study emphasized the need to carefully consider the selection of multipliers.

2.3 Closure of the Cargill Beef Plant in Plainview, TX

Cargill announced in January 2013 that it would close its Plainview, TX, beef packing plant beginning in February. Texas A&M AgriLife Extension Service economists were asked to produce an economic estimate of the plant's closure on Hale County, where the plant was located, and on the surrounding counties of Castro, Floyd, Lamb, and Swisher, where many commuting workers resided.

Data on the plant and its closure were scarce. The local AgriLife Extension agriculture agent was able to confirm that the 2,000 lost jobs reported by media outlets were accurate. Data on annual plant sales, wages, or taxes were not available. A ReferenceUSA report available through Texas A&M's subscription to the database service indicated a 2012 local sales volume of $1,667,514,000 and corroborated the employment of 2,000 workers (ReferenceUSA, 2013). However, that sales volume seemed high based on local perceptions and IMPLAN data, which placed sales around $1 billion. The 2009 IMPLAN (2017) data reported 2,145 meat packing jobs and $947,225,000 in sales for Hale County, which included some small processing plants. Further, the plant's closure was coming on the heels of a national recession and drought, and cattle inventories had been falling in Texas and the U.S. (USDA-NASS, 2013, 2016a,b), although prices were rising (Schulz, 2017). Still, Cargill cited tight cattle supplies as the reason for the closure so an assumption that the plant was operating at full capacity was suspect. Desiring accurate but conservative estimates tempered by available data, the study elected to use employment of 2,000 jobs and an adjusted sales amount of $866,616,697 based on that employment using IMPLAN data.

A decrease in cattle numbers had already occurred in the region and was a cause, not an effect, of the plant closure. Furthermore, existing and future cattle from feedlots in the region were likely to be shipped to plants in other locations. To eliminate overestimation of cattle ranching impacts, the animal slaughter spending pattern was modeled in the default state with the local purchase percentage for cattle set to zero, and the difference between the spending pattern impacts was subtracted from the full industry change model based on plant sales and employment. This allowed changes in purchase patterns by remaining businesses and households to continue to affect the local ranching sector.

The loss in output was attributed completely to Hale County because the plant's sales were based in this county alone. This sales figure served as loss to final demand based on the understanding that almost all the product was exported outside the county. Jobs and wages were apportioned according to plant commuting estimates the county agent obtained from local sources as well as US Census Bureau (2012) commuting data. While the jobs were directly located in Hale County, more than a quarter were held by people living outside the county. Only 1,462 jobs and $41,017,872 in labor income were attributed to Hale County with the remaining jobs and $19 million in income being apportioned to other counties (Dudensing et al., 2013). This was accomplished by running the impact of the $866 million loss and 2,000 jobs in Hale County and then subtracting the direct and induced impacts of the jobs and labor income attributed to other counties. This method had the advantage of capturing indirect effects and the induced effects resulting from those indirect effects in the central, regional trade center (Hale County) while still attributing spending from wages by commuting workers to their home counties. In truth, this method further contributed to conservative estimates of Hale County impacts because plant workers were likely to spend part of their wages at Plainview businesses for items such as gas and groceries. Literature supports this logic as it has been determined that retail sales are higher in locations with in-commuting and lower in places with out-commuting (Burkey and Harris, 2003; Shields and Deller, 1998).

The 2013 ex ante report estimated direct losses of more than $867 million in gross sales, $60 million in labor income, and 2,000 jobs resulting in a total loss of $1 billion in gross sales, $97 million in labor income, and 2,595 jobs in Hale County alone (Table 1) (Dudensing et al., 2013).

Economic losses in surrounding counties were primarily a result of reduced incomes. Losses ranged from $70,800 to $436,000 in gross sales (Table 2). These figures are low relative to the $4.4 million in income loss across the four counties because of leakages in spending. A large portion of residents' incomes are spent outside these counties in larger trade centers such as Plainview, Lubbock, and Amarillo (Dudensing et al., 2013).

Table 1: Economic loss impacts of packing house closure on Hale County, net of workers residing in surrounding counties.

Impact Type	Output	Value Added	Labor Income	Employment
Direct Effect	$866,616,700	$199,865,500	$45,719,100	1,462.00
Indirect Effect	$132,918,800	$63,935,400	$39,784,700	767.4
Induced Effect	$36,872,300	$22,056,100	$11,667,400	366
Total Effect	$1,036,407,800	$285,856,900	$97,171,200	2,595.40

Table reproduced from the original 2013 report (Dudensing, et al., 2013).

Table 2: Induced economic loss impacts to surrounding counties resulting from reduced labor income.

County	Output	Value Added	Labor Income	Employment
Castro	$70,800	$44,700	$25,000	0.6
Floyd	$436,000	$278,500	$122,000	4.6
Lamb	$284,600	$180,900	$78,700	2.6
Swisher	$418,600	$250,500	$113,000	4.4

Table reproduced from the original 2013 report (Dudensing, et al., 2013).

3 Methods

In theory, validating economic impact estimates relative to actual change is a simple equation with the difference between predicted and actual economic changes. The input-output modeling framework (Miernyk, 1965; Shaffer, 1999) reduces to

$$X_i = X_{ij} + Y_i \tag{1}$$

where total sales by a sector i (X_i) is the sum of sector i*'s* intermediate sales to all other sectors j including to household sectors (X_{ij}) and final demand sales (Y_i). Dividing industry j*'s* use of industry i*'s* product by the sum of industry i*'s* total sales results in a direct requirements table that describes demand by sector j for sector i*'s* products (X_{ij}) as a function of sector j*'s* level of production (X_j) given final demand Y:

$$X_{ij} = a_{ij}X_j \tag{2}$$

where a_{ij} is a coefficient describing the dollar value of sector i production required to produce a dollar of sector j output.

Substituting Equation 2 into Equation 1 yields:

$$X = AX + Y \tag{3}$$

with Y representing the vector of final demand, X the matrix of industry sales, and A the matrix of a_{ij} coefficients. This reduces to

$$X = (I - A)^{-1}Y \tag{4}$$

where I is an identity matrix and the $(I - A)^{-1}$ matrix provides the Leontief (1966) multipliers.

In validating the accuracy of estimated sales (as well as value added, labor income, and employment based on these sales), researchers can consider the difference, or estimation error ϵ between actual data on economic changes ($\dot{X}$) and estimated impacts (X):

$$\epsilon = \dot{X} - X \tag{5}$$

It is also possible to consider total sales at the industry or sector level (X_i and $\dot{X}_i$), for example, inspecting the performance of the manufacturing sector. However, economies are not static, and economic changes rarely

exist in a vacuum. Researchers must also account for a vector of other, often unknown, changes (V) in the regional economy:

$$\epsilon = \dot{X} - X - V \tag{6}$$

A relevant time period for economic change must be established in determining , and elements of V should be accounted for as well as possible. Input-output models, including the IMPLAN model, tend to assume a period of one year. However, actual impacts may not be fully realized in a one-year period or, more commonly, within an annual reporting year for statistical purposes. For example, Cargill layoffs did not all occur at the same time, and there was a partially-compensated adjustment period for workers to find new work and businesses to establish new contracts. The timing of reporting periods and lags in releasing state and federal data can also affect how economic adjustments are observed in data sets. Of course, these factors are outside the realm of a static I-O model, but they occur in real life and are part of the actual economy against which impact estimates are measured. In this study, data sets were analyzed to consider the timeline over which economic losses occurred. Most negative impacts in the manufacturing and specifically food manufacturing sectors appeared within two years as expected based on workforce transition information available when the closure was announced.

4 Data

The packing plant closure was a large event in a relatively small economy. The closure was also a permanent change to the economy rather than a short-lived fluctuation such as a tourist event. More than four years later, the plant remains closed. While Cargill was willing to sell the facility, they would not allow it to be sold to a potential competitor, and no other business has purchased the plant. Local leaders expressed concerns about large negative shocks to the economy, school enrollment, and the tax base. However, the actual effects were less severe than initially feared, and the economy has experienced growth areas as well (Fox, 2017).

The authors live and/or work frequently in the region, have continually followed economic forces there, and maintain relationships with local leaders who can provide additional insight into the changing economy. Together, these factors made it easier to compare the ex ante impact estimates with actual outcomes in the years following the plant closure, although challenges in tracking economic changes remained substantial.

A review of publically available data provided the basis for the determining actual changes since the 2013 closure. Table 3 lists the data sources and the metrics each provided. The 2013 IMPLAN (2017) data were used for most of this analysis because it reflects the actual economy in the closure year. IMPLAN data available for years preceding the closure were compared to see how changes in government data are incorporated into the model and to study the effects of dataset selection on estimates outcomes. An interview with the Plainview/Hale County Economic Development Corporation (EDC) director and a review of EDC press releases and local newspaper articles supplemented the published federal data and provided additional context for local economic changes.

5 Results

5.1 Comparison of Estimated Impacts and Documented Economic Changes

One of the easiest impact estimates to compare is employment because there are multiple federal sources of employment data. The 2,000 plant jobs were the equivalent to 13 percent of Hale County's labor force, had all employees lived within the county. The 1,462 jobs attributed to county residents in the initial study were equivalent to almost 9.5 percent of the labor force and 10.2 percent of county employment. The Bureau of Labor Statistics (Bureau of Labor Statistics, 2017) provides labor force and unemployment data based on the Current Population Survey (US Census Bureau, 2017a), which account for employee residence rather than business location. The data show that employment statistics in Hale County held fairly steady after an initial drop into the Great Recession but had declined somewhat since late 2011, perhaps due to an ongoing drought in the region and increased fracking that drew workers to other parts of the state. In the

Table 3: Data sources and metrics for Hale County economic change.

Bureau	Data Set or Table	Metric
Bureau of Economic Analysis (BEA)	CA25N Total Full-Time and Part-Time Employment by NAICS Industry	Employment by industry (2-digit NAICS)
	CA5N Personal Income by Major Component and Earnings by NAICS Industry	Income by earning source and industry (2-digit NAICS)
Bureau of Labor Statistics (BLS)	Local Area Unemployment Statistics (LAUS)	Unemployment rate, unemployment #, employment #, labor force # from the Current Population Survey
Census Bureau (Census)	American Community Survey	Population
	County Business Patterns	Establishments and employment by industry
	Non-employer Statistics	Non-employer establishments by industry
IMPLAN	2009, 2012, and 2013	Output, labor income, employment by industry

year following the plant closure, BLS reports a 1,417 decline in overall employment of Hale County residents relative to December 2012, (Table 4, Figure 1). That number dropped further in 2014, with a total loss of 2,596 jobs over the two-year period. Other local businesses may have faced an adjustment period in addressing the economic changes from the closure. In the first year following the closure, employment losses outstripped labor force changes as unemployment rose by 4.9 percent. That spike reversed the following year as more people found jobs or left the county labor force.

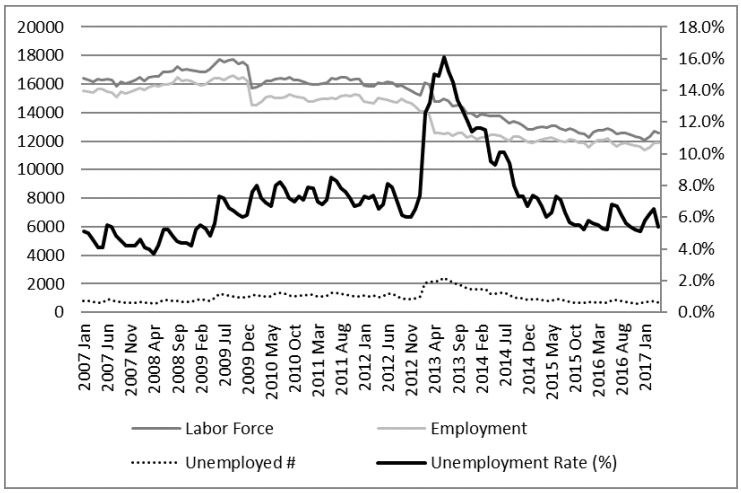


Figure 1: Changes in labor force data, January 2007 - January 2017 (BLS, 2017).

The Bureau of Economic Analysis (Bureau of Economic Analysis, 2016a,b) provides employment and labor income data based on business location rather than employee residence. Thus the BEA data report all lost plant jobs in Hale County. The BEA data also allow researchers to look at industries at the two-digit

Table 4: Comparison of Changes in Hale County Employment Following Plant Closure.

Measure by Data Source	2012 to 2013 Change	2013 to 2014 Change	Two-year Change
BLS			
Labor Force	-1,417	-1,119	-2,536
Employment	-2,011	-386	-2,397
Unemployed #	594	-733	-139
Unemployment Rate (%)	4.90%	-4.70%	0.20%
BEA			
Total employment (number of jobs)	-1,834	-372	-2,206
Wage and salary employment	-1,846	-456	-2,302
Nonfarm proprietors employment	2	79	81
Manufacturing employment	-1,605	-438	-2,043
Census			
Total Jobs (Employees and Non-employers)	-1486	-436	-1922
Total Employees	-1483	-553	-2036
Manufacturing Employees	-1420	-454	-1874
Total Non-employers	-3	117	114
IMPLAN Job Loss Estimate			
Direct (Sector Animal Slaughter)	-1462		
Total	-2595.4		

NAICS level, except where data face disclosure issues. Hale County wage and salary employment declined by 1,846 jobs from 2012 to 2013 and by 2,302 jobs between 2012 and 2014 (Table 4, Figure 2). Manufacturing jobs decreased by 2,043 jobs over the two years, from 2,799 in 2012 to 756 in 2014. However, the number of non-farm proprietors increased by 81 in the two years following the plant closure for a net job loss of 2,221 jobs.



Figure 2: Changes in employment data, 2005-2015 (BEA, 2017).

Similarly, County Business Patterns (CBP) data report employment, establishments, and wages based on business location for firms with employees (US Census Bureau, 2017c). The non-employer statistics provide establishments and sales for non-employer firms (US Census Bureau, 2017b). The CBP data note a loss of 1,486 total jobs in Hale County from 2012 to 2013 and 1,922 between 2012 and 2014 (Table 4, Figure 3). Employee positions decline by 1,483 from 2012 to 2013 and 2,036 between 2012 and 2014. Manufacturing employment declined by 1,420 in the first year and 484 in the second for a two-year loss of 1,874 jobs. As with the BEA data, the number of proprietors increased. The non-employer data set reported an increase of 114 proprietors in the county, although the Census data reports fewer non-farm proprietors than do BEA data;

the BEA classification of proprietor is broader than the Census non-employer definition and also includes partnerships and other unincorporated private businesses (Fox et al., 2016).

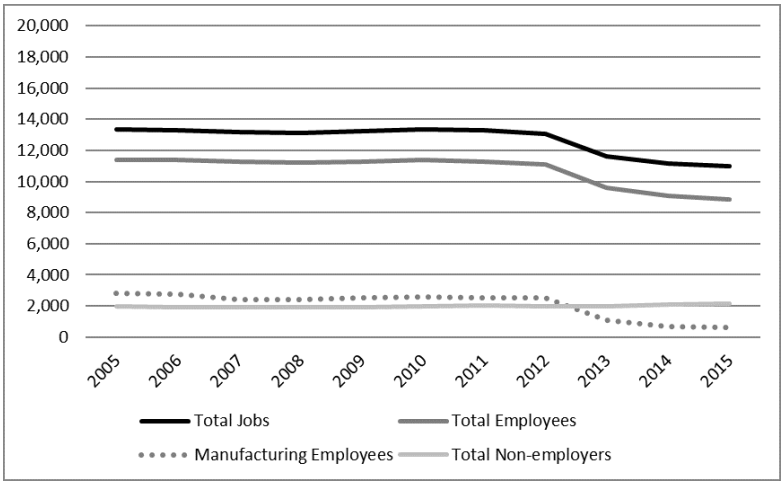


Figure 3: Changes in employment data, 2005-2015 (Census, 2017).

The original plant closure study estimated the direct loss of 1,462 animal slaughter jobs, which is similar to the 1,420 manufacturing jobs identified in the CBP data, although smaller than the 1,605 manufacturing jobs lost in the BEA data. We seem to have done a reasonable job customizing our model for the plant closure study. Economy-wide job loss estimates were less accurate. The study's predicted one-year loss of 2,595 jobs is much lower than the loss of 2,011 jobs reported by the BLS, the data showing the largest job loss. It is possible that indirect and induced losses were deferred as business struggled to establish new contracts, and the two-year BEA and BLS loss calculation of more than 2,300 jobs is closer to our IMPLAN estimate.

Of course, the study did not account for countervailing forces from other strong sectors in the local economy. A continued wind energy boom in the area required truck drivers and services from hotels, restaurants, and retail establishments (Fox, 2017). The BEA data show losses in construction and transportation employment from 2012 to 2013 but slight gains in 2014 and substantial gains in 2015. BEA compensation data provide information at a more specialized level, and construction specialty trade contractors saw strong earnings growth in 2014 and 2015. Machinery manufacturing also experienced strong wage growth. Truck transportation experienced growth from 2013 to 2014 after 2012-13 losses. Food and drinking places did not experience losses after the closure but grew more slowly in 2013 and increased over the following years. Overall retail employment and income was relatively stable (Bureau of Economic Analysis, 2016a,b), but compensation data show that growth was mixed among retail subsectors with gas stations and general merchandise stores performing well. Data on accommodations were limited. Several EDC press releases during this period tout wind energy development. In December 2013, Plain View Orchard Wind Farm was reported to be adding 200 local construction workers and 8-10 permanent operating positions.

A hospital expansion improved employment and wages in that sector according to EDC director Fox (2017). Data support higher employee compensation in the health sector although employment was undisclosed (Bureau of Economic Analysis, 2016a,b). Fox noted that Plainview acquired three car dealerships, forming a local auto sales cluster and supporting employment in that sector. Compensation in the motor vehicle and parts retail sector contracted very slightly in 2012 and grew slowly in 2013 and began growing faster in 2014. The county also saw relatively stable farm employment and compensation in 2013and 2014 following a regional drought (Bureau of Economic Analysis, 2016a,b), although farm receipts were generally lower (Johnstone and Robinson, 2017). Warehousing was also a strong sector, with both employment and compensation growth. An EDC press release reported the Walmart distribution center was adding 45 employees and noted that Walmart was then the city's largest employer. Finally, the Texas oil boom lured a number of workers into that sector, some of whom continued to reside in the county and others who relocated, at least temporarily (Fox, 2017).

The Bureau of Economic Analysis (2016a) also reports both wage and salary earnings and proprietors income, including earnings for manufacturing sub-sectors. More than $52.4 million in total wages was lost from Hale County during that between 2012 and 2013 with an additional $3.6 million lost between 2013 and 2014 (Table 5, Figure 4). Manufacturing wages made up the bulk of these losses. Manufacturing wages dropped by $52.7 million in the first year and $24.4 million in the second. Although the data experience disclosure issues from 2009 to 2012, the wages in non-durable goods and food manufacturing closely track manufacturing in other periods. The food manufacturing sub-sector experienced a $29.9 million reduction in wages between 2013 and 2014.

Table 5: Comparison of Changes in Hale County Labor Income Following Plant Closure.

Measure by Data Source	2012 to 2013 Change	2013 to 2014 Change	Two-year Change
BEA			
Wages and salaries	($52,376,000)	($3,664,000)	($56,040,000)
Nonfarm proprietors' income	($12,812,000)	$1,581,000	($11,231,000)
Manufacturing	($52,768,000)	($24,411,000)	($77,179,000)
Nondurable goods manufacturing	D	($25,452,000)	D
Food manufacturing	D	($29,865,000)	D
Census			
All Payroll	($36,607,000)	($7,814,000)	($44,421,000)
Manufacturing Payroll	($52,911,000)	($13,360,000)	($66,271,000)
IMPLAN Labor Income Loss Estimate			
Direct (Sector Animal Slaughter)	($45,719,100)		
Total	($97,171,200)		

D: Data not disclosed for 2012 so no change can be calculated.

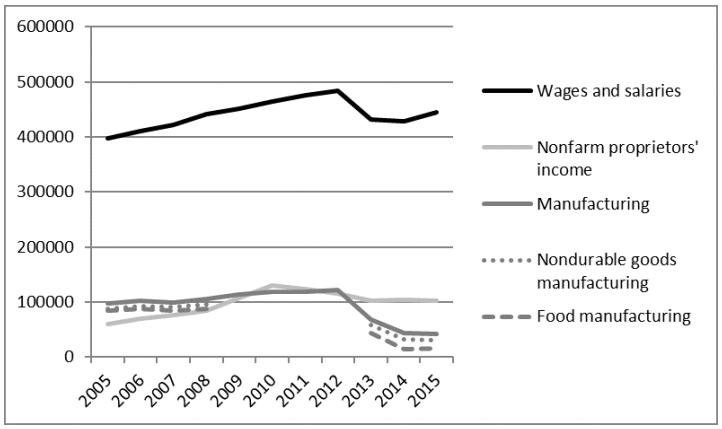


Figure 4: Changes in labor income data, 2005-2015 (BEA, 2017).

Considering labor income with Census data is more difficult because non-employer income is not reported. However, by far, most jobs are wage and salary jobs, and these figures provide a solid basis to approximate income changes. The CBP reports a total payroll decline of $36.6 million from 2012 to 2013 and $7.8 million between 2012 and 2014 (Table 5, Figure 5). One source of difference between the BEA and CBP data is BEA's inclusion of farm wages, which increases sharply in 2013, following prior years' drought. Manufacturing payroll was much more similar to BEA data with decreases of $52.9 million in the first year and a more modest $13.4 million in the second.

The plant closure study's estimated $45.7 million direct labor income change falls between the CBP and BEA data for the manufacturing sector. Given the wide range of these figures and the differences in methods for calculating BEA and CBP wages, falling within this range remains less than encouraging. Direct

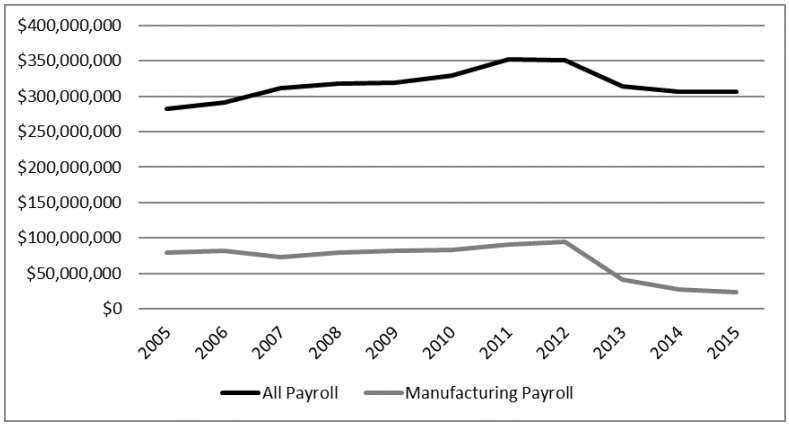


Figure 5: Changes in labor income data, 2005-2015 (Census, 2017).

changes in animal slaughter wages should probably more closely align with the losses BEA reports for food manufacturing. Estimated economy-wide losses of labor income far exceed losses reported by BEA or the Census Bureau. Inspection of available industry level data does not show a precise reason for these changes. The study estimated a $15.5 million wage loss to trucking sector labor income. However, many truckers simply went to work in the oil field. By 2014, farm incomes also experienced strong growth, as did incomes in other sectors as described when discussing employment.

Even in the case of a large and specific economic loss, economies experience strong countervailing forces. It may take several months or years for closure effects to be fully realized. In that time, other industries may experience growth or decline, either unrelated to the closure or resulting from excess labor and capital. These fluctuations and their impacts are difficult to measure precisely, and they pose a challenge to determining if, to what extent, and in what sectors a model was inaccurate. Given these issues of time and variable economic responses, the appropriateness of a static input-model is debatable. Yet such analyses are common given their relative affordability and ease of use. No ex ante study, whether I-O or Computerized General Equilibrium (CGE) is able to account for unrelated, unanticipated changes in the economy. The magnitude of change to the Hale County economy and the persistent nature of that change (Figures 1 through 5) suggest that a computable general equilibrium model may have underestimated the impacts of the closure, subject of course to the parameters of the CGE. Furthermore, CGEs are rarely available at the county level. Regardless of the model used, economists should be able to separate unrelated economic changes from modeling errors and from failures to anticipate foreseeable downstream impacts.

5.2 Differences in IMPLAN Data by Year

The 2013 plant closure study relied on 2009 IMPLAN data as newer data had not been purchased for two reasons. First, Texas A&M AgriLife Extension had accepted state budgets cuts during the Great Recession that reduced operating budgets. Second, given the two-year lag in IMPLAN data availability, faculty believed data coming directly off the recession, which Texas entered in September 2009, would not accurately reflect the economy until it stabilized. Using the 2011 data, which was the most recent IMPLAN (2017) data available in February 2013, we would have been applying recession multipliers to recovery conditions. The agency resumed annual county-level data purchases with the 2012 IMPLAN data set in February 2014.

Inspection of IMPLAN study area data over time shows that the researchers' choice of data year likely affected estimates greatly (Table 6). On-the-ground sources and ReferenceUSA (2013) quoted the plant's sales at $1 billion or more, similar to the IMPLAN data for 2009. However, the 2012 IMPLAN data noted a much smaller industry output of only $628.8 million, including the sales of other small plants in the county. The 2012 data provide only slightly lower employment and employee compensation numbers. While the 2012 data was not yet available when the report was completed, 2011 data likely would have reflected reduced cattle supplies and may have tempered the $1 billion sales assumption. The loss of employment in the animal slaughter sector is reflected in 2013 and 2014 data. The IMPLAN employee compensation data as well as

the BEA income data suggest that the research team should have estimated higher direct labor income.

Table 6: Study Area Data for Select IMPLAN Model Years.

Year	Industry Code	Output	Employee Compensation	Employment
2009	59	$947,225,024	$76,026,480	2,145
2012	59	$629,761,719	$70,062,576	2,012
2013	89	$481,030,945	$30,793,751	802
2014	89	$160,829,117	$9,273,456	277

Simply running the loss of 2,000 employees in the animal slaughter sector of an IMPLAN model results in vastly different direct output and total impacts depending upon the data year (Table 7). Using the 2012 data, if available, would have produced employment numbers larger than most 2012-2013 differences but smaller than two-year employment changes in the Hale County economy shown in Table 3. Direct labor impact estimates would have been more accurate, although total labor income changes still would have been vastly overestimated. But, again, the model would not have accounted for positive changes in other sectors. The inclusion of results from a 2013 model shows the danger of using a model that does not represent local conditions. As with other I-O models, IMPLAN is linear and does not prohibit total employment from exceeding either the employment within a single sector or the overall economy. Running a loss of 2,000 jobs in the 2013 animal slaughter sector, which had only 802 employees and more accurately reflected smaller packing operations, resulted in larger impact estimates than produced in the original study. Because IMPLAN data lags by about two years, selecting a data year with similar conditions to the economic period of interest and then customizing that model to be even more accurate are important steps in performing an accurate impact or contribution analysis.

Table 7: Economic Impact of 2,000 Employee Loss to the Animal Slaughter Sector Using Different IMPLAN Data Years.

Year	Direct Output	Output	Value Added	Labor Income	Employment
2009	$866.6 M	$1.0 B	$285.9 M	$97.2 M	2,595.40
2012	$626.1 M	$662.1 M	$69.1 M	$73.8 M	1,759.00
2013	$1.2 B	$1.4 B	$254.5 M	$139.7 M	2,728.90

6 Conclusions and Suggestions for Future Work

This study compared estimates from an IMPLAN-based impact analysis of a beef slaughter plant closure with federal data reporting employment and income in the study area. The analysis incorporated outside data sets (e.g., ReferenceUSA, Census Bureau, BEA, BLS) and multiple IMPLAN datasets as well as the local expertise of economic leaders in the area). Direct employment estimates were reasonable, and total employment estimates appear reasonable given countervailing positive changes in the wind energy, fracking, hospital, and auto sales industries. Direct labor income was underestimated and could have been improved at that time by incorporating BEA industry-level earnings data. At the same time, overall income impacts were over-estimated. Unrelated forces raised income in other sectors, including trucking, warehousing, and retailing of motor vehicles and parts. However, available data may have overestimated the plant's 2012 sales. Reducing direct sales would have reduced the total impact of all outcomes, including income. This points to the need for conservatism in making estimates, although the study did rely on the more conservative available data.

The investigation suffers from a number of limitations. First, it was difficult given available data to identify all the various other shocks to the Hale County economy following the plant closure. The research team analyzed publically available and purchased IMPLAN data, local EDC press releases, and newspaper

articles and interviewed the EDC director. We still do not have a complete account of all business start-ups and closures. Limited data is available for home-based and side businesses, which often become more important in times of economic crisis. Sector aggregation and data suppression hamper efforts. While the research team attempted to consider global shocks, including swings in agricultural and energy prices and production, we did not consider all possible shocks that could have affected specific industries. The static I-O model does not account for clustering effects, technological change, or input substitution, and the research team is not embedded in the community and local industries to be able to adapt the model to reflect these complex forces. Thus, the validation exercise does not include all countervailing shocks and forces. Further, the I-O analysis does not tell us if former Cargill employees switched industries or moved out while new employees moved in.

This exercise of checking IMPLAN results ex post demonstrates the challenges of validation studies but also offers several suggestions for improving future ex ante modeling efforts. Assumptions about direct effects and modeling methodologies should be considered carefully. Direct impacts reported by local entities should be verified against multiple sources to ensure accuracy. Businesses and local leaders may be overly optimistic about new activity or overly pessimistic about potential losses. Businesses may be reluctant to disclose actual sales or losses, and they may have operated under capacity prior to closing. Triangulation across multiple government and private datasets (including time trends over recent years, quarters or months and outcomes in other locations) and local knowledge may challenge the business's or community's narrative. However, this information may not be available in real time as federal data often lags by about two years.

Where input disruptions contribute to the failure of another business (as in tight cattle supplies resulting in packing plant closure), inclusion of modeled effects from the disrupting sector will overstate indirect impacts. Similarly, new businesses located to take advantage of local inputs (e.g., cattle or corn) should not be attributed with the effects of that existing economic activity. Model customizations should always address these realities. The actual input mix and use of local inputs for a specific business are usually unknown to researchers, especially those not contracted by the business itself. At minimum, it is critical to evaluate the use of local versus imported inputs, including labor, and to adjust labor costs to reflect the business and the region, as wages have a substantial effect on overall income and value added outcomes.

Default models that have not been customized will rarely provide an accurate representation of specific conditions. Using the most recent modeling data (e.g., the latest IMPLAN data year, which is lagged by about two years) may not represent current conditions. It may be better to use a more similar data year and/or customize the affected industry to represent current conditions. Agriculture and energy, in particular, faces year-to-years swings in prices and profitability that can affect results. It may be helpful to use multiple models or at least multiple IMPLAN modeling years to ensure the study provides accurate, stable data that reflect current economic conditions. Regardless, model customization is paramount. While most economic impact studies assume changes occur immediately, often implicitly defined as a year, economies may adjust more slowly, and lags in data reporting can further obscure the adjustment process.

Verifying the accuracy of ex ante studies requires researchers to collect updated data and revisit past work. They often must obtain data or at least context from the same local leaders who relied on their original estimates, exposing model shortcomings to their clientele and partners if not the academic community. Clearly, this involves effort, reputational risk, and some discomfort where ex ante estimates do not align with actual outcomes. Even major economic events do not occur in a vacuum; economies experience constant countervailing forces. Economists should be able to critically consider the nature of economic change when studying the accuracy of ex ante estimates and identify modeling errors, event-related and partially predictable responses, and unrelated economic events or trends. Such effort demonstrates our commitment to improving and maintaining the credibility of our models.

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