TWO ESSAYS ON FOOD MANUFACTURER RESILIENCE:
REGIONAL FACTORS AND WORKFORCE CHALLENGES

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The undersigned, appointed by the dean of the Graduate School, have examined the thesis entitled

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REGIONAL FACTORS AND WORKFORCE CHALLENGES

presented by Catherine Isley,

a candidate for the degree of Master of Science,

and hereby certify that, in their opinion, it is worthy of acceptance.

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ABSTRACT

Researchers and policymakers worldwide have increasingly viewed resilient food systems as important. In the wake of the COVID-19 pandemic, there has been particular emphasis on food manufacturer resilience. This thesis investigates factors related to food manufacturer resilience. The first study defines resilience through a workforce lens. Utilizing logit models and Firth's penalized maximum likelihood estimation, it examines what drives worker shortages. Results suggest that food manufacturing plants prioritizing training and education face reduced odds of worker shortages. Additionally, results suggest plants view automation as a way to mitigate worker shortages, but that this strategy may not be effective.

The second study defines resilience through a plant survival lens. Using Cox proportional hazards models, it explores what factors are related to meat processing plant survival, particularly small- and medium-sized plant survival. Results suggest that the relationship with survival is strongest and most robust for plant characteristics. This holds especially true for small- and medium-sized processors. However, local labor market characteristics are also related to plant survival. Specifically, probability of survival is higher where the county manufacturing employment share is higher, where plants are relatively remote, and where unemployment is lower, all else being equal.

Overall, the two essays examine food processor resilience in largely different contexts – one with detailed survey data and only in Missouri, the other national with high-level plant data – but two themes do emerge: workforce factors matter for resilience, and plant-level factors matter for resilience. Results of the two essays have important implications, suggesting practices that may help both business managers as well as policymakers strengthen food manufacturer resilience.

CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

Resilient food systems have long been a popular topic amongst researchers, policymakers, and economic development practitioners, with a resurgence in local and regional food systems beginning 20 years ago. In the face of challenges such as population growth, increasing climactic variability, financial crises, and health crises, a multitude of recent national and international reports have emphasized the need for increased food system resilience (Harris & Spiegel, 2019; Sperling et al., 2022; Ulimwengu, et al, 2021). The COVID-19 pandemic stressed food supply chain dynamics and resilience further (Thilmany et al., 2021).

Resilience can be defined as an ability to recover from or adjust easily to disruptions and challenges. Several food system-specific definitions have also been proposed. The Food and Agriculture Organization (FAO) defines resilient food systems as having, "the ability to prevent disasters and crises as well as to anticipate, absorb, accommodate or recover from them in a timely, efficient and sustainable manner," (FAO, 2016). And in their influential 2015 paper, Tendall et al. (2015) define resilience in food systems as the, "capacity over time of a food system and its units at multiple levels to provide sufficient, appropriate and accessible food to all, in the face of various and even unforeseen disturbances."

By these definitions, it is clear that resilient food systems do not just involve the production side of agriculture – resilient food systems require resilience at every step in the food supply chain, from farm to fork. Thus, having a resilient food manufacturing industry is a necessary condition for achieving food systems resilience.

Throughout the past two years, researchers, policymakers, and industry leaders have placed particular emphasis on food manufacturing resilience. The COVID-19 pandemic caused disruptions for food manufacturers. During the initial months of the pandemic, outbreaks of the virus greatly impacted meat processors; many plants shut down or reduced capacity, causing disruptions to U.S. meat supply. And food manufacturers across many additional subindustries faced labor shortages and struggled to keep up with consumer demand.

1.2 Research Objectives

Given the recent emphasis on resilient food systems and the resilience challenges food manufacturers have faced, this thesis explores the following: What factors are related to food manufacturer resilience? More specifically, this thesis investigates the following two research questions:

1) What workforce-related factors are related to food manufacturer resilience?

2) What factors are related to meat processor resilience?

I was interested in these two sub-objectives given the widespread labor shortages seen in 2020 and 2021 – which began prior to the pandemic – as well as the challenges meat processors faced over this period. Additionally, policymakers have been interested in both labor shortages and meat processing industry resilience, so these research questions are policy-relevant and ripe for investigation.

1.3 Thesis Outline

This thesis is composed of four chapters. This chapter has introduced my research objectives as well as high-level background and motivation for my work. The second and third chapters are separate studies addressing my stated research questions. These studies approach food manufacturing resilience from two different perspectives. One study uses detailed plant-level data from Missouri in 2020. The other study uses regional data and high-level plant-level data for processors across the U.S, 1997 to 2020. Together, these two studies provide complementary perspectives on food manufacturing resilience with respect to regional characteristics and workforce challenges.

Chapter two is titled “Determinants of Labor Shortages in Missouri’s Food Manufacturing Industry.” This study addresses my first research question. In this study, I define resilience through the lens of worker shortages. Specifically, I investigate what plant-level factors are associated with worker shortages. This study provides perspectives on how business managers and policymakers can reduce labor shortages in food manufacturing plants, thus increasing industry resilience.

Chapter three is titled “Meat Processor Resilience: Plant Survival and Workforce Impacts.” This study addresses my second research question. In this study I define resilience as plant survival. Specifically, I investigate what plant-level characteristics and regional characteristics are associated with likelihood of meat processing plant survival. This study provides information on how policymakers could target recent industry funds to increase meat processor survival and industry resilience. Finally, chapter four summarizes and synthesizes results from the two studies.

CHAPTER 2: DETERMINANTS OF LABOR SHORTAGES IN MISSOURI'S FOOD MANUFACTURING INDUSTRY

Abstract

This paper explores which characteristics separate Missouri food manufacturing plants not experiencing worker shortages from those that are. I analyze responses from a survey of Missouri food, agriculture, and forestry establishments, conducted January through early March 2020. Logistic models, estimated using Firth's penalized maximum likelihood estimation, are used. I find that firms offering training and education – particularly apprenticeships, customized community college trainings, financial support for education, and flexible schedules for education – face lower odds of worker shortages. Additionally, evidence suggests food manufacturers see automation as one way to alleviate worker shortages, but I find no relationship between worker shortages and current automation levels.

2.1 Introduction

This study explores the characteristics of Missouri food manufacturing plants experiencing worker shortages compared to the characteristics of plants not experiencing worker shortages, self-defined. For example, are primarily small plants facing labor shortages? Or plants which lag in adopting automated processes? How do hiring practices and benefits impact worker shortages? These are relevant questions given currently tight U.S. labor markets.

This work is important given that for the food manufacturing industry, a worker shortage is not just a business issue – it has implications for supply chain resilience and national food security. Supply chain resilience is particularly important and policy-relevant in light of the COVID-19 pandemic, an era in which governments have increased investment in resilient supply chains. Just last year, USDA dedicated $500 million to expanding meat and poultry processing capacity, while another $4 billion will be used to strengthen and diversify food supply chains more broadly (U.S. Department of Agriculture, 2021a, 2021b). States have also invested in agricultural supply chains. In 2021, the Missouri Department of Agriculture awarded nearly $17 million in Coronavirus Aid, Relief, and Economic Security (CARES) funding to Missouri meat and poultry processors for expansions (Missouri Department of Agriculture, 2021). Given that an adequate workforce is one key to supply chain resilience, this paper may provide preliminary evidence on how these investments could be targeted. Additionally, this work provides valuable insights for businesses on practices that may help alleviate worker shortages.

I use logistic models to explore the relationship between various factors – plant-level characteristics, economy-wide structural factors, internal plant business practices – and odds of worker shortages. I define a plant as experiencing a labor shortage if it reports that shortages of workers with knowledge or skills is a barrier to expanding employment. Results suggest that offering training and education may mitigate worker shortages. Specifically, providing financial support for continuing education, flexible work schedules for education, apprenticeship programs, and customized community college training programs are associated with between four- and ten-times reduced odds of worker shortages. Evidence also suggests respondents see automation as a way to alleviate employee shortages, but I find no relationship between worker shortages and current automation levels. Plant characteristics – such as size and subindustry – also have no significant relationship with odds of worker shortages, at least when controlling for a variety of other factors.

This study makes several contributions to the existing literature. First, little academic work examines workforce issues in food manufacturing, so this essay helps fill that gap. Second, I use original establishment-level data, collected through a survey of Missouri food manufacturers. Lastly, I apply an econometric method relatively new to economics – Firth penalized maximum likelihood estimation – that provides unbiased estimates in small sample sizes.

The paper begins by exploring literature on the U.S. labor environment and what plants can do to mitigate labor shortage issues. Next, I discuss my survey data and analysis methods. Then I examine results and explore implications for businesses and policymakers. Finally, I discuss future work and conclude.

2.2 Literature Review

2.2.1 State of the U.S. Labor Environment

2.2.1.1 Post-pandemic

The U.S. unemployment rate fell to 3.9% in December 2021, the lowest level since April 2020 (14.7%), but still slightly higher than the pre-pandemic rate of 3.5% (Bureau of Labor Statistics, 2022b). Total nonfarm payroll employment increased by 199,000, bringing nonfarm payroll employment to the highest levels since April 2020, but still down approximately 3.6 million from pre-pandemic levels (Bureau of Labor Statistics, 2022b). While not fully recovered, these two metrics have seen large and consistent improvements since May of 2020, painting an encouraging picture of the U.S economic recovery. However, labor force participation and employment-population ratio tell a different story. At 61.9%, the labor force participation rate has stagnated since June 2020; this is compared to 63.4% in February 2020 (Bureau of Labor Statistics, 2022b). Given that the U.S. civilian non-institutionalized population was 262 million as of December 2021, this 1.5 percentage point difference translates to 3.9 million fewer workers in the labor force as of December 2021. The employment-population ratio also remains low: 59.5% in December 2021 compared to 61.2% in February 2020 (Bureau of Labor Statistics, 2022b). This low unemployment rate combined with moderate employment gains, a low labor force participation rate, and low employment-population ratio suggests a substantial segment of the population dropped out of the labor force during the course of the pandemic, potentially creating ideal conditions for a labor shortage.

Reports do suggest this labor shortage has materialized. A nationwide survey conducted in June 2021 found that nearly nine in ten organizations currently struggled to fill open positions (Society of Human Resource Management, 2021). And as of September 2021, 51% of small business owners reported being unable to fill job openings in the previous month (National Federation of Independent Business, 2021). Moreover, the seasonally adjusted job openings reached 6.9% in July 2021, nearly twice the rate in February of 2020 and an all-time high (Bureau of Labor Statistics, 2021a).

2.2.1.2 Pre-pandemic

While much of the recent narrative blames the pandemic for these labor market conditions, labor shortage conditions were occurring even pre-pandemic. Employers have long expressed concerns regarding worker shortages, even years before the pandemic began. Much of this discussion focused on STEM and healthcare worker shortages, in particular. Some studies disputed these labor shortages (Stevenson, 2014; Lowe, 2013), while other work confirmed them (Kalafsky, 2008). Most studies, however, found that labor shortages were not widespread, but instead confined to certain subindustries, skillsets, and geographical locations (Holzer, 2015; West, 2013; Xue & Larson, 2015).

Concerns surrounding worker shortages became more widespread in 2018 and 2019. The percent of small businesses with at least one unfilled job opening hit then-record highs in 2019 (National Federation of Independent Business, 2021). Additionally, record numbers of business owners reported receiving few or no qualified applicants for positions (National Federation of Independent Business, 2021). The 2018-2019 labor shortage can also be observed in BLS data. In March of 2018, the number of job openings exceeded the unemployment level for the first time in series history (Bureau of Labor Statistics, 2022c). Throughout 2018 and 2019, the number of job openings exceeded the unemployment level by about one million (growing to nearly three million as of November 2021). A report published by The Conference Board, a global business membership and research group, explored the state of the U.S. labor market as of late 2019. The document's introduction summed up the situation as follows:

> "For decades, employers complained about the difficulty of finding qualified workers even in loose labor markets when widespread shortages did not exist. … [W]e argue that this time is different. Employers' complaints have merit, and the labor shortages problem is having a strong impact on the US economy." (Levanon et al., 2020).

2.2.1.3 Manufacturing sector workers

The employment situation has been similar in the manufacturing industry. As of February 2020, the U.S. employment level in manufacturing was 12.799 million (Bureau of Labor Statistics, 2020b). Employment dropped to 11.414 million in April of 2020 and increased to 12.610 million as of December 2021 (Bureau of Labor Statistics, 2020a, 2022b). This represents a recovery rate of about 86% of jobs, in line with U.S. total employment recovery.

Like other U.S. sectors, manufacturing has faced a labor shortage. For years, numerous studies and reports have documented labor shortages amongst manufacturers. A 2005 study found that many manufacturers in North Carolina – a historically manufacturing-heavy state – faced labor shortages despite the nationwide decline in manufacturing jobs during this time (Kalafsky, 2008). Findings showed the labor shortage was more pronounced amongst advanced manufacturers, with plants primarily relying on un-skilled labor reporting the lowest degrees of shortages. Additionally, insights from a 2012 Federal Reserve-sponsored manufacturing summit suggested the same pattern – manufacturers were having a difficult time finding labor, specifically skilled labor (Fee, 2012). Several other reports examining the Great Recession period and post-Great Recession arrived at the same conclusions (West, 2013; Xue & Larson, 2015). This pattern has continued amid the pandemic. One 2021 report found that 49% of manufacturing firms had difficulty recruiting skilled talent during the pandemic, while 63% of manufactures struggled to fill critical labor gaps (Eckert & Zenk, 2021; Wellener et al., 2021).

On its face, this labor shortage seems puzzling, as the narrative surrounding manufacturing has for years emphasized the decline of the industry and loss of jobs. While it is true that manufacturing jobs declined drastically – the U.S. economy lost about six million manufacturing jobs between 2000 and 2010 – about 1.3 million jobs returned between 2010 and 2019 (Harris, 2020). Additionally, manufacturing's share of U.S. GDP has remained relatively stable over time, though increasing manufacturing productivity has largely driven this trend (Baily & Bosworth, 2014). The type of manufacturing job examined may also explain these two diverging worker shortage narratives. As discussed above, general labor is the least difficult to find (Kalafsky, 2008) and many of the jobs lost in the early 2000s and prior were unskilled roles (Orr & Deitz, 2006). Skilled roles – such as machinists and technicians – appear quite difficult to fill (Wellener et al., 2021; Xue & Larson, 2015; Eckert & Zenk, 2021) and are likely driving reports of labor shortages in the manufacturing industry.

2.2.2 The "Why" Behind Manufacturing Labor Shortages and Potential Mitigation Strategies

There are, of course, pandemic-related reasons behind the nationwide labor shortage. 32% of unemployed individuals in May 2021 cited fear of COVID-19 exposure as one reason they remained unemployed (Society of Human Resource Management, 2021). There was also evidence that unemployment benefits played a role in the pandemic-era labor shortage; 11% of unemployed individuals in May 2021 cited increased benefits as a reason they remained unemployed (Society of Human Resource Management, 2021). However, additional analysis suggested that enhanced unemployment benefits played a role in the Food and Hospitality sector's labor shortage but were not necessarily impacting higher-wage industries, such as manufacturing (Petrosky-Nadeau & Valletta, 2021). Additionally, throughout the pandemic, manufacturers reported a spike in the number of employees quitting for personal reasons, such as childcare duties (Eckert & Zenk, 2021).

Several additional factors were problematic even before the pandemic began. One major issue has been the aging workforce and, as a result, increased retirements. This issue has particularly impacted manufacturing. The industry employs relatively few young people – as of 2018, 52% of manufacturing workers were over the age of 44, while 43% of workers in all U.S. industries were over this age (U.S. Census Bureau, 2022). This shrinks to 27% and 23%, respectively, for workers over age 54 (U.S. Census Bureau, 2022). Even before the pandemic, the manufacturing industry faced high retirement rates – in 2019, 40% of manufacturing hiring managers reported a spike in retirements over the prior twelve months (Eckert, 2020). Retirement rates further accelerated economy-wide during the pandemic – estimates of excess retirements were between 1.7 million and 2.4 million as of 2021 – due to soaring home and stock prices and threat of the virus to older individuals (Davis et al., 2021; Faria-e-Castro, 2021).

Manufacturing's perception among potential workers is another longstanding issue. Multiple studies in the wake of the dot-com recession cited poor perception of the industry – that jobs are dirty, repetitive, and dangerous – as a main reason why manufacturers struggled to fill roles (Fee, 2012; Kalafsky, 2008). This sentiment is echoed in more recent work (Eckert, 2020; Eckert & Zenk, 2021; Wellener et al., 2021). Desirability of manufacturing work appears to be a particularly large issue among Millennials and Gen Z. Over half of manufacturing hiring managers say negative industry perceptions impact their ability to recruit Millennial and Gen Z workers (Eckert & Zenk, 2021). Additionally, increasing rates of college education among young people have led to decreased interest in blue-collar careers, and large drops in labor force participation among college-aged individuals opting for education over work (Wellener et al., 2021).

Fortunately, a large body of literature explores what factors impact attraction and retention of workers. A large and varied number of factors are impactful. Several studies suggest work-life balance and job flexibility help attract and retain workers – factors such as ability to telework (Bourhis & Mekkaoui, 2010; Choi, 2020), flexible scheduling (Bourhis & Mekkaoui, 2010), and reduced work hours/generous leaves (Bourhis & Mekkaoui, 2010; Clark, 2001; Schlechter et al., 2015) have all been shown to matter to workers. However, manufacturing production workers generally cannot utilize telework or flexible scheduling, perhaps explaining some of the undesirability of the work. Career opportunities and development also matter to employees. In fact, one large study of HR managers and over 5,000 workers found that career opportunities had the strongest impact on employee intentions to leave (de Vos & Meganck, 2009). Another study found that opportunities for training and career advancement substantially increased job attractiveness to potential recruits (Schlechter et al., 2015). More traditional compensation factors should not be forgotten, however. Multiple studies show pay and benefits – particularly healthcare and retirement benefits – do play a large role in worker attraction and retention (Clark, 2001; de Vos & Meganck, 2009; Pregnolato et al., 2017). The above literature should be generalized with caution, however, as many studies show preferences are not homogenous among workers, varying by characteristics such as gender (Schlechter et al., 2015; Pregnolato et al., 2017), age (Society of Human Resource Management, 2021; Heisler & Bandow, 2018), and type of role (Pregnolato et al., 2017).

While the above studies cover multiple industries in aggregate, several studies have explored specifically what manufacturing employees value. A relatively new concept called job embeddedness has been shown to decrease turnover in U.S. manufacturing (Skelton et al., 2020). Job embeddedness refers to how linked an individual is with their community and employer, how good a fit their community and employer are, and how costly it would be to break those links (Mitchell et al., 2001). Company culture also matters. Positive culture aspects such as empathy and caring, autonomy and empowerment, and transparent communication from company leadership positively impact engagement and retention (Colbert, 2012). Another study found employee burnout significantly increased turnover intentions of manufacturing line workers (Santhanam & Srinivas, 2020).

Automation is another potential strategy for mitigating labor shortages, though evidence of the effectiveness of this strategy is mixed. One study found that one new industrial robot reduces employment by about 3.3 workers; this number may be even larger for certain segments of the manufacturing industry (Acemoglu & Restrepo, 2020). Conversely, other researchers have found that automation does not decrease total employment but does reduce employment of low-skill workers (Graetz and Michaels, 2018). In general, the literature paints a similar picture, showing that automation's impact on jobs varies (Acemoglu & Restrepo, 2019), and is often task-specific, with lower-skill jobs usually cut and replaced by high-skill jobs (Autor et al., 2003; Autor, 2015). Since manufacturers currently face a particular shortage of high-skill workers, this raises the question of whether automation can effectively reduce labor shortages. Indeed, training and skill of employees does appear related to the success of automation. A 2020 McKinsey & Company study showed that training of employees is one key factor important to automation adoption success. Companies which had a successful transition to a more automated workplace emphasized training employees on the new technologies; workforce training mediated automation success, as automation creates new ways of working. Despite the challenges surrounding employee skills, plants appeared to increase automation during the pandemic, with one study finding that two-thirds of firms increased levels of automation to help mitigate COVID-19 impacts (Watson et al., 2020).

2.3 Hypotheses

Looking at the literature outlined above, it is clear two different types of factors are related to an establishment's ability to recruit and retain sufficient numbers of adequately skilled workers: longer-term structural factors, and internally driven shorter-term practices. Long-term structural factors include factors discussed above such as an aging workforce (Eckert, 2020), automation (Autor et al., 2003), pandemic-related drivers (Society of Human Resource Management, 2021), perception of the manufacturing industry (Fee, 2012; Kalafsky, 2008), and economy-wide technical and STEM skills shortages (West, 2013; Xue & Larson, 2015). Most of these issues are longstanding and economy-wide, originating externally to food manufacturing plants.

Internal factors are also related to worker recruitment and retention, and thus labor shortages. These factors include things like benefits offered (Pregnolato et al., 2017), flexibility of work hours (Bourhis & Mekkaoui, 2010), stress and burnout (Santhanam & Srinivas, 2020), and company culture (Colbert, 2012). Most of these factors are human resources-oriented in nature and easier for a company to control than many of the structural issues previously discussed.

Given these findings, I test the following hypotheses:

1. Structural factors are related to the probability of plants facing worker shortages.
2. Internally driven factors are related to the probability of plants facing worker shortages.

I do not explore all structural nor all internal practices discussed in my literature review, only those for which I have survey data. The survey does include variables not explored in my literature review, however – for example, recruitment practices, hiring arrangements, and access to transportation and childcare. I classify these variables as either structural or internal and include them in my analysis.

In addition to structural and internal factors, the survey captured plant characteristics – such as number of employees, subindustry, rurality of location, seasonality of work, physicality of work, growth expectations, and single-unit versus multi-unit facility. These variables are of interest as the manufacturing survival literature finds plant characteristics, in part, explain plant success (Anderson et al., 1998; Low & Brown, 2017; Bernard & Jensen, 2002).

Little academic work has directly explored the relationship between plant characteristics and worker shortages, however. This is likely because widespread worker shortages only began to emerge in the past several years. Work does suggest a relationship between plant characteristics and worker shortages may exist, however. Firm size, for example, is related to many aspects of human resource management. Large organizations, as compared to small and medium (SME) organizations, generally utilize a wider range of staffing and recruitment practices (Terpstra & Rozell, 1993); provide higher levels of investment in education and training (De Kok & Uhlaner, 2001; Saari et al., 1998); and provide more diverse career opportunities, more opportunities for advancement, and higher pay (Baron et al., 1986; Kalleberg & Van Buren, 1996). Additionally, establishment size may be linked to worker shortages simply because larger establishments have more jobs to fill. Rurality is another plant characteristic which appears related to workforce issues. For one, population, and thus an establishment's prospective labor pool, is far smaller in rural areas compared to urban areas. Additionally, there is evidence that rural establishments struggle to recruit for management and skilled worker positions (Keeble et al., 1992), both relevant for food manufacturing. Subindustry may be yet another plant-level factor relevant for worker shortages. There is large variation in the types of skills required by subindustry – for example, an average meat processing employee must be physically strong and able to safely handle knives, while spirits production involves more technical work and less physical work. Moreover, literature clearly shows that some skills are more in-demand than others (Wellener et al., 2021; Xue & Larson, 2015; Holzer, 2015), thus it is logical that levels of worker shortages may differ by subindustry.

Given the above, I formulate a third hypothesis: that plant characteristics are related to the probability of plants facing worker shortages.

2.4 Data

2.4.1 Survey

This work utilizes an original establishment-level dataset compiled from an employer survey of Missouri's food, agriculture, and forestry industries. The survey was developed and distributed as part of a separate project, the goal of which was to understand a wide range of workforce issues facing these industries. The survey was conducted in January through early March 2020 by University of Missouri Extension with support from Missouri Agricultural and Small Business Development Authority, the Missouri Agricultural Foundation, and the Missouri Department of Agriculture. It was distributed to a convenience sample of food and agriculture establishments via email, social media, industry organization meetings, and Extension meetings.

The survey included 26 questions divided into six sections. The first two sections asked respondents for basic information about their plant and its workforce, such as establishment subindustry, plant location, number of employees, and seasonality of jobs. The third section covered job vacancies and job growth – how the establishment plans to add employees, barriers to expanding employment, what positions are most difficult to fill, and issues surrounding an aging workforce. The fourth section asked establishments about their recruitment practices, as well as the benefits and incentives they offer employees. The fifth section asked about employee training methods and which skills are in high demand. The sixth section covered automation – whether respondents use automation, barriers to automation, and impacts of automation. The appendix (Table A.1) contains a full list of survey questions.[1]

The survey received 430 responses. Of these respondents, 104 did not employ workers in the food, agriculture, or forestry industries in the state of Missouri and thus were screened out. Of

[1] For a detailed report of the full set of survey findings – for all agriculture-related subindustries, not just food manufacturing – please see White et al., 2020. Further information on the original project may be found at this link: https://extension.missouri.edu/programs/exceed-community-economic-and-entrepreneurial-development/workforce-needs-assessment-for-missouri-s-agriculture-and-forestry-sector.

the remaining 326 establishments, food manufacturing plants composed 93 of these responses. Given that 636 food manufacturers were in the sample frame as of 2020 (Bureau of Labor Statistics, 2021b), the response rate was 15%, relatively high for a convenience sample.

2.4.2 Data

For my analysis, I used only responses from food manufacturing plants. I further reduced the set of 93 respondents mentioned above to 76 plants, as 17 plants either did not answer the question regarding worker shortages (my variable of interest), were coded as "not applicable" for this question, or left the majority of questions blank. There appeared to be few differences in characteristics between dropped plants and plants kept in the sample. On average, plants in the sample employed 172 individuals, compared to 153 for dropped plants. Both groups were also similar across rurality and seasonality of work. However, many more of the dropped plants were "other" food manufacturers – 47% of dropped plants fell into this group, compared to 13% of plants kept in the sample. Thus, my results may not be representative of "other" food manufacturers – businesses such as egg processors, ingredient manufacturers, and pet food manufacturers.

Additionally, I kept only multiple-choice questions in the dataset. I removed free answer and text questions, as analyzing qualitative results is beyond the scope of this study. I also dropped several multiple-choice questions as they did not relate to worker shortages. With 19 questions remaining in the dataset and about six answers per question on average, this still left over 100 explanatory variables to explore.

I coded my dependent variable in response to survey Question #9: Which of the following are potential barriers to expanding employment within this business? Respondents that selected "Shortage of workers with knowledge or skills" were coded as a "Yes" for my worker shortage variable. Plants that did not select this answer were coded as a "No", as long as they did not leave the question blank nor select "No barriers to expanding". If respondents left the question blank or reported they faced no barriers to expanding employment (seven companies), I coded the variable as “Not applicable”. Thus, my results may also be biased in the sense that I only included firms looking to expand employment.

I recognize that respondents could have interpreted this question and corresponding answers in different ways, and that this question may not be a perfect proxy for whether a plant was currently facing worker shortages at the time of asking. However, answers to Question #9 were corroborated elsewhere in the survey. Many of the plants coded as “yes” for worker shortages cited specific examples of skills and roles they struggled to fill. Additionally, Question #10 asked how businesses had adapted to a lack of skilled job applicants. None of the 58 plants coded as “yes” for worker shortages reported that they had not experienced a lack of skilled applicants, suggesting that plants indeed answered Question #9 based on worker shortage conditions within their own establishment.

It is also important to reiterate that responses, collected January through early March 2020, do not reflect workforce issues in the COVID-19 era. However, I believe responses do provide helpful insight into today’s labor market nonetheless because, as discussed in my literature review, labor shortages were widespread even pre-pandemic. Survey results confirm this, with 58 of 76 respondents (76%) experiencing worker shortages.

2.4.3 Summary Statistics

Summary statistics are available in Table 1. Most plants in the sample are meat processors – 53%. Plants employ 172 people on average; however, this ranges from 1 to 2900 employees, with a median of 14. Most plants are growing their workforce, with 57% expecting their workforce to increase slightly over the next year. Nearly all plants – 89% -- are single-location plants. Seasonality of jobs is rare, with 82% of plants reporting that less than a quarter of employees are seasonal. The majority of plants (61%) report the average job within their plant is moderately physically demanding.

Table 1: Summary statistics and table of variables used in Study 1

Survey Question	Answer or Description	Variable Name	Observations	Mean
How many workers do you employ in the state of Missouri?	Natural log of the number of workers employed in the state of Missouri	logsize	74	3.098
Which category best describes your business?	Animal slaughter, meat processing, poultry processing	sub_meatpoultry	72	0.528
	Fruit and vegetable manufacturing	sub_fruitveg	72	0.083
	Flour milling, rice milling, bread and bakery products, soybean or oilseed processing	sub_grainoilseed	72	0.069
	Dairy product manufacturing	sub_dairy	72	0.069
	Breweries, distilleries, wineries	sub_alcohol	72	0.097
Where does the majority of your workforce work?	Metro county (coded by researchers)	county_metro	75	0.427
	Nonmetro county (coded by researchers)	county_nonmetro	75	0.493
What percentage of your employees are seasonal?	0% to 25%	seasonal_low	76	0.816
	75% to 100%	seasonal_high	76	0.105
How do you expect the size of your business's workforce to change over the next 12 months?	Decrease significantly	size_decsig	76	0.026
	Decrease slightly	size_decslight	76	0.026
	Increase slightly	size_incslight	76	0.566
	Increase significantly	size_incsig	76	0.066
	Remain the same	size_same	76	0.263
	Not sure	size_unsure	76	0.053
How physically demanding is the average job in your business?	Not physically demanding	phys_not	76	0.026
	Occasionally physically demanding	phys_occasional	76	0.250
	Moderately physically demanding	phys_moderate	76	0.605
	Intensely physically demanding	phys_intense	76	0.118
How does the business plan to add employees?	Hiring new part-time employees	a_pttime	76	0.513
	Hiring new full-time employees	a_fulltime	76	0.566
	Using a temporary agency	a_temp	76	0.105
	Hiring contract workers	a_contract	76	0.026
	Recalling workers from a lay-off list	a_recall	76	0.026
	Other methods to add workers	a_other	76	0.079
Which of the following are potential barriers to expanding employment within the business?	Shortage of workers with knowledge or skills	b_workshort	76	0.763
	Government policies or regulations	b_govreg	76	0.342
	Economic conditions	b_econcond	76	0.342
	Lack of transportation access	b_transpaccess	76	0.132
	Lack of childcare access	b_careaccess	76	0.145
	Shortage of available training programs	b_trainshort	76	0.053
	Lack of information	b_infolack	76	0.026
How has the business adapted to a lack of skilled job applicants?	Forced to hire less experienced workers and then train them	c_lessexp	71	0.901
	Offering increased wages due to shortage of experienced workers	c_incrwage	71	0.437
	Hiring from outside the area	c_outsidearea	71	0.127
	Hiring contractors	c_contractors	71	0.113
	Hiring from outside the United States	c_outsideus	71	0.028
	Investing in automation	c_investauto	71	0.296

Survey Question	Answer or Description	Variable Name	Observations	Mean
What recruitment practices do you use to fill current jobs?	Employee referrals and networks	d_referrals	73	0.849
	Social media sites	d_socmedia	73	0.699
	Advertise on the business website	d_advertise	73	0.247
	College/university recruiting	d_collegerecruit	73	0.219
	Industry specific job boards	d_indspec	73	0.205
	External recruiters and agencies	d_externalrec	73	0.178
	Advertise at job centers	d_jobcenters	73	0.192
	Billboards and door signs	d_billboards	73	0.178
	Work with the media to talk about our business/ events	d_media	73	0.055
	Other	d_other	73	0.137
Which, if any, of the following benefits or incentives does your business offer employees?	Flexible work schedule	e_flexible	76	0.500
	The ability to work remotely	e_remote	76	0.092
	Providing housing or a vehicle	e_housecar	76	0.066
	Performance based pay increases or bonuses	e_payincr	76	0.500
	Financially support continuing education	e_education	76	0.197
	Childcare	e_childcare	76	0.000
	Paid vacation	e_vacation	76	0.566
	Other	e_other	76	0.224
	None of the above	e_none	76	0.053
Does your business hire, or would you consider hiring, the following workers?	Ex-offenders	f_exoffend	74	0.554
	Veterans	f_veterans	74	0.905
	H-2A guest workers	f_h2a	74	0.216
	Interns or co-ops	f_interns	74	0.635
	High school students	f_highschool	74	0.581
	Recent retirees	f_retirees	74	0.581
	None of the above	f_none	74	0.027
What skills are most difficult to find?	Truck drivers	g_truckdrive	72	0.111
	Automotive repair & mechanical	g_autorepair	72	0.014
	Electrical	g_electrical	72	0.139
	Automation & robotics knowledge	g_automation	72	0.111
	Heavy equipment operation	g_equipop	72	0.014
	Communication & interpersonal skills	g_com	72	0.264
	Problem solving & analytical	g_probsolve	72	0.264
	Financial management	g_finmgmt	72	0.042
	Leadership & supervisor skills	g_leadership	72	0.444
	Agronomy	g_agronomy	72	0.042
	Programming & software applications	g_program	72	0.028
	Customer service & sales	g_custservice	72	0.292
	Reliability & general work readiness	g_reliability	72	0.639
	Animal husbandry	g_animalhusb	72	0.042
	Livestock handling	g_livestock	72	0.222
	Other	g_other	72	0.194

Survey Question	Answer or Description	Variable Name	Observations	Mean
Which of the following methods does your business use to increase the skills of current workers?	On-the-job training	h_onthejob	73	0.986
	Flexible schedule for continuing education	h_flexible	73	0.205
	In-house classroom training	h_inhouse	73	0.233
	Vendor training	h_vend	73	0.137
	Online courses	h_online	73	0.192
	Tuition reimbursement	h_reimburse	73	0.219
	Hire only workers who are already trained	h_alreadytrain	73	0.055
	Apprenticeship programs	h_apprentice	73	0.205
	Community College provided customized training or education	h_commcoll	73	0.096
	Vocational trainings	h_voctrain	73	0.041
	Other	h_other	73	0.041
	None of the above	h_none	73	0.000
What challenges do you face when providing training for your existing workforce?	Finding relevant training options	j_relevance	67	0.403
	Can't afford existing training options	j_cantafford	67	0.134
	Lack of time for in-service training	j_lacktime	67	0.657
	Poor experience with previous training providers	j_poorexp	67	0.030
	Lack of online training options	j_lackonline	67	0.149
	Lack of space for training	j_lackspace	67	0.104
	Fear of losing trained employees	j_loseemp	67	0.343
	Other	j_other	67	0.030
How is greater automation impacting jobs within your business?	Decreased the number of jobs	k_decjobs	52	0.269
	Increased the number of jobs	k_incjobs	52	0.192
	Changed the type of jobs we hire	k_jobschng	52	0.462
	We need to provide our workers with more on the job training	k_moretrain	52	0.250
	No impact	k_noeffect	52	0.250
	Not applicable - we don't automate	k_noauto	52	0.286
What barriers does your business face as you adopt new technology and processes?	Insufficient broadband capacity	l_bb	66	0.273
	Cannot afford to implement	l_implement	66	0.545
	Workforce lacks capacity to implement automated processes	l_capacity	66	0.182
	Lack of information about available technologies	l_lackinfo	66	0.197
	Other	l_other	66	0.061
	No barriers	l_nobarriers	66	0.197
	New technologies are not applicable	l_notapp	66	0.136
What is the most common reason workers leave positions at your business?	Desire for more flexible or regular	leave_flex	71	0.113
	Higher compensation/benefits from other employers	leave_comp	71	0.169
	Retirement	leave_retire	71	0.056
	Seeking different type of work activities	leave_difftype	71	0.211
	The job is too physically demanding	leave_physical	71	0.183
	Workers rarely leave	leave_rare	71	0.169
	Other	leave_other	71	0.099
Which of the following best describes your business leadership's feelings about internal process automation?	Automation has significant potential for our business and we are planning to make investments in automating our processes	auto_potential	70	0.200
	Automation is on our radar, but we have no current plans to invest in it	auto_onradar	70	0.300
	We are already making significant investments in automation	auto_investing	70	0.229
	We are not looking to automate our processes	auto_noplan	70	0.271

When it comes to barriers to expanding employment, lack of workers with skills or knowledge is most commonly listed as a barrier – 76% of plants report this. Most plants have dealt with this worker shortage by hiring less experienced workers and training them (90%), though offering increased wages is also common (44%). Plants report the most difficult skill to find is reliability and general work readiness (64%) – so-called soft-skills. Leadership and supervisor skills also appear to be in short supply, with 44% of companies saying workers with these skills are difficult to find.

Most plants rely on typical hiring arrangements; 57% are hiring full-time workers, 51% hiring part-time workers, and relatively few plants hiring contract, recall, or temp agency workers. On the other hand, a variety of worker classes appear common in plants – only 3% of plants say they do not or would not hire ex-offenders, H-2A guest workers, high school students, interns, recent retirees, or veterans. Plants rely on a wide variety of recruitment practices, but overall, social media posts (70%) and employee referrals and networks (85%) are the most common.

Insights also emerge surrounding automation. Respondents hold mixed attitudes towards automation – relatively equal numbers of plants report they already invest in automation, will not invest in automation, or may invest in automation. 46% of plants report automation has changed the types of jobs for which they are hiring. 27% say automation has decreased the number of jobs, 19% say it has increased the number of jobs, 25% say training requirements have increased, and 25% say automation has not impacted jobs. The biggest barrier to adopting new technology and processes appears to be cost – 55% of plants report cost is a problem. Approximately 27% of establishments report that insufficient broadband has limited new technology adoption.

Summary statistics also cover training and benefits. Nearly all plants utilize on the job training – 99%. Other training options are less utilized, however; the next most popular method is in-house classroom training, with 23% of plants utilizing this option. Regarding challenges surrounding training, it appears that lack of time for in-service training is the largest problem – 66% of plants report this is an issue. Finding relevant training options (40%) and fear of losing trained employees (34%) are also common concerns. Regarding benefits and incentives, 57% of plants offer paid vacation, 50% offer a flexible work schedule, and 50% offer performance-based pay increases or bonuses. Other forms of benefits (childcare, paid housing) are much less common.

2.5 Model and Empirical Method

2.5.1 Model Specification

My analysis utilizes logistic regression. Logistic regression is used to model outcomes when the dependent variable is binary; in my dataset, plants either face a labor shortage or do not face a labor shortage. Logistic models are s-shaped curves, given by the equation:

$$f(z) = \frac{1}{1 + e^{-z}} \tag{1}$$

In logistic regression, *z* is a function of an intercept-like constant, independent variables, and coefficients. Coefficients represent the change in log odds of an outcome per unit change in an independent variable. Alternatively, logistic coefficients can be converted to odds ratios by exponentiating the coefficient. Due to ease of interpretation, I report odds ratios, not logistic coefficients.

The economics profession generally utilizes probit models, not logit models. Probit models and logit models are similar – practically speaking, the only difference is probit models have slightly larger tails than logit models – and the two models can be interchanged without issue in nearly all cases (Fitzmauric, Laird, and Ware, 2012). I opt to break convention to take advantage of a particular small-sample estimation technique only applicable to logistic models.

As mentioned above, z in equation (1) is a function of a constant, independent variables, and coefficients. For my analysis, I specify z as follows:

$$z = \beta_0 + \beta_1 logsize + \beta_2 single\_unit + \beta_3 \Phi + \beta_4 \Psi + \beta_5 \Omega + \beta_6 x \quad (2)$$

where *logsize* represents the log of company size, as measured in number of employees; *single_unit* is a dummy variable equaling one when a plant is an independently owned single-location establishment; Φ represents a vector of dummy variables indicating subindustry (meat and poultry processing, fruit and vegetable processing, grain and oilseed processing, dairy processing, and alcoholic beverage production); Ψ represents a vector of dummy variables indicating rurality of plant location (metro county or non-metro county); and Ω represents a vector of dummy variables measuring seasonality of work (low seasonality, with less than 25% of a company's jobs being seasonal, or high seasonality, with greater than 75% of the company's jobs being seasonal; 25% to 75% was the omitted condition). x represents a variable of interest; I estimate the above model one time for each variable of interest.

The first six terms of equation (2) serve as a "base model" or base set of controls, composed of plant characteristics. I layered each variable of interest individually on top of the base model. This approach is necessary given my small sample size and large number of independent variables. This method preserves degrees of freedom and reduces multicollinearity while still controlling for important confounding factors.

I chose five establishment characteristics for inclusion in the base model. I included these characteristics based on their expected relationships with worker shortages, as well as their potential to control for confounding factors. First, as discussed in the hypotheses section, there is reason to believe plant size is related to the prevalence of worker shortages. Intuitively, larger plants may struggle to hire employees at higher rates simply because of the sheer number of roles they must fill. Additionally, large organizations and small organizations differ substantially across a wide variety of workforce practices (De Kok & Uhlaner, 2001; Baron et al., 1986; Terpstra & Rozell, 1993; Kalleberg & Van Buren, 1996). Thus, including plant size in the base model should control for a variety of workforce-relevant factors.

Secondly, many workforce-relevant factors vary by subindustry. For example, as discussed in the hypotheses section, different food manufacturing subindustries require different skills. Moreover, pay varies widely between subindustries; yearly compensation for an average meat processing working totaled $53,200 in 2020, while compensation for the average distillery worker totaled $67,500 (Bureau of Labor Statistics, 2022d, 2022e). Thus, it is clear subindustry is also a useful control. Rurality is also related to worker shortages (Keeble et al., 1992). Additionally, rurality is associated with many workforce-relevant factors – such as age of the workforce, prevalence of disability, and income (Smith & Trevelyan, 2019; Zhao et al., 2019; Cromartie, 2017) – that my analysis otherwise does not control for.

Finally, plant location type and seasonality of employment appear related to workforce and human resource management factors, and potentially worker shortages. Franchises and multi-unit establishments face unique workforce challenges, such as increased difficulty coordinating HR practices between locations and difficulty tailoring business practices to local conditions (Chang & Harrington, 2002; Zolfagharian & Naderi, 2019). Seasonality of employment also poses unique challenges to businesses, such as difficulty managing and maintaining employee-employer relationships from year to year (Newman & Drost, 2008) and low commitment to the organization among seasonal workers (Ainsworth & Purss, 2009).

2.5.2 Estimation Method

I estimate the above model using Firth's penalized maximum likelihood estimation, as developed by Firth, 1993. I chose this method for several reasons. Firstly, maximum likelihood estimation – the usual estimator utilized for logistic regression – is only asymptotically unbiased and thus is often heavily biased in small sample sizes (McCullagh & Nelder, 2019). This is a relevant pitfall for this study, as most regressions involve between 60 and 75 observations. Additionally, maximum likelihood estimates are heavily biased, or even nonexistent, when separation exists in a dataset – when a given predictor is only associated with one outcome (Albert & Anderson, 1984). Given the small sub-sample size for many variables – for example, only three plants offer vocational training, and five plants provide paid housing or transport – separation often occurs in my dataset. And indeed, maximum likelihood estimation could not be executed for many of these variables. For these reasons, Firth's method has become quite popular in recent years, particularly for the analysis of rare medical events, where events occur at rates of ten to thousands of times less than non-events (Kotloff et al., 2013; Visser et al., 2009; Fritsche et al., 2016; King & Zeng, 2001).

Several methods can circumvent the problems associated with small datasets and data separation. Exact logistic estimation may be used; however, this method is often prohibitively computationally expensive (Cox & Snell, 2018; Mehta & Patel, 1995). Indeed, I could not execute this estimation method due to my large number of regressors. King and Zeng's (2001a, 2001b) bias correction method is also a viable method; however, it overcorrects for bias in extremely small samples, and this method is not readily available in many statistical packages (Leitgöb, 2013). Firth's (1993) penalized maximum likelihood estimation method does not suffer from overcorrection, and it is user-friendly. Thus, I use this method to estimate my coefficients.

The method is similar to maximum likelihood estimation, but the likelihood function is penalized via a term sensitive to decreasing sample size and decreasing sub-sample size, i.e. increasing separation (Firth, 1993). For a logistic regression model $\mathrm{P}(\mathrm{Y} = 1|x_i) = \frac{1}{1+exp(-x_i\beta)}$ with i = 1, … N, the maximum likelihood estimate $\hat{\beta}_{ML}$ is given by the vector that maximizes the log-likelihood function, $L(\beta)$. The maximum likelihood estimate is generally computed by solving the score equations $\partial L/\partial\beta_j = 0$ with j = 0, …p, where p is the number of independent variables in the regression model. Firth (1993) showed that an alternative set of score equations could be solved to produce an estimate with greatly reduced bias in small samples. This set of score equations is given by:

$$\sum_{i=1}^{N}(y_i - \pi_i + h_i(1/2 - \pi_i))x_{ij} = 0, \; j = 0, \ldots p$$

Where h_{i} is the i-th diagonal element of the hat matrix $\boldsymbol{W^{1/2}X(X'WX)^{-1}X'W^{1/2}}$, with $\mathbf{X}$ representing the design matrix; **W** represents the diagonal matrix $\pi_i(1 - \pi_i)$. $\pi_i = \frac{1}{1+exp(-x_i\beta)}$ and the predicted probability for the i-th observation.

2.6 Results

I separate discussion of results into three subsections, with each subsection corresponding to one of my hypotheses. The first subsection details what types of plant characteristics are related to worker shortages. The second subsection explores shorter-term internal business practices – hiring, training, and retention. The last subsection focuses on longer-term structural factors.

It is important to note that I use $\alpha = 0.10$ for my statistical significance threshold. Given the small sample size of less than 75 for most questions, a more generous alpha-level than the conventional $\alpha = 0.05$ is appropriate. Marginally insignificant findings ($p < 0.15$) are also discussed, as this is a small-sample exploratory study aiming to broadly capture themes for further analysis. Given the aims of my study, the workforce focus (as compared to a high-stakes discipline like medicine), and my low-precision sample, this flexible approach appears justified (Dallal, 1999; Krueger, 2001).

Additionally, I would like to note that results are not necessarily causal. Firth's penalized maximum likelihood estimation is not a causal approach; readers should interpret results as mere associations. Additionally, given my degree of freedom constraints, I could include few variables in my models. Thus, omitted variable bias may also be a concern.

2.6.1 What types of plants are experiencing worker shortages?

Relatively few plant characteristics seem linked to whether a plant faces worker shortages (Table 2, Table 3). No variables in the base model are significant. However, since answers within the subindustry, rurality, and seasonality categories are mutually exclusive, there is a high degree of multicollinearity for these variables. Thus, I use t-tests to determine significance for groups of variables within the base model.

Table 2: Odds ratios for base model

Question	Variable	Odds Ratio	P-Value
How many workers do you employ in the state of Missouri?	logsize	1.227	0.318
Which category best describes your business?	sub_meatpoultry	2.039	0.455
	sub_fruitveg	3.207	0.395
	sub_grainoilseed	0.990	0.994
	sub_dairy	1.343	0.822
	sub_alcohol	0.646	0.707
Where does the majority of your workforce work?	county_metro	2.769	0.582
	county_nonmetro	1.531	0.817
What percentage of your employees are seasonal?	seasonal_low	3.917	0.203
	seasonal_high	0.672	0.757
N/A	single_unit	0.900	0.951
	constant	0.211	0.372

*** p<0.01, ** p<0.05, * p<0.10, **bold** p<0.15
Red shading indicates a significant odds ratio greater than one. Green shading indicates a significant odds ratio less than one.

Table 3: Odds ratios for firm characteristics

Question	Variable	Odds Ratio	P-Value
How do you expect the size of your business's workforce to change over the next 12 months?	**size_decsig**	**22.971**	**0.146**
	size_decslight	0.576	0.788
	size_incslight	1.068	0.922
	size_incsig	1.024	0.984
	size_same	0.867	0.853
	size_unsure**	**0.060**	**0.048**
How physically demanding is the average job in your business?	phys_not	0.859	0.936
	phys_occasional	0.343	0.192
	phys_moderate	1.916	0.319
	phys_intense	0.887	0.897

*** p<0.01, ** p<0.05, * p<0.10, **bold** p<0.15
Red shading indicates a significant odds ratio greater than one. Green shading indicates a significant odds ratio less than one.

Using joint t-tests, I find that neither rurality nor subindustry are linked to prevalence of worker shortages. However, seasonality of work is marginally insignificant (p-value of 0.1364). Additionally, there is a link between expecting to decrease workforce size and likelihood of worker shortages – plants that report they expect to decrease workforce size greatly are about 23 times as likely to face a worker shortage than plants that do not have this expectation (Table 3). Worker shortages could be forcing plants to cut back on employee numbers at high rates. Alternatively, factors like automation and establishment financial health could be omitted variables driving both these measures. Plants which are unsure of their size expectations are estimated to be 18.5 times less likely to be experiencing a worker shortage. This finding seems puzzling; perhaps omitted variables are driving this relationship. Finally, there appears to be no relationship between job physicality and the ability to find and retain workers.

2.6.2 What types of human resource practices – recruitment, hiring, training, and retention practices – are related to worker shortages?

Several training and retention practices are associated with reduced odds of worker shortages (Table 4). Establishments which provide flexible work schedules for continuing education are 4.5 times less likely to experience worker shortages. Plants which offer

Table 4: Odds ratios for hirings and talent management practices

Question	Variable	Odds Ratio	P-Value
How does the business plan to add employees?	a_pttime	0.867	0.826
	a_fulltime**	**6.638**	**0.012**
	a_temp	1.036	0.972
	a_contract	0.544	0.683
	a_recall	18.938	0.179
	a_other	0.280	0.280
How has the business adapted to a lack of skilled job applicants?	**c_lessexp***	**6.477**	**0.077**
	c_incrwage	0.819	0.787
	c_outsidearea	0.628	0.658
	c_contractors	0.796	0.852
	c_outsideus	0.603	0.818
What recruitment practices do you use to fill current jobs?	d_referrals	2.582	0.298
	d_socmedia	0.651	0.561
	d_advertise	2.648	0.341
	d_collegerecruit	0.748	0.738
	d_indspec	1.304	0.770
	d_externalrec	0.284	0.177
	d_jobcenters	1.096	0.925
	d_billboards	0.520	0.458
	d_media	0.289	0.332
	d_other	0.416	0.287
Which, if any, of the following benefits or incentives does your business offer employees?	e_flexible	0.503	0.333
	e_remote	2.138	0.613
	e_housecar	6.193	0.271
	e_payincr	1.341	0.639
	e_education*	**0.110**	**0.081**
	e_childcare	Omitted due to perfect collinearity	
	e_vacation*	**8.185**	**0.050**
	e_other	0.649	0.556
	e_none	9.793	0.287
Does your business hire, or would you consider hiring, the following workers?	f_exoffend	0.646	0.526
	f_veterans	0.721	0.748
	f_h2a	0.585	0.525
	f_interns	0.433	0.237
	f_highschool	2.432	0.176
	f_retirees	1.661	0.469
	f_none	0.676	0.789
Which of the following methods does your business use to increase the skills of current workers?	h_onthejob	Omitted due to perfect collinearity	
	h_flexible*	**0.223**	**0.062**
	h_inhouse	0.636	0.603
	h_vend	0.757	0.769
	h_online	0.772	0.772
	h_reimburse	0.656	0.748
	h_alreadytrain	2.327	0.632
	h_apprentice**	**0.133**	**0.019**
	h_commcoll**	**0.107**	**0.029**
	h_voctrain	0.311	0.321
	h_other	3.705	0.483
	h_none	Omitted due to perfect collinearity	
What is the most common reason workers leave positions at your business?	leave_flex	1.235	0.849
	leave_comp	1.338	0.774
	leave_other	**0.244**	**0.140**
	leave_difftype	2.894	0.230
	leave_physical	2.243	0.390
	leave_rare**	**0.153**	**0.022**

*** p<0.01, ** p<0.05, * p<0.10, **bold** p<0.15

Red shading indicates a significant odds ratio greater than one. Green shading indicates a significant odds ratio less than one.

apprenticeship programs are 7.1 times less likely to experience worker shortages. And plants offering community-college provided customized training are 9.3 times less likely to experience worker shortages. Regarding benefits, plants that provide financial support to their employees for continuing education are 9.3 times less likely to face worker shortages.

Interesting results also emerge surrounding employment separations (Table 4). Establishments reporting workers rarely leave are, unsurprisingly, less likely to face labor shortages – 6.1 times less likely. This suggests improving worker retention, not just attracting new applicants, may mitigate labor shortages. Alternatively, employees may be less likely to leave companies not facing labor shortages, simply because well-staffed companies may be less stressful and less burnout-inducing. Plants reporting workers leave due to “other reasons” are 4.3 times less likely to face labor shortages. Other reasons listed include factors such as health issues, caretaking responsibilities, lack of transportation, and lack of work-readiness.

Several practices are also associated with *increased* worker shortage odds (Table 4). Plants hiring fulltime employees are 6.7 times more likely to face worker shortages than plants hiring through other means (part time, temp agencies, contract employment, or recall lists). Fulltime employees may be in shorter supply than other types of workers, or the skills and roles fulltime workers fill may be in particularly high demand. Alternatively, plants experiencing worker shortages may seek to hire fulltime workers, as they would need to hire fewer fulltime workers to do the same amount of work as parttime workers. Plants offering paid vacation are 8.3 times more likely to experience worker shortages. This association may simply be driven by the difficulty in hiring fulltime workers, as these two variables are correlated (correlation coefficient of 0.57). Alternatively, plants experiencing worker shortages may offer paid vacation at increased rates to attract workers. Lastly, plants which report having to hire less experienced employees are 6.7 times more likely to face a worker shortage, indicating that companies may be filling gaps with less qualified individuals, or that plants may hold unrealistic expectations regarding worker qualifications.

2.6.3 What types of long-run and structural factors are related to worker shortages?

Several long-run, structural factors are associated with decreased odds of worker shortages (Table 5). Plants reporting they have no plans to automate internal processes are less likely to experience worker shortages – 3.9 times less likely. Perhaps the lack of labor shortages is driving the decision to not automate – if a company does not have a problem finding workers, it may face less pressure to automate. Plants that report programming and software application skills are most difficult to find are 8.3 times less likely to face labor shortages. This suggests there is relatively high supply of these workers, perhaps because these jobs tend to be more white-collar and better paying. Alternatively, perhaps facing a shortage of programmers and software engineers is a "good problem" for companies – this may indicate a company is highly automated and advanced, and thus has resolved many issues related to worker shortages. Plants reporting transportation access and lack of childcare are barriers to expanding employment within the business are less likely to experience labor shortages. And lastly, plants that report "other" barriers to adoption of new technology and processes are less likely to be facing labor shortages. Looking at the qualitative survey data, "other" primarily encompasses factors like an aging workforce and lack of skills surrounding new processes.

Some long-run, structural factors are associated with *increased* odds of worker shortages (Table 5). Plants that report livestock handling skills are most difficult to find face worker shortages at 29.5 times increased odds. My base model controls for subindustry, so this is not implying that meat and poultry processing plants are struggling to find workers. Difficulty finding electrical skills is also associated with increased odds of worker shortages – 11.5 times greater odds. Additionally, planning to make investments in internal process automation is associated with a 12.8 times greater likelihood of experiencing a worker shortage.

Table 5: Odds ratios for structural and long-term factors

Question	Variable	Odds Ratio	P-Value
Which of the following are potential barriers to expanding employment within the business?	b_govreg	0.636	0.487
	b_econcond	0.813	0.746
	b_transpaccess	**0.224**	**0.143**
	b_careaccess**	**0.131**	**0.040**
	b_trainshort	1.980	0.658
	b_infolack	2.071	0.691
How has the business adapted to a lack of skilled job applicants?	c_investauto	1.336	0.751
What skills are most difficult to find?	g_truckdrive	0.792	0.844
	g_autorepair	4.114	0.532
	g_electrical	**11.452**	**0.146**
	g_automation	7.393	0.318
	g_equipop	4.114	0.532
	g_com	0.540	0.421
	g_probsolve	0.754	0.683
	g_finmgmt	1.955	0.684
	g_leadership	1.000	1.000
	g_agronomy	1.301	0.854
	g_program	**0.138**	**0.131**
	g_custservice	0.893	0.886
	g_reliability	1.074	0.912
	g_animalhusb	0.219	0.356
	g_livestock	**28.581**	**0.101**
	g_other	0.625	0.519
What challenges do you face when providing training for your existing workforce?	j_relevance	0.755	0.704
	j_cantafford	0.468	0.413
	j_lacktime	1.605	0.538
	j_poorexp	0.279	0.327
	j_lackonline	0.258	0.172
	j_lackspace	1.987	0.671
	j_loseemp	1.723	0.475
	j_other	0.055	0.240
How is greater automation impacting jobs within your business?	k_decrjobs	0.873	0.871
	k_incrjobs	0.347	0.318
	k_jobschng	1.077	0.926
	k_moretrain	2.199	0.441
	k_noeffect	1.972	0.511
	k_noauto	0.684	0.627
What barriers does your business face as you adopt new technology and processes?	l_bb	0.619	0.507
	l_implement	0.881	0.871
	l_capacity	1.416	0.804
	l_lackinfo	4.544	0.295
	l_other*	**0.086**	**0.109**
	l_nobarriers	0.908	0.920
	l_notapp	0.672	0.662
Which of the following best describes you business leadership's feelings about internal process automation?	**auto_potential**	**12.837**	**0.117**
	auto_onradar	0.770	0.704
	auto_investing	1.237	0.845
	auto_noplan	**0.255**	**0.110**
What is the most common reason workers leave positions at your business?	leave_retire	1.659	0.744

*** p<0.01, ** p<0.05, * p<0.10, **bold** p<0.15

Red shading indicates a significant odds ratio greater than one. Green shading indicates a significant odds ratio less than one.

2.7 Discussion and Implications

2.7.1 Training and Education

The first theme that emerges in my results surrounds training and education. To recap, my results show that establishments which support education and training are less likely to experience worker shortages. In particular, plants that offer flexible schedules for continuing education, apprenticeship programs, customized community college trainings, or that financially support continuing education are far less likely to face labor shortages. These results are largely consistent with the literature, which shows training and education are factors many employees consider when it comes to both looking for work and remaining at a company (de Vos & Meganck, 2009; Schlechter et al., 2015; Pergnolato et al., 2017).

However, there is ample evidence that manufacturers struggle to offer effective training and education (Eckert, 2020; Wellener et al., 2021). Many case studies and reports have explored this issue, providing best practices on how training and education can be made easier and more effective for manufacturers. Several of these reports indeed recognize two of the above methods – apprenticeships and customized community college trainings for current employees – as effective (NIST MEP, 2014; National Governors Association, 2013; Andrew et al., 2020; Eckert, 2020). Programs involving educational institutions – four-year colleges, community colleges, and technical schools – partnering with manufacturing companies and state/local governments is another effective approach. These programs undertake a wide variety of activities, such as collaborating to develop manufacturing-centric college classes and curricula, providing students with real manufacturing problems to solve as part of coursework, and providing work-based learning opportunities like internships (NIST MEP, 2014; National Governors Association, 2013; Wellener et al., 2021). One last approach that has been shown to be effective is targeting manufacturing education and training programs towards specific cohorts – such as high school students, low-income individuals, and veterans (NIST MEP, 2014; Wellener et al., 2021). As my results show that training and education opportunities are related to worker shortages, it may be helpful for companies facing labor shortages to explore some of the above approaches.

The state of Missouri has prioritized food manufacturing industry growth (Missouri Department of Agriculture, 2020). If policymakers want to help alleviate food manufacturing worker shortages – essential if the industry is to grow – potential policy implications of my results might be further investment in Missouri Enterprise training resources; further investment in and promotion of community college and industry training partnerships; and investing in communications and marketing about careers in food manufacturing, making high school students and parents aware of opportunities in the sector and working to change perceptions of these jobs.

It is important to note that my training and education results may perhaps be explained by omitted variables, such as quality of company culture or company financial position. Companies that emphasize a healthy culture of employee well-being and engagement have less employee turnover (Colbert, 2012; Glen, 2006) and would also likely be more apt to invest in employee training. Additionally, training employees requires financial investment; establishments in good financial positions are better able to afford training opportunities. And financially successful workplaces are often less stressful, leading to less turnover and fewer worker shortages. Company culture and company financial position were not captured in the data, so I cannot rule out these spurious correlations.

2.7.2 Automation

The second theme that emerges from my analysis surrounds automation. Plants which say automation has potential for the business and that plan to automate processes are far more likely to face worker shortages. Conversely, plants not looking to automate processes are less likely to face worker shortages. These two statements suggest worker shortages are a driver for automation in food manufacturing. Since this question asked about future *plans* for automation, this makes the possibility of reverse causality – of higher degrees of current automation driving worker shortages, perhaps through lack of automation-relevant skills – like likely. Multiple industry reports also support the finding that worker shortages drive automation, showing that the majority of firms have relied on automation to mitigate COVID-19 related challenges, including labor shortages (Watson et al., 2020; Wellener et al., 2021).

Interestingly, it does not appear that the *current* level of automation is related to whether a plant experiences a worker shortage. Both questions asking about a plant's current level of automation show automated plants are no less likely to face worker shortages. This could be due to the nature of the jobs cut and subsequently created by automation. As discussed in my literature review, there is much debate regarding the impacts of automation on jobs, but most of the recent literature suggests low-skill jobs are replaced by automation and, in turn, automation creates new high-skill jobs (Graetz and Michaels, 2018; Autor, 2015; Acemoglu & Restrepo, 2019). Thus, it is possible that plants adopting automation do not actually benefit in regard to labor shortages. However, I do acknowledge that automation may benefit plants in other ways, such as reducing costs or increasing profits.

One implication of these findings is that companies thinking about automation due to labor shortages should consider their specific circumstances and labor needs before automating. Automation may be most appropriate in settings where shortages of non-skilled workers outweigh shortages of skilled workers. Alternatively, automation may also be successful in settings where plants are willing to train and upskill employees on new technologies. Multiple industry reports show training and upskilling is essential to the success of automation and robotics implementation (Herzberg et al., 2020; Wellener et al., 2021; PwC and The Manufacturing Institute, 2019).

Small plants in particular may want to carefully consider their approach to automation. On average, smaller plants automate at lower rates than larger plants (Herzberg et al., 2020). This is, in part, because industrial robots may be prohibitively expensive for SME plants, but also because the automation integration process itself is quite money- and knowledge-intensive (Sanneman et al., 2020). Thus, to avoid costly mistakes, small plants especially may want to consider their workforce needs prior to automating.

Policymakers interested in supporting food manufacturing may consider investing in training programs targeted towards maintaining and operating automated manufacturing equipment, and in programs encouraging young people to pursue these careers. These jobs often pay more than production worker jobs, creating higher per capita incomes and potentially enhancing the competitiveness of regional food manufacturers. As mentioned in the training section above, such training may be conducted in partnership with industry and community colleges.

2.8 Conclusions

Several themes emerged from my results. First, plants that invest in their workforce through education and training experience less difficulty attracting and retaining workers. Specific practices that were significant included apprenticeships, partnerships with community colleges on customized training, offering flexible schedules to facilitate continuing education, and financially supporting continuing education.

Second, results also showed a relationship between plants experiencing worker shortages and their plans to further automate operations. This suggests plants view increased automation as a way to alleviate worker shortages. This analysis, however, showed no relationship between *current* levels of automation and worker shortages. As a result, this research cannot determine the extent to which greater automation actually mitigates labor shortages. Therefore, further work is needed to better understand this phenomenon.

This paper made several contributions. First, the plant-level survey dataset provided unique insight into establishment-level issues. Second, this work contributed to the relatively sparse food manufacturing workforce literature, a particularly relevant accomplishment in a time of increased agricultural labor shortages and food security concerns. Finally, this analysis used Firth's penalized maximum likelihood estimation – a method relatively new to the field of economics – to produce estimates with reduced bias under small sample size conditions.

Future research, both quantitative and qualitative, should focus on a deeper-dive into the training and education and automation themes this thesis identified. A nation-wide survey would have a larger survey frame and eliminate any geographic bias from which this research suffers. The survey utilized was specific to Missouri and utilized a convenience sample; however, it benefitted from a relatively high response rate due to the personal relationships the survey team forged with food manufacturers. Other researchers conducting work in this space should consider using a quantitative survey designed with causal analysis methods in mind. My analysis only allowed correlative statements to be made; investigating these themes from a causal standpoint would add further nuance and color to my findings. Finally, omitted variable bias and endogeneity limits the applicability and extension of this study, but a nationwide survey frame and causal analysis framework would address these limitations.

CHAPTER 3: MEAT PROCESSOR RESILIENCE: PLANT SURVIVAL AND WORKFORCE IMPACTS

Abstract

This paper examines factors related to meat processor survival, in particular the survival of small- and medium-sized processors. I utilize a large dataset of over 8,000 plants nationwide, spanning 1997 to 2020. Cox proportional hazards is utilized to estimate models containing vectors of plant characteristics, input market factors, workforce variables, policy and infrastructure variables, and industry concentration measures. I find that each vector does have a relationship with plant survival, though the size and strength of those relationships vary. The

relationship between survival and plant characteristics is largest and most robust, particularly for small- and medium-sized plants, though workforce factors also have a robust relationship with survival.

3.1 Introduction

During the height of COVID-19-related disruptions, meat processing output was reduced by 40% due to spread of the virus among workers, and subsequent plant shutdowns and capacity reductions (Ijaz et al., 2021; Bina et al., 2021). These disruptions were particularly severe for large plants, which tend to employ large numbers of people who work in tight quarters at low temperatures, conditions which were conducive to the virus' spread (Taylor et al., 2020; Cunningham et al., 2021). Other events during the pandemic period, including a major fire at JBS's Grand Island, Nebraska plant and a ransomware attack against the company, further contributed to meat processing industry disruptions.

Not only did these disruptions lead to greatly reduced meat output and supply, but also led to adverse price impacts for both farmers and consumers. As demand for live hogs and cattle fell due to mass plant closures in the second quarter of 2020, prices for these animals plummeted, hurting farmer bottom lines. Conversely, as meat supply fell, consumers were hit with higher prices – from February 2020 to June 2020 steak prices increased 25%, while pork chop prices increased 23%, in part due to meat supply chain disruptions (Bureau of Labor Statistics, 2022a).

There is also concern amongst experts that these price fluctuations may be due to market power within the meat processing industry. Concentration of animal slaughtering and meat packing has been a concern for decades; in 1980 the four-firm concentration ratio for the steer and heifer slaughter industry was 36, while in 1997 the CR4 was 80 (MacDonald et al., 2000). Hog slaughter has followed a similar, though less extreme, trend; in 1980 the CR4 was 34, while in 1997 it was 54 (MacDonald et al., 2000). Since the late 1990s or early 2000s, the concentration rate of both industries has slowed, and in the case of beef processing, completely leveled off (Ward, 2010; Crespi et al., 2012). There is much debate amongst economists on whether these high concentrations reflect market power and anti-competitive behavior or are merely due to increasing technology intensivity and economies of scale. Nonetheless, market power among meat processors remains a concern for many industry analysts and policymakers.

As a result of disruptions to major industry players throughout 2020 and 2021 and concerns surrounding market power, there has been much interest in increasing meat processing industry resilience through investing in small and medium plants. At the Federal level, the Biden administration has dedicated $1 billion in funds from the American Rescue Plan – President Biden's COVID-19-related stimulus package – to improving resilience in the industry (U.S. Department of Agriculture, 2021; The White House, 2022). Up to $750 million will go towards increasing capital for independent processors through grants and loans, $100 million for meat processing workforce development, $100 million towards reducing food inspection costs for independent processors, and $50 million in technical assistance for independent processors (U.S. Department of Agriculture, 2021; The White House, 2022). States have also responded to industry resilience problems with investments in small and medium processors and policy innovation. For example, Missouri put nearly $17 million in funds form the CARES act towards expanding and supporting small and medium meat processors, while Iowa's Department of Agriculture and Land Stewardship dedicated $4 million in CARES funds towards the same (Missouri Department of Agriculture, 2021; Iowa Department of Agriculture & Land Stewardship, 2020). Wyoming revised their Food Freedom Act to encourage consumer patronage of custom slaughter facilities by relaxing regulatory policies (Thilmany et al., 2021).

Despite this interest in supporting small and medium meat processing plants, to my knowledge there have been no quantitative studies examining what factors influence success of these plants. Even tangential literature, examining location decisions and food manufacturing survival more broadly, is sparse. Thus, the purpose of my work is to fill this gap in the literature and explore what factors are associated with meat processor resilience, particularly the resilience of small and medium processors. Understanding what factors are associated with plant survival is a crucial first step in allocating the hundreds of millions of dollars set aside by Federal and state governments.

In this paper, I explore the relationship between various plant-level and local characteristics and the survival of meat processing plants. Cox proportional hazard models are used to estimate hazard ratios. Results show that all vectors of interest – plant-level variables, input market access, workforce characteristics, infrastructure and policy, and industry concentration – are related to meat processor survival. Plant-level variables have a stronger and more robust relationship with survival than local context variables; this is especially true for small- and medium-sized plants.

This study makes several contributions to the existing literature. As mentioned above, to my knowledge this is the first study quantitively examining the survival of small and medium meat processors. Additionally, this study includes a large number of plants – over 8,000 – across a twenty-four-year period. The study is national in scope and includes a number of plant-level characteristics.

This paper commences by exploring the existing literature on manufacturer survival and food manufacturer location and growth. Then hypotheses are formed, and my conceptual model – the survival model – is discussed. Next, I cover my data and empirical models, followed by results. Finally, I provide policy implications for my work, and conclude.

3.2 Background and Hypotheses

Two strands of literature inform my hypotheses and model construction. First is the manufacturing plant survival literature. At a high level, survival analysis, also known as hazard or duration analysis, is used to model likelihood of survival over time. Survival analysis can be used in a wide variety of contexts – to measure success of medical treatments, longevity of machine parts, duration of business start-ups, and much more – as long as the underlying data are captured at the individual level and at uniform periods over time. Survival analysis has been widely used to understand the U.S. manufacturing industry. However, survival analysis has largely not been applied to meat processing; I have found only one study examining meat processing plant survival, and it utilized probit models, not hazard models. Thus, I also draw upon location literature. Food processing plants – and specifically meat processing plants – have been the subject of many site selection, or location, studies. These studies provide me with additional sector-specific considerations not covered in the manufacturing survival literature.

3.2.1 Survival Literature

Most manufacturing survival studies include at least one descriptive plant-level variable. Establishment size, measured with employment, and ownership structure – single-unit or multi-unit – are common choices, used by Audretsch and Mahmood (1994), Bernard and Jensen (2002), Agarwal and Audretsch (2001), and Audretsch and Mahmood (1995). In these studies, size consistently has a positive relationship with survival (the larger the plant at its initial startup date, the higher its chances of survival). Most of these studies found that independent plants have higher survival rates than multi-unit plants. Recent ownership changes (i.e. sales of plant facilities), multi-national ownership, multi-product plants, and plant-level wages are lesser-used plant variables. Multi-national ownership and recent ownership change of plants have been found to have a negative relationship with survival, while multi-product production and plant wages have a positive relationship with survival (Bernard & Jensen, 2002; Audretsch & Mahmood, 1995).

In addition to plant-level characteristics, general manufacturing survival literature has also investigated the relationship between microeconomic theory-based variables and survival.

For example, key variables included in Audretsch and Mahmood (1994) include measures of minimum efficient scale, technological intensity, and innovation. This approach can also be seen in other manufacturing survival studies, with Bernard and Jensen (2002) including variables related to country-level manufacturing specialization, labor and capital utilization, and trade; Agarwal and Audretsch (2001) investigating the impacts of the economic life cycle and technology-intensity of various subindustries; and Audretsch and Mahmood (2001) examining factors such as industry concentration and price-cost margin. In nearly all cases, the above studies find that these variables are significant and influence survival in the direction economic theory would suggest.

Low and Brown (2017) differs from the above in that it examined manufacturing plant survival through a more regional economics-centric lens. Two vectors of variables were examined: establishment-level traits (which included number of employees, hourly pay, local sales percentage, local inputs percentage, and perception of local tax burden) and local context variables (which included rurality, population, regional competition, regional specialization, and economic diversity). Major findings include that smaller independent plants have higher survival rates than multi-unit plants and larger plants, that plant survival differs by U.S. region and manufacturing subindustry, and that survival is more predictable for single-unit plants than multi-unit plants.

The study most relevant for my work is Anderson et al. (1998), which used probit regressions to model likelihood of plants exiting the beef packing industry throughout the early 1990s. This study used three vectors of explanatory variables: plant-level variables (capacity, age, vertical and horizontal integration, number of related plants), market structure (entry rate, Herfindahl-Hirschman Index (HHI), a number of novel competition measures), and supply and demand shifters (wages, cattle prices, population, per capita income). Plant-level data were constructed through use of Food Safety and Inspection Service databases, allowing several unique variables to be used. The concentration variables were calculated at the "cattle procurement area" level (i.e., for within a 150-mile radius of each plant), while the market structure variables were at the BEA region level (similar to commuting zones). Anderson et al. (1998) found that plant-level variables are more closely related to exits than regional variables; all plant-level variables were significant, while no supply and demand shifters and few market structure variables were significant.

3.2.2 Plant Location and Growth Factor Literature

Assuming that plants are profit maximizing and will locate in areas where they anticipate the greatest levels of success, there is a clear link between where a firm chooses to situate a plant and that plant's subsequent hazard or survival rate. Thus, I look to several studies examining plant location decisions and growth factors to further inform my hypotheses. As mentioned above, this literature is much more food processor- and meat processor- focused than the survival literature, which further aids in developing my hypotheses.

Several studies examine location of food manufacturing plants broadly, without further segmentation by subindustry. Asiseh et al., (2009) looked at the change in number of food manufacturing establishments in a county using six vectors of explanatory variables: agricultural input markets, output markets, labor market variables, agglomeration, economic effectiveness (i.e., productivity), and other. This analysis is particularly useful, as it segmented establishments by size, much like my analysis does. The authors found that for small plants, agricultural product value and population were positively related to the change in number of food manufacturing plants. Per capita income, proportion of the population with at least a high school degree, poverty rate, and number of food manufacturing establishments were negatively related to the change in the number of establishments. Similarly, Low et al., 2021 examined the number of food manufacturing startups in each county, using a variety of vectors: "AgriCulture" factors (i.e., factors representing niche and innovative food production), entrepreneurial ecosystem variables, rurality, infrastructure, and local economy measures. They found that all of these vectors had a significant relationship with the number of food manufacturing startups.

A number of studies segment plants into supply-oriented establishments, demand-oriented establishments, and footloose establishments – a classification based on location theory as pioneered by Connor and Schiek (1997) – and investigate how various county-level factors are related to the location of new manufacturing plants in each segment. These studies used a standard set of vectors: input and output markets, labor quality and availability, agglomeration, infrastructure, and fiscal policies. Henderson and McNamara (2000) examined which of the above factors were related to the number of new food manufacturing plants locating in a county from 1987 to 1996. For supply-oriented plants – the category to which meat processing plants belong – crop sales, livestock sales, density of interstates, number of other meat processing plants, and county economic center status had a positive relationship with meat processor start-up locations. Unemployment rates and tax rates had a negative relationship. Lambert and McNamara (2007) also examined the number of new food manufacturing establishments in a county. Many factors in each vector were significant for supply-oriented plants, and no vector seemed to matter more than another for location decisions. Conversely, in Lambert and McNamara's 2009 study, they found that for supply-oriented plants, input and output market factors were generally significant and had a positive relationship with the number of new food manufacturing plants. The significance of labor measures, infrastructure measures, and tax measures was more mixed and tended to depend on whether a county was metro, micro, or non-core.

Finally, two studies examine growth and location decisions by food manufacturing subindustry, including for meat processing. Goetz (1997) investigated net change in the number of food processing plants at the county level using the traditional five vectors influenced by location theory: output market access, raw material market access, labor force composition, transportation infrastructure, and state and local policy. Results showed that for meat processors, relatively few factors mattered – the percentage of population with high school degrees was positively related to the net change in plants, while the population and number of other meat processing plants per capita was negatively related to net change. Davis and Schluter (2005) conducted a very similar analysis using a slightly later timeframe and different dependent variable – total number of new food processing plants in a seven-year period, for counties. In contrast to Goetz, they found that many factors were related to the location decisions of meat processing plants – rurality, education, population, manufacturing employment share, taxes, population density, per capita income, highway access, right-to-work legislation, number of other meat processing establishments, livestock receipts, and geographic region of the U.S.

3.3 Conceptual Model

It is clear that a wide range of approaches are used in exploring survival, location, and growth in manufacturing, food processing, and meat processing plants. Given the policy motivation behind this work, I chose to investigate meat processing survival from a regional economics perspective; it is easier to formulate policy-relevant implications surrounding tangible regional factors than the theory-based measures used in the seminal manufacturing survival studies.

I formulate three hypotheses given the above literature:

- Plant-level variables are related to the survival of meat processing plants.
- Several vectors of regional factors – input market access, workforce variables, policy and infrastructure, and industry concentration – are related to the survival of meat processing plants.
- Plant-level variables have a stronger relationship with plant survival than regional variables.

My first hypothesis was formulated given that the importance of plant-level variables is well-established in the literature. Every survival study covered above shows that at least one plant-level factor, and usually many more than one, is related to plant survival. My second hypothesis is based on the location and growth literature. Regional factors are not widely explored in the survival literature discussed above, but they do often emerge as important in the location and growth literature. My final hypothesis is based on the key finding of Anderson et al. (1998) – that regional variables are generally not associated with plant survival, but plant-level variables tend to have strong relationships with plant survival.

Survival models are one way to test these hypotheses. Survival models were first developed in the 1950s to test effectiveness of medical treatments (Cutler & Ederer, 1958; Armitage et al., 1959). Their use in economics dates to the 1970s and 1980s. Lancaster and Nickell were two pioneers in economic survival models. Their analyses applied survival models to unemployment data to explore what factors were related to individuals exiting the unemployment pool (Nickell, 1979; Lancaster & Nickell, 1980). In the 1990s, the use of survival models was expanded to explore manufacturing plant survival. Audretsch and Mahmood were two pioneers in this arena, applying survival models to test how various microeconomic variables – labor and capital productivity, technology, innovation – were related to U.S. manufacturing plant survival (Audretsch & Mahmood, 1994; Audretsch & Mahmood, 1995). In the past 10 to 20 years, however, survival models have seen reduced use in economics.

The primary survival model used in the economics literature is Cox proportional hazards (Cox, 1972, 1975). Cox proportional hazards is a semi-parametric model that combines the realistic nature of the non-parametric Kaplan-Meier survival model with the convenient mathematical properties of parametric survival models, such as the exponential model. As with other survival models, the Cox hazard function estimates conditional probabilities – the probability that a plant will exit in the next time period (in my case in the next year) conditional on the plant being alive in the current year. There is one unique assumption for Cox proportional hazard models, however: as the name suggests, hazards between the two groups being compared must be proportional throughout time. As illustrated in the Empirical Model section, this allows the conditional probability of a plant exiting to reduce to a simplified form. Examining the Kaplan-Meier survival curves (Figure B.1), this assumption does appear to be satisfied to a reasonable degree.

Several characteristics of the Cox proportional hazards model make it appropriate for my analysis. Firstly, unlike parametric hazard models, Cox models do not require assumptions to be made regarding the distributions of hazard rates. This is essential for my analysis, as I include plants of varying ages and lifecycle stages. Their hazard rates do not follow a known distribution that, for example, start-ups follow (i.e., high hazard in the first five years, lower hazard age five to nine, and relatively low hazard after age 10). Another benefit is that the method corrects for problems created by censored data. This is important for my analysis, as I do not observe plants before 1997 or after 2020 – the data is censored on both the left (1997) and right (2020). The Cox proportional hazards model is not without downsides, however. Unlike for parametric models, the survival function cannot be estimated, as it cancels out due to the assumption that it is equal for all plants (Equation 2). Cox regressions also rely on the order of failures, not the time of survival. Thus, ties in failures can be problematic, but in my analysis this is remedied by using Breslow's approximation (Breslow, 1975).

3.4 Data and Empirical Model

3.4.1 Establishment-Level Data

The establishment dataset was purchased from a private vendor, Data Axle, and originally included all establishments with five or more employees that had any portion of their business in NAICS divisions 311611 (Animal, except Poultry, Slaughtering) or 311612 (Meat Processed from Carcasses). For my analysis, only plants whose primary businesses involved meat processing were included, as there were some establishments in the dataset not meeting this definition. The original dataset included information on up to ten NAICS categories; plants were used in this study only if one of their top three NAICS was listed as 311611 or 311612, for at least half of the years observed. Additionally, only plants in the continental U.S. were utilized due to poor 1997 Census of Agriculture coverage of Alaska and Hawaii. Data from all years available – 1997 to 2020, inclusive – were used. The original dataset included 8,970 establishments. 8,040 plants remained after dropping establishments located outside the continental U.S., establishments not categorized as meat processors, and establishments located in counties not covered by the 1997 Census of Agriculture (heavily urban counties such as Cook County, Illinois and the New York City boroughs).

Plant birth year was coded as the first year each plant appeared in the dataset, and plant death year was coded as the last year each plant appeared in the dataset. Given that plants only appeared in the dataset for a given year if they had five or more employees in that year, *birth* and *death* are not reflective of true birth and death – they reflect the first year a plant had more than four employees, and the last year a plant had more than four employees. As in other studies (Piazza & Hill, 2021; Eurostat, 2007; Low & Brown, 2017), the smallest plants are omitted from our analysis because they create much statistical noise due to large numbers and high turnover rates.

The two variables needed for survival analysis – years alive and whether failure occurred – were generated from *birth* and *death*. Years alive was calculated as *death* less *birth*, plus one. Failure occurred if a plant dropped out of the dataset and did not return; thus, if *death* was 2019 or earlier, the plant was said to have failed. Consistent with studies using BLS data, a plant was also coded as a failure if it moved out of state; I am interested in the impact of local and regional factors on the plant, and moving out of state suggests the local context was better elsewhere. Thus, death year was recorded as the last year the plant was located in its initial state.

Several plant-level variables included in this proprietary dataset were used in the survival analysis. Executive gender was listed for most observations. I created a dummy variable, *female*, that was coded as one if executive gender was female in the plant's birth year, and zero if executive gender was male or left blank in the plant's birth year. Location type was also included in the original dataset – establishments were labeled as single-unit, branch, headquarters, or subsidiary. Consistent with the literature, I created the dummy variable *single-unit* and assigned one if the plant was a single-unit establishment in its birth year, and zero if it was a branch, headquarters, or subsidiary in its birth year; the number of observations for headquarters and subsidiary were small enough that they had to be combined with branch plants into a multi-unit omitted condition, as in Low and Brown (2017). Establishment employment was also included for each year in the dataset. The size variable I utilized was the log of the number of employees each plant had in its birth year. This variable was logged due to its highly skewed distribution (see Table 6).

I generated additional plant-level variables using information included in the proprietary dataset. I coded plants as retail meat markets if they had NAICS code 44521 (Meat Markets) listed in a top three NAICS category for at least half of years, and meat wholesalers if they had NAICS code 42447 (Meat and Meat Product Merchant Wholesalers) listed a top three NAICS category for at least half of years. I also created a variable, *dummy_1997*, to control for left censoring of the data – coded as one if the plant first appeared in the dataset in 1997 and zero if otherwise.

Finally, I classified plants into size categories based on number of employees. A plant was categorized as very small if it had less than ten employees in its birth year, small for 10 to 49 employees, medium for 50 to 249 employees, and large for at least 250 employees. These definitions were based on USDA's Food Safety Inspection Service size definitions, with cutoffs for medium and large plants adjusted to better reflect the distribution of sizes in my dataset.

Table 6: Summary statistics for variables used in Study 2

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
birth_year	8,040	2003.7	7.2	1997	2020
death_year	8,040	2012.3	8.0	1997	2020
years_alive	8,040	9.6	8.1	1	24
failure	8,040	0.623	0.485	0	1
meat_market	8,040	0.225	0.417	0	1
meat_wholesale	8,040	0.237	0.425	0	1
dummy_1997	8,040	0.283	0.451	0	1
female	8,040	0.066	0.249	0	1
single_unit	8,040	0.878	0.328	0	1
log_size	7,893	2.735	1.250	1.609	8.923
size	8,040	60.8	268.8	0	7500
west	8,040	0.190	0.392	0	1
south	8,040	0.322	0.467	0	1
northeast	8,040	0.138	0.345	0	1
log_cattle	7,641	5.209	4.306	-4.605	13.639
log_hogs	7,594	5.964	4.931	-4.605	14.455
farmer_age	8,040	54.3	2.5	35.9	61.0
log_farm_sales	8,040	11.132	0.896	6.970	14.372
pct_organic	8,040	0.055	0.128	0	1.049
pcthsonly2000	8,040	30.9	7.6	10.9	53.0
level_lt_2yrs	8,040	0.663	0.473	0	1
mfg_wage	8,040	40.968	12.000	4.409	82.996
mfg_emp_share	8,040	14.1	7.8	0.3	55.1
unemp_rate	8,040	5.0	2.5	1.1	28.4
white	8,040	85.8	13.9	18.5	99.8
foreign	8,025	8.5	9.8	0.1	50.9
dt100k	7,981	62.2	76.5	0.0	516.1
hwy_exit	8,040	0.813	0.390	0	1
railroad	8,040	0.982	0.133	0	1
rtw97	8,040	0.412	0.492	0	1
gov_spend	8,040	7.14	1.48	3.34	9.36
taxes	8,040	5.53	0.84	3.53	7.34
num_plants	8,040	7.07	15.47	0	81
num_plants_large	8,040	0.52	1.35	0	7
processing_emp	8,040	579	1300	0	6444
size_ratio	6,485	0.080	0.199	0	1
plant_emp_share	6,487	81	564	0	24000
lq_avg_size	6,485	1.150	2.881	0.059	57.004
lq_meat_mfg	8,040	3.070	9.728	0.000	155.005
lq_meat_emp	8,040	3.662	16.253	0.000	278.056

This plant-level dataset is not without pitfalls. First, as mentioned above, plants were only included in the dataset for a given year if they employed five or more people in that year. Thus, there is some margin of error surrounding birth (entry) and death (exit) years from the study. Moreover, employment is modeled in some years, introducing additional error. Second, the dataset's coverage is not perfect; 15% of plants are missing from the dataset at least one year between their birth and death years. This is not simply due to plants dropping below five employees, as the issue also impacts plants with many more than five employees. Additionally, this issue is not due to plants closing and re-opening, as plants that re-open are counted as births and receive a new identification number. Thus, there is clearly a coverage issue, potentially distorting years to failure, our dependent variable. This problem is most impactful for our 2019 exits; we estimate that approximately 15% of 2019 exits may be false as a result.

Also note that for this dataset, data quality is not as high as *Quarterly Census of Employment and Wages* (QCEW). Proprietary longitudinal establishment-level datasets aim to emulate the gold standard QCEW, produced by each state through a cooperative agreement with the U.S. Bureau of Labor Statistics. Of course, without access to the confidential unemployment insurance files and on-the-ground state Labor Market Information specialists used to create and improve the QCEW, proprietary vendors are disadvantaged. Instead, Dun and Bradstreet proprietary records, publicly available records such as business registrations and the Yellow Pages (via call centers), plus modeling were used to create the Data Axle dataset.[2] Data Axle is incentivized to produce a good product, else it will lose commercial purchases and jeopardize the Dun and Bradstreet financial data; indeed, several studies have examined quality of datasets such as ours, and top economics journals publish research using these data (Rupasingha et al. 2018).

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[2] For more information see, https://www.dataaxleusa.com/about-us/data-quality/

These studies generally find the proprietary data, other than sales data, are appropriate for survival analysis. Consequently, we did not include plant sales data in our analysis. These pitfalls introduce uncertainty into our variables of interest. However, given our large N and others' success using these data for survival analysis, we chose to document these pitfalls and move forward with analysis.

Summary statistics for all plant-level variables may be found in Table 6. On average, plants survived 9.6 years; 9% of plants were alive throughout the entire duration of the dataset, while 15% of plants survived only one year. 38% of plants had not failed as of 2020. 22% of plants had a retail meat market business, while 24% of plants had a wholesaling business. There is little overlap between these categories, with only 4% of plants reporting both a retail and wholesaling businesses. On average, plants employed 61 people. Few plants were operated by female executives – only 7%. And at 88%, most plants were single-unit establishments, though single-unit establishments only accounted for 51% of employment in the dataset.

3.4.2 Explanatory Variables from Other Sources

As discussed in the hypotheses section, I utilize four vectors of explanatory variables in addition to plant-level variables: input access (i.e., access to raw inputs), labor (i.e., production worker availability), infrastructure and policy, and industry concentration. These variables are lagged to reduce endogeneity issues; I use data for 1997, the beginning of the study period, where possible. I do not use time-varying explanatory variables as several key input variables are available only quinquennially. Explanatory variables and their sources are listed in Table 7. Summary statistics for all variables are described in Table 6.

The input vector consists of log of head of cattle sold for slaughter, log of market hog inventory, farmer age, log of farm sales, and percent of pasture and rangeland that is organic. Livestock variables are included per the location and growth studies (Goetz, 1997; Henderson & McNamara, 2000; Lambert & McNamara, 2007; Lambert & McNamara, 2009). Farm sales,

Table 7: Table of variables used in Study 2

Name	Vector	Description	Year	Source
birth_year	-	First year the plant appeared in dataset	-	Data Axle USA
death_year	-	Last year the plant appeared in dataset	-	Data Axle USA
years_alive	-	Years the plant was alive -- death year less birth year, plus one	-	Data Axle USA
failure	-	Equals 1 if the plant failed; the last year the plant appeared in the dataset was 2019 or before	-	Data Axle USA
meat_market	Base	Equals 1 if one of the plant's first three NAICS was 445210 for at least 50% of years	-	Data Axle USA
meat_wholesale	Base	Equals 1 if one of the plant's first three NAICS was 424470 for at least 50% of years	-	Data Axle USA
dummy_1997	Base	Equals 1 if the first year the plant appeared in the dataset was 1997	-	Data Axle USA
female	Base	Equals 1 if executive gender was female in birth year	-	Data Axle USA
single_unit	Base	Equals 1 if location type was single unit in birth year	-	Data Axle USA
log_size	Base	Log of employee size in birth year	-	Data Axle USA
west	Base	Equals 1 if plant is located in the Western US Census Region	-	US Census Bureau
south	Base	Equals 1 if plant is located in the Southern US Census Region	-	US Census Bureau
northeast	Base	Equals 1 if plant is located in the Northeastern US Census Region	-	US Census Bureau
log_cattle	Inputs	Log of head of cattle sold for slaughter, county level	1997	USDA NASS Census of Agriculture
log_hogs	Inputs	Log of market hog inventory, county level	1997	USDA NASS Census of Agriculture
farmer_age	Inputs	Average farmer age in years, county level	1997	USDA NASS Census of Agriculture
log_farm_sales	Inputs	Log of average farm sales in dollars, county level	1997	USDA NASS Census of Agriculture
pct_organic	Inputs	Percent of pasture and rangeland that was organic, state level	1997	USDA ERS
pcthsonly2000	Labor	Percent of population with a high school degree only, county level	2000	US Census Bureau
level_lt_2yrs	Labor	Equals 1 if the county contains an educational institution whose highest level offered is less than a two-year degree (e.g. vocational and trade schools)	1997	National Center for Education Statistics
mfg_wage	Labor	Manufacturing wage, calculated as manufacturing earnings divided by manufacturing employment, county level	1997	Author calculations via Bureau of Economic Analysis
mfg_emp_share	Labor	Percent of total employment that is in manufacturing, county level	1997	Author calculations via Bureau of Economic Analysis
unemp_rate	Labor	Unemployment rate, county level	1997	Bureau of Labor Statistics
white	Labor	Percent of population that is white, county level	1997	US Census Bureau
foreign	Labor	Percent of population that is foreign-born, county level	2000	US Census Bureau
dt100k	Labor	Drive time from county centroid to the nearest city of 100,000+ people	2000, 2009	US Census Bureau (population), ESRI (drive time)

Name	Vector	Description	Year	Source
hwy_exit	Infrastructure and Policy	Equals 1 if there is a highway exit in the county	2010	ESRI
railroad	Infrastructure and Policy	Equals 1 if there is a railroad in the county	2010	ESRI
rtw97	Infrastructure and Policy	Equals 1 if a state enacted right-to-work laws in 1997 or prior	1997	National Conference of State Legislatures
gov_spend	Infrastructure and Policy	Government spending index, state level	1997	The Fraser Institute
taxes	Infrastructure and Policy	Tax index, state level	1997	The Fraser Institute
num_plants	Concentration	Number of meat processing plants in the county	1997	Author calculations via Data Axle USA
num_plants_large	Concentration	Number of meat processing plants in the county with greater than 250 employees	1997	Author calculations via Data Axle USA
processing_emp	Concentration	Number of meat processing jobs in the county	1997	Author calculations via Data Axle USA
size_ratio	Concentration	Number of large meat processing plants in the county divided by all meat processing plants in the county	1997	Author calculations via Data Axle USA
plant_emp_share	Concentration	Each plant's share of the 1997 county-level meat processing employment	1997	Author calculations via Data Axle USA
lq_avg_size	Concentration	Average size location quotient: (meat processing employment in county/meat processing plants in county) / (meat processing employment in US/meat processing plants in US)	1997	Author calculations via Data Axle USA
lq_meat_mfg	Concentration	Meat processing employment to manufacturing employment location quotient: (meat processing employment in county/manufacturing employment in county) / (meat processing employment in US/manufacturing employment in US)	1997	Author calculations via Data Axle USA and BEA
lq_meat_emp	Concentration	Meat processing employment to all employment location quotient: (meat processing employment in county/total employment in county) / (meat processing employment in US/total employment in US)	1997	Author calculations via Data Axle USA and BEA

farmer age, and organic production are included as "AgriCulture" variables, as used in Low et al. (2021). Measures of local and niche food production were not available at the county level for 1997, thus average farm size and average farmer age are included as proxies for small and beginning farmers – two groups that are often associated with niche food production (Low et al., 2015). Farm sales, as well as livestock measures, are logged due to the skewed distributions for these variables.

My labor vector consists of education (as measured as the percent of population with only a high school degree), presence of a vocational or trade school in the county, average manufacturing wage, manufacturing employment share, unemployment rate, percent of population that is white, percent of population that is foreign-born, and drive time from the county's population centroid to the nearest city of at least 100,000 people. All of these variables, except *white* and *foreign,* were included in various studies discussed in the Background section. *White* and *foreign* are included above and beyond variables in the existing literature because of the unique demographics of meat processing workers compared to other manufacturing workers; the majority of meat processing employees are non-white or Hispanic (Artz, 2012). Predominant races and ethnicities among meat processing workers are Hispanic (35% of workers), Black (23% of workers), and Asian (7% of workers) (Fremstad et al., 2020), but the inclusion of all three of these demographic groups caused issues with multicollinearity. *Foreign* was included due to the high proportion of immigrants working in meat processing – as of 2010, about one-third of meat processing workers were foreign-born (Artz, 2012).

The infrastructure and policy vector consists of dummy variables for whether a county has a four-lane highway exit, railroad lines in a county, and whether each state was a right-to-work state in 1997. State-level government spending and tax indices, developed and promulgated by The Fraser Institute and used by Rupasingha and Goetz (2007), are also included. These variables are all widely used in studies referenced in the Background section, including Goetz (1997), Low et al. (2021), and Lambert and McNamara (2009).

Finally, I include a variety of industry size and concentration measures. Number of plants and ratio of large plants to all plants are two measures previously explored in the literature (Goetz, 1997; Asiseh et al., 2009). Thus, I include these two variables. I also include various location quotients, similar to Low et al. (2021). I include a plant size location quotient, calculated as the average plant size for each county divided by the average plant size for the U.S.; a meat processing-to-manufacturing employment location quotient, calculated as the ratio of meat processing jobs to manufacturing jobs in a county, divided by the same for the U.S.; and a meat-processing-to-total employment location quotient, calculated as the ratio of meat processing jobs to all jobs for each county, divided by this number for the U.S. I also included three variables for which there was no precedent in the literature. First was number of large plants in a county. Second was the number of meat processing jobs in a county. And third was plant share of county meat processing employment – number of employees for each plant divided by the number of meat processing jobs in a county. Note that all concentration variables were calculated based on 1997 data, i.e., number of plants, number of large plants, and number of meat processing jobs in a county were all as of 1997. Again, this was done to reduce endogeneity. The disadvantage of this approach is that some counties had no meat processing plants nor meat processing employment in 1997, but later did. Thus, denominators for some of the concentration variables were zero, leading to missing calculations for a number of plants.

3.4.3 Empirical Model and Approach

The Cox proportional hazard model can be formulated as:

$$h(t) = h_0(t) * exp(\Phi'\beta_1 + \Psi'\beta_2 + \Omega'\beta_3 + \Theta'\beta_4 + \Gamma'\beta_5) \qquad (1)$$

where h(t) is the conditional hazard rate for a plant and $h_0(t)$ is the unspecified non-negative baseline hazard function. Φ represents a vector of plant-level variables, Ψ represents a vector of input variables, Ω represents a vector of labor variables, Θ represents a vector of infrastructure and policy variables, and Γ represents concentration measures. The conditional probability that the *j*th plant exists at time *t*, given that one plant exited in time *t*, is the ratio of the hazards, as given by:

$$Pr_j = \frac{\exp(\Phi'\beta_1 + \Psi'\beta_2 + \Omega'\beta_3 + \Theta'\beta_4 + \Gamma'\beta_5)}{\sum_{j \in R} \exp(\Phi'\beta_1 + \Psi'\beta_2 + \Omega'\beta_3 + \Theta'\beta_4 + \Gamma'\beta_5)} \qquad (2)$$

Where $j \in R$ indicates only those plants that are at risk before time t. Since the baseline hazard is assumed to be identical for all plants, it cancels out of the above equation.

Cox (1972, 1975) illustrates that the partial likelihood function, then, is given by:

$PL(\beta, \Phi, \Psi, \Omega, \Theta, \Gamma)$

$$= \prod_{j \in R}^{k} \left(ex\,\mathrm{p}(\Phi'^{\beta_1} + \Psi'^{\beta_2} + \Omega'\beta_3 + \Theta'\beta_4 + \Gamma'^{\beta_5} \right) / \sum ex\,\mathrm{p}(\Phi'\beta_1 + \Psi'\beta_2 + \Omega'\,\beta_3 + \Theta'\,\beta_4 + \Gamma'\beta_5))$$

(3)

The coefficients are estimated by maximizing this partial likelihood function. Coefficients can be interpreted in their original form or converted to a hazard ratio, which is simply the exponentiated coefficient. Negative coefficients indicate a decrease in hazard, while positive coefficients indicate an increase in hazard. Thus, as hazard ratios are the exponentiated coefficient, hazard ratios below one indicate a decrease in hazard, while hazard ratios above one indicate an increase in hazard.

I utilize two different sets of model specifications in my analysis. The first is an extended model containing all vectors included above – plant-level variables, agricultural input variables, labor variables, and infrastructure and policy variables. Eight concentration measures are individually layered on top of these vectors, for a total of eight different extended specifications. Due to the large number of variables included, multicollinearity was a concern for many of the input, labor, and policy variables. Thus, I also estimated three shortened models – plant characteristics plus the agricultural inputs vector, plant characteristics plus the labor vector, and plant characteristics plus the infrastructure and policy vector. The shortened models were estimated for each size category (i.e., all plants, very small plants, small plants, medium plants, and large plants). Two specifications of the extended model – the specification containing average size location quotient and specification containing plant size ratio – were also estimated across size categories.

3.5 Results and Discussion

Discussion of results is organized by vector – my base vector composed of plant characteristics and regional indicator dummies, followed by the inputs vector, labor market vector, policy vector, and concentration variables. Given the current policy focus on small to medium sized independent plants, I also provide a summary of results specifically for these size categories. Results generally focus on the extended model specifications, but also cover findings from the shortened models when multicollinearity levels warrant.

Several caveats do apply to all results. First, I do not claim that results are causal. Endogeneity and reverse causality should be reduced given my lagged explanatory variables, but nonetheless, survival analysis is not an approach that facilitates true causal inference. Second, where regression results are compared across plant sizes, note that sample sizes vary considerably, with nearly 4,000 plants in the very small category and approximately 400 in the large plant category. Consequently, statistical power varies across these categories, with many variables significant for smaller plants and insignificant for larger plants. This does not necessarily indicate that these variables have no relationship with the survival of larger plants, rather, the power may not be large enough in the smaller-N categories to detect effects.

3.5.1 Plant Characteristics

As I expected based upon the plant survival literature, several plant-level variables are associated with decreased hazard (Table 8). The meat market and meat wholesale variables are significant, with hazard ratios of 0.57 and 0.60, respectively. This indicates that plants with retail meat markets are 43 percent more likely to survive than plants without, and that plants that are also meat wholesalers are 40 percent more likely to survive than plants that are not. Both these variables are significant at the 1% level for very small and small plants. Meat wholesale is significant for medium plants but not large plants, while meat market is significant for large plants but not medium plants. These findings suggest that business diversification and/or

Table 8: Hazard ratios for extended survival models

	Model I All Plants	Model II Very Small	Model III Small	Model IV Medium	Model V Large
meat_market	**0.571*** **	**0.588*** **	**0.467*** **	0.893	**0.502* **
meat_wholesale	**0.601*** **	**0.612*** **	**0.539*** **	**0.743*** **	0.961
dummy_1997	**0.805*** **	**0.778*** **	**0.850*** **	**0.767*** **	**0.606*** **
female	0.995	0.908	1.078	1.228	3.33e-19
single_unit	**0.789*** **	0.955	**0.777*** **	**0.655*** **	1.037
log_size	**0.885*** **				
west	**1.166** **	**1.192* **	1.106	1.089	1.211
south	**1.126* **	**1.169* **	0.959	1.348	1.080
northeast	0.953	0.937	0.919	0.931	1.073
log_cattle	0.995	0.995	1.001	0.997	0.999
log_hogs	1.000	1.006	0.996	1.000	0.969
farmer_age	1.000	1.009	**0.977* **	1.007	0.956
log_farm_sales	0.973	0.953	0.967	1.016	1.042
pct_organic	1.266	1.015	1.560	**2.031* **	1.090
pcthsonly2000	0.994	0.990	1.002	1.001	0.967
level_lt_2yrs	1.037	1.062	1.053	1.128	0.697
mfg_wage	1.003	1.002	1.001	1.010	1.008
mfg_emp_share	**0.995* **	0.995	0.997	0.988	**0.973** **
unemp_rate	**1.017* **	**1.044*** **	0.986	1.004	1.037
white	0.998	0.996	0.998	1.004	0.994
foreign	0.996	0.994	0.998	1.011	0.983
dt100k	**0.999** **	**0.999* **	0.999	1.001	0.999
hwy_exit	0.944	0.910	1.122	0.828	**0.608* **
railroad	0.927	0.795	1.221	2.787	0.392
rtw97	1.022	1.084	1.017	0.974	0.978
gov_spend	0.994	1.012	0.992	0.965	0.862
taxes	1.014	0.981	1.048	1.053	1.305
size_ratio	**1.214** **	1.118	1.147	1.088	**1.926** **
N	5797	2638	2188	813	292

Hazard ratios displayed
* p<0.10, ** p<0.05, *** p<0.01

integration may be an important strategy for meat processing plant survival, especially for smaller plants. This result is in line with several studies showing that integration decreases probability of establishment exits, both for cattle slaughtering plants (Anderson et al., 1998) and manufacturing and processing plants more broadly (Bernard & Jensen, 2002).

Birth of a plant in 1997 – the year the dataset began – or before is a significant factor in lowering hazard. Plants that were established in 1997 or before are 19 percent more likely to survive than plants that were not, *ceteris paribus*. This relationship holds for all size categories. This relationship may be reflective of the fact that startups and young businesses have high failure rates, due to factors such as lower brand awareness among consumers and inexperienced owners and operators (Haltiwanger, et al., 2013; Thilmany et al., 2019)

Being a single-unit plant also lowers hazard; single-unit plants are 21 percent more likely to survive than multi-unit plants. This result is consistent with findings of most other manufacturing survival studies (Low & Brown, 2017; Audretsch & Mahmood, 1995; Bernard & Jensen, 2002). Independent plants may have more operational flexibility to respond to market conditions than branch plants, thus increasing odds of survival. Alternatively, single unit plants may be more likely to survive simply because they are more likely to continue operations when marginal costs exceed marginal revenues; as Low (2017) details for rural plants, they may remain open longer than economically rational because they may be family businesses or have stronger ties to their community and workers.

Log of employee size is also related to the survival of meat processing plants. The hazard ratio for log of size is 0.89. Thus, for every unit increase in the log of number of employees, plants are 11% more likely to survive; a plant with 165 employees is 11% more likely to survive than an average-sized plant of 61 employees. This finding is in line with previous results surrounding cattle slaughtering plant exits (Anderson et al., 1998) and is not surprising given that efficiency gains from high-capacity plants can be large, and that economies of scale in the meat processing industry have been growing for decades (Ward, 2010; MacDonald et al., 2000).

Regional location also appears related to the survival of meat processing plants. Plants that are located in the West are 17% less likely to survive than plants located in the Midwest. Plants located in the South are 13% less likely to survive than plants located in the Midwest.

These relationships are driven by results for the very small category; these relationships do not appear to hold for small, medium, and large plants. However, it is important to note that multicollinearity is high for the variables West and South.[3] Thus, multicollinearity may be to blame, in part, for lack of significance of these variables across size categories. Looking at results for the base model only, where multicollinearity for these variables is much lower, we see that West and South are indeed significant for most size categories (Table 9).

Table 9: Hazard ratios for base survival models

	Model I All Plants	Model II Very Small	Model III Small	Model IV Medium	Model V Large
meat_market	**0.607***	**0.619***	**0.518***	0.913	0.612
meat_wholesale	**0.653***	**0.691***	**0.578***	**0.771***	1.054
dummy_1997	**0.804***	**0.763***	**0.866***	**0.795***	**0.762**
female	1.040	1.000	1.065	1.172	8.29e-18
single_unit	**0.775***	**0.858***	**0.720***	**0.706***	1.076
log_size	**0.897***				
west	**1.227***	**1.264***	1.074	**1.413***	**1.663**
south	**1.278***	**1.486***	0.988	**1.239**	**1.395**
northeast	1.078	1.077	1.009	1.166	1.007
N	7893	3950	2775	944	371

Hazard ratios displayed
* p<0.10, ** p<0.05, *** p<0.01

3.5.2 Input Market Characteristics

The extended model provides very little evidence that input market characteristics affect plant survival (Table 8). However, some of these null results may be due to multicollinearity and inflated standard errors. Indeed, when examining shortened models, several variables emerge as significant.

Cattle and hog sales are not significant in the extended model, but multicollinearity is somewhat high.[4] Turning to the shortened model (Table 10) where multicollinearity is less of a

[3] Variance inflation factors of 3.3 and 2.7 for these variables, respectively
[4] Variance inflation factors of 2.9 and 2.5, respectively

concern, both are significant, albeit at the 10% level. In Model I, the coefficient on log of cattle sold is 0.991, indicating that for every logged unit increase in cattle sales in a county, a plant is 0.9% more likely to survive; a plant in a county with 31,200 beef cattle sold is 0.9% more likely to survive than a plant in a county with an average number of beef cattle sold (11,500). The coefficient on log of market hog inventory is 0.993, indicating that for every logged unit increase in hog inventory in a county, a plant is 0.7% more likely to survive; a plant in a county with 59,000 market hogs is 0.7% more likely to survive than a plant in a county with an average number of market hogs (21,700). Understanding the direction of causality for these results, though, is impossible using my current methods. It is possible that access to more animals drives plant survival, but it is also possible that the presence of a plant brings more animal production to the area.

Table 10: Hazard ratios for inputs vector

	Model I All Plants	Model II Very Small	Model III Small	Model IV Medium	Model V Large
meat_market	**0.597*** **	**0.622*** **	**0.482*** **	0.866	**0.588***
meat_wholesale	**0.634*** **	**0.673*** **	**0.568*** **	**0.740*** **	0.997
dummy_1997	**0.820*** **	**0.801*** **	**0.869** **	**0.756*** **	0.810
female	1.024	0.975	1.069	1.266	3.52e-15
single_unit	**0.759*** **	**0.852***	**0.716*** **	**0.682*** **	1.108
log_size	**0.895*** **				
west	**1.211*** **	**1.257*** **	1.066	**1.414*** **	**1.554***
south	**1.180*** **	**1.343*** **	0.964	1.132	**1.387***
northeast	0.990	1.007	0.925	1.012	0.936
log_cattle	**0.991***	**0.988***	1.000	0.985	0.984
log_hogs	**0.993***	0.993	0.989	1.004	0.976
farmer_age	1.008	1.017	0.983	**1.035***	0.991
log_farm_sales	**0.960** **	0.973	**0.927** **	0.961	1.076
pct_organic	1.179	0.942	1.352	**1.944***	1.070
N	7157	3521	2565	879	332

Hazard ratios displayed
* p<0.10, ** p<0.05, *** p<0.01

In Table 10, log of farm sales also has a positive relationship with plant survival. Multicollinearity for this variable was not a concern in the full model, however, so this result may be due to omitted variable bias.

It is not surprising that log of cattle and log of hogs are significant in the reduced model because, as discussed in the literature review, meat processing plants are establishments with relatively large input transportation costs (Connor & Schiek, 1997). Thus, the more animals in a county, the lower the transportation costs for nearby plants, and the higher plant profits. It is perhaps surprising that percent organic pasture, log of farm sales, and farmer age are not consistently significant, especially for very small and small plants. Low et al. (2021) showed that "AgriCulture" factors – such as organic production and farm-to-table sales, which are often pursued by beginning farmers and farmers with smaller operations (Low et al., 2015) – are positively related to the number of food manufacturing startups. However, Low et al. focused on location decisions (not survival), as well as on food manufacturing more generally (not meat processing). Additionally, farmer age, farm sales, cattle sales, and hog sales are county-level variables. A larger areal unit may have produced stronger results, as input procurement is not limited by county borders – indeed, Low et al. use many of their input variables at the state-level, not county-level.

3.5.3 Labor Market Characteristics

County-level manufacturing employment share, unemployment rate, and drive time to the nearest city all appear to be related to meat processing plant survival (Table 8). The hazard ratio for manufacturing employment share is 0.995, indicating that for every percentage point increase in the share of a county's employment that is in manufacturing, plants are 0.5% more likely to survive. This result appears to be driven by the large plant category, where manufacturing employment share is even more important, with a hazard ratio of 0.973. Some of this relationship may be simply driven by size's positive relationship with plant survival, which is not controlled for in the size category regressions. Alternatively, having a high proportion of the county's employment in manufacturing could be helpful to plant survival from a workforce point of view – having access to a large number of blue-collar workers who are already trained in manufacturing jobs likely benefits meat processing plant survival, particularly the survival of large plants that require a higher-than-average number of workers. Survival studies have not examined this variable, but this result is in line with location study results. Lambert and McNamara (2007, 2009) found that percent of manufacturing employment generally has a positive relationship with the number of new supply-oriented food manufacturing startups, while Davis and Schluter (2005) found that percent of manufacturing employment has a positive, though small, relationship with the number of new meat processing plants locating in a county.

Unemployment rate is also significant (Table 8). The hazard ratio of 1.017 indicates that for every percentage point the unemployment rate increases, plants are 1.7% more likely to fail. This result appears to be driven by the very small plant category. Unemployment rate was originally included as a measure of labor availability – the more unemployed individuals, the more workers are available for plants, suggesting we would see a decreased risk of plant failure. However, perhaps the poor economic conditions associated with high unemployment outweigh the impact of available labor on plant survival, resulting in the increased risk of failure we see in the results. Very small plants serving a localized area may be particularly susceptible to changes in county-level economic conditions. Audretsch and Mahmood (1995) analyzed the impact of unemployment rate on manufacturing plant survival and found a negative relationship as well. However, in the location literature, unemployment rate generally does not have a significant relationship with new meat processing plant locations (Goetz, 1997; Davis & Schluter, 2005; Lambert & McNamara, 2007).

The hazard ratio for drive time is 0.999 (Table 8), indicating that for every minute further a county is from a city of 100,000-plus, plants in that county are 0.1% more likely to survive – a relatively large magnitude, compared to other local context variables. This result is driven by the very small plant category, suggesting some sort of cultural or competition effect in which less connectivity with thick, urban markets increases the probability of survival (e.g., people in remote areas may be more likely to eat game, often processed by very small butchers; there may be less creative destruction or business dynamism in rural areas). Drive time to the nearest city was originally included as a measure of proximity to major labor pools, but could also represent proximity to consumers and output markets. From both these perspectives this result is counterintuitive – I would expect that the further a plant is from labor and consumers, the lower its rate of survival. However, individuals living closer to large towns may have a larger array of employment options, thus making them less likely to choose meat processing. Distance to cities is not included in any other manufacturing survival papers, to my knowledge, but is included in several location studies. These studies all find that distance to cities is not related to the location decisions of supply-oriented food processing firms (Henderson & McNamara, 2000; Lambert & McNamara, 2007; Lambert & McNamara, 2009).

Manufacturing wages, presence of a trade or vocational school, percentage of individuals with only a high school degree, percentage of the population that is white, and percentage of population that is foreign-born have no relationship with meat processing plant survival in the expanded model. The null results for education and foreign-born may be due to high multicollinearity.[5] Indeed, examining the labor-only model (Table 11) we see that both education and foreign-born are significant. Higher percentages of the population with a high school degree only and higher percentages of the population that is foreign-born are both associated with increased survival (0.8% and 0.4%). Percentage of the population that is white is also significant

[5] Variance inflation factors of 4.24 and 3.36, respectively

in the shortened model. As there is little multicollinearity for *white* in the expanded model, it is probable that its significance in the shortened model is simply due to omitted variable bias.

Table 11: Hazard ratios for labor vector

	Model I All Plants	Model II Very Small	Model III Small	Model IV Medium	Model V Large
meat_market	**0.603*** **	**0.614*** **	**0.518*** **	0.913	0.668
meat_wholesale	**0.617*** **	**0.638*** **	**0.555*** **	**0.745*** **	1.032
dummy_1997	**0.810*** **	**0.783*** **	**0.866*** **	**0.801** **	**0.758** **
female	1.039	1.003	1.072	1.201	2.90e-18
single_unit	**0.781*** **	0.897	**0.733*** **	**0.708*** **	1.025
log_size	**0.888*** **				
west	**1.146** **	1.125	1.115	1.205	1.381
south	**1.181*** **	**1.287*** **	0.981	**1.327** **	1.042
northeast	1.002	0.972	0.968	1.048	1.033
pcthsonly2000	**0.992** **	**0.989** **	1.000	1.007	0.974
level_lt_2yrs	1.052	1.067	1.127	1.121	0.850
mfg_wage	1.002	1.000	1.002	1.009	1.007
mfg_emp_share	**0.996** **	**0.994** **	0.997	0.995	0.985
unemp_rate	**1.016** **	**1.025*** **	1.000	0.988	1.022
white	**0.997** **	**0.996** **	0.998	1.000	**0.990* **
foreign	**0.996* **	0.996	0.996	1.012	0.981
dt100k	**0.999** **	**0.999** **	0.999	1.000	1.001
N	7822	3921	2742	932	371

Hazard ratios displayed
* p<0.10, ** p<0.05, *** p<0.01

These significant results are not surprising, as both foreign-born individuals and individuals with high school degrees only make up large portions of the meat processing workforce; 71% of meat processing employees have a high school degree or less (Fremstad et al., 2020), while as of 2010 about one-third of meat processing employees were foreign-born (Artz, 2012). Lack of significance of manufacturing wages is also not surprising, as both Low and Brown (2017) and Anderson et al. (1998) find this variable to have no relationship with the survival of manufacturing plants and cattle slaughtering plants, respectively.

3.5.4 Policy Variables

Looking at Table 8, it appears that none of the policy and infrastructure variables are related to meat processor survival. High degrees of multicollinearity may be driving null results for government spending, taxes, and right-to-work.[6] Looking at correlations, these inflated standard errors appear to be related to the inclusion of regional dummy variables, which is logical because several of the policy variables are state-level. Thus, I estimated a shortened policy model without the regional indicator variables, dropping multicollinearity for these variables to acceptable levels (Table 12).

Table 12: Hazard ratios for policy vector

	Model I All Plants	Model II Very Small	Model III Small	Model IV Medium	Model V Large
meat_market	**0.597*** **	**0.606*** **	**0.515*** **	0.920	0.658
meat_wholesale	**0.643*** **	**0.677*** **	**0.570*** **	**0.746*** **	1.067
dummy_1997	**0.802*** **	**0.758*** **	**0.858*** **	**0.796*** **	**0.772***
female	1.048	1.012	1.063	1.204	3.49e-15
single_unit	**0.778*** **	0.887	**0.724*** **	**0.707*** **	1.051
log_size	**0.893*** **				
hwy_exit	**1.129*** **	**1.147*** **	**1.139***	**1.260***	0.979
railroad	1.058	1.028	1.143	2.069	0.496
rtw97	**1.105*** **	**1.212*** **	0.950	1.060	1.327
gov_spend	**0.943*** **	**0.929*** **	0.988	**0.918** **	**0.849** **
taxes	**1.101*** **	**1.131*** **	1.058	1.081	1.130
N	7893	3950	2775	944	371

Hazard ratios displayed
* p<0.10, ** p<0.05, *** p<0.01

In this model, the state-level government spending index is significant and has a hazard ratio of 0.943, indicating that for each unit increase in the government spending index (a higher value indicates lower levels of government spending as a percentage of income) the chances of survival by plants in that state increases by 5.7% (Table 12). Since transfer payments and subsidies make up the largest share of this index, and at the state level much of these payments go

[6] These variables have variance inflation factors of 3.65, 3.54, and 2.72, respectively

towards older Americans (McClure, Van Leuven, and Low, 2021), this may simply be reflective of a relationship between plant survival and population age, income, and productivity. The tax index is also significant, suggesting that for each unit increase in the tax index (a higher value indicates lower levels of taxation) the chances of failure by plants in that state increases. Since both these variables are indices and not true levels of government spending or taxes, these findings should be interpreted with a large degree of caution. Additionally, as suggested above, I cannot rule out that omitted variables are driving these results, especially considering these variable were not significant in the extended model.

The right-to-work variable is significant, with a coefficient of 1.105, indicating that if a state had right-to-work laws in place in 1997 or prior, plants in that state are 10.5% more likely to fail (Table 12). This result appears to be driven by the very small plant category, which at 1.212 has an even larger hazard ratio. Strong unions may provide value for employers, perhaps by contributing to workforce training, so it is plausible that not having access to these benefits hurts smaller plants.

Lastly, highway access is significant and large, with a hazard ratio of 1.129. The highway access dummy variable is highly correlated with rurality (-0.58, p-value of less than 0.001), however, with urban areas being much more likely to have highway access than rural areas. Controlling for rurality, using Rural-Urban Continuum Codes, highway exit becomes insignificant in all models.

3.4.5 Concentration and Size Variables

All three location quotients are statistically significant, as well as economically significant when considering means and standard deviations of these variables (Table 13). The hazard ratio for the meat processing-to-manufacturing employment location quotient is 1.006, while the hazard ratio for the meat processing-to-total employment location quotient is 1.002. These results indicate that the larger meat processing employment is relative to both

Table 13: Hazard ratios for concentration and size measures, for all plants

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII
meat_market	**0.595*** **	**0.595*** **	**0.595*** **	**0.571*** **	**0.571*** **	**0.571*** **	**0.594*** **	**0.594*** **
meat_wholesale	**0.614*** **	**0.614*** **	**0.614*** **	**0.601*** **	**0.599*** **	**0.601*** **	**0.615*** **	**0.614*** **
dummy_1997	**0.820*** **	**0.820*** **	**0.820*** **	**0.805*** **	**0.795*** **	**0.805*** **	**0.817*** **	**0.821*** **
female	1.031	1.031	1.031	0.995	0.995	0.996	1.029	1.030
single_unit	**0.769*** **	**0.769*** **	**0.769*** **	**0.789*** **	**0.779*** **	**0.791*** **	**0.781*** **	**0.777*** **
log_size	**0.888*** **	**0.886*** **	**0.886*** **	**0.885*** **	**0.894*** **	**0.885*** **	**0.881*** **	**0.885*** **
west	**1.223*** **	**1.240*** **	**1.246*** **	**1.166** **	**1.158** **	**1.168** **	**1.221*** **	**1.209*** **
south	**1.172** **	**1.192*** **	**1.199*** **	**1.126* **	**1.124* **	**1.131* **	**1.171*** **	**1.157** **
northeast	0.975	0.988	0.994	0.953	0.944	0.952	0.966	0.960
log_cattle	0.998	0.998	0.997	0.995	0.995	0.994	0.996	0.997
log_hogs	0.997	0.998	0.998	1.000	1.000	1.000	0.998	0.997
farmer_age	0.999	0.998	0.997	1.000	1.000	1.000	1.001	1.001
log_farm_sales	0.968	0.967	0.966	0.973	0.976	0.973	**0.963* **	**0.966* **
pct_organic	1.270	1.274	1.268	1.266	1.282	1.252	1.237	1.257
pcthsonly2000	0.995	0.995	0.995	0.994	0.994	0.994	0.994	0.995
level_lt_2yrs	1.059	1.058	1.057	1.037	1.034	1.035	1.064	1.063
mfg_wage	1.002	1.002	1.002	1.003	1.003	1.003	1.002	1.002
mfg_emp_share	**0.996* **	**0.996* **	**0.996* **	**0.995* **	0.996	**0.995* **	**0.996* **	**0.995* **
unemp_rate	1.010	1.010	1.010	**1.017* **	**1.017* **	**1.018* **	1.012	1.011
white	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998
foreign	0.995	**0.995* **	**0.994* **	0.996	0.996	0.995	**0.995* **	0.996
dt100k	**0.999*** **	**0.999*** **	**0.999*** **	**0.999** **	**0.999** **	**0.999** **	**0.999*** **	**0.999*** **
hwy_exit	0.943	0.941	0.942	0.944	0.944	0.943	0.956	0.949
railroad	1.007	1.006	1.006	0.927	0.933	0.924	1.007	1.004
rtw97	1.031	1.029	1.031	1.022	1.028	1.019	1.005	1.018
gov_spend	0.999	0.997	0.998	0.994	0.998	0.993	0.995	0.996
taxes	0.989	0.990	0.988	1.014	1.006	1.013	0.997	0.997
num_plants	1.001							
num_plants_large		**1.024* **						
processing_emp			**1.000* **					
size_ratio				**1.214** **				
plant_emp_share					1.000			
lq_avg_size						**1.016** **		
lq_meat_mfg							**1.006*** **	
lq_meat_emp								**1.002* **
N	7086	7086	7086	5797	5799	5797	7086	7086

Hazard ratios displayed
* p<0.10, ** p<0.05, *** p<0.01

manufacturing employment and total employment, the more likely it is for a plant to fail. Average plant size location quotient is also related to increased likelihood of failure; for every unit increase in the location quotient, a plant's chance of failure increases by 1.6%. This indicates that the larger the average plant is in size relative to other counties, the higher the likelihood of plants failing. All three of these hazard ratios suggest that increased competition for resources –

certainly workers, but also potentially inputs like cattle and hogs – increases failure rates of meat processing plants. Alternatively, competition may be inducing so-called creative destruction, inducing the least productive plants to close and, ultimately, creating more competitive plants.

Size ratio – the ratio of the number of large plants in a county to the number of all plants in a county – is also significant. With a hazard ratio of 1.214, this indicates that for every 0.1 increase in the size ratio, a plant faces a 2.1% increased risk of failure. Given that the mean of this variable is 0.08 and standard deviation is 0.20, this appears to be an economically significant relationship. This relationship suggests that the higher the number of large plants relative to small plants, the higher the likelihood of plant failure. I also find a relationship between number of large plants and hazard, and a relationship between number of meat processing jobs and hazard. However, both these variables – unlike the other concentration measures – are highly correlated with population (correlation coefficients of 0.68 and 0.74, respectively, with p-values of less than 0.001). Population is not controlled for in my models, so results for these two variables may simply be driven by population; indeed, when adding in population as a control, the significance of these two variables is not robust.

The two size variables – size ratio and average size location quotient – were also included in models that were estimated by size of plant. Results are shown in Table 8 and Table 14. It appears that significant results for both variables are driven by results for the large plant category. Both variables are significant for large plants (at the 5% and 1% levels) but are not significant for very small, small, and medium plants. This is perhaps a surprise, as much of the narrative surrounding concentration has focused on its negative impact on smaller plants. But my analysis suggests concentration may actually be hurting other large plants – with hazard ratios above one for both variables, increasing concentration is associated with increased likelihood of failure for large plants. Perhaps since large plants demand high levels of resources, the existence of other large plants in the county poses a greater threat to availability of animal and labor supplies. This higher level of demand would increase input costs for plants, decreasing their profits and increasing odds of failure.

Table 14: Hazard ratios for extended models, with average size location quotient

	Model I All	Model II Very Small	Model III Small	Model IV Medium	Model V Large
meat_market	**0.571*** **	**0.588*** **	**0.467*** **	0.895	**0.476** **
meat_wholesale	**0.601*** **	**0.612*** **	**0.539*** **	**0.743*** **	0.953
dummy_1997	**0.805*** **	**0.781*** **	**0.849*** **	**0.765*** **	**0.679** **
female	0.996	0.911	1.079	1.230	3.85e-16
single_unit	**0.791*** **	0.967	**0.777*** **	**0.656*** **	1.067
log_size	**0.885*** **				
west	**1.168** **	**1.197* **	1.104	1.084	1.325
south	**1.131* **	**1.174* **	0.960	1.345	1.155
northeast	0.952	0.939	0.917	0.928	1.053
log_cattle	0.994	0.994	1.001	0.997	0.997
log_hogs	1.000	1.006	0.996	1.000	0.965
farmer_age	1.000	1.009	**0.977* **	1.007	0.959
log_farm_sales	0.973	0.952	0.968	1.017	1.042
pct_organic	1.252	0.996	1.555	**2.037* **	0.960
pcthsonly2000	0.994	0.990	1.002	1.001	0.968
level_lt_2yrs	1.035	1.062	1.051	1.125	**0.624* **
mfg_wage	1.003	1.002	1.001	1.010	1.009
mfg_emp_share	**0.995* **	0.995	0.997	0.988	**0.962*** **
unemp_rate	**1.018* **	**1.045*** **	0.986	1.004	1.039
white	0.998	0.996	0.998	1.003	0.993
foreign	0.995	0.994	0.997	1.011	**0.972* **
dt100k	**0.999** **	**0.999* **	0.999	1.001	0.999
hwy_exit	0.943	0.911	1.120	0.830	**0.613* **
railroad	0.924	0.791	1.224	2.782	0.364
rtw97	1.019	1.077	1.018	0.976	0.978
gov_spend	0.993	1.011	0.993	0.966	0.829
taxes	1.013	0.982	1.045	1.051	1.310
lq_avg_size	**1.016** **	1.016	1.008	1.002	**1.046*** **
N	5797	2638	2188	813	292

Hazard ratios displayed
* p<0.10, ** p<0.05, *** p<0.01

3.4.6 Results Summary for Small and Medium Plants

Looking at Table 8, results suggest that diversification and integration, year of establishment, and being a single unit plant are related to small and medium meat processor survival. These hazard ratios are large in magnitude, and consistently significant at the 1% level. Small (10 to 49 employees) and medium (50 to 249 employees) plants that have diversified into meat wholesale and distribution are 46% and 26% more likely to survive, respectively. Small plants that have diversified into offering a retail meat market are also much more likely to survive – 53% more likely.

Being established in 1997 or prior affects survival of these plants as well – small and medium plants that were founded on or before this date are 15% and 23% more likely to survive than newer plants. Being a single-unit plant as opposed to a multi-unit plant also increases survival chances – by 22% for small plants and 34% for medium plants.

There appears to be a relationship between region of the U.S. and medium-sized plant survival. While the variables *West* and *South* do not show up as significant in Table 8, this is likely due to high degrees of multicollinearity with state-level variables.[7] In the base model (Table 9), these variables are highly significant for medium plants (as well as for very small and large plants) but not small plants. Medium sized plants located in the West are 41% more likely to fail, while medium plants located in the South are 24% more likely to fail. Small plants in the West and South are no more likely to fail than plants in the Midwest or Northeast. This finding may be demand-related, as very small plants are often custom processors, while medium and large plants often produce a more homogenous, affordable product.

I have less certainty surrounding a number of additional factors: farmer age, percent organic pasture, farm sales, highway exits, and government spending. These factors are not

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[7] Variance inflation factors of 3.26 and 2.65, respectively

consistently significant for small and medium plants – they may be significant in only one model, may be significant for only one of the size categories of focus, may be marginally statistically significant, or may be marginally economically significant. All other variables are not significant for small and medium plants.

3.6 Policy Implications

This research was designed to provide insights on how funds may be deployed to most effectively increase resilience of small- and medium-sized meat processors.

A portion of the Biden administration's $1 billion commitment to the industry appears to be set aside for investment in new plants (The White House, 2022). My analysis shows that SMEs which are diversified, are single-unit plants, and are located in the Midwest or Northeast are more likely to survive than those that are not. Additionally, the more employees a plant has, the more likely it is to survive, although this result is nonlinear. Thus, targeting new plant investments towards establishments that fit these characteristics may more effectively increase future resilience to industry shocks, such as those experienced in 2020 and 2021.

Alternatively, if the administration's goal is to help existing SMEs that otherwise may not survive, several types of plants could be targeted: multi-unit plants, plants with fewer employees, startup plants, and plants in the South or West. Plants with these characteristics appear to be particularly vulnerable to failure. Additionally, providing funding to help plants diversify into offering a retail meat market or wholesaling business (retail meat markets may be more appropriate for smaller plants) may help increase SME resilience. One caveat, though, is that the success of small retail meat markets may be contingent upon local demand. As smaller plants usually cannot compete on price, and instead compete in the market for local and regional foods, the products they sell direct to consumer tend to be more niche and value-added (Johnson et al., 2012; Siebert et al., 2000). Thus, retail meat markets may not be successful in areas where demand for niche products is weak, or where incomes are not high enough to support sales of high-value-added products.

Additionally, as $50 million is dedicated to technical assistance (The White House, 2022), I would argue that some of this funding should first be utilized to further economic and business research relevant to SME meat processors. In exploring literature related to meat processing, I was surprised at how little work has been conducted surrounding meat processor success and survival, particularly for SME meat processors. Thus, a wider knowledge base on the economics and business best practices of SME meat processors may first need to be developed before helpful business-related technical assistance can be provided.

3.7 Conclusion

Overall, I found that, as hypothesized, plant-level characteristics mattered more for plant survival than local characteristics. Plant size was related to survival – plants with larger numbers of employees were more likely to survive than smaller plants – though this relationship was not linear. Single-unit plants were more likely to survive than multi-unit plants, but this relationship only held for small- and medium-sized plants. Established plants had higher survival rates than younger plants, and plants in the South and West were less likely to survive than those in the Midwest. Additionally, vertically integrated processors – processors with retail meat markets or meat wholesaling operations – had higher survival rates. Plant-level results tended to be large in magnitude and robust across size categories and model specifications. Additionally, these results are all in line with literature exploring impacts of plant size (Agarwal & Audretsch, 2001; Audretsch & Mahmood, 1995), location type (Bernard & Jensen, 2002; Low & Brown, 2017), region of the U.S. (Low & Brown, 2017), and integration (Anderson et al., 1998) on plant survival.

Local context variables did affect hazard rates. Several labor market characteristics were related to hazard probability; relative size of the manufacturing workforce (manufacturing employment share), unemployment rate, and proximity to a city of more than 100,000 people were significant in the extended model. In the more parsimonious model, demographics also emerged as significant – percent of the population that was white, percent that was foreign-born, and percent with a high school education only. Industry concentration was related to hazard, though this result was driven by the large plant category; large plants appear to be negatively affected by competition from other large plants. Input and policy variables had a weaker and less robust relationship with plant survival. No input and policy variables were significant in the extended model, but access to cattle and hogs and several policy variables (right-to-work, government spending, and taxes) were significant in the shortened models. For SME plants, very few local context variables mattered for plant survival; SME survival was primarily driven by plant characteristics.

This paper makes several contributions to the literature. To my knowledge, this is only the second quantitative study to examine meat processor survival, and the first quantitative study to examine plant survival by size. This is a particularly relevant and timely contribution given the policy emphasis on industry resilience in the wake of the COVID-19 pandemic. Additionally, this work is comprehensive in scope. This study included data from over twenty years, from over 8,000 plants, and spans the entire continental U.S., providing confidence in my results and their generalizability. This paper used county-level explanatory variables, however, which is a potential downfall. Multi-county commuting zones may provide more realistic results, particularly for input variables, workforce variables, and concentration variables, as markets for animals and labor are usually not limited by county.

Finally, just as the areal unit could be broader, the definition I used for meat processors could have been narrower. A visual scan through establishment names suggests meat processing is not the primary business activity for a number of establishments. Perhaps results would be more true-to-life if a stricter definition of meat processing was used. There is opportunity for future work to improve upon this study by conducting a commuting zone-level analysis and exploring various definitions of meat processing plants. However, despite its limitations, this research sheds light on the impact of plant-level characteristics and local labor market characteristics on long-term meat processor survival, and suggests potential policy-relevant levers for plant resilience.

CHAPTER 4: CONCLUSION

4.1 Summary and Synthesis

This thesis examined factors related to food manufacturer resilience. The first study explored factors related to worker shortages, a key barrier to achieving resilience in the food manufacturing industry. This study had two primary findings. First, offering education and training opportunities is associated with reduced plant-level worker shortages. Second, worker shortages may drive automation *intentions*, but no evidence suggests that greater *current* levels of automation are associated with reduced worker shortages – perhaps because automation often creates skilled positions as it eliminates unskilled positions. Results of the first essay had implications for how managers and policymakers can reduce worker shortages, thus increasing industry resilience.

The second study examined what characteristics, both plant-level and regional, are related to meat processing plant survival. Overall, this essay found plant-level characteristics had a larger magnitude of influence on the probability of survival than regional characteristics. This holds especially true for small- and medium-sized plants (i.e., those with 10 to 249 employees). That is not to say regional characteristics have no relationship with plant survival, however; results suggest workforce characteristics, in particular, may affect a plant's probability of survival. This study provided implications for policymakers focused on strengthening meat processing industry resilience.

The two studies largely examined food manufacturer resilience through different lenses and in different geographic contexts, but several themes did emerge. First, both studies found plant-level factors matter for food processor resilience. This is good news for business owners, as this implies managers can do much at the establishment level to increase plant resilience. Second, workforce-related factors matter for food processor resilience. Workforce-related variables – such as education, training, size of the workforce, and demographics – were related to resilience in both studies.

4.2 Contributions and Future Work

Both studies were complementary in their approach and contributions. The first study utilized a small, statewide sample, but data were detailed and in-depth. The second study utilized a large nationwide sample, but fewer plant-level variables were available, and data contained little detail. Thus, the two studies provided helpful contrast, better informing our understanding of food manufacturer resilience. One limitation of this overarching body of work, however, was that it only utilized quantitative analysis. A qualitative study would have addressed several unanswered questions – particularly surrounding causality – and would have provided additional context, color, and nuance to findings. Future work addressing food manufacturer resilience through a qualitative lens would make a valuable contribution to the literature.

The primary contribution of this thesis, however, is that it provides policy-relevant analysis at a time when food manufacturer resilience is of great interest to policymakers, analysts, and researchers. This thesis fills gaps in the academic literature and provides results which may help mitigate labor shortages and improve meat processor resilience, two issues with the potential to affect U.S. food security.

LITERATURE CITED

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APPENDIX A: SURVEY INSTRUMENT

Table A.1: Survey questions

Q1: Screening Question:

- I employ workers in the food, agriculture, or forestry industry in the state of Missouri and I am willing to take this voluntary survey on workforce needs for my business
- I do not employ workers in the food, agriculture, or forestry industry in the state of Missouri.

Q2: Which category best describes your business?

- Production Agriculture
- Food and Related Products Manufacturing
- Agriculture and Forestry Inputs and Support Services
- Forestry and Wood Products Manufacturing

Q2.3: Which category best describes your business? (Food and Related Products Manufacturing)

- Animal slaughter and meat processing
- Fruit and vegetable manufacturing
- Dairy product manufacturing
- Wineries
- Breweries
- Bread and bakery products
- Distilleries
- Dog and cat food manufacturing
- Poultry processing
- Flour milling
- Rice milling
- Soybean or oilseed processing
- All other food manufacturing

Q3: Where does the majority of your workforce work? (Missouri counties were listed)

Q4: How do you expect the size of your workforce to change over the next 12 months?

- Increase significantly
- Increase slightly
- Remain the same
- Decrease slightly
- Decrease significantly
- Not sure

Q5: How many workers do you employ in the state of Missouri?

Q6: What percent of your employees are seasonal?

- None
- 1-25%
- 26-50%
- 51-75%
- >75%

Q7: How physically demanding is the average job in your business?

- Intensely physically demanding
- Moderately physically demanding
- Occasionally physically demanding
- Not physically demanding

Q8: How does your business plan to add employees?

- Hiring new full-time employees
- Hiring new part-time employees
- Other methods to add workers
- Hiring contract workers
- Using a temporary agency
- Recalling workers from lay-off lists

Q9: Which of the following are potential barriers to expanding employment within the business?

- Shortage of workers with knowledge or skills
- Economic conditions
- Government policies or regulations
- Not looking to expand
- Lack of transportation access
- Lack of childcare access
- Shortage of available training programs
- No barriers to expanding
- Lack of information

Q10: How has the business adapted to a lack of skilled job applicants?

- Forced to hire less experienced workers and then train them
- Offering increased wages due to shortage of experienced workers
- Investing in automation
- Hiring from outside the area
- Hiring contractors
- No lack of skilled applicant
- Hiring from outside the United States

Q11: What is the most common reason workers leave positions at your business?

- Higher compensation/benefits from other employers
- Workers rarely leave
- Seeking different type of work activities
- Desire for more flexible or regular schedule
- The job is too physically demanding
- Other
- Retirement

Q12: What critical positions are the most difficult to fill?

- Mechanic/welders/maintenance/technicians and other skilled positions
- Line workers/production line/slaughterers and meat cutters
- General labor/physical/unskilled work
- CDL and equipment operators
- General farm labor
- Management
- Customer service/sales
- Specialists (engineers, plant scientists, foresters, etc.)
- Applicator
- None
- Animal/livestock handling
- Specific time/shift related
- Chefs/cooks/kitchen/food prep
- Fermentation
- Veterinarians and veterinarian technicians
- Accounting/clerical

Q13: What critical positions will be most affected by an aging workforce?

- Production/physical labor
- Production/skilled labor
- CDL and equipment operators
- Management
- Mechanic/welders/maintenance/technicians
- Slaughter
- All jobs
- Relationship/networks/experience/knowledge
- Work ethic
- Animal/livestock handling
- Applicator
- Veterinarian technicians and veterinarians
- Product development
- Fermentation
- Accounting/clerical
- Specific time/shift related
- Customer service/sales

Q14: What recruitment practices do you use to fill current jobs?

- Employee referrals and networks
- Social media sites
- College/university recruiting
- Advertise on the business website
- Advertise at job centers
- Industry specific job boards
- External recruiters and agencies
- Other
- Billboards and door signs
- Work with the media to talk about our business/events

Q15: Which, if any, of the following benefits or incentives does your business offer employees?

- Paid vacation
- Performance based pay increases or bonuses
- Flexible work schedule
- Other
- Financially support continuing education
- Providing housing or a vehicle
- The ability to work remotely
- Childcare

Q16: Does your business hire, or would you consider hiring, the following workers?

- Veterans
- Recent retirees
- High school students
- Interns of co-ops
- Ex-offenders
- H-2A guest workers
- None of the above

Q17: What does your business do to promote careers in food, agriculture, and/or forestry to youth?

- Work with 4-H, FFA or other youth groups
- Provide facility tours
- Speak in schools
- Social media campaign
- None of the above
- Other

Q18: What skills are most difficult to find?

- Reliability and general work readiness
- Leadership and supervisor skills
- Problem solving and analytical
- Truck drivers
- Customer service and sales
- Communication and interpersonal skills
- Livestock handling
- Heavy equipment operation
- Other
- Automotive repair and mechanical
- Agronomy
- Electrical
- Animal husbandry
- Financial management
- Automation and robotics knowledge
- Programing and software applications

Q19: Which of the following methods does your business use to increase the skills of current workers?

- On-the-job training
- Flexible schedule for continuing education
- In-house classroom training
- Vendor training
- Online courses
- Apprenticeship programs
- Tuition reimbursement
- Community College provided customized training or education
- Hire only workers who are already trained
- Vocational trainings
- Other
- None of the above

Q20: What training methods do you feel are most effective?

- On-the-job training
- Flexible schedule for continuing education
- In-house classroom training
- Vendor training
- Online courses
- Apprenticeship programs
- Tuition reimbursement
- Community College provided customized training or education
- Hire only workers who are already trained
- Vocational trainings
- Other
- None of the above

Q21: What challenges do you face when providing training for your existing workforce?

- Lack of time for in-service training
- Finding relevant training options
- Fear of losing trained employees
- Can't afford existing training options
- Lack of online training options
- Lack of space for training
- Other
- Poor experience with previous training providers

Q22: Which of the following best describes your business leadership's feelings about internal process automation?

- We are already making significant investments in automation
- Automation has significant potential for our business, and we are planning to make investments in automating our processes
- Automation is on our radar, but we have no current plants to invest in it
- We are not looking to automate our processes

Q23: How is greater automation impacting jobs within your business?

- We don't automate
- Changed the type of jobs we hire (e.g., more technically skilled or more educated)
- No effect
- We need to provide our workers with more on the job training
- Decreased the number of jobs
- Increased the number of jobs

Q24: What barriers does your business face as you adopt new technology and processes?

- Cannot afford to implement
- Insufficient broadband capacity
- No barriers
- Workforce lacks capacity to implement automated processes
- Lack of information about available technologies
- New technologies are not applicable
- Other

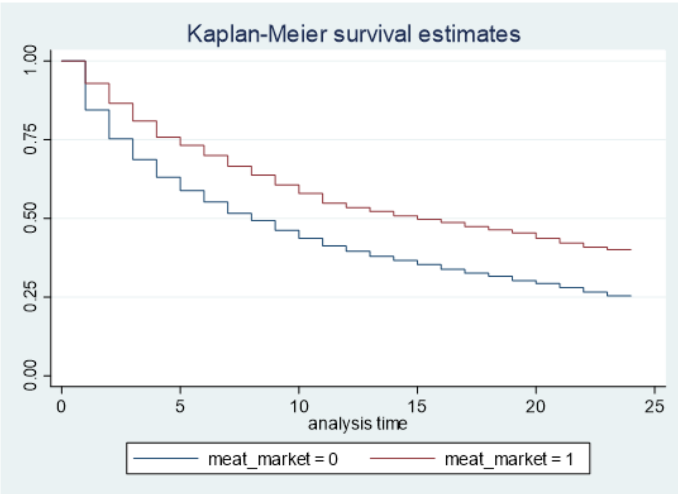
Q25: What specific jobs have been most impacted by changing technologies or automation in your business?

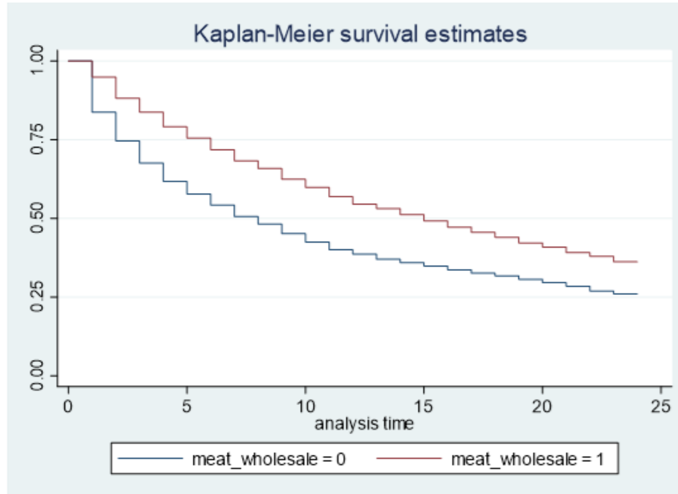
- Manual labor
- Equipment operator
- Technical/IT
- Office/admin
- Packaging
- Production machine operators
- Meat processor
- Maintenance
- Service
- Crop scouting
- Manager
- N/A

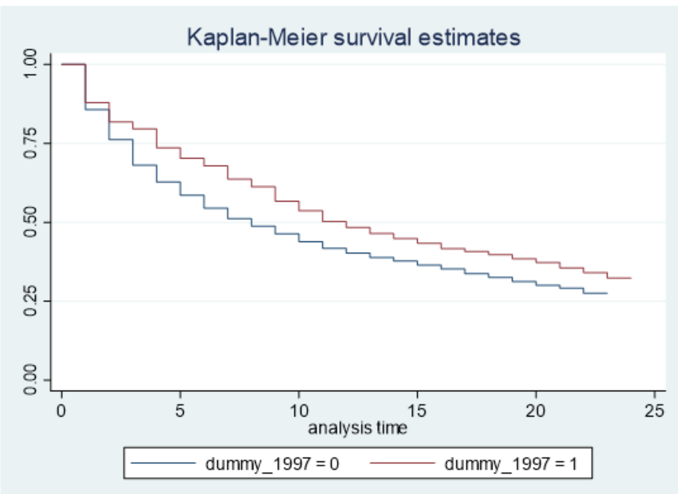
Q26: What is your businesses top workforce priority over the next ten years?

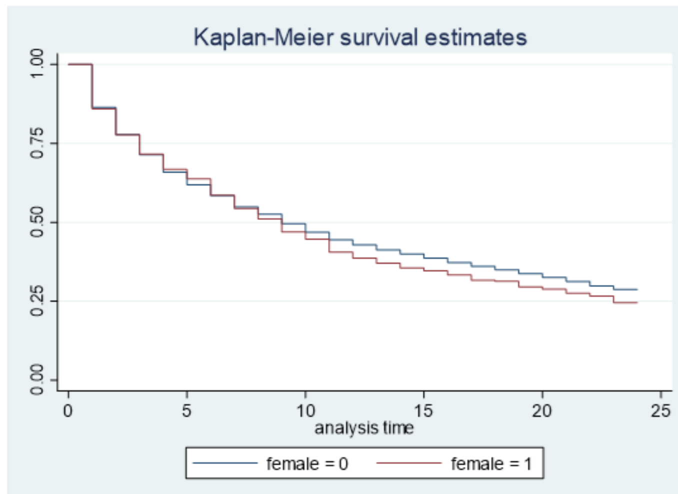
- Hiring capable and reliable staff
- Hiring for critical positions and specific skills
- Retention
- Business growth and/or sustainability
- Skills and training
- Automation and technology
- Aging workforce and/or succession planning
- Other business concerns
- N/A

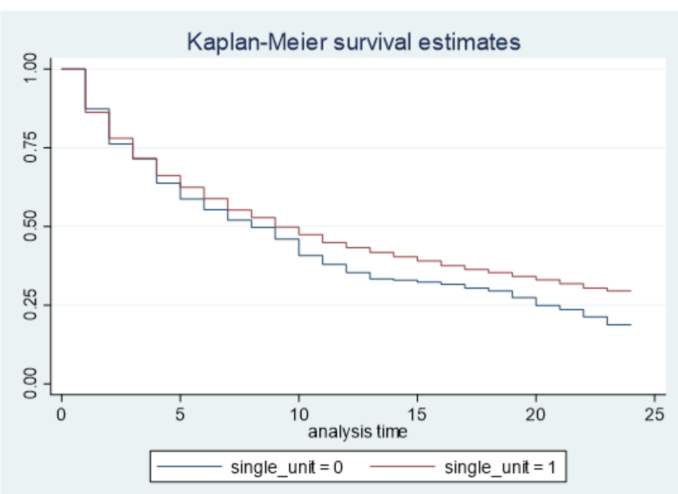
APPENDIX B: KAPLAN-MEIER GRAPHS

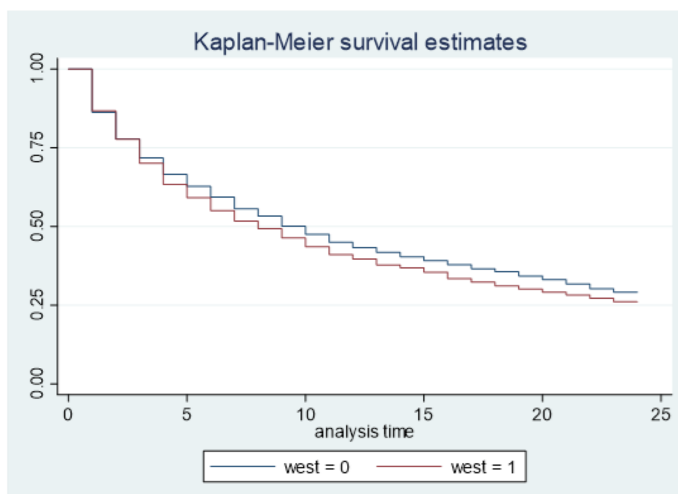


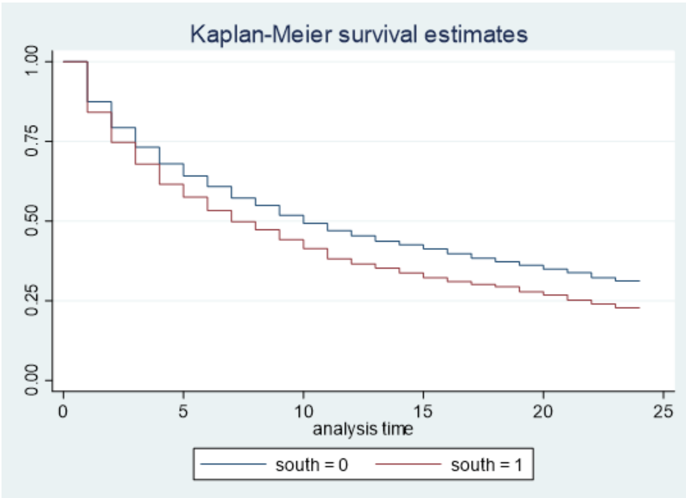








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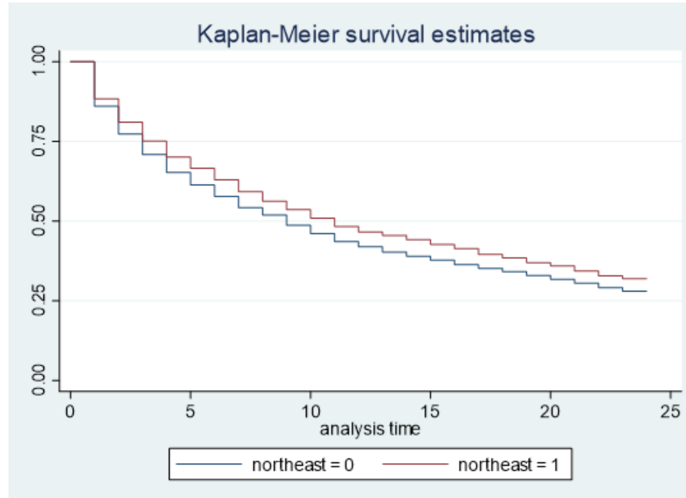
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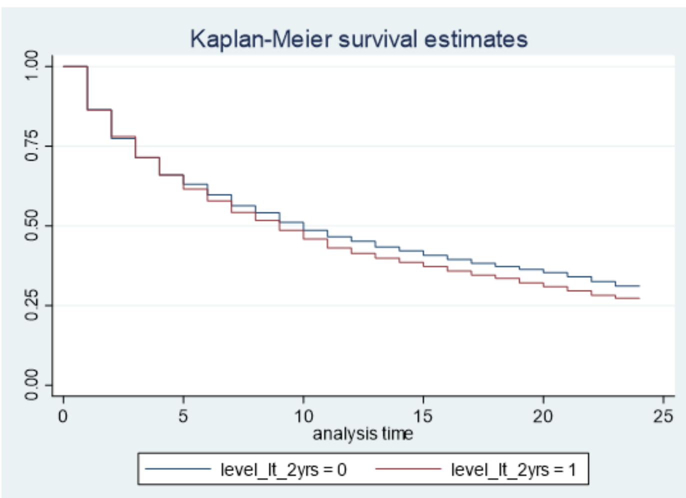
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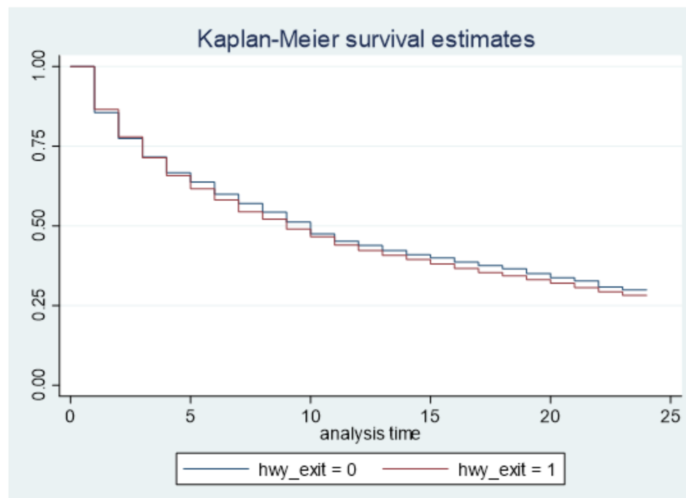
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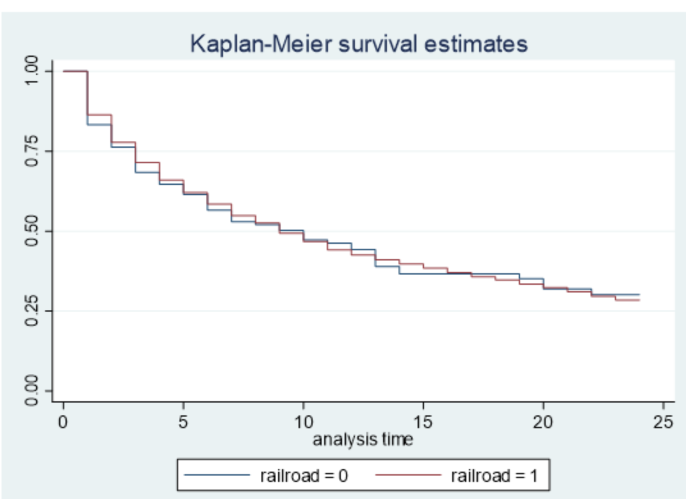
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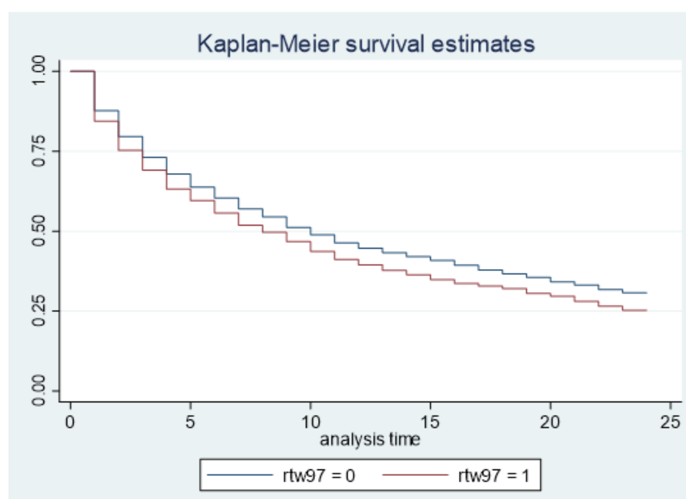
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