From Classroom to Paycheck: Vocational Education in Massachusetts

Matthew T. Sher

Advisor: Joanna Venator, Ph.D.

Boston College Department of Economics

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From Classroom to Paycheck: The Impact of CTE Vocational Programs on Wages in Massachusetts*

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Abstract

This paper explores the impact of Career and Technical Education (CTE) programs on wage outcomes in the U.S. labor market, particularly against a backdrop of shifting economic conditions and workforce needs. The study delves into how various CTE programs, specifically state-approved programs with stringent standards and federally-approved programs with more flexible requirements, shape the wage trajectories of high school students. The analysis is structured in two main phases: the first phase involves a detailed mapping of CTE courses to real-world occupations as categorized by the North American Industry Classification System (NAICS), highlighting the alignment—or lack thereof—between educational offerings and labor market demands. The second phase employs an Ordinary Least Squares (OLS) regression with fixed effects to analyze the influence of CTE program participation on wage outcomes across different industry sectors and counties. This approach allows for a nuanced examination of how local industry definitions affect the perceived effectiveness of CTE programs and underscores the complex trade-offs involved in prioritizing vocational training for immediate employment versus broader educational and career advancement opportunities. The findings reveal significant variability in the impact of CTE programs on wages, influenced by the specificity of job sectors and the breadth of skills taught, with implications for policy decisions aimed at enhancing the role of vocational education in fostering economic mobility.

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1 Introduction

Low-wage jobs account for 36 million out of 37 million jobs created by the United States private sector from Q3 1992 to Q1 2020 (Bureau of Labor Statistics, 2021). These jobs are particularly prevalent among individuals possessing less than high school, high school, and some college experience with 57% of the low-wage workforce in these educational categories. I examine the wage effect of two types of vocational education programs in Massachusetts teaching high school students career skills in high-wage jobs. One program is a state-approved option with stricter industry standards, while the other is a federally-approved program with less stringent requirements for graduation. I find that the higher-standard program funnels over twenty percent more graduates into immediate employment or short-term education and the lower-standard program funnels twenty percent more graduates into longer-term two-year or four-year colleges. I then use ordinary least squares (OLS) with fixed effects for year, town, and industry cluster to identify effects of the program and grade enrollment on average weekly wages using exogenous variation in local industry wages, and find that program existence and grade 12 program enrollment have opposite effects. The existence of any program is associated with increased weekly wages by two to three dollars. The program enrollment for grade 12 is associated with a minuscule decrease of less than a dollar in weekly wages. It is important to note the wage gains I estimate have a small magnitude of effect given the observed Massachusetts average weekly wage range of $928-$1097 from 2012 to 2018. Further, it appears that the marginally higher gains to higher-standard programs equalize near year four after graduation and fall after five years indicating college cohorts may receive higher wage benefits in the long run.

The effect of both vocational programs on graduate wages appears to diminish when analyzing more specific job sectors within the local economy. When running OLS across the

North American Industry Classification System (NAICS) industry hierarchies, the program effect on wages decreases as we move from broad to narrow job categories. This suggests that the program effect on wages gets diluted as OLS consider many industries instead of focusing on the specific industries the programs train for. The dilution of effect is particularly prevalent for high-standard programs that are designed for very specific industries as they experience a steeper decline in effect compared to low-standard programs. This implies that high-standard programs may limit the options of their graduates to a narrower range of industries. Lower-standard programs experience a more gradual drop in wages across industry specification suggesting their graduates are placed into a wider variety of occupations. The variance in program effect may explain why prior research found a mismatch between vocational training and national labor market demand (Sublett and Griffith, 2019).

Further analysis reveals that programs with higher standards exhibit a broader diversity in course offerings and attract higher enrollment numbers. These programs typically provide a wide range of specialized tracks that cater to various high-demand industries, reflecting a robust and dynamic curriculum. In contrast, programs with lower standards show less variety in their course offerings, with a noticeable shift towards emphasizing business and technology sectors. This trend suggests a narrower focus, possibly driven by perceived immediate job market needs rather than a comprehensive vocational training approach. Additionally, a significant distinction is observed between counties experiencing high wage growth and those with low wage growth, particularly in terms of healthcare sector enrollments. In high wage growth counties, there is a marked increase in healthcare-related vocational training, indicating that such programs are in tune with local industry demands and are possibly tailoring their curriculums to address specific labor market shortages. This alignment may be less pronounced in lower wage growth areas, where healthcare enrollments remain stagnant or do not correspond with industry needs.

My contribution suggests that how local industries are defined can significantly influence the perceived effectiveness of vocational programs. Furthermore, my results support prior research highlighting how program course offerings can restrict the opportunities of graduates in the context of local job demands (Sutton, 2017). If a vocational program prioritizes local jobs that don't require a college degree, it may inadvertently limit the options for high-achieving students seeking to pursue higher education.

1.1 Low-wage jobs: Identifying Causes

The narrative beings in the late 20th century when the United States earned fame as "The Great American Jobs Machine." From 1973 to 1984, the labor market generated 26 million new jobs outpacing the combined efforts of most other industrialized nations (Bluestone and Harrison, 1986). However, job quantity came at the expense of job quality. In the decade before, 20% of newly created jobs offered wages below the median wage from 1963 to 1979. In contrast, nearly 60% of new jobs after 1979 paid wages less than half of the median wage of 1973 (Bureau of Labor Statistics, 2021). This trend of increasing low-wage jobs persisted into the 21st century. From 1992 to 2020, the U.S. private sector added 37 million jobs, but a staggering 36 million of these were categorized as low-wage jobs (Bureau of Labor Statistics, 2021). This ongoing trend of low-wage job creation has profound implications for social and economic welfare. On the economic front, low incomes result in individual poverty, material deprivation, and macroeconomic reduction in growth, innovation, and investment. On the social front, societies that are more unequal have worse social outcomes on average than more egalitarian societies on health and social problems being positively correlated with the level of income inequality (Polacko, 2021).

Due to its detrimental effects, researchers have investigated the causes of the increase in wage differentials. Initial explanations were related to the increase in international trade between countries and the resulting diffusion of exchange (Borjas et al. 1997). Yet, trade explanations were insufficient to account for more than a small proportion of the overall widening of the wage structure over the 1980s and have played only a modest role in the expansion of the college-high school wage differential in the United States (Borjas et al. 1997). Over time, other explanations began to examine the changes in labor demand. Katz and Murphy (1992) laid the groundwork for understanding Skill-Biased Technological Change (SBTC) by demonstrating a disproportionate shift in labor demand towards high-skilled workers. Skill-Biased Technological Change (SBTC) attributes the decline in middle-wage jobs to a shift in labor demand towards higher-skilled jobs because high-skill workers experience greater boosts to productivity from technological advancements (Bound and Johnson, 1992; Katz and Murphy, 1992). In effect, low-skill workers are left with lower demand and lower wages. Acemoglu and Restrepo (2013) built upon the foundation provided by Katz and Murphy by identifying the demand for worker characteristics within jobs. Automation has substituted routine tasks typically associated with middle-wage jobs while complementing the abstract, creative, problem-solving, and coordination tasks performed by highly-educated workers (Autor and Dorn, 2013). Displaced middle-wage workers are forced to reallocate their labor supply to low-wage service occupations that are challenging to automate due to their reliance on dexterity, interpersonal communication, and physical proximity. Thus, skillsets that cannot be replaced by technology resulted in a rise in high-skill wages and skillsets that can be replaced accounted for 50-70% of increased wage inequality from 1980-2020 (Acemoglu and Restrepo, 2022).

The result of this labor demand shift is job polarization. This economic phenomenon describes a widening gap in the labor market between the number of high-skill, high-wage jobs and low-skill, low-wage jobs, with a decline in the number of middle-skill, middle-wage jobs. Job polarization helps explain why the decline of middle-wage jobs isn't solely due to a lack of demand for workers. While SBTC highlights the rise of high-skilled jobs due to technology, job polarization emphasizes the simultaneous decrease in middle-skill jobs and the growth of low-wage jobs in sectors like service industries. This trend creates a challenging scenario for both policymakers and educators. They must grapple with how to equip the workforce with the skills needed to thrive in this new economic landscape, where the middle ground is shrinking and the poles of high-skill and low-skill jobs are expanding.

1.2 Adapting Labor Market Policies to Demand Shocks

Classical economics predicted that the labor supply will adapt to shifted labor demand by upskilling. However, the real-world labor market has not witnessed the same ease of transition. One instance is the "China Shock" of persisting wage differentials two decades beyond the initial shock. In 2001, China's entry into the World Trade Organization and the normalization of U.S.-China trade relations allowed an influx of inexpensive Chinese imports that devastated the U.S. manufacturing sector. By 2011, this competition from China was linked to the loss of nearly 1 million U.S. manufacturing jobs and about 2.4 million jobs in total (Autor, Dorn, Hanson, and Price, 2016). By 2022, the affected regions continue to struggle with reduced employment-to-population ratios, lower earnings, and an increased dependency on government transfer benefits in 2022 (Autor et al., 2016). The China trade shock caused spatially concentrated job losses that persisted for two decades with lasting declines in both employment and income levels in the most exposed communities. Autor, Dorn, and Hanson (2021) suggest that existing policies in the U.S. failed to adequately insulate workers from mass-layoff and wage polarization events such as the China trade shock. With an eye on future labor market demand shifts, the global economy will continue face repeated localized shocks from the energy transition, advanced automation, and even China's massive industrial policy intended to support its technology sector. Motivated by concerns surrounding localized job losses and the anticipated displacement of workers in specific sectors, this paper evaluates the effectiveness of labor market policies aimed at upskilling workers toward higher-paying jobs.

1.3 Types of Labor Market Policy

In the 1980s, Organisation for Economic Cooperation and Development (OECD) countries adopted two main responses to high unemployment. Formally, passive labor market policies (PLMPs) are social welfare policies that include unemployment benefits and active labor market policies (ALMPs) are interventions designed to improve the employability of job seekers through measures that include training, job search assistance, and wage subsidies (Pignatti Clemente and Van Belle Eva, 2021). These proactive interventions aim to address the limitations of relying solely on market forces for worker adaptation.

On one hand, passive labor market policies are aimed at providing financial support to unemployed individuals through unemployment benefits including unemployment insurance, welfare benefits, income support allowances, and severance pay. The focus is on mitigating the immediate financial hardships associated with unemployment rather than actively assisting individuals in finding new employment. PLMPs do not necessarily encourage the return to work or skill development, and instead, offer a safety net that cushions the economic impact on individuals who lose their jobs. The nature of PLMP is protective as a safety net during periods of joblessness, helping individuals and families maintain a socially acceptable standard of living irrespective of their market performance.

On the other hand, active labor market policies are integrative labor policies designed to integrate disadvantaged individuals into working life. These proactive interventions aim to address the limitations of relying solely on market forces for worker adaptation. The underlying concept of ALMPs is rooted in social investment that yields returns in increased employability, incomes, and productivity of economic agents (Pignatti Clemente and Van Belle Eva, 2021). ALMPs can be categorized into four broad areas: vocational training, wage subsidies or private sector employment incentives, public sector employment, and assistance in the job search process (OECD, 2006; Kluve, Card, and Weber, 2007). Among these, vocational training is of significance because it seeks to upskill human capital when labor demand shifts outward.

This paper prioritizes discussing vocational training over other forms of active labor market policies such as wage subsidies, public sector employment initiatives, and job search assistance due to the unique economic implications of each. While vocational training directly addresses the enhancement of worker skills and productivity, thus aligning closely with the demands of a competitive labor market, other ALMPs may not. First, wage subsidies can distort labor market dynamics by encouraging firms to hire based on financial incentives rather than genuine labor demand or worker suitability. This approach can lead to inefficiencies where businesses employ individuals who may not be the best fit for the roles, merely to capitalize on subsidies. Prior research finds the complex effects of wage subsidies on wages and employment. For instance, Elvery et al. (2022) found that wage subsidies can distort market wages depending on the relative elasticity of labor supply and demand. If there is a high supply of labor and low demand, a subsidy might entice employers to offer lower wages. Conversely, in a tight labor market, the subsidy's impact on wages might be minimal.

This highlights how subsidies can disrupt the natural wage-setting mechanisms. Additionally, Hamersma (2008) suggests that only around 38% of a wage subsidy may translate into higher wages for workers. This raises questions about the efficacy of subsidies in genuinely improving worker well-being, as opposed to merely increasing company profits or covering inefficiencies. Further research reveals both positive and limited impacts of wage subsidies on employment. Saez et al. (2019) documented a modest increase in youth employment due to Swedish payroll tax cuts, suggesting job growth potential. However, Cahuc et al. (2018) observed that short-time work subsidies during the Great Recession mainly preserved jobs temporarily without fostering significant skill development or long-term job security. In conclusion, while wage subsidies can offer some temporary employment benefits, they can distort the labor market by focusing on short-term gains rather than worker suitability. This mismatch can lead to inefficiencies and doesn't directly address the core issue of skill gaps.

Second, public sector employment is less responsive than the labor market's actual demands. For instance, public sector jobs may be created to fulfill social or political agendas, even if the economic justification is weak. According to Holmlund and Linden (1993), public sector employment expansion can have unintended consequences beyond a mismatch of skills and needs. Their theory suggests that a significant increase in public jobs might not only crowd out private sector employment where qualified workers are lured by public sector benefits, but also increase overall unemployment. This could happen if attractive public sector working conditions incentivize more individuals to enter the workforce, exceeding the number of jobs created. Empirical evidence from a study by Algan et al. (2002) analyzing OECD countries between 1960 and 2000 supports this theory. Their findings suggest that on average, for every 100 public sector jobs created, there is a net loss of around 150 private sector jobs. Additionally, they observed a slight decrease in overall labor market participation alongside an increase in unemployment by about 33 individuals. These findings highlight the potential drawbacks of public sector employment expansion when it is not driven by clear economic needs.

Third, while job search assistance is crucial for matching workers with employers, it does not directly improve the skills or productivity of workers. It simply enhances the process of job matching without addressing the qualitative aspects of labor that contribute to economic growth. This focus on quantity over quality can have unintended consequences. Prior studies (Marinescu, 2017; Marinescu, 2007; Lalive et al., 2015), have found that job search requirements can have adverse effects. By pressuring the unemployed to find work quickly, these programs may lead them to accept lower-quality jobs with lower wages and less stability. In Austria, an increase in benefit duration for some of the unemployed resulted in lower unemployment duration for those who did not qualify and were searching in the same region (Lalive et al., 2015). Additionally, the pressure to find work rapidly can discourage some individuals from searching altogether, potentially pushing them towards disability benefits as an alternative (Marinescu, 2007). This highlights the importance of striking a balance between job placement and skill development. While connecting workers with open positions is essential, neglecting to address skill gaps can limit long-term economic growth.

Vocational training programs stand out as a targeted approach within active labor market policies. Unlike subsidies and public sector initiatives, which can distort market dynamics, vocational training directly equips workers with the specific skills employers seek. This focus on skill development aligns perfectly with the evolving demands of a competitive labor market, fostering a more skilled and competitive workforce. This paper investigates vocational training programs because they offer a unique and impactful approach to economic growth. By directly enhancing the capabilities of the workforce, vocational training has the potential to drive long-term economic prosperity.

1.4 Vocational Training: Career and Technical Education

Federal legislation stands as the singular most influential force shaping vocational education in the United States. Until the National Defense Education Act of 1958, federal funding for education solely targeted vocational programs (Harden, 1981). This financial leverage granted the federal government a crucial role in directing the development of vocational education across the nation. The Smith-Hughes Act of 1917 marked the official beginning of formalized vocational education. Recognizing the influx of working-class students entering high schools for the first time, this act advocated for a distinct curriculum separate from the traditional, college-preparatory track (Gray, 1991). This new curriculum aimed to address the specific needs of these students who weren't pursuing professional careers. Over the next century, federal vocational education policy and funding at the high school level underwent a series of targeted shifts but the overarching goal remained consistent: preparing students for specific jobs in the evolving economy. The focus transitioned from defense preparedness in the 1920s to addressing unemployment in the 1930s, supporting war efforts in the 1940s, and fostering post-war economic growth in the 1950s. This resulted in a continuous rise in high school vocational education enrollment, peaking in the early 1980s (Lynch, 2000).

By 1982, Levesque et al (2008) find that the average American high school student took roughly 22% of 21.6 credits in vocational courses. However, by 1994, this number had shrunk dramatically to 16% even as the total number of credits required for graduation increased to 24.2. This significant decline in vocational education enrollment between 1982-1994 can be attributed to concerns over the falling competitiveness of the U.S. in the global market, coupled with consistently low scores by American students on standardized tests. Additionally, the business community voiced growing dissatisfaction with the skills and abilities of high school graduates entering the workforce (Gordon, 2020). Furthermore, equity concerns mounted as the Smith-Hughes Act also inadvertently established a system known as "tracking." This system channeled working-class students into practical skillsets focused on agriculture and industry, while reserving the classical curriculum for students from wealthier backgrounds who were expected to pursue professional careers (Lynch, 2000). In essence, the initial vocational programs emerged from a national need to equip a growing blue-collar workforce with the practical skills necessary to support the nation's burgeoning industrial and agricultural sectors. Yet, by the 1980s, the needs of the nation were dramatically different. International tensions from World War II called for reforms after the publication of "A Nation at Risk" in 1983 by the National Commission on Excellence in Education. This report highlighted the declining international competitiveness of the U.S. and partially attributed it to the low standards and performance of the American education system. It emphasized the need for a workforce adaptable to rapid technological advancements, advocating for foundational skills and acknowledging the growing importance of technology across various industries and the military sector.

Thus, two waves of secondary educational reform sought to rectify the academic concerns and equity concerns in the 1980s (Asche, 1993). The first wave, often dubbed "academic reform," sought to enhance the existing system's rigor. This included stricter graduation requirements with more academic courses, heightened college entrance demands, extended school days and years, and an emphasis on standardized testing for students and teachers. These initial reformers viewed a focus on academic education, not vocational training, as the answer to lagging U.S. competitiveness against Japan and Germany in manufacturing (Lewis, 1988). By the mid-1980s, a second wave of reform emerged emphasizing generic skills over specific vocational training. The National Commission on Secondary Vocational Education (1984) in "The Unfinished Agenda" highlighted the expanded goals of vocational education. They argued it should cultivate personal skills and attitudes, communication, numeracy, and technological literacy, employability, a wider range of vocational skills and knowledge alongside specific skills, and a foundation for career planning and lifelong learning.

The landmark Carl D. Perkins Vocational Education and Applied Technology Act of 1984 reflects a culmination of academic and equity reforms in vocational education. Responding to concerns about discrimination and curriculum quality, the act established a dual focus – economic and social (Congress of the U.S., 1984). It aimed to bolster workforce skills and prepare adults for jobs (economic), while also creating a level playing field by providing equal access to vocational education for all adults (social). This act shifted federal funding priorities from simply expanding programs to improving existing ones and directing resources towards at-risk populations. Subsequent iterations of the Perkins Act continued to refine and broaden the definition of vocational education. Notably, the Perkins II Act of 1990 championed inclusivity and equal access. It mandated programs that strengthen "academic and occupational skills of all segments of the population" (American Vocational Association, 1990). Significantly, this was the first time the legislation targeted the entire population. This act paved the way for a three-pronged approach to improve workforce preparation: integrating academic and vocational education to bridge the gap between theory and practice, facilitating smoother transitions between secondary and postsecondary vocational programs, and creating stronger linkages between school and work through real-world work experiences (Gordon, 2020). These changes represented a significant departure from the historical model of vocational education in the U.S.that often segregated vocational education from the rest of the school system. Building on these reforms, the Perkins IV Act of 2006 officially rebranded "vocational education" as Career and Technical Education (CTE). This reflected the program's expanded focus on preparing students for a wider range of career paths, including pathways to higher education. Moreover, the Perkins IV Act of 2006 introduced a key concept called Programs of Study (POS). Defined by the U.S. Department of Education as "a comprehensive approach for delivering academic and career and technical education," POS aimed to prepare students for both postsecondary education and successful careers (Shumer and Digby, 2013). This concept established career clusters for students to pursue, fostering a more intentional focus on specific industry sectors. The most recent Perkins V Act of 2018 further emphasized the importance of job quality at the local level. This legislation mandated alignment of CTE programs with local economic needs, requiring programs to target "high-skill, high-wage, or in-demand occupations" as defined by individual states (Pew Research Center, 2020).

Reflecting on the history of the Career Technical Education (CTE) program, CTE has evolved significantly since its inception in the Smith-Hughes Act's tracking system. Originally criticized for perpetuating social inequality, CTE has transformed into a federal program intending to bridge the skills gap for high-wage, high-demand careers and equip all segments of the population for upward mobility. However, the question remains whether the good intentions of CTE have come to fruition in terms of worker's wages in the local economy. While past research on the impact of Career and Technical Education (CTE) programs on local labor markets has yielded mixed results, with a recent trend towards more positive findings, a key limitation exists: most studies rely on national data with less granular data or fail to account for variations in program quality in the local context. I choose the CTE program as my vocational program of choice because of it's representative and federal purview of vocational programs.

Here, the Commonwealth of Massachusetts offers a compelling setting to investigate the impact of Career Technical Education (CTE) programs on worker wages. Three key factors contribute to this suitability. First, the state provides a unique opportunity to compare the effectiveness of programs with varying quality standards. Massachusetts administers both federally-funded (non-Chapter 74) and state-regulated (Chapter 74) CTE programs. Chapter 74 programs operate under stricter regulations, featuring industry-aligned curriculum, a minimum of 900 hours of dedicated training, and specialized licensure for instructors with relevant industry experience. Many of these programs go beyond traditional classroom learning and allow you to stack industry-recognized certificates (IRCs) like Microsoft Office, Cisco Systems, and ServSafe. Earning these certifications while still in high school gives you a significant edge when entering the workforce. IRCs are like badges that showcase your practical skills and knowledge, making you a more attractive candidate to employers in specific fields. These credentials demonstrate that you're not just theoretically knowledgeable but also possess the hands-on abilities that companies are actively seeking.

In contrast, non-Chapter 74 programs offer more flexibility with less stringent regulations, requiring a minimum of 300 training hours and a standard high school teaching license for instructors, without mandatory industry experience (Massachusetts Department of Elementary and Secondary Education, 2023). This variation in program quality allows for an economic analysis that isolates the impact of stricter regulations and potentially higher-quality instruction on worker wages. Second, Massachusetts offers rich data resources for a geographically nuanced analysis. The state provides detailed CTE program and outcome data at the town and county level. This granular data availability facilitates a geographic analysis that explores how factors beyond policy itself, such as regional labor market conditions or industry clusters, might influence program effectiveness and subsequent wage outcomes. Third, the state's long history with CTE programs enables a longitudinal analysis. Massachusetts boasts a long-standing tradition of providing CTE programs. This extended track record allows the present study to examine the program's impact on wages over time, potentially revealing the long-term economic benefits of CTE participation for workers. Notably, research suggests that Massachusetts invests significantly more per vocational student compared to other programs (Dougherty, 2022). This additional investment strengthens the case for analyzing the program's economic impact. In conclusion, the variations in program quality across federal and state programs, the geographically diverse data availability, and the state's long history with CTE make Massachusetts ideal to assess the economic impact of upskilling programs on wages.

2 Literature Review

Historically, Career and Technical Education (CTE) programs have been viewed as a path for lower-achieving or unmotivated students. Research by Gamoran and Mare (1989) supports this notion by demonstrating the benefits of a college-bound track for both academic achievement and graduation rates. Their study compares two potential models for student track assignment. One model, the maximization model, prioritizes maximizing student benefit based on existing skills and background. In this scenario, students are placed in tracks where they are expected to perform the best based on prior achievements and learning potential. The other model, the quota model, acknowledges resource constraints, particularly limitations on the number of spots available in the college-prep track. Gamoran and Mare (1989) compare these models with a standard model based solely on observed student characteristics and a more general model that considers both observed and unobserved student and school characteristics. Their groundbreaking research ultimately revealed that non-college tracks do not improve graduation rates. In fact, the study suggests a startling finding: all students would be more likely to graduate if placed in the college-prep track. College tracks consistently led to higher achievement and graduation rates compared to non-college tracks, controlling for students with similar backgrounds. These results led Gamoran and Mare (1989) to conclude that tracking within schools widens the achievement gap between different student groups, potentially hindering the overall success of the student body.

Reinforcing the concerns raised by Gamoran and Mare (1989) regarding student tracking, Kelly and Price (2005) point out the existence of selection bias and demotivating externalities of vocational education. Their research suggests a concerning selection bias and a potential dampening effect on career aspirations. Utilizing data from the National Education Longitudinal Survey (NELS:88), which tracked students throughout high school, they employed a technique called propensity score matching. This method helps isolate the causal effect of taking vocational courses by statistically accounting for students' prior academic background and social-psychological adjustment in eighth grade. They then categorized students into four groups based on their likelihood or propensity to take vocational courses and their actual enrollment: high propensity with high enrollment, high propensity with low enrollment, low propensity with high enrollment, and low propensity with low enrollment. By comparing the achievement and aspirations of these groups, Kelly and Price (2005) found evidence of a selection bias: students with lower career and vocational aspirations were more likely to be enrolled in vocational programs. Furthermore, their research suggests that taking vocational courses itself may lead to a further decrease in students' career aspirations. These findings add to the growing body of evidence suggesting potential negative consequences associated with student tracking into vocational programs.

In the past decade, recent research explores the positive economic impact of Career and Technical Education (CTE) programs, in approval of ongoing CTE legislative revisions and quality improvements (Brunner, Dougherty, and Ross, 2019; Dougherty, 2018; Stevens, Kurlaender, and Grosz, 2019). Studies examining specialized CTE high schools offer compelling evidence. Brunner, Dougherty, and Ross (2019) analyze Connecticut's vocational high schools using a Fuzzy Regression Discontinuity Design (FRDD). This approach leverages the score-based admissions system at these schools, creating a natural experiment where students scoring just above the cutoff are more likely to be admitted compared to those scoring slightly below. The analysis reveals significant benefits for male students who attend these schools, including a ten percentage point increase in graduation rates, a half-semester reduction in college completion time, and substantially higher earnings (44% overall increase, 32% quarterly increase).

In Massachusetts, Dougherty (2018) examines the impact of a specialized high school-based CTE program. He leverages the state's specific selection criteria for their specialized high school-based CTE program (RVTS) to minimize selection bias. These criteria, based on middle school grades, attendance, and disciplinary records, are likely linked to future academic success. Dougherty employs two econometric techniques: Ordinary Least Squares (OLS) with fixed effects estimates the average treatment effect (ATE) of participating in the RVTS program on graduation rates. This controls for student and local factors that might otherwise influence outcomes. Additionally, a Regression Discontinuity Design (RDD) analysis focuses on students on the margin of admission, isolating the program's causal effect for this specific group. These complementary approaches offer valuable insights. The OLS model provides external validity allowing its results to be generalizable to similar programs while the RDD boasts strong internal validity to isolate the program's true effect. Both models suggest that participation in this high-quality CTE program increases the probability of on-time high school graduation by seven to ten percentage points for higher-income students.

Finally, Stevens, Kurlaender, and Grosz (2019) in California estimate returns on CTE programs using administrative data from the California Community College system linked to earnings records. Their analysis employs multiple estimation approaches, including individual fixed effects and individual specific trends, to account for unobserved characteristics that might affect both program participation and earnings. These models reveal average returns to quarterly earnings from CTE certificates and degrees ranging from fourteen to fourty-five percent. Notably, these positive outcomes are concentrated in specialized CTE high schools where all students only had CTE coursework. This does not include CTE programs within comprehensive high schools with traditional courses and CTE classes. This suggests that program design and structure may be crucial factors in maximizing the benefits of CTE for students. While selection bias remains a slight concern, recent research using robust econometric methods paints a generally positive picture of the economic impact of high-quality CTE programs.

Despite the generally positive economic impact of high-quality CTE programs, conflicting evidence exists regarding the timing and duration of these benefits. Some studies tout the long-term wage benefit while others find diminishing returns over time. In support of long-term benefits, Silliman and Virtanen (2022) examine Finland's vocational system and find a significant long-term advantage for graduates. They utilize a Regression Discontinuity Design (RDD) to comapre students who narrowly gained admission (due to slightly higher scores) with those who narrowly missed admission (due to slightly lower scores). The study reveals a six percent annual income increase of €1800 for vocational graduates at age 33 compared to their general high school counterparts. Notably, this benefit seems to accumulate over time and doesn't diminish with age.

Conversely, Hanushek (2017) highlights potential drawbacks. Using a Difference-in-Differences (DID) approach, the study compares employment rates across different age groups for individuals with general and vocational education in eleven countries. This method allows researchers to isolate the effect of education type by comparing changes in employment rates for each group over time. The findings suggest that vocational graduates have an initial advantage in youth employment, but this benefit diminishes with age. The DID analysis estimates a "crossover point" where individuals with general education begin to experience better employment prospects. While imprecise, this crossover point appears to be around age fifty for males. This could be due to the traditional breadwinner role model, where men might endure employment hardships before accepting unemployment. According to Hanushek (2017), this trend aligns with the idea that vocational skills may become less adaptable over time compared to broader skill sets acquired through a general education. These contrasting results highlight the need for further research to understand the nuances of timing and longevity of benefits associated with CTE programs.

Research on vocational education faces limitations beyond timing and duration. A major issue is program heterogeneity and alignment with the local labor market. Prior studies often don't consider program quality, which can significantly impact student outcomes in terms of employment and wages. Further, there is a lack of literature on the local labor markets despite its growing emphasis in CTE legislation. In 2018, the Perkins V Strengthening Community Colleges and Career Readiness Act emphasized tailoring CTE programs to local economic demands (Molly, 2019). The limited focus on local labor markets is surprising given its growing importance. The goal of this legislation is to enhance social mobility by ensuring graduates have the skills needed for good local jobs. Research by Bui and Miller (2015) highlights why this local focus is crucial. Their study shows that most adults, especially those with lower education or income, tend to stay close to home after high school. With limited geographic mobility, strong local CTE programs become even more critical for career success.

To my knowledge, Sublett and Griddith's (2019) appears to be the only extensive literature into local labor markets. They use innovative data analysis to explore the connection between CTE programs and local job markets. By combining information on CTE courses taken by a nationally representative group of students from the High School Longitudinal Study of 2009 with job and wage data by location from the Bureau of Labor Statistics' Occupational Employment Statistics, they create a unique dataset. This allows them to examine how local factors like the number of jobs and average wages in specific career fields, such as IT or Agriculture, influence student enrollment in related CTE courses. Their analysis uses linear probability models to account for other student characteristics and understand these relationships. Sublett and Griddith's (2019) research reveals some interesting economic findings. They found that students are more likely to take CTE courses in fields with a high number of local jobs. For example, a strong local IT sector is associated with more students taking IT courses. However, they also discovered a surprising trend where students are less likely to enroll in CTE programs for higher-paying industries. This "paradox" could be explained by several factors. High wages might signal an oversupply of workers in that field, or economic prosperity might encourage students towards other educational paths like college. Additionally, there might be a disconnect between the skills taught in CTE programs and the evolving needs of high-wage industries.

Further research by Sublett and Tovar (2021) reinforces the complexity of vocational training and local labor markets. Sublett and Tovar (2021) merged data from two sources: the Beginning Postsecondary Students Longitudinal Study (BPS:12/14) and the U.S. Department of Labor's job projections (2016-2026). The BPS:12/14 tracked a cohort of students from 2011-2012 through 2013-2014, allowing them to analyze the programs students chose at public, two-year community colleges. They then compared these choices with long-term job market projections in those fields. Their analysis, using logistic regression models, controlled for both observed and unobserved state-level factors. Their results identified a lack of clear correlation between the programs students choose and long-term job market projections. This suggests several possibilities: students might not be effectively connecting their education to career opportunities, or there might be a lack of strong CTE programs in certain areas, or existing programs might not offer the necessary skills for high-demand jobs. These findings highlight the need for further research on aligning CTE programs with local job market needs and ensuring program quality.

In my study, I address the three main concerns in prior research regarding the lack of causal experiments for schools with CTE programs outside CTE-only schools, timing and duration of CTE programs, and the lack of program quality controls. To include all programs, I implement the data merging practices within Sublett and Griddith (2019) and Sublett and Tovar (2021) to combine enrollment and wage datasets. I intend to use the Department of Economic Research (DER) of Massachusetts and enrollment data from the Massachusetts Department of Elementary and Secondary Education create a town-level dataset that includes all CTE programs crosswalked onto the towns of Massachusetts. To address the timing and duration of CTE programs, I utilize graduate follow-up surveys from 2012-2018. This will allow me to assess post-graduate placements after the program. To address the lack of program quality controls, I choose to utilize run OLS regressions on the unique CTE program implementation in Massachusetts to distinguish between lower-standard non-Chapter 74 (N74) set by federal law and higher-standard Chapter-74 (C74) programs set by state law.

2.1 Data

My OLS regression investigates how vocational education and enrollment influence wages by combining two types of data: wage data and enrollment data. The wage data is sourced from the Department of Economic Research (DER) of Massachusetts. This specific dataset, named "All Towns 202 under Annual Average Employment and Wages All Published Industries," provides a detailed breakdown of average weekly wages for various job titles within both public and private sectors.

Expanding on the wage data for overlapping industries, I separate the wage data into five datasets based on specificity of industry label according to the North American Industry Classification System (NAICS). NAICS is a hierarchical system used to categorize business establishments for the purpose of collecting, analyzing, and publishing statistical data related to the U.S. economy. The system is divided into several levels, from broad sectors (level 0) to specific industries (level 4). For example, the profession of a boat dealer is categorized differently based on level. The first two digits "44-45" denote the sector, which is "Retail Trade". The first three digits "441" represent the subsector "Motor Vehicle and Parts Dealers". The first four digits "4412" specify the industry group "Other Motor Vehicle Dealers". The first five digits "44122" indicate the NAICS industry "Motorcycle, Boat, and Other Motor Vehicle Dealers". The full six digits "441222" represent the national industry "Boat Dealers", the most specific classification. For my study, I focus on all industries (level 0), industry sector (level 1), and industry sub-sector (level 2). These levels are chosen because they provide substantial variation in job types and industries without the complications of overly granular data, which can be difficult to compare across different geographic regions due to varying local industry representations. Otherwise, regression results may be insignificant as shown in my base regression results.

The enrollment data is sourced from the Massachusetts Department of Elementary and Secondary Education, specifically covering students in public school Career Vocational Technical Education (CVTE) programs. This dataset includes data on regular and special education students across 71 distinct vocational programs and 134 district programs statewide. It provides detailed records on the number of graduates per program, per year, and per vocational school. Each annual enrollment is collected and collated for the school years 2012-2018. By aggregating the data under different variables such as program quality and program name, I am able to identify the number of C74 and N74 programs by county and year and also identify the specific program of study by county and year. Furthermore, the Massachusetts DESE provides a supplementary dataset of "Graduate Follow-up Survey Results" that allow me to identify vocational graduate outcomes six months after graduation. I use this to compare the outcomes of C74 and N74 students.

Expanding on the enrollment data for delayed effects, I incorporate five time lags in the enrollment data to reflect various pathways graduates might take after finishing their education. This includes immediate employment or continuing education at technical schools, two-year colleges within two years, or four-year universities within four years. This staggered approach allows me to capture a broader range of post-graduation activities, providing a more detailed and nuanced understanding of the long-term impacts of vocational education on wage trajectories.

When combining the datasets, I align the enrollment data with the wage data based on three key identifiers: town, year, and industry. This method ensures that the wage information for each town matches up accurately with the corresponding number of vocational programs and the enrollments of twelfth-grade students. By doing so, each data entry links the wages to both the vocational programs and student enrollments specifically for that town, in that particular year, and within that industry. This merging process is carried out for each of the five NAICS categories and six graduation cohorts. The combination of the original enrollment data with five time lags and five wage hierarchies results in a total of 30 different datasets, each representing a different level of industry specificity and graduate cohort. This comprehensive data structure lays the foundation for an OLS regression between CTE program participation and post-graduation wages.

After running an OLS for the entirety of Massachusetts, I run my OLS separately for three geographical areas determined by wage growth to find the associations between specific vocational program courses and wage growth. Doing so will hopefully point toward a causal mechanism that can be explored in future research. I determine the geographical areas using data from the "Information Earnings Structure & Performance by County Massachusetts, 2001-2022" report from the Massachusetts Regional Economic Analysis Project. This data, compiled annually by the Regional Income Division and Regional Product Division of the Bureau of Economic Analysis (BEA), U.S. Department of Commerce, spans over five decades, from 1969 to 2022. It provides a comprehensive overview of economic performance across all Massachusetts counties, allowing me to categorize counties based on their industry growth.

3 Descriptive Statistics

In the descriptive statistics section of my analysis, I explore the trends within wages and vocational program enrollments. The data indicates a positive correlation between the total number of vocational education graduates and wage levels across most counties, except Suffolk. Additionally, there are distinct outcomes for C74 and N74 programs: 20% more C74 students proceed directly into employment, while 20% more N74 students continue their education at two-year or four-year institutions. This divergence in outcomes necessitates a closer examination of the courses offered by these vocational programs. I find that while lower-standard N74 programs have a higher proportion of graduates in business and technology sectors, both C74 and N74 programs exhibit growth in these areas. However, the greater variety of courses in C74 programs complicates direct assessments of their impact on wages.

Two main challenges arise in this analysis: the potential for reverse causality and the omission of other local economic factors. There is a plausible scenario where higher wages could incentivize more individuals to enroll in vocational programs, seeking pathways to lucrative employment. Moreover, other labor market dynamics, such as employment rates and industry demands, might also play a role and should be considered to prevent misleading conclusions. Although descriptive statistics illuminate these correlations, they fall short of establishing causality. Therefore, OLS regressions can help increase causal inference. Such models would refine the analysis by controlling for external influences and more accurately isolating the effects of vocational education on wages.

Table 1: Yearly Data of Inflation Adjusted Median Wages, C74, N74, and Graduates

Year	Wages (Adj. for Inflation)	C74 Graduates	N74 Graduates	Total CTE Graduates
2012	771.00	9365	3778	13143
2013	774.65	9612	3427	13039
2014	774.90	9767	3201	12968
2015	809.82	10009	3227	13236
2016	814.08	10397	3378	13775
2017	817.70	10656	3636	14292
2018	830.21	10578	3478	14056

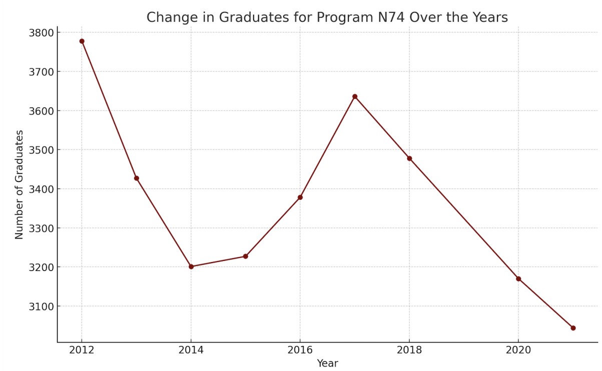


Figure 1: N74 Graduates

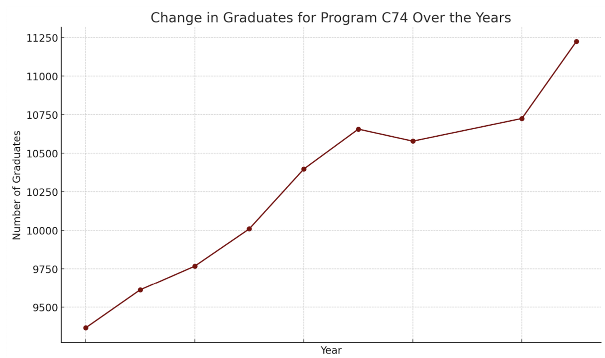


Figure 2: C74 Graduates

3.1 Trends in Wages and Enrollment

Across 2012-2018, wages and total enrollment rose. Wages are aggregated at the median instead of the mean due to the data's rightward skew, which suggested the presence of outliers at the higher wage spectrum that could artificially inflate the typical wage value. The median of average weekly wages, standardized for inflation in terms of 2012 dollars, rose from \$771 to \$830 indicating an increase of 7.7%. At the same time, program enrollment increased across Massachusetts. There was an approximate increase of one thousand students across all graduates from Career and Technical Education (CTE) programs. However, the increased aggregate growth comes from a larger increase in C74 programs that overshadow the decreases in N74 program enrollment. Enrollments in the lower-tier N74 programs fell by 300 students, whereas the higher-tier C74 programs saw an increase of 1,200 students. These changes resulted in a respective eight percent decrease and a thirteen percent increase in graduates from N74 and C74 programs. The simplistic trends in wages, total enrollment, and program quality bring to question the underlying heterogeneity and causality of vocational education on wages. First, I aim to understand the heterogeneity by courses offered by vocational programs. Next, I aim to understand the heterogeneity by outcomes offered by vocational programs. Then, I aim to understand the heterogeneity by county. Finally, I run OLS regressions for greater causal inference between vocational education and wages.

3.2 Trends in Vocational Courses

From 2012 to 2018, I analyzed the total enrollment for each Career and Technical Education (CTE) vocational course offered annually, focusing on the change in enrollments between these years. Notable decreases in enrollment, each exceeding fifty graduates, were observed in graphic communications, family and consumer studies (formerly known as home economics), and drafting. Additionally, the programs in office technology and facilities management were discontinued during this period. Conversely, programs that saw increases of approximately fifty or more graduates predominantly fell within business and technology categories. In the business sector, significant gains were noted in marketing/finance, marketing, and business technology. In the technology sector, notable increases were observed in biotechnology, electronics, electricity, and programming. Other courses showing growth included criminal justice, dental assisting, and early education. The highest increases, ranging from one hundred to three hundred graduates, were in programming, business technology, and marketing, each attracting roughly five hundred graduates per cohort. These shifts suggest a growing demand for courses geared toward the technology and business sectors. Despite these trends, the courses with the highest enrollment remained in health assisting, culinary arts, cosmetology, and early education, each attracting between five hundred to a thousand graduates per cohort, indicating a sustained interest in service and social service sectors.

Further analysis on the differences between C74 and N74 programs shows growth in both sectors, particularly in business and technology. However, N74 programs exhibit a proportionally larger emphasis on these sectors due to fewer courses achieving over fifty enrollments annually. Notable enrollment increases in N74 programs occurred mainly in business and technology, with exceptions like culinary arts and carpentry, which grew by 51 and 64 graduates respectively. This disproportionate emphasis in N74 compared to C74 may also be influenced by the discontinuation of seven courses, including telecommunications, power equipment technology, office technology, metal fabrication, heating/ventilation/AC/Refrigeration, facilities management, and hospitality management, which suggests these programs were either closed or transformed into C74 offerings, as all except facilities management and office technology continue to exist in the C74 curriculum. Evidence of potential program cannibalization includes the decline of the N74 early education program by 71 graduates, while the C74 counterpart increased by 146, and a decrease in N74 design and visual communications by 167 enrollments, with a corresponding increase of 173 in the C74 program.

Conversely, C74 programs not only maintain high enrollments but also exhibit significant growth in more diverse courses outside of business and technology. High enrollments in C74 are noted in fields traditionally linked with vocational education, such as animal science, automotive collision repair, carpentry, drafting, machine tool technology, masonry, metal fabrication, and plumbing. This diversity suggests that the higher standards of C74 programs make them conducive environments for industry certification in conventional trade jobs, extending beyond the realms of business and technology.

4 Differences in Outcomes by Vocational Program

Using graduate placement survey data, the differences in the educational and employment pathways of graduates from the C74 and N74 vocational programs between 2012 and 2018 reveal distinct differences in graduate placement. About fifty-five percent of C74 graduates secure employment right after graduation, with thirty percent finding jobs in industries directly related to their fields of study and the remaining twenty-five percent working in unrelated fields. This high placement rate, especially in related industries, indicates a strong alignment of the C74 curriculum with industry demands. It suggests that the C74 programs are effectively equipping students with the skills and knowledge that are immediately applicable and valued in the job market, thereby facilitating a smoother transition from education to employment.

Table 2: CTE Post-Graduate Placements (2012-2018)

Year	Program	Military	Employment Related	Employment Not Related	Education	2 Year College	4 Year College	Apprenticeship	Technical School	Unknonwn School
2012	C74	3.84%	32.66%	26.79%	62.37%	25.59%	28.87%	1.84%	4.37%	1.70%
2013	C74	3.62%	31.11%	26.91%	64.41%	24.81%	31.81%	1.70%	4.26%	1.83%
2014	C74	3.53%	33.95%	26.12%	62.81%	23.40%	31.31%	2.23%	4.17%	1.70%
2015	C74	3.45%	34.44%	25.06%	63.03%	22.60%	32.80%	2.21%	3.49%	1.93%
2016	C74	3.25%	34.08%	25.89%	62.48%	23.12%	32.35%	2.23%	3.49%	1.28%
2017	C74	3.04%	32.86%	25.77%	65.35%	21.84%	35.74%	3.03%	3.25%	1.49%
2018	C74	3.43%	32.76%	24.05%	64.28%	20.58%	35.37%	3.34%	3.44%	1.54%
Year	Program	Military	Employment Related	Employment Not Related	Education	2 Year College	4 Year College	Apprenticeship	Technical School	Unknonwn School
2012	N74	3.65%	8.63%	21.90%	81.18%	24.69%	51.66%	0.19%	2.18%	2.46%
2013	N74	2.24%	9.99%	22.47%	82.12%	26.61%	51.82%	0.19%	1.82%	1.68%
2014	N74	1.72%	11.36%	15.12%	81.03%	24.24%	53.40%	0.35%	1.57%	1.47%
2015	N74	1.36%	8.72%	20.11%	80.52%	22.53%	54.12%	0.29%	1.84%	1.74%
2016	N74	1.58%	8.32%	16.96%	83.27%	23.43%	56.35%	0.72%	1.40%	1.36%
2017	N74	2.02%	10.13%	16.89%	85.02%	22.83%	58.25%	0.81%	1.57%	1.57%
2018	N74	2.52%	11.62%	22.14%	82.21%	19.46%	59.23%	0.68%	1.49%	1.35%

In addition to securing direct employment, C74 graduates are significantly more inclined to engage in apprenticeships or technical schooling, with participation rates that are

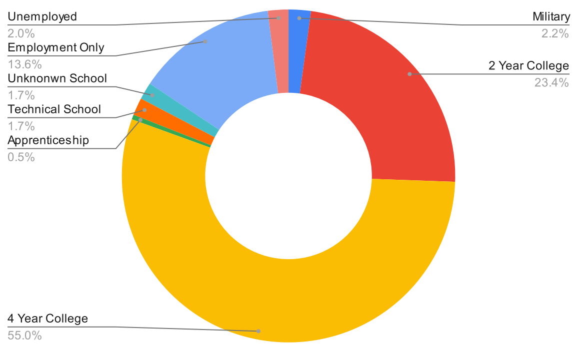


Figure 3: C74 Program Placements 2012-2018

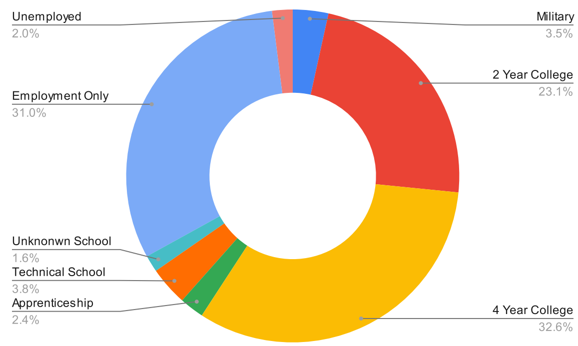
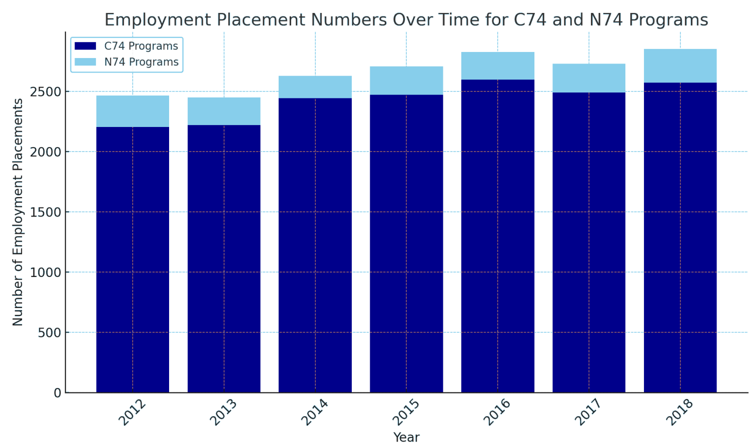
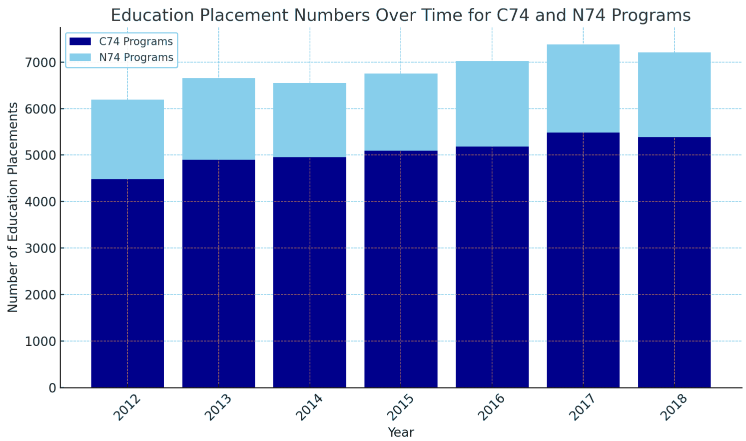


Figure 4: N74 Program Placements 2012-2018



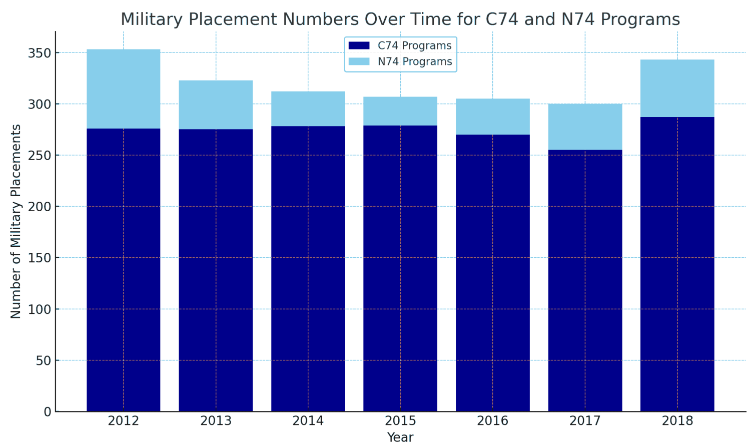
two to three times higher than those of N74 graduates. This trend points to the C74 curriculum's emphasis not only on foundational vocational skills but also on continuous professional development. Apprenticeships and further technical education allow graduates to hone specialized skills that enhance their employability and career progression in their chosen fields. In stark contrast, the pathway for N74 graduates differs markedly. Only thirty-three percent of these graduates enter the workforce immediately after their studies, with a substantial proportion opting for further education. Notably, sixty percent of N74 graduates pursue four-year college degrees, which is significantly higher compared to thirty-five percent of C74 graduates. This suggests that N74 programs may place a stronger emphasis on broad educa-



tional foundations and theoretical knowledge, which prepares students for a more academic or diversified career path rather than immediate vocational employment.

These contrasting pathways underscore the distinct educational philosophies and objectives of the C74 and N74 programs. While C74 is tailored to meet immediate industry needs, providing practical skills that are directly applicable in the workplace, N74 appears to foster a broader educational approach, potentially setting the stage for further academic achievement and versatility in career options.

Another aspect of post-graduation outcomes is military enrollment. C74 graduates join the military at a rate of three and a half percent, compared to two percent of N74 graduates. This difference might suggest that C74 programs either attract a different type of student or perhaps instill qualities that make military service a more attractive option. It is important to consider whether this reflects intrinsic differences in student characteristics or if it points to external influences related to the program's structure and focus. This analysis reveals significant variations in the impact of different vocational programs on subsequent wages and career paths. The increase in C74 graduates, who are more likely to enter directly into the workforce in related industries, suggests these programs are well-aligned with immediate employment opportunities. However, it remains to be determined whether this alignment translates into long-term wage advantages compared to the broader educational benefits that might accrue from the higher college attendance rates among N74 graduates. Finding the wage impacts of these programs will require an OLS regression that controls for the possible post-graduate placements.



However, a potential challenge to the Ordinary Least Squares (OLS) regression analysis arises from an unexpected variation in military enrollment rates among vocational program graduates. Specifically, C74 graduates join the military at a rate of three and a half percent, compared to only two percent of N74 graduates. This disparity in military enrollment rates could introduce selection bias or reflect externalities from the programs. Firstly, the higher rate of military enrollment among C74 graduates might suggest that these programs attract a distinct type of student, or that they impart qualities that make military service a more appealing option. For instance, students that choose C74 programs may inherently possess a higher propensity for discipline, teamwork, and structured career paths—qualities highly valued in the military. This scenario would imply that the observed wage differentials might stem more from the preferences and intrinsic qualities of the students rather than the vocational programs themselves. However, according to Dougherty (2018), access to C74 programs in Massachusetts is primarily determined by a student's residential location, with significant efforts required to secure a tuition transfer to a C74 program in another district. This process requires approvals from both the sending and receiving districts, suggesting that while selection bias could be a concern, its impact on the OLS regression is likely limited. On the other hand, the C74 programs may exert an externality effect that differentiates their graduates from those of the N74 programs. For example, if C74 curricula emphasize skills like leadership, physical endurance, and strategic thinking—skills that are directly applicable to military roles—this could make a career in the armed forces a more logical and attractive progression for graduates. Understanding whether the disparity in military enrollment is due to intrinsic student characteristics or the educational emphasis of the C74 programs is crucial. This difference in military placement suggests that C74 programs may fundamentally differ from N74 programs, impacting graduates' career paths and potentially influencing wage outcomes. For the OLS regression, this points to a stronger potential for causal inference by minimizing concerns about selection bias and emphasizing the effects of the program itself.

4.1 Trends in Wages and Enrollment by County

Finally, I aggregate my program enrollment data by county for geographical analysis. In order to simplify my analysis, I choose three geographical regions with distinct wage growth patterns. This approach leverages data from the "Information Earnings Structure & Performance by County Massachusetts, 2001-2022" report by the Massachusetts Regional Economic Analysis Project. By focusing on two representative counties within each wage category—high, medium, and low growth—I aim to explore how vocational education plays out

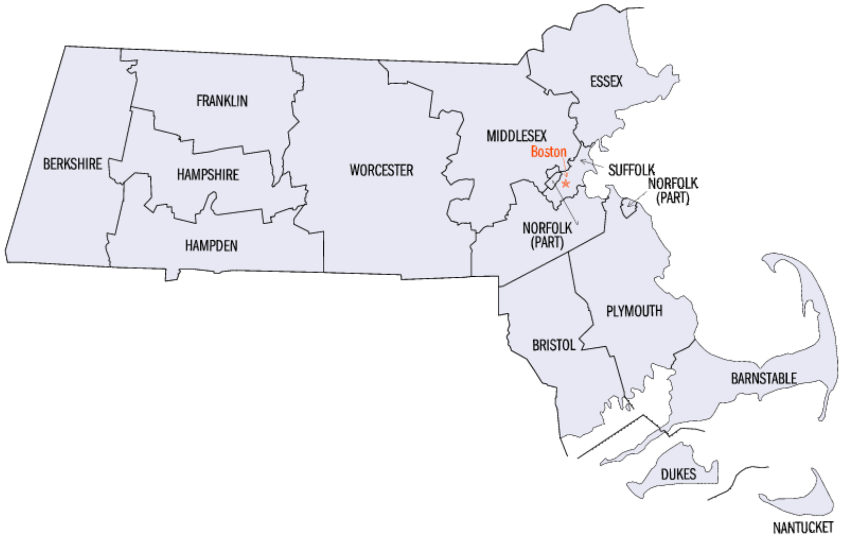


Figure 5: Map of Massachusetts Counties

in these diverse economic landscapes. The rationale for this regional segmentation lies in the potential for varying economic conditions and industrial compositions to influence the effectiveness of vocational training. For instance, a high-growth region with a booming tech industry might value and reward vocational skills differently compared to a region dominated by traditional manufacturing or retail sectors experiencing stagnant or declining wages. By conducting separate OLS regressions for each wage growth category, this study seeks to provide a more nuanced understanding of the associations between vocational education and local economic factors.

Based on wage growth data from "Information Earnings Growth by County: Massachusetts from 2011-2019," adjusted for inflation, I have categorized two counties each into three groups. For the high wage growth category (3-5%), I selected Middlesex and Suffolk counties in Eastern Massachusetts. Their proximity to Boston, a major hub for higher education and innovation, primarily motivates this choice. The presence of these institutions often drives high-growth industries like technology, which might value specific vocational skills differently, potentially influencing wage effects distinctively compared to other regions. Berkshire County was excluded from this category despite its location in Massachusetts, as it lies on the western border near New York, making it geographically and economically distinct from Middlesex and Suffolk, thereby serving as an outlier.

For the medium wage growth category (2-3%), I chose Essex and Plymouth counties. These counties' wage growth rates are aligned closely with the state average, making them suitable representatives of the broader economic trends in Massachusetts. Geographically, these counties are positioned on the outer fringes of the state, thus providing a representative comparison for other similar areas.

In the low wage growth category (-1 to -2%), Franklin and Hampden counties were selected. These counties show the lowest wage growth within the state, lagging behind the state average by four to five percentage points. Located deep within Western Massachusetts, their inclusion allows for a contrasting comparison with the more economically vibrant Eastern Massachusetts. This stark economic disparity may highlight how local economic conditions influence the impact of vocational education on wages.

Moving forward, these three groups of counties will form the basis for my descriptive statistics and OLS regression analyses. Counties not selected for this study either lacked sufficient data, making them less reliable for robust statistical analysis, or had wage growth rates that were marginally negative or positive, which could obscure any significant differences in the effects of their vocational programs.

Figure 6: 2011-2019 Averages for County Growth

County	**Growth Rate (%)**	**Local-State Growth**	**Local-National Growth**
Franklin	-1.9	-4.5	-5.8
Hampden	-1.4	-4.0	-5.3
Worcester	-0.6	-3.2	-4.5
Barnstable	-0.5	-3.1	-4.4
Norfolk	0.9	-2.6	-3.9
Plymouth	1.9	-0.7	-2.0
Essex	2.6	0.0	-1.3
Middlesex	3.1	0.5	-0.7
Suffolk	4.8	2.1	0.9
Berkshire	5.6	3.0	1.7

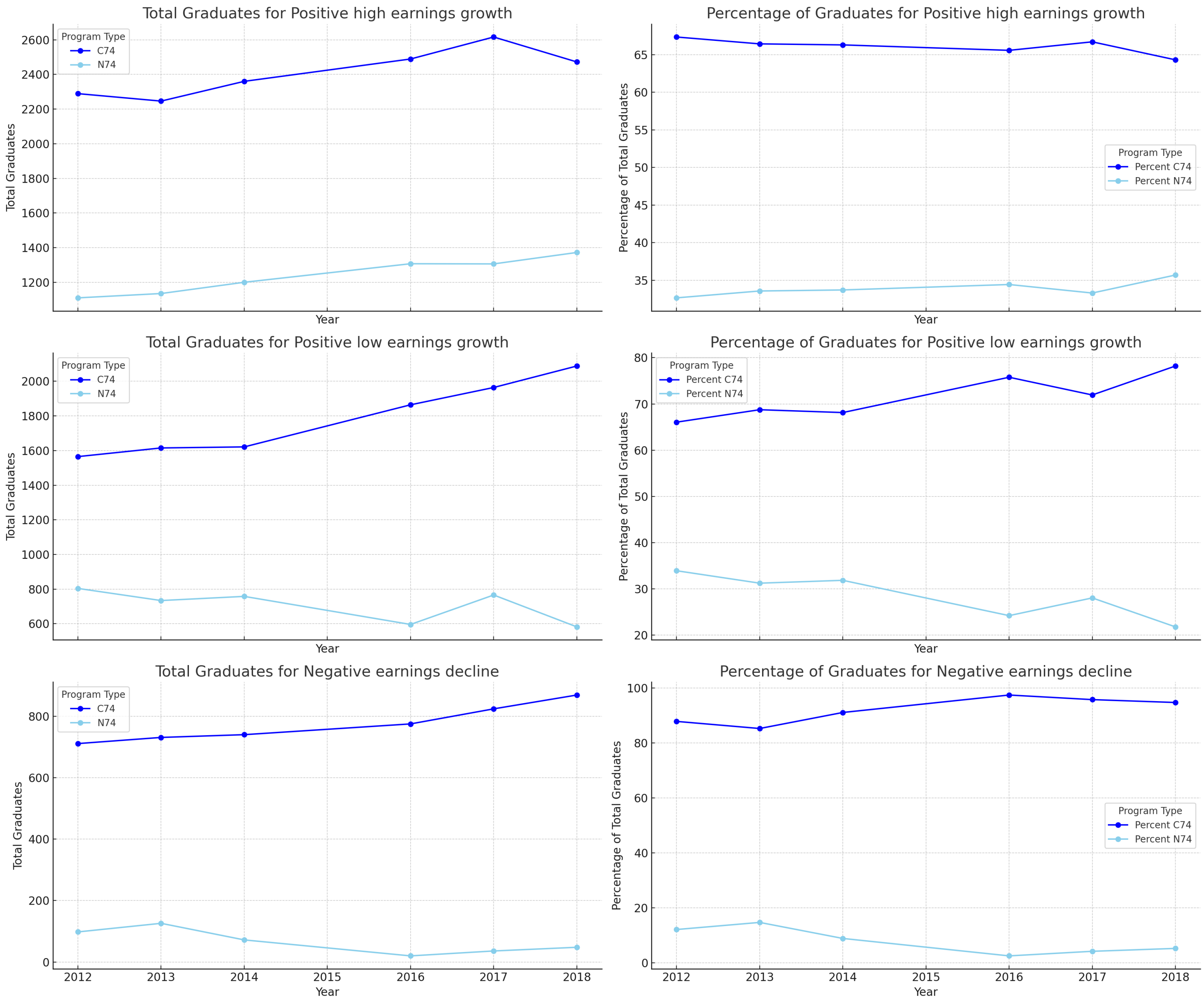
Counties with insufficient data not included. Calculations by the Massachusetts Regional Economic Analysis Project (MA-REAP) with data provided by the U.S. Department of Commerce, Bureau of Economic Analysis

Table 3: Yearly Total Graduates Data by County

Year	Suffolk	Middlesex	Essex	Plymouth	Hampden	Franklin
2012	595	2804	1529	840	689	120
2013	501	2880	1561	788	747	110
2014	512	3048	1633	746	701	111
2016	438	3358	1702	758	678	117
2017	386	3536	1798	932	748	112
2018	377	3467	1808	862	806	111
Total	**2809**	**19093**	**10031**	**4926**	**4369**	**681**

Consistent with the overall growth in graduates across Massachusetts, most counties experienced an increase in the total number of vocational education graduates. However, Suffolk County presents a notable exception, showing a significant decrease of 218 graduates from a total of 595, representing a 36.6% decline. In contrast, Franklin County experienced only a marginal decrease of 9 out of 120 graduates, which amounts to a 7.5% drop. The decline in Suffolk is particularly unexpected considering that wage earnings growth in this county has been the second highest in the state, trailing only behind Berkshire. This suggests that the factors driving wage growth in Suffolk may extend beyond the scope of vocational education programs alone. Despite this, Suffolk stands out as an outlier when compared to other counties, where the number of vocational graduates remains stable or shows strong increases.

When examining the distribution of total graduates across C74 and N74 programs in counties with varying levels of earnings growth, a counterintuitive pattern emerges. In counties experiencing high earnings growth, there is an unexpected decline in graduates from the higher-standard C74 programs and an increase in graduates from the lower-standard N74 programs. Specifically, within this period, C74 programs saw an increase of 183 graduates, whereas N74 programs experienced a more significant increase of 262 graduates. Conversely, in counties with low earnings growth, this trend is reversed: N74 programs saw a decrease of 22 graduates, while C74 programs saw a substantial increase of 523 students. In counties with negative earnings growth, both C74 and N74 programs saw declines, each dropping by nearly 40 graduates.



Intuitively, one might not expect a positive correlation between lower-standard programs and wage growth. To explore which courses may be driving these shifts, I analyzed changes in enrollments for each course from 2012 to 2018. Figures 11 to 13 illustrate these changes, with green indicating an increase in enrollment and red a decrease. Figure 11 displays overall changes in Career and Technical Education (CTE) course offerings, Figure 12 focuses on changes within C74 programs, and Figure 13 details changes within N74 programs.

Figure 11 suggests that for CTE programs generally, business and technology courses are the primary drivers of enrollment changes. Figure 12 shows that C74 programs have higher enrollments in a diverse array of courses, ranging from traditional vocational programs like carpentry to business and technology courses such as coding, covering a total of forty-seven courses. In contrast, Figure 13 shows that N74 programs have a smaller variety and lower total number of courses, totaling thirty-nine. However, it notes that there are six courses with fewer than twenty participants and two courses that seem to have had no enrollments in recent years, indicating possible discontinuation. Interestingly, this smaller scope and variety in N74 programs result in proportionally higher enrollments in business and technology courses compared to C74 programs.

The data from all three figures suggest that the increase in enrollments may be linked to a rise in business and technology graduate cohorts. N74 programs, with fewer courses overall, see proportionally higher enrollments. Conversely, C74 programs, which are higher-standard and feature a wider array of course options, do not show as strong a correlation with wage growth. This diversity in program offerings might obscure any straightforward visual correlations from the graphical data, suggesting that enrollment patterns alone may not fully explain the dynamics of wage growth in relation to vocational training.

Indeed, when aggregating program course changes by county in Figure 7, it is clear that counties experiencing high wage growth also witness substantial increases in certain N74 programs. Notably in fields like programming, engineering technology. Yet, there are also growing fields like health assisting, and radio broadcasting which are expanding within C74 programs, complicating the task of isolating the direct impact of these programs on

Figure 7: Changes in CTE Courses by County (2012-2018)

Program Title	Middlesex and Suffolk	Plymouth and Essex	Hampden and Franklin
Automotive Collision Repair & Refinishing	-14	-7	17
Automotive Technology	-2	13	12
Biotechnology	33	104	
Carpentry	54	22	-20
Construction Craft Laborer	-4		
Cosmetology	-7	10	-3
Culinary Arts	57	-57	1
Dental Assisting	36		
Design & Visual Communications	-41	4	17
Drafting	-59	-2	-4
Early Education and Care	28	47	-26
Electricity	13	38	14
Electronics	8	-10	2
Engineering Technology	101	61	-6
Environmental Science & Technology	4	17	
Family & Consumer Studies	-35	-40	
Graphic Communications	-22	41	-3
Health Assisting	130	-67	-5
Heating, Ventilation, A/C, Refrigeration	8	12	-2
Horticulture	3	-19	-1
Hospitality Management	-10		17
Information Support Services & Networking	-44	0	20
Machine Tool Technology	25	31	8
Marketing	67	74	
Marketing/Finance	57	0	-1
Masonry & Tile Setting	-6	4	
Medical Assisting	11		
Metal Fabrication & Joining	4	27	-10
Painting & Design Technologies	-12		
Plumbing	-5	33	-6
Programming & Web Development	127	31	7
Radio & Television Broadcasting	76	-40	
Robotics and Automation Technology	15	3	16
Telecommunications - Fiber Optics	-1	2	

wage growth. This underscores the complexity of the relationship between vocational program standards and economic outcomes across various regions. In counties with low positive wage growth, there is also a noticeable increase in the business and technology sectors, with significant gains observed in marketing (74 graduates) and biotechnology (104 graduates). However, the magnitude of growth in these sectors is less pronounced compared to that in high wage growth counties, where these courses experience more substantial spikes in enrollments. Conversely, counties with negative wage growth do not show any significant trends in program enrollments, with many lacking comprehensive enrollment data and none showing growth exceeding 20 graduates. These regions appear to have negligible or insignificant changes in program enrollments. This analysis suggests that while vocational education programs, particularly those with higher standards like C74, contribute to economic outcomes, the correlation varies significantly across different regions and economic contexts. Such variability highlights the need for targeted educational strategies that align more closely with regional economic conditions and labor market demands. In my next section, I introduce the labor supply and demand framework that underpins my OLS design. The aim is to get an accurate assessment of CTE programs on wages.

5 Research Design

In this section, I develop an analytical framework to understand changes in wages resulting from returns to vocational education, employing an Ordinary Least Squares (OLS) regression analysis. This framework draws on a simple yet illustrative model of supply and demand equilibrium in a perfectly competitive market setting, where the labor market comprises a demand and a supply function. Specifically, the labor demand function represents firms within a town that determine the marginal revenue product of labor, while the labor supply function encapsulates the total hours workers are willing to work at a prevailing wage rate. In the context of vocational education, graduates of vocational programs are considered integral components of the labor supply.

The wage in this framework is defined as the average weekly wage paid by town-level firms, a figure that results from the equilibrium between market demand and supply for labor. To discern the impact of vocational education on wages, I start by isolating the labor demand curve. This involves controlling for factors such as the number of establishments within the town and its respective industry. An establishment, in this context, is a single economic unit that produces goods or services at a particular location, focusing primarily on one type of economic activity. I use the number of establishments as a control variable in my analysis to adjust for broader economic shocks that influence labor demand. This adjustment is critical because economic changes can lead firms to open new locations or close existing ones, directly impacting the demand for labor. For example, an increase in the number of establishments typically signifies a rightward shift in the labor demand curve, indicating higher demand for labor, whereas a decrease suggests a leftward shift, indicating a reduction.

However, this method of control is not without limitations. Changes within firms, such as expansions or reductions in the workforce, can introduce an omitted variable bias. This bias might distort the analysis, exaggerating the perceived impact of vocational training programs on wages. Despite these challenges, I regard the number of establishments as a robust indicator for assessing changes in labor demand. This perspective is supported by findings from Akbar Sadeghi, an economist at the Office of Employment and Unemployment Statistics, who observed that new establishments accounted for ninety percent of employment growth in 2019 (Sadeghi 2022). This insight confirms the significant role that the opening of new establishments plays in labor demand.

After adjusting for changes in labor demand, I further isolate the influence of changes in labor supply on wages through several approaches. First, the period of my study, spanning from 2012 to 2018, strategically avoids other potential influences on the labor market. It takes place after the direct impacts of the Great Recession, during a relatively stable political timeframe, and aligns with consistent enrollment data reporting standards established by the Perkins VI data guidelines and avoids the new Perkins V guidelines passed in 2018. Second, I directly link changes in labor supply to vocational education by conducting an OLS regression on average weekly wages, factoring in the impacts of vocational programs (C74 and N74) while including fixed effects for year, town, and industry. These fixed effects help control for unobserved characteristics specific to each year, town, and industry, thus enhancing the likelihood that observed relationships between wages and vocational education are closer to causal rather than correlational. For industry classification, I utilize the North American Industry Classification System (NAICS) to differentiate industries by specificity of jobs, focusing on levels 1 and 2—sector and subsector. These levels are selected because they offer a balanced level of specificity, providing substantial variation in job types and industries without the complications of data that is too detailed, which can be challenging to compare across different geographic regions. Third, my regression model incorporates data on 12th-grade enrollments, which allows me to gauge the impact of vocational education graduates entering the labor market. This allows me to isolate the impact of vocational education on wages in Massachusetts through an annual cohort of program graduates:

In my OLS, I acknowledge that not all graduates immediately enter the workforce. To enhance the accuracy of my model, I have incorporated five time lags. These time lags allow for a nuanced account of the varied trajectories graduates may follow shortly after completing their education, such as delayed entry into employment, further technical training, or advancing to two-year or four-year college programs. This approach enables a

$$
\begin{aligned}
\text{Average weekly wage}_{iyt} = {} & \beta_0 + \beta_1 \text{C74}_{iyt} + \beta_2 \text{N74} + \\
& \beta_6 \text{Grade } 12_{iyt} + \\
& \beta_7 \text{Average monthly employment}_{iyt} + \beta_8 \text{Number of establishments}_{iyt} + \\
& \alpha_{\text{Year}} + \alpha_{\text{Town}} + \alpha_{\text{NAICS Title}} + \epsilon_{iyt}
\end{aligned} \tag{1}
$$

Figure 8: Depiction of the econometric model where average weekly wage$_{iyt}$ is the dependent variable Y, representing wages for industry i in year y and town t, classified under NAICS title c. Fixed effects α_{Year}, α_{Town}, and $\alpha_{\text{NAICS Title}}$ adjust for annual, locational, and industry-specific heterogeneity, respectively.

more comprehensive assessment of the long-term impacts of Career and Technical Education (CTE) programs, extending beyond the immediate outcomes post-graduation. Additionally, I address the issue of reverse causality, where higher wages might influence the rate of graduation. By introducing these time lags, I am able to interpret the impact of past graduation cohorts on present wage outcomes:

$$
\begin{aligned}
\text{Average weekly wage}_{iyt} = {} & \beta_0 + \beta_1 \text{C74}_{iyt-k} + \beta_2 \text{N74}_{iyt-k} + \beta_6 \text{Grade } 12_{iyt-k} + \\
& \text{Controls} + \alpha_{\text{Year}} + \alpha_{\text{Town}} + \alpha_{\text{NAICS Title}} \quad \text{for } k = 1, 2, 3, 4, 5
\end{aligned} \tag{2}
$$

Figure 9: This equation models the average weekly wage by incorporating time lags $k = 1, 2, 3, 4, 5$ years to account for delayed workforce entry and further education among graduates. This approach quantifies the extended economic impacts of vocational training and clarifies the longitudinal effects of Career and Technical Education (CTE) on earnings.

5.1 Hypothesis

The descriptive statistics suggest certain coefficients will be of increasing importance given the post-graduate placement survey:

$$
\begin{aligned}
\text{Average weekly wage}_{iyt} = {} & \beta_0 + \beta_1 \text{C74}_{iyt} + \beta_2 \text{N74} + \\
& \beta_6 \text{Grade } 12_{iyt} + \\
& \beta_7 \text{Average monthly employment}_{iyt} + \beta_8 \text{Number of establishments}_{iyt} + \\
& \alpha_{\text{Year}} + \alpha_{\text{Town}} + \alpha_{\text{NAICS Title}} + \epsilon_{iyt}
\end{aligned} \tag{3}
$$

The parameters of interest are β_1, β_2, and β_6. β_1 and β_2 represents the impact of a single C74 and N74 program on average weekly wages. β_6 represents the impact of a 12th grader on average weekly wages.

However, as the enrollment dataset begins for the school year, the student does not graduate until the following June. Therefore, I do not expect an OLS regression without any time lags to have any significance. On the other hand, OLS regressions with time lags from one to five years will match the incoming graduation cohorts and I expect to see greater statistical significance in those regressions. Following the summary statistics, the outcome of students suggest the majority of graduates either enter employment within a year after graduation or enter two-year or four-year colleges. Thus, I expect to see peaks in β_1, β_2, and β_6 for time lags one, three, and five. Time lag one will signify the impact CTE on wages six months after graduates enter employment. Time lag three will signify six months after graduates complete two-year colleges. Time lag five will signify six months after graduates leave four year colleges.

Table 4: OLS Regression without Time Lags

	(1) Average weekly wages for All Industries	(2) Average weekly wages for Industry Sectors	(3) Average weekly wages for Industry Sub-Sectors
C74	3.118***	3.167	1.747
	(0.654)	(2.852)	(2.733)
N74	2.182	0.101	-3.894
	(1.373)	(3.426)	(3.306)
GR_12	-0.0346	0.0831	0.0148
	(0.046)	(0.113)	(0.108)
avgemp	0.0113***	0.00850***	0.0122***
	(0.001)	(0.001)	(0.001)
estab	-0.0334***	-0.0830***	-0.0778***
	(0.007)	(0.017)	(0.020)
_cons	769.3***	1018.0***	1074.9***
	(4.117)	(33.842)	(33.325)
r2	7670	9026	14739

Standard errors in parentheses

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

Note: Massachusetts Department of Economic Research (DER) defines 'avgemp' as 'Average monthly employment.'
Note: Massachusetts Department of Economic Research (DER) defines 'estab' as 'Number of employer establishments in the industry.'

6 The Effect of Time Lags on Statistical Significance

I begin my exploring the impact of time lags on the statistical significance of Ordinary Least Squares (OLS) regressions, particularly in relation to vocational education and wage outcomes. Initially, I conducted a preliminary OLS regression as presented in Table 4, utilizing three different NAICS hierarchies without incorporating any time lags. This preliminary model was critical for illustrating the infeasibility of drawing causal inferences immediately following vocational training, as graduates would not have had sufficient time to integrate into the labor market and influence wage dynamics.

The lack of time lags in this model led to insignificant results, as reflected in the p-values. Across all NAICS levels, the p-values predominantly exceeded 0.10. This suggests there is more than a ten percent chance that, under the null hypothesis where the true coefficient is zero, one would observe a coefficient as extreme as, or more extreme than, the one calculated. Particularly notable were some coefficients where p-values reached as high as 0.97, indicating that the regression outcomes could largely be attributed to random chance.

Moreover, the large standard errors, often surpassing the coefficients themselves, indicated substantial uncertainty in the estimates. This uncertainty was so pronounced that the 95% confidence intervals for the coefficients ranged from zero to more than double the estimated impacts.

These findings strongly support my hypothesis that omitting a time lag results in a model that lacks the statistical robustness required for causal inference regarding the effects of vocational education on wages. The inclusion of appropriate time lags in subsequent models is necessary to adequately capture the delayed effects of vocational training on economic outcomes. For the subsequent phase of my analysis, I introduced a time lag of one year into the OLS regression model to better capture the effects of vocational training on wage outcomes.

Table 5: OLS Regression with Time Lag 1

	(1) Average weekly wages for All Industries	(2) Average weekly wages for Industry Sectors	(3) Average weekly wages for Industry Sub-Sectors
C74	4.072***	3.096***	2.477***
	(0.630)	(0.694)	(0.663)
N74	3.576***	3.807***	3.259**
	(1.327)	(1.451)	(1.388)
GR_12	-0.0780*	-0.00797	-0.0225
	(0.044)	(0.048)	(0.045)
avgemp	0.0114***	0.00795***	0.0134***
	(0.001)	(0.000)	(0.001)
estab	-0.0400***	-0.0687***	-0.0593***
	(0.007)	(0.010)	(0.012)
_cons	774.5***	892.6***	916.6***
	(4.021)	(1.476)	(1.472)
r2	7594	60676	91424

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Massachusetts Department of Economic Research (DER) defines 'avgemp' as 'Average monthly employment.'
Note: Massachusetts Department of Economic Research (DER) defines 'estab' as 'Number of employer establishments in the industry.'

The results in Table 5 indicate a significant improvement in statistical validity. All p-values in this regression are below 0.05, suggesting there is less than a five percent probability that the vocational programs have no effect on wages, assuming the null hypothesis is true.

This enhancement in statistical significance marks a crucial step towards establishing a causal relationship, although it still does not confirm causality definitively. The introduction of a time lag allows for a more realistic assessment of the training's impact, as it provides time for vocational program graduates to assimilate into the labor market. After establishing greater statistical significance, I interpret the coefficients of the OLS regression from Table 5 as my base regression.

6.1 Interpretation of OLS

7 OLS Results

In my analysis presented in Table 5, the base regression model employs Ordinary Least Squares (OLS) with a time lag of one year, timed to correspond with the entry of the graduating cohort into the labor market, typically about five months after their graduation. This model notably reveals significant coefficients for variables related to the C74 and N74 vocational programs, as well as for individuals one year post-graduation.

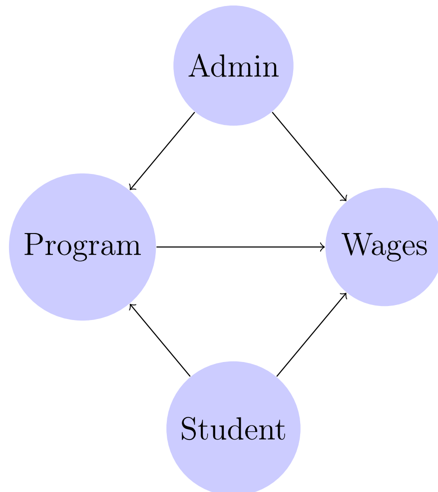
Analyzing the coefficients for individuals one year after graduation (GR_12), the coefficients are consistently slightly negative across various industries, ranging from -0.02 to -0.08. This negative correlation implies that each additional graduate entering the labor market a year after graduation is associated with a reduction in weekly wages by about two to eight cents. This phenomenon is more pronounced in the all-industries category, where each additional graduate correlates with a wage decrease of about seven to eight cents. Considering the average weekly wage in Massachusetts from 2012 to 2018 was between $928 and $1097, the magnitude of this effect appears modest but is economically significant. One explanation for this negative wage effect comes by shifts in the labor supply curve. The entry of additional graduates likely causes an outward shift in the labor supply curve. If labor demand remains constant while supply increases, the result is a surplus of labor. This surplus enhances the bargaining power of employers, as they have more potential employees to choose from, leading to more competitive conditions among job seekers. This increased competition allows employers to offer lower wages, thus driving down the average wage. This negative trend is consistent across time lags.

Conversely, the coefficients for the C74 and N74 programs are positive, indicating that these specific vocational programs are associated positively to wage outcomes. For the C74 program, the analysis shows an increase in weekly wages of $4.07, with a standard error of sixty-three cents. The N74 program also shows a positive effect on wages, with an increase of $3.58, though it has a higher standard error of $1.33. The larger standard errors associated with the N74 program likely result from fewer observations available for this program type, which broadens the 95% confidence interval, indicating less precision in the estimated wage increase. Considering the average weekly wage in Massachusetts from 2012 to 2018 was between $928 and $1097, this indicates about a 0.5% increase in weekly wages. This positive trend is consistent across time lags, but changes in magnitude. This will be further explored in Section 7.3.

In assessing the impact of vocational programs on wages, it's important to consider the findings of my study in the context of prior research. Notably, studies like Brunner, Dougherty, and Ross (2019) report substantial earnings benefits for vocational program participants. They found up to 44% higher total earnings and 32% higher average quarterly earnings for male participants in Connecticut. Additionally, data from the Department of Education indicate that among 10th-grade public school students in 2002 who were Career and Technical Education (CTE) concentrators in high school, median annual earnings eight years post-graduation were \$23,950, compared to \$20,015 for non-concentrators—a nearly \$4,000 or 20% increase in median earnings. These findings suggest significant economic benefits associated with vocational training. However, it's crucial to recognize that these positive outcomes may reflect a consideration of counterfactual scenarios involving lower-performing students, which could potentially inflate the perceived earnings gains. Moreover, the positive effects identified in such studies contrast with the findings from my own research, where a fixed effects model incorporating multiple controls—town, year, and industry—yields much smaller coefficients for the impact of vocational training on wages. The discrepancy can be attributed to the methodological rigor of using fixed effects in regression analysis. By controlling for unobserved, invariant characteristics within each group, the fixed effects model more precisely isolates the impact of the training program from other confounding variables. This approach reveals that some of the benefits observed in less controlled models might actually be due to differences across towns, years, or industries, rather than the vocational training itself. When these factors are accounted for, the attributed effect of the training on wage increases is considerably reduced.

7.1 Interpreting Positive Program Coefficients

In interpreting the positive coefficients associated with the C74 and N74 programs, my interpretation considers multiple potential sources for these results, specifically addressing the concept of reverse causality and the possibility of genuine causal relationships. For one potential case of reverse causality, I find myself constrained by my dataset's limitations, particularly in controlling for reverse causality related to students selecting courses based on their wage expectations. The data available does not allow for a thorough isolation of this effect, as it lacks a control group of students with similar qualifications who chose not to



enroll in these programs. This limitation prevents a definitive conclusion regarding whether students are enrolling in these programs primarily because they anticipate higher wages in lucrative sectors. Despite these limitations, there is also compelling circumstantial evidence suggesting a causal relationship where the programs genuinely contribute to wage increases. This evidence is drawn from Dougherty (2018) that uses restricted data to control for student choices and finds statistical significant gains to industry certification.

The following diagram illustrates the potential interactions within this context. This diagram underscores the hypothesized pathways influencing wages, including the direct impact of the program on wages, the role of administrative decisions, and the choices made by students, thus the causal pathways from decision makers outside of the program.

The first scenario of reverse causality suggests that the anticipation of higher future wages might be planned for by program administrators rather than being a direct result of the training and skills acquired through the programs. Upon reviewing the course offerings from 2012 to 2018, it becomes evident that the number of courses has remained largely stable, with significant administrative changes limited to the discontinuation of courses in office technology and facilities management in 2013 and the introduction of new courses in fields like biotechnology, building maintenance, and construction craft labor. The consistent interest and growth in enrollment for courses in marketing, engineering, and programming seem to reflect student demand rather than strategic administrative planning. This observation undermines the idea that program administrators are merely positioning these programs in anticipation of higher wages, suggesting instead that they are responding to existing student interest.

The second reverse causality scenario involves the motivations of the students themselves. It considers the possibility that students may choose these programs specifically because they expect higher wages in lucrative business or technology sectors. This hypothesis is supported by enrollment data showing notable increases in business and technology courses, as highlighted in Figure 7. The lack of a control group—comprising students with similar qualifications who do not enroll in these programs—leaves this explanation viable. Studies like that of Dougherty (2018), which utilize administrative data from oversubscribed schools in Massachusetts, offer a more controlled environment by comparing students just above and below the admissions cutoff. However, such detailed data was not available for this study, limiting the ability to definitively rule out this form of reverse causality.

In considering the causality of how vocational programs like C74 impact wages, the causal argument is that these programs effectively deliver skills and qualifications that are highly valued in the labor market. This causal relationship is supported by the design of the study, which includes controls for variations in the demand curve and incorporates time lags to increase causal inference. Further circumstantial evidence supporting this causal interpretation comes from the research conducted by Dougherty (2018). Dougherty's study managed to control for the very factors missing from our dataset: accounting for students on the margin of program admission. Dougherty found significant, positive impacts on earnings for students who earned an industry-recognized certificate, a clear indicator of human capital acquisition. This circumstantial evidence suggests that similar vocational programs do indeed enhance skills that translate into higher wages, supporting the hypothesis of a causal relationship between program participation and wage increases.

7.2 Coefficients across NAICS industry hierarchies

Across various NAICS industry sectors, there is a noticeable trend where both the coefficients and their statistical significance decrease as the industry categorization becomes more specific. Table 6 illustrates the diminishing coefficients using my base regression of time lag 1 across all NAICS industry specifications.

Table 6: OLS Regression across NAICS levels, Time Lag 1

	(1) Weekly wages for All Industries	(2) Weekly wages for Industry Sectors	(3) Weekly wages for Industry Sub-Sectors	(4) Weekly wages for Sub-Sector Groups	(5) Weekly wages for NAICS Industries
C74	4.072***	3.096***	2.477***	-0.806*	-0.498
	(0.630)	(0.694)	(0.663)	(0.476)	(0.420)
N74	3.576***	3.807***	3.259**	3.442***	2.720***
	(1.327)	(1.451)	(1.388)	(0.983)	(0.853)
GR_12	-0.0780*	-0.00797	-0.0225	0.0556*	0.00200
	(0.044)	(0.048)	(0.045)	(0.032)	(0.027)
avgemp	0.0114***	0.00795***	0.0134***	0.0154***	0.0293***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
estab	-0.0400***	-0.0687***	-0.0593***	0.0285**	0.0812***
	(0.007)	(0.010)	(0.012)	(0.012)	(0.015)
_cons	774.5***	892.6***	916.6***	895.4***	921.8***
	(4.021)	(1.476)	(1.472)	(1.209)	(1.193)
r2	7594	60676	91424	179681	262168

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Massachusetts Department of Economic Research (DER) defines 'avgemp' as 'Average monthly employment.'
Note: Massachusetts Department of Economic Research (DER) defines 'estab' as 'Number of employer establishments in the industry.'

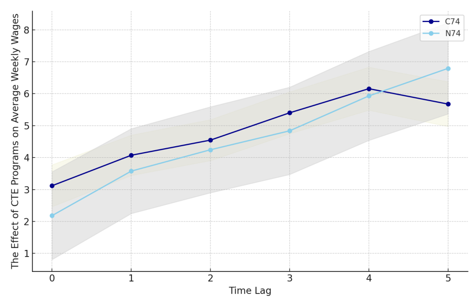
For example, the role of a "Boat Dealer" may have differing coefficients. There may significant effects in broader categorizations such as "All Industries" and "Retail Trade," and even within subsectors such as "Motor Vehicle and Parts Dealers." However, as the focus narrows to more specialized levels such as "Other Motor Vehicle Dealers" and "Boat Dealers" national industry, the detectable effects of C74 programs diminish and become statistically insignificant. This pattern illustrates that the efficacy of C74 programs is more readily apparent in broader industrial contexts but becomes harder to discern in niche markets. The p-values associated with these findings vary significantly with industry specificity: I observe a p-value of less than 1% in "All Industries" suggesting strong evidence against the null hypothesis of no effect. However, this p-value increases to 23.6% in the specific "National Industry" category, indicating a much weaker evidence against the null hypothesis, hence suggesting a higher likelihood that any observed effect could be due to random variation rather than the influence of the C74 training.

This trend may suggest that C74 programs provide a broad set of skills that are not specifically tailored for highly specialized fields. For example, a trainee from an "Automotive Technology" course might work in various roles within the "Motor Vehicle and Parts Dealers" category, resulting in a noticeable impact in broader sectors. However, as the industry specification tightens to areas like boat dealing, the general skills provided may not directly enhance job performance or wages, leading to an insignificant statistical impact.

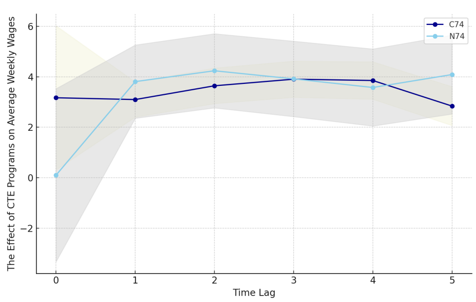
Conversely, the impacts of N74 programs are remarkably consistent across different levels of industry specification. This is reflected in the consistently low p-values (less than 0.01) across nearly all industry classifications in the first time lag, providing strong evidence against the null hypothesis across a broad range of applications. This indicates that the skills imparted by N74 programs are broadly applicable and not confined to specific sub-industries. These differences might reflect the targeted training focus of each program. N74 programs, often centered around business and technology sectors, equip participants with universally applicable skills. In contrast, the broader educational scope of C74 programs leads to a wide dispersion of graduates across various industries, resulting in a more diluted impact as the level of industry specificity increases.

7.3 Coefficients across five time lags

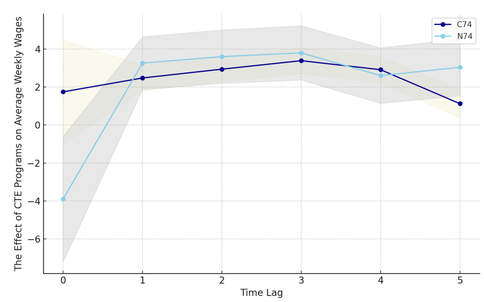
In this section of the analysis, I explore the impacts of different graduation cohorts entering the labor market, with a focus on how outcomes shift at specific time lags that correspond to typical graduation timelines from educational institutions. Previously, I hypothesized that significant changes in labor market outcomes would be evident at time lags of 1, 3, and 5 years. These time lags were chosen to align with the completion of high school, two-year associate degree programs, and four-year bachelor's degree programs, respectively.



(a) All Industries



(b) Industry Sectors



(c) Industry Sub-Sectors

Figure 10: The Effect of CTE Programs on Average Weekly Wages Across Different Industry Levels

The OLS results, illustrated by Figure 10 and detailed across Tables 9 to 12, largely confirm the anticipated patterns. At time lag 1, all coefficients became significantly distinct from those at time lag 0, indicating a stronger causal connection. The coefficients for C74 programs are consistently higher than those for N74 programs until time lag 4. At this juncture, the impact of both program types on wages converges, suggesting a similar economic benefit from completing two-year educational programs and C74 training a year and a half post-graduation. By time lag 5, the advantages associated with C74 programs diminish further, while the benefits for N74 graduates continue to rise. This trend implies that graduates who pursue four-year education programs experience higher wage outcomes than those who complete C74 programs shortly after graduation. This pattern is consistent across more specific industry sectors, although the data becomes more variable as C74 programs exhibit increased variability in their impact. This progression across time lags highlights the evolving influence of vocational education on wage trajectories, demonstrating a more nuanced interaction between educational completion timing and subsequent wage outcomes. The initial gains from C74 programs suggest immediate employability and skill application, but over time, the enduring educational investment represented by N74 programs appears to be associated with greater long-term wage benefits.

7.4 Coefficients across counties

Across counties, I repeated my Ordinary Least Squares (OLS) regressions for each group. Table 7 presents my OLS results for time lag 1. This initial regression revealed that the trends observed at time lag 1 persisted across subsequent time lags without significant deviation. Specifically, in counties experiencing negative wage growth, such as Franklin and Hampden, the regression results show that the coefficients for N74 programs and the graduation cohort are not statistically significant. This insignificance is likely due to a small sample size in these counties, as indicated by the descriptive statistics. However, the coefficient for C74

Table 7: All Industry by County Regressions

	(1) -2 to -1% Growth Counties	(2) 2-3% Growth Counties	(3) 3-5% Growth Counties
C74	4.593***	-2.932**	7.663***
	(1.075)	(1.483)	(1.653)
N74	-1.331	-13.29***	12.00***
	(6.626)	(2.662)	(3.376)
GR_12	-0.126	0.400***	-0.316***
	(0.138)	(0.107)	(0.102)
avgemp	-0.00288	0.0176***	0.0119***
	(0.005)	(0.003)	(0.001)
estab	0.0462***	-0.0524***	-0.0728***
	(0.015)	(0.012)	(0.014)
_cons	635.8***	777.3***	981.1***
	(21.783)	(24.566)	(18.927)
N	1029	1342	1276

Standard errors in parentheses

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

programs is notably high. Figure 7, the changes in courses by county group, suggests the increased demand for courses in traditional trades like automotive technology and hospitality may be a driving factor. In contrast, counties with high wage growth show significant and positive coefficients for both N74 and C74 programs. Notably, the N74 coefficient is very high at 12, implying that each additional N74 program can increase weekly wages by about $12. The coefficient for C74 is lower at $7.66. This lower coefficient for C74 programs may appear misleading because the C74 category includes a broader array of programs than N74, encompassing both high-wage potential programs and traditional, lower-wage occupations. This diversity within C74 programs leads to higher variability, which might blur the apparent impact on wages compared to N74 programs.

Figure 7 allows for an interpretation of coefficients through course offerings. Specifically, counties with higher wage growth experienced a notable increase of 130 enrollments in the health sector, whereas those with lower wage growth saw a decrease of 67 enrollments in the same sector. This variation suggests that the composition of local industries, particularly the healthcare sector, significantly influences post-graduation employment opportunities. It raises the possibility that counties like Middlesex and Suffolk, which are likely to offer more opportunities in healthcare, could be better positioning their vocational program graduates for successful employment outcomes. This observed disparity in vocational program enrollments and outcomes, particularly within the healthcare sector across different economic contexts, points to significant avenues for future research. Future studies could delve deeper into the relationship between local industry composition and the effectiveness of vocational training programs.

8 Conclusion

In this research, I explore into the wage impacts of two vocational education programs in Massachusetts. C74, a state-approved program adhering to stringent industry standards, and N74, a federally-approved program with less rigorous requirements. The study draws on data from 2012 to 2018, examining the correlation between vocational education graduates and wage levels across counties. Generally, wages rise at the same time C74 program enrollment rises and N74 enrollment falls.

Interestingly, while vocational program presence generally corresponds with wage increases, the correlation vary by county. In high-wage-growth counties, an unexpected trend emerges: N74 programs exhibit a positive correlation with wages, whereas C74 programs show a negative correlation. This suggests that in economically dynamic areas, the more flexible N74 programs, with a heavier concentration in business and technology courses, may be better aligned with rapidly evolving market demands. These courses, often associated with higher wages, contrast with the traditional trades more common in C74 programs.

Significant differences in outcomes between C74 and N74 programs also emerge: 20% more C74 graduates enter the workforce directly after graduation, while an equivalent proportion of N74 graduates pursue further education at two-year or four-year institutions. This variation in post-graduation placements indicates differing career trajectories influenced by the type of vocational training received.

To establish a causal link between vocational training and wages, I employed an Ordinary Least Squares (OLS) regression with fixed effects for year, town, and industry cluster. Initial analyses without time lags indicated insignificant results, underscoring the need for introducing time lags of one to five years to align with the typical educational timelines of high school, two-year associate degrees, and four-year bachelor's degrees. This methodological adjustment significantly enhanced the model's capability to capture the delayed effects of vocational training on wage dynamics. With the inclusion of a one-year time lag, the results displayed a robust causal connection, with all p-values falling below 0.05, affirming the statistically significant impact of vocational programs on wages. The existence of any program is associated with increased weekly wages by two to three dollars. The program enrollment for grade 12 is associated with a minuscule decrease of less than a dollar in weekly wages. Subsequent timelags across different NAICS industry sectors find associated wage increase from C74 programs falls below N74 programs beyond five years suggesting that four-year college cohorts may yield higher returns in the long-run. The magnitude of wage increases by 0.5% is much lower than the 30%-40% range from other studies, the cause may be the additional fixed effects by industry and town included in my model.

Further OLS regressions by county indicated that the impacts of vocational programs varied significantly depending on local economic conditions. In counties experiencing positive wage growth, both C74 and N74 programs demonstrated beneficial wage impacts, with the N74 programs showing a more pronounced effect. However, in counties with stagnant or declining wage growth, the influence of vocational training was less evident, likely due to smaller sample sizes. Referring back to changes in course offerings, Figure 7 showed that higher-standard programs offer a greater variety of courses and attract more students. These programs provide a range of specialized tracks that cater to various high-demand industries, indicating a robust and adaptable curriculum. In contrast, programs with lower standards tend to have a more limited range of course offerings, with a distinct emphasis on business and technology sectors. This suggests a narrower focus, potentially shaped by immediate job market demands rather than a comprehensive vocational training strategy. A notable difference was also observed in the enrollment patterns between counties with high and low wage growth. Counties with high wage growth saw significant increases in enrollments for healthcare-related vocational training, suggesting that these programs are closely aligned with local industry needs and may be tailored to meet specific labor market shortages.

A limitation of this study is the potential for reverse causality, where the expectation of higher wages may drive more enrollments in vocational programs, instead of the programs directly leading to wage increases. The absence of a controlled comparison group in this study prevents a definitive conclusion on this matter. However, external research such as Dougherty's 2018 study, which used data from oversubscribed schools in Massachusetts, supports the existance of a causal relationship between vocational training and wage increases. Dougherty's controlled environment showed higher earnings growth for students earning industry-recognized certificates indicating my results are aligned with prior research.

In summary, this study examines the trade-offs between C74 and N74 vocational programs and their impact on wage outcomes across Massachusetts. The findings corroborate existing research, indicating that vocational education not only enhances the labor market but might also limit opportunities depending on local economic demands. Business and technology sectors, associated with higher wages and extended educational pursuits beyond high school, contrast with trades that provide immediate employment benefits, offering a valuable alternative to exiting the workforce. Although this research does not establish causality, it aims to detail the complexities of local labor markets, addressing gaps highlighted in previous literature. This study underscores the critical balance vocational education must maintain between meeting immediate economic needs and nurturing long-term career prospects for students.

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Appendices

Table 8: Effect of Vocational Education on Average Weekly Wages with Time Lag 2

	(1) Average weekly wages for All Industries	(2) Average weekly wages for Industry Sectors	(3) Average weekly wages for Industry Sub-Sectors
C74	4.546***	3.641***	2.940***
	(0.640)	(0.703)	(0.672)
N74	4.244***	4.236***	3.602**
	(1.345)	(1.469)	(1.405)
GR_12	-0.114**	-0.0501	-0.0552
	(0.045)	(0.049)	(0.046)
avgemp	0.0113***	0.00794***	0.0133***
	(0.001)	(0.000)	(0.001)
estab	-0.0391***	-0.0684***	-0.0591***
	(0.007)	(0.010)	(0.012)
_cons	775.3***	893.2***	917.0***
	(4.027)	(1.454)	(1.447)
r2	7594	60676	91424

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Note: Massachusetts Department of Economic Research (DER) defines 'avgemp' as 'Average monthly employment.'
Note: Massachusetts Department of Economic Research (DER) defines 'estab' as 'Number of employer establishments in the industry.'

Table 9: Effect of Vocational Education on Average Weekly Wages with Time Lag 3

	(1) Average weekly wages for All Industries	(2) Average weekly wages for Industry Sectors	(3) Average weekly wages for Industry Sub-Sectors
C74	5.401***	3.903***	3.388***
	(0.652)	(0.717)	(0.685)
N74	4.837***	3.915***	3.798***
	(1.365)	(1.494)	(1.429)
GR_12	-0.171***	-0.0668	-0.0868*
	(0.046)	(0.050)	(0.047)
avgemp	0.0113***	0.00793***	0.0133***
	(0.001)	(0.000)	(0.001)
estab	-0.0381***	-0.0679***	-0.0588***
	(0.007)	(0.010)	(0.012)
_cons	775.1***	893.9***	917.5***
	(4.029)	(1.437)	(1.426)
r2	7594	60676	91424

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Massachusetts Department of Economic Research (DER) defines 'avgemp' as 'Average monthly employment.'
Note: Massachusetts Department of Economic Research (DER) defines 'estab' as 'Number of employer establishments in the industry.'

Table 10: Effect of Vocational Education on Average Weekly Wages with Time Lag 4

	(1)	(2)	(3)
	Average weekly wages for All Industries	Average weekly wages for Industry Sectors	Average weekly wages for Industry Sub-Sectors
C74	6.156***	3.851***	2.913***
	(0.672)	(0.741)	(0.707)
N74	5.929***	3.574**	2.603*
	(1.390)	(1.526)	(1.462)
GR_12	-0.220***	-0.0644	-0.0515
	(0.047)	(0.051)	(0.048)
avgemp	0.0114***	0.00792***	0.0133***
	(0.001)	(0.000)	(0.001)
estab	-0.0381***	-0.0675***	-0.0585***
	(0.007)	(0.010)	(0.012)
_cons	774.5***	894.6***	918.3***
	(4.032)	(1.422)	(1.409)
r2	7594	60676	91424

Standard errors in parentheses

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

Note: Massachusetts Department of Economic Research (DER) defines 'avgemp' as 'Average monthly employment.'
Note: Massachusetts Department of Economic Research (DER) defines 'estab' as 'Number of employer establishments in the industry.'

Table 11: Effect of Vocational Education on Average Weekly Wages with Time Lag 5

	(1)	(2)	(3)
	Average weekly wages for All Industries	Average weekly wages for Industry Sectors	Average weekly wages for Industry Sub-Sectors
C74	5.675***	2.838***	1.123
	(0.700)	(0.769)	(0.734)
N74	6.792***	4.086***	3.039**
	(1.425)	(1.561)	(1.495)
GR_12	-0.208***	-0.0362	0.0161
	(0.049)	(0.053)	(0.050)
avgemp	0.0114***	0.00791***	0.0133***
	(0.001)	(0.000)	(0.001)
estab	-0.0374***	-0.0670***	-0.0584***
	(0.007)	(0.010)	(0.012)
_cons	775.1***	895.5***	919.4***
	(4.036)	(1.409)	(1.393)
r2	7594	60676	91424

Standard errors in parentheses

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

Note: Massachusetts Department of Economic Research (DER) defines 'avgemp' as 'Average monthly employment.'
Note: Massachusetts Department of Economic Research (DER) defines 'estab' as 'Number of employer establishments in the industry.'

Class of Year	Agricultural Mechanics	Animal Science	Automotive Collision Repair & Refinishing	Automotive Technology	Biotechnology
2012	31	186	305	670	30
2013	41	175	298	724	46
2014	35	174	297	705	71
2015	32	163	274	667	141
2016	39	184	313	661	135
2017	45	193	290	648	196
2018	55	205	300	698	201
Difference	24	19	-5	28	171

Class of Year	Building/Property Maintenance	Business Technology	Cabinetmaking	Carpentry	Construction Craft Laborer
2012			95	662	6
2013		7	107	652	18
2014	78	516	97	678	15
2015	66	566	101	632	20
2016	102	480	89	666	19
2017	69	526	69	699	18
2018	84	359	87	710	15
Difference	84	359	-8	48	9

Class of Year	Cosmetology	Criminal Justice	Culinary Arts	Dental Assisting	Design & Visual Communications
2012	490	50	1111	98	666
2013	496	63	1096	134	570
2014	501	81	1094	153	532
2015	495	100	1185	181	518
2016	482	163	1136	188	596
2017	511	216	1079	215	672
2018	463	165	1086	204	672
Difference	-27	115	-25	106	6

Class of Year	Diesel Technology	Drafting	Early Education and Care	Electricity	Electronics
2012	29	413	584	602	138
2013	17	360	616	631	180
2014	18	345	584	576	165
2015	15	334	673	638	153
2016	22	357	646	641	178
2017	11	403	638	660	163
2018	25	330	659	673	153
Difference	-4	-83	75	71	15

Class of Year	Engineering Technology	Environmental Science & Technology	Exploratory	Facilities Management	Family & Consumer Studies
2012	438	182	31	77	224
2013	454	101	49	57	184
2014	467	74	33		201
2015	431	93	28		149
2016	531	115	46		121
2017	470	100	54		161
2018	748	165	34		125
Difference	310	-17	3	-77	-99

Class of Year	Fashion Technology	Graphic Communications	Health Assisting	Heating, Ventilation, A/C, Refrigeration	Horticulture
2012	51	569	1096	261	217
2013	53	592	1085	266	234
2014	45	475	1049	266	249
2015	46	497	1049	245	210
2016	48	427	1102	289	249
2017	39	467	1150	300	216
2018	43	451	1126	275	181
Difference	-8	-118	30	14	-36

Class of Year	Hospitality Management	Information Support Services & Networking	Machine Tool Technology	Marine Service Technology	Marketing
2012	54	368	283	29	371
2013	52	349	289	33	337
2014	65	358	290	28	386
2015	67	371	306	29	450
2016	86	353	333	26	558
2017	62	388	345	28	677
2018	74	400	334	21	518
Difference	20	32	51	-8	147

Class of Year	Marketing/Finance	Masonry & Tile Setting	Medical Assisting	Metal Fabrication & Joining	Office Technology
2012	388	62	152	331	597
2013	415	56	170	356	467
2014	500	61	132	370	
2015	417	61	171	373	
2016	491	69	180	354	
2017	553	53	204	388	
2018	433	69	175	341	
Difference	45	7	23	10	-597

Class of Year	Painting & Design Technologies	Plumbing	Power Equipment Technology	Programming & Web Development	Radio & Television Broadcasting
2012	56	361	11	316	349
2013	54	314	15	310	383
2014	59	348	15	269	359
2015	53	347	15	314	372
2016	58	369	11	323	395
2017	59	376	9	374	323
2018	41	417	14	444	363
Difference	-15	56	3	128	14

Class of Year	Robotics and Automation Technology	Sheet Metalworking	Stationary Engineering	Telecommunications - Fiber Optics
2012	40	36	10	17
2013	92	19	11	11
2014	115	12	16	11
2015	148	25	9	6
2016	104	13	12	15
2017	135	16	13	11
2018	83	14	5	18
Difference	43	-22	-5	1

Figure 11: CTE Course Offerings (2012-2018)

Class of Year	Agricultural Mechanics	Animal Science	Automotive Collision Repair & Refinishing	Automotive Technology	Biotechnology
2012	31	185	305	617	30
2013	41	174	298	637	42
2014	35	174	297	659	46
2015	32	163	274	632	34
2016	39	184	313	643	128
2017	45	193	290	643	166
2018	55	205	295	676	121
Difference	24	20	-10	59	91

Class of Year	Building/Property Maintenance	Business Technology	Cabinetmaking	Carpentry	Construction Craft Laborer
2012			39	588	6
2013		1	36	590	18
2014	51	267	37	603	14
2015	53	277	34	562	12
2016	74	254	42	577	10
2017	50	284	34	569	7
2018	63	236	47	572	5
Difference	63	236	8	-16	-1

Class of Year	Cosmetology	Criminal Justice	Culinary Arts	Dental Assisting	Design & Visual Communications
2012	490		860	98	227
2013	496	27	878	134	249
2014	501	44	829	152	274
2015	495	50	894	181	331
2016	482	57	853	188	318
2017	511	65	769	215	360
2018	463	91	784	204	400
Difference	-27	91	-76	106	173

Class of Year	Diesel Technology	Drafting	Early Education and Care	Electricity	Electronics
2012	29	366	304	602	137
2013	17	323	326	631	179
2014	18	315	348	576	158
2015	15	306	485	638	147
2016	17	329	451	641	173
2017	11	373	438	660	162
2018	20	307	450	673	144
Difference	-9	-59	146	71	7

Class of Year	Engineering Technology	Environmental Science & Technology	Exploratory	Facilities Management	Fashion Technology
2012	163	66	20	73	24
2013	189	55	22	50	24
2014	229	73	32		28
2015	250	81	23		25
2016	246	99	45		27
2017	231	92	51		23
2018	365	117	32		23
Difference	202	51	12	-73	-1

Class of Year	Graphic Communications	Health Assisting	Heating, Ventilation, A/C, Refrigeration	Horticulture	Hospitality Management
2012	386	759	248	217	40
2013	431	791	246	234	36
2014	408	764	259	249	48
2015	390	772	231	210	67
2016	327	746	289	249	80
2017	308	778	300	216	62
2018	304	786	275	181	74
Difference	-82	27	27	-36	34

Class of Year	Information Support Services & Networking	Machine Tool Technology	Marine Service Technology	Marketing	Masonry & Tile Setting
2012	290	283	19	371	62
2013	293	289	24	337	56
2014	294	290	21	386	61
2015	282	306	21	450	61
2016	270	301	26	558	69
2017	309	335	22	677	53
2018	331	302	21	518	69
Difference	41	19	2	147	7

Class of Year	Medical Assisting	Metal Fabrication & Joining Technologies	Office Technology	Painting & Design Technologies	Plumbing
2012	111	326	270	56	361
2013	125	354	292	54	314
2014	115	370		59	348
2015	134	373		53	347
2016	139	354		58	369
2017	140	388		59	376
2018	142	341		41	417
Difference	31	15	-270	-15	56

Class of Year	Power Equipment Technology	Programming & Web Development	Radio & Television Broadcasting	Robotics and Automation Technology	Sheet Metalworking
2012	6	167	66	17	23
2013	15	178	61	13	10
2014	11	188	88	13	8
2015	15	165	92	17	14
2016	11	188	109	29	12
2017	9	171	136	39	12
2018	14	224	108	56	14
Difference	8	57	42	39	-9

Class of Year	Stationary Engineering	Telecommunications - Fiber Optics
2012	10	17
2013	11	11
2014	16	11
2015	9	6
2016	12	11
2017	13	11
2018	5	7
Difference	-5	-10

Figure 12: C74 Course Offerings (2012-2018)

Class of Year	Animal Science	Automotive Collision Repair & Refinishing	Automotive Technology	Biotechnology	Building/Property Maintenance
2012	1		53		
2013	1		87	4	
2014			46	25	27
2015			35	107	13
2016			18	7	28
2017			5	30	19
2018		5	22	80	21
Difference	-1	5	-31	80	21

Class of Year	Business Technology	Cabinetmaking	Carpentry	Construction Craft Laborer	Criminal Justice
2012		56	74		50
2013	6	71	62		36
2014	249	60	75	1	37
2015	289	67	70	8	50
2016	226	47	89	9	106
2017	242	35	130	11	151
2018	123	40	138	10	74
Difference	123	-16	64	10	24

Class of Year	Culinary Arts	Design & Visual Communications	Diesel Technology	Drafting	Early Education and Care
2012	251	439		47	280
2013	218	321		37	290
2014	265	258		30	236
2015	291	187		28	188
2016	283	278	5	28	195
2017	310	312		30	200
2018	302	272	5	23	209
Difference	51	-167	5	-24	-71

Class of Year	Electronics	Engineering Technology	Environmental Science & Technology	Exploratory	Facilities Management
2012	1	275	116	11	4
2013	1	265	46	27	7
2014	7	238	1	1	
2015	6	181	12	5	
2016	5	285	16	1	
2017	1	239	8	3	
2018	9	383	48	2	
Difference	8	108	-68	-9	-4

Class of Year	Family & Consumer Studies	Fashion Technology	Graphic Communications	Health Assisting	Heating, Ventilation, A/C, Refrigeration
2012	224	27	183	337	13
2013	184	29	161	294	20
2014	201	17	67	285	7
2015	149	21	107	277	14
2016	121	21	100	356	
2017	161	16	159	372	
2018	125	20	147	340	
Difference	-99	-7	-36	3	-13

Class of Year	Hospitality Management	Information Support Services & Networking	Machine Tool Technology	Marine Service Technology	Marketing/Finance
2012	14	78		10	388
2013	16	56		9	415
2014	17	64		7	500
2015		89		8	417
2016	6	83	32		491
2017		79	10	6	553
2018		69	32		433
Difference	-14	-9	32	-10	45

Class of Year	Medical Assisting	Metal Fabrication & Joining Technologies	Office Technology	Power Equipment Technology	Programming & Web Development
2012	41	5	327	5	149
2013	45	2	175		132
2014	17			4	81
2015	37				149
2016	41				135
2017	64				203
2018	33				220
Difference	-8	-5	-327	-5	71

Class of Year	Radio & Television Broadcasting	Robotics and Automation Technology	Sheet Metalworking	Telecommunications - Fiber Optics
2012	283	23	13	
2013	322	79	9	
2014	271	102	4	
2015	280	131	11	
2016	286	75	1	4
2017	187	96	4	
2018	255	27		11
Difference	-28	4	-13	11

Figure 13: N74 Course Offerings (2012-2018)