Frontier Culture and Modern Labor Market Resilience: Evidence from the Great Resignation

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Abstract

Can cultural orientation be at the root of new labor and entrepreneurial trends triggered by the COVID-19 shock in the U.S.? The frontier conditions that shaped early American settlement are known to foster self-reliance, inventiveness, and rugged individualism—traits that may influence labor supply decisions in the face of uncertainty. Using the Total Frontier Experience (TFE) measure developed by Bazzi et al. (2020) and modern census data on job quits and new business applications, I show that counties with greater historical frontier exposure experienced significantly higher rates of both voluntary quitting and self-employment following the COVID-19 shock. These patterns reflect the broader labor market shifts often characterized as the Great Resignation. The results are robust to controls for pandemic severity, resistance to vaccine mandates, and variation in government transfers. By linking frontier-driven cultural traits to modern labor market behavior, this paper adds a labor supply dimension to the literature on cultural persistence and offers a cultural explanation for regional variation in labor market dynamics during the pandemic recovery.

Keywords: Cultural Orientation, The Great Resignation, Individualism, Entrepreneurship, Frontier Culture,, Job Separations, Quits.

JEL: J22, J23, J63, M13, N91

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1. INTRODUCTION

The COVID-19 pandemic triggered a dramatic re-evaluation of work and life balance, giving rise to two defining labor market trends: a historic surge in voluntary job resignations, known as the "Great Resignation," and a parallel boom in new business applications (Fairlie, 2020). These concurrent shifts reshaped the economic landscape and posed serious challenges for employers and policymakers. While widespread, their intensity varied markedly across the United States. Some regions saw sharp exits from formal employment alongside bursts of entrepreneurial activity, while others remained relatively stable (Haltiwanger, 2021). This striking heterogeneity suggests that local factors beyond pandemic severity or policy responses shaped how individuals navigated the pandemic shock.

This paper explores whether deeper cultural forces help explain these divergent labor market responses. In particular, I examine the legacy of frontier settlement in shaping regional norms around self-reliance, independence, and resistance to external constraint. These traits, often described as rugged individualism, emerged during the westward expansion as settlers adapted to harsh and uncertain environments. Bazzi et al. (2020) document how exposure to historical frontier conditions has left a durable imprint on local attitudes, influencing political ideology, religiosity, and family structure. Building on this framework, Bazzi et al. (2021) show that frontier culture also shaped how communities responded to the COVID-19 pandemic, including vaccine uptake and compliance with public health measures. Drawing from these insights, I ask whether frontier-driven cultural norms also influenced labor supply decisions during the pandemic. Specifically, I test whether counties with stronger frontier legacies exhibited greater adaptive behavior, reflected in higher rates of voluntary job quitting and new business formation during the recovery period.

To examine this question, I combine the Total Frontier Experience (TFE) measure developed by Bazzi et al. (2020) with modern county and state-level data on job quits, seperations and new business applications. I find that counties with greater historical exposure to the frontier experienced significantly larger increases in both voluntary separations and entrepreneurial activity following the COVID-19 shock. These patterns persist after controlling for pandemic severity, public health compliance, government transfer exposure, and local labor market characteristics. The effects are especially pronounced among women, consistent with recent findings that frontier culture shapes gender-specific beliefs about autonomy and labor force participation.

By linking a historical determinant of culture to modern labor market behavior, this paper makes two key contributions. First, it adds a labor supply dimension to the literature on cultural persistence, showing that long-run cultural traits influence not only political and social attitudes but also core economic decisions. Second, it offers a cultural explanation for the uneven geography of the Great Resignation, highlighting how deeply rooted norms can shape responses to uncertainty and economic disruption.

The remainder of the paper proceeds as follows. Section 2 reviews the relevant literature on the TFE theory and establishes the main stylized facts about U.S. labor market transitions during the pandemic. Section 3 describes the administrative and survey data sources that are used throughout the empirical analysis; it also discusses the proposed estimation strategy to capture the effects of the degree of individualism on quits and subsequent business openings applications. Section 4 and 5 discuss the main empirical results at both county and state levels as well as provides several robustness checks. Finally, Section 7 concludes and adds further discussion for future research on this issue.

2. BACKGROUND

This section motivates the paper by tracing the historical, theoretical, and empirical foundations behind the main argument: that the Great Resignation and boom in entrepreneurial activity reflect not just pandemic-related shocks, but the enduring influence of American frontier culture.

2.1 The Frontier Experience Hypothesis

The idea that American culture has been uniquely shaped by the frontier dates back to the influential "frontier thesis" of historian Frederick Jackson Turner. He argued that the westward expansion of "free land" between the 18th and 19th centuries formed a distinct cultural identity rooted in self-reliance, inventiveness, and resistance to authority (Turner, 1893).[1] Life on the frontier demanded adaptation to harsh environments, frequent violence, and limited state

[1] Turner's concept of "free land" has been criticized for overlooking the displacement of Native American communities and the role of settler colonialism. See Cronon (1991) for a critical perspective.

protection. This selective and adaptive process fostered what later scholars have termed ”rugged individualism” (Billington and Ridge, 2001).[2] These cultural traits were not only shaped by frontier conditions but were transmitted across generations and embedded in local norms.[3]

While Turner's thesis was primarily historical and qualitative, it laid the foundation for a long tradition in sociology and political science linking geography to values. Elazar (1966) categorized American political cultures as moralistic, individualistic, or traditionalist, often tracing regional differences to settlement patterns. Lipset (1996) later argued that America's distinctive ideological foundation—marked by anti-statism and entrepreneurialism—can be traced to these frontier dynamics. More recently, scholars have sought to empirically test these claims with historical data.

More recently, economists have developed empirical strategies to test these historical claims. A major breakthrough came with Bazzi et al. (2020), who construct a county-level measure of Total Frontier Experience (TFE) to capture the intensity and duration of historical frontier exposure. They find that counties with greater TFE exhibit significantly higher levels of individualism today, as reflected in political attitudes, religiosity, family structure, and resistance to redistribution. Their study provides compelling evidence that the frontier experience is not just a historical footnote, but a persistent determinant of modern local culture. Building on this framework, Bazzi et al. (2021) examine how frontier culture shaped collective responses to the COVID-19 pandemic. They show that counties with stronger frontier legacies were less likely to adopt protective behaviors such as mask-wearing, social distancing, or vaccine uptake—despite higher levels of COVID-related risk. Barrios et al. (2021) link frontier culture to modern patterns of startup formation, highlighting its enduring economic influence wile Bazzi et al. (2023) examine the long-run legacy of the frontier on gender norms. Collectively, these suggest that frontier-based cultural norms continue to affect how communities respond to collective challenges, particularly those that require compliance with central authority or coordination.

These studies indicate that frontier legacies continue to shape economic and social outcomes

[2]The term “rugged individualism” gained political prominence through Herbert Hoover's 1928 campaign speech, but its intellectual roots can be traced to the frontier thesis and American transcendentalist thought.

[3]Cultural traits can be transmitted across generations via family socialization, local institutions, and peer effects. See Bisin and Verdier (2001) for a model of cultural transmission, and Fernández (2008) for empirical evidence on intergenerational cultural persistence.

in the present day. This idea aligns with broader findings in the cultural persistence literature, which documents how historical conditions shape long-run preferences and behavior (Alesina and Giuliano, 2015; Giuliano and Nunn, 2021; Nunn, 2009). Grosjean (2014)) shows that a legacy of violence in the U.S. South still affects modern attitudes toward conflict and authority. Voigtländer and Voth (2012) trace antisemitic behavior in 20th-century Germany back to medieval persecution patterns. Likewise, Giuliano and Nunn (2021) demonstrate that societies with a history of plough exhibit more persistent gender inequality today. Together, these studies show that historical shocks can produce cultural imprints that persist for generations.

Building on this literature, this paper examines whether frontier-based cultural traits—especially autonomy, individualism, and self-reliance—help explain geographic variation in labor market responses to the COVID-19 shock. I test whether counties with greater historical frontier exposure were more likely to experience elevated job quits and higher rates of new business formation during the pandemic recovery. If the frontier fostered cultural resistance to constraint and a preference for self-directed action, then we should expect these areas to be disproportionately represented in both the Great Resignation and the entrepreneurial boom.

2.2 Entrepreneurial Activities - Business Applications

The COVID-19 pandemic triggered an unexpected surge in new business applications across the United States. After a sharp decline in the first quarter of 2020, business formations rebounded rapidly by mid-year and reached historically high levels throughout 2021 and 2022 (Appendix Figure A.15). This sharp rise in business formation is particularly noteworthy given the growing role played by gig workers in the U.S. labor market (Abraham et al., 2018), and the fact that new startups are widely considered a key driver of creative destruction and long-term productivity growth (Douglas and Shepherd, 2002).

This entrepreneurship surge differed substantially from previous economic downturns. Recent studies show that business application dynamics during the COVID-19 recession diverged markedly from those observed during past recessions (Cortes and Forsythe, 2020; Dinlersoz et al., 2021). Instead of declining and remaining depressed, as seen during the Great Recession, applications recovered quickly and remained elevated. These trends suggest that the pandemic created unique structural conditions—such as digitization, job displacement, and a re-evaluation of work that may have spurred a broader reevaluation of career paths and opportunities.

On the other hand, the rise in business applications was not evenly distributed. It varied significantly across sectors, with larger increases in industries amenable to remote work or online service delivery (See Appendix Figures A.14 and A.18). Haltiwanger (2021) argues, this sectoral heterogeneity likely reflects a structural shift in economic activity toward digital and flexible forms of employment.[4] Yet even after accounting for industry mix, substantial geographic heterogeneity remains. Some counties and states experienced dramatic surges in entrepreneurship, while others saw only modest changes. Appendix Figure A.18 from Haltiwanger (2021) visualizes the variation. This spatial variation suggests that economic or policy differences alone cannot fully explain the observed patterns.

In this context, cultural factors, especially those tied to historical experience, offer a compelling explanation. A growing body of research has documented the role of values such as risk tolerance, independence, and self-efficacy in shaping entrepreneurial intent and behavior (Giannetti and Simonov, 2009; Henrekson and Sanandaji, 2014). Scholars have also emphasized the historical roots of these traits. Bazzi et al. (2020) find that Total Frontier Experience (TFE) predicts persistent cultural traits that may influence entrepreneurial entry. In this respect, a closely related study to mine on the effects of historical-cultural factors on entrepreneurship has shown that geographically fixed effects could explain 75% of the variation in startup formations (Barrios et al., 2021). These authors document that the frontier culture contributes positively to entrepreneurship using startup data from the Startup Cartography project for 1988-2016. However, their results do not reflect the increased heterogeneity and structural change in the labor market followed by the Covid-19 growing frustration.

This paper builds on those findings by examining whether frontier culture also explains spatial differences in entrepreneurship during the pandemic recovery. If frontier legacies continue to shape economic behavior, then counties with deeper exposure to frontier settlement should exhibit stronger entrepreneurial responses to the COVID-19 shock induced structural change. My contribution to the scarce literature on frontier culture's effects on the economy is to show

[4]High-growth sectors during this period included professional services, e-commerce, online education, logistics and delivery, and remote health services. These industries were more amenable to remote or digital operations.

that the pandemic has accelerated cultural traits' influence on both entrepreneurial activities and labor supply decisions. It also suggests that the frontier effect on business applications before the pandemic is rather weaker than the effect during the post-pandemic period. Together, the evidence suggests that entrepreneurial activity during COVID-19 was not just a product of economic dislocation or technological change, but also of deeper, culturally rooted behavioral norms. These patterns point to a broader mechanism through which historical experiences continue to shape modern economic adaptation.

2.3 The Great Resignation

In parallel with the rise in business formation, the U.S. labor market experienced an unprecedented surge in voluntary job quits beginning in mid-2020. [5] As with business applications, quit rates fell sharply during the initial months of the COVID-19 crisis but began climbing steadily from May 2020 onward. By 2021, resignations had reached all-time highs each month, a trend that became widely recognized as "The Great Resignation" (Appendix Figure A.16). This steeper new trend has also been reflected on social media, while it never received much media attention during previous recessions.

According to data from the Job Openings and Labor Turnover Survey (JOLTS), more than 4 million workers quit their jobs in April 2021 alone, representing over 2% of the labor force. This figure continued to rise in subsequent months, signaling a large-scale reassessment of job satisfaction and work-life balance. Klotz (2021a) has coined this phenomenon "The Great Resignation," arguing that the pandemic had jolted workers into reevaluating their priorities and long-term goals.[6] Klotz (2021b) and Krugman (2021) suggest that this phenomenon was driven less by wage pressures or job losses and more by emotional exhaustion, identity realignment, and a newfound appreciation for autonomy.

Several factors contributed to this behavioral shift. Remote work became widespread, allowing employees to spend more time at home and reconsider their lifestyles (Barrero, Bloom, and Davis, 2021; Bick et al., 2020). Generous federal stimulus payments and enhanced unemploy-

[5] Unlike layoffs, which are employer-driven, quits are voluntary separations and may signal confidence, dissatisfaction, or search for autonomy.

[6] Recent work in labor economics frames voluntary quits as a form of expressive behavior tied to identity and preferences, rather than just economic optimization. See Krueger (2022) for a behavioral perspective.

ment benefits provided a financial buffer, while the personal savings rate skyrocketed—from 7.7% in April 2019 to 33.8% in April 2020 and 26.6% in March 2021 (U.S. Bureau of Economic Analysis, 2021). These conditions created the economic flexibility for many to walk away from traditional employment or pursue self-employment.

Psychological research supports this behavioral turn. Individuals with high entrepreneurial drive are more likely to quit wage jobs and start their own ventures. Ahmetoglu et al. (2021) links entrepreneurial intention to voluntary separation. Other scholars have emphasized the role of personality traits such as autonomy-seeking, openness to experience, and aversion to authority in predicting labor supply behavior (Bauder, 2001; Schneider, 1987; Treglown et al., 2018).[7] These insights suggest that cultural and psychological traits help explain why certain individuals and by extension, certain regions were more likely to experience elevated quit rates.[8] Several remote work surveys confirm this argument (Nela Richardson, 2022; Owl Labs, 2020).[9]

From this perspective, the Great Resignation is not solely a macroeconomic or policy-driven phenomenon. It also reflects the activation of deeper cultural tendencies that shape how people respond to disruption. In particular, traits associated with frontier culture such as individualism, risk tolerance, and preference for autonomy may help explain the regional variation in quit behavior and its overlap with entrepreneurship.

This paper contributes to the literature by investigating whether historically rooted cultural traits, particularly those linked to frontier experience, influenced labor market behavior during the COVID-19 recovery. While economists and policymakers have extensively debated the causes and consequences of the Great Resignation, little attention has been paid to how culture mediates these responses. By connecting quits and new business formation to a shared cultural root, this paper offers a unified explanation for their co-movement and regional clustering during the pandemic. Figure 1b illustrates the correlation between job quits and business applications.

[7] These traits are commonly studied in occupational and entrepreneurial psychology. For example, autonomy-seeking and entrepreneurial intent are measured using the Big Five Inventory and Entrepreneurial Orientation frameworks.

[8] Autonomy has long been recognized as a driver of occupational choice. See Deci and Ryan (1985) on self-determination theory, and Leotti et al. (2010) on the intrinsic value of choice.

[9] Surveys by Owl Labs (2020) and the ADP Research Institute (2021) document widespread employee preference for flexible work arrangements, even after lockdown ended. See also Barrero, Bloom, Davis, and Meyer (2021).

The strong co-movement reinforces the notion that a common cultural mechanism may underlie both. If frontier culture fosters resistance to constraint and a preference for self-determination, it could plausibly drive individuals away from traditional employment and toward independent ventures in times of upheaval.

3. EMPIRICAL STRATEGY

3.1 Data

The primary explanatory measure of cultural differences comes from Bazzi et al. (2020), in which they compute the number of decades each U.S. county experienced the frontier line between 1790 and 1890. Following these authors, this study defines frontier counties as those with a population of less than 6 per square mile within 100 km of the frontier line. The sample consists of 2040 baseline counties that have experienced frontier conditions between 1790 and 1890. The Total Frontier Experience (TFE hereafter) measure varies from 0 to 6.3 decades, with the top quartile counties having more than 2.4 decades and the bottom quartile having less than 1.1 decades of frontier exposure. Mean and median TFE are 1.6 and 1.7 decades, respectively.

In addition to Bazzi et al. (2020)'s county-level measure of TFE, this paper constructs three different state-level aggregate proxies frontier culture: (i) the cumulative number of years each county in a given state has been on the frontier, (ii) the average frontier years experienced by each state, and (iii) a weighted average of frontier years based on land area, to account for historical land availability. Regarding interpretation, the second measure provides more intuitive results than the cumulative one. By weighting the average TFE of states with land, the last measure of state-level TFE provides more statistically significant results since it yields higher variability of frontier experience than the previous two TFE measures. Table A.1 provides descriptives of all the above TFE measures. The main variables of interest regarding entrepreneurial activity come from the Business Formation Statistics (BFS) of the U.S. Census Bureau. On the one hand, the BFS provides a detailed account of the early stages of new business formations and their applications. The business applications are defined as Employer Identification Number (EIN) applications for business purposes originating from IRS SS4-Form. On the other hand, it also covers business formations which are the new business registers following business applications. Unlike the literature, this study uses EIN applications to reflect entrepreneurial intentions rather than actual successful business formations. Actual business registers may depend on additional factors that might act as confounding factors in the analysis, including ability and economic conditions. In fact, this data source has also been used to model the likelihood that an application becomes an employer business (Bayard et al., 2018). Therefore, applications are likely to capture better the growing intention of those workers who first quit and then become self-employed. Lacking county-level data on the monthly frequency of the relevant outcomes, this paper uses monthly state-level and yearly county-level data. Admittedly, though monthly county data availability would have been preferable, given the relatively short period spanned by the pandemic, both state and county-level results are sufficiently consistent to lead to the same conclusions. In particular, while the county-yearly level analysis provides the main conclusions, the more frequent state-monthly level analysis yields supporting information on the dynamics of the point estimates at each period of time.

The second key outcome of interest is job quits and separations, measuring the extent of the Great Resignation. Two different data sources are used for these variables. The Job Openings and Labor Turnover Survey (JOLTS) program of the Bureau of Labor Statistics provides monthly job openings, hires, quits, and separations of states. This survey data presents demand-side indicators of labor shortages, and it covers all total non-farm sectors for 49 states of the U.S. Quarterly Workforce Indicators (QWI) by the Bureau of Labor Statistics are used for county-level analysis, which includes separations, hires, firm job gains, and job losses. Although, unlike JOLTS, they do not differentiate layoffs and quits in their measure of separations, the measure of total separations can arguably represent the Great Resignation phenomenon. Furthermore, since separation changes are mainly a result of changes in quits, rather than layoffs, after May 2020 they can be chosen to be an outcome of interest (see Appendix Figure A.17). This paper tries different ways to represent the labor market response of workers using quits, separations, hires and job openings. As most measures yield similar results in the subsequent empirical analysis, the paper sticks to the separations for county analysis and refers to them as quits for convenience in the following sections. Yet, results for the other two variables are available upon request.

The county-yearly empirical estimation includes the data between 2018 and 2022. The estimation uses the data for 2019Q3 as the reference point. Note that, using the third quarter in the yearly analysis provides some advantages for business applications and job separations because 2019Q3 is closer to pre-pandemic conditions, and 2020Q3 is unlikely to capture immediate responses to labor supply decisions. Most of the separations in 2020Q2 are due to forced layoffs (See Haltiwanger (2021)), and the frustration triggered by the Covid-19 crisis started to rise after this quarter. In effect, the sudden massive drop in business applications, quits, and separations start to take off after May 2020. Therefore, using third quarters fits well with the goal of this paper as it better explains the new paradigm of labor supply decisions that may take some time rather than the immediate effects of pandemic declarations and mandates.

Besides TFE, the analysis and robustness checks make use of different state and county-level covariates, such as population density, government impact payments, age distribution (older than 65 and younger than 18), race (percentage of white and hispanic), personal income, female population share, foreign-born share, education, and the number of covid cases. Among those, the government impact payments from CARES and ARP ACT are drawn from the U.S. Treasury Department. Yearly and monthly covid-related statistics are aggregated from the COVID-19 Data Repository by Johns Hopkins University Center for Systems Science and Engineering (Dong et al., 2020). Personal income by state and county are obtained from the U.S. Bureau of Economic Analysis of the Department of Commerce, while the remaining demographic controls mentioned above are collected from The U.S. Census Bureau of Economic Analysis.

Figure 2 shows percentage point changes in quits and business applications compared to February 2020 for the top and bottom quartiles of the distribution of TFE by state and county. Both outcomes experienced significant drops in March and April 2020. The number of business applications is 30 p.p. lower in April 2020 than in February 2020, while the number of quits is 40 p.p. lower. After April, business applications start surging steadily until they become 40 p.p higher than before the pandemic. Meanwhile, quits start to increase after May 2020, reaching their highest level by the end of 2020. More importantly, Figure 2 illustrates a large degree of heterogeneity in the growth of business applications and quits across different TFE groups of states and counties. Foremost, Figures 2a and 2b show that the rise in both variables after the pandemic is more prominent in high average TFE states. The states in the top 25% of the average TFE distribution had 5-20 p.p. more business applications depending on the month, reaching a record level of 60 extra p.p. in July 2020. Likewise, the increase in quits following the pandemic is more widespread in high average TFE states, with those at the first quartile of the TFE distribution reaching in 2021 from 5 to 20 p.p. more quits than those at the bottom.

Figures 2c-2d display the annual p.p change of business applications at the county level, again relative to the pre-pandemic year 2019. As before, counties with the top 25% TFE had 7 p.p and 15 p.p more business applications in 2020 and 2021, respectively, than those at the bottom 25%. Note that, as business applications started to increase in early 2020 and the highest jumps occurred during that year, the 2020 annual data reflects more heavily the increase from May than the fall in applications during March and April. Although the figures at different frequencies are not to be compared directly the number of monthly and yearly applications yield similar findings, namely, the positive co-movement of quits and applications seems to be more prevalent in counties with higher TFE. As regards quits, since their growing path started later than the jump in business applications (in late 2020), their drop due to quarantines dominates the 2020 path. Hence, the jump in quits take place mainly in 2021, consistent with both level graphs. However, the divergence in this dimension between the two TFE quartile groups prevails in both 2020 and 2021, with jumps of 4 p.p and 7 p.p, respectively. Those gaps emerge after the pandemic declaration month of March 2020 and the pre-pandemic year third quarter of 2019. This suggests an important link to the frontier culture.

In sum, since the previous descriptive evidence suggests a potential role of TFE in explaining the geographical heterogeneity of labor supply responses, the next empirical section examines whether this is the case when controlling for some other confounding factors that may be correlated both with TFE and the pandemic response in terms of labor supply.

3.2 Estimating Equations

The estimation strategy relies on event-study regressions to reveal distinctive trends in business formation applications, quits, and separations across high and low TFE counties and states around the beginning of the pandemic. Similar to Bazzi et al. (2020) several event-study analyses are applied to the outcome of interests. The state-monthly level analyses involve the following regression equation:

$$(1) \quad Y_{st} = \alpha + \sum_{j=\min}^{\max} \beta_j TFE \times \mathbf{1}(\text{months since March 2020} = j) + \theta_s + \gamma_t + \varepsilon_{st},$$

where Y_{st} represents business applications and quits of state s at month t, with both outcome variables being drawn from BFS and JOLTS. textitTFE stands for the three different measures of state-level TFE discussed earlier, which are repeated here for convenience: (i) average frontier experience, (ii) average frontier experience weighted by land area of the state, and (iii) aggregation of TFE of counties belonging to a given state. In turn, 1(months since March 2020 =j) are indicator variables for the time periods before and after March 2020. Next, θ_s and γ_t are state and time fixed effects. Finally, ε_{st} is a zero-mean i.i.d. error term.

The county-yearly level analyses relies on a similar regression equation, namely:

$$(2) \quad y_{ct} = \alpha + \sum_{j=\min}^{\max} \beta_j TFE \times \mathbf{1}(\text{ years since/after Q3 2019 } = j) + \theta_c + \gamma_t + X_{ct} + \varepsilon_{ct},$$

where Y_{ct} represents the labor outcomes of county c in year t, also drawn from BFS and QWI. In line with Bazzi et al.(2020, 2021), *TFE* for counties is expressed in decades. 1(years since/after 2019 =j) are time dummies for each year before and after 2019. Note that, since data on quits and separations at the county level are only available for the third quarter of each year, the effect of the pandemic shock is observed in 2020 and 2021, while 2019 Q3 is considered to be the pre-treatment period. As in equation (1), county and time fixed effects are included. X_{ct} includes population density, race (Hispanic share and white share), the share of the population with age 65+, personal income per capita, percentage of college graduates, foreign born share, female share, income transfers from government and direct economic impact payments. In addition to these controls, I introduce further sets of covariates in (2), namely, interactions of the time and state-fixed effects to account for specific state-time trends confounding variables.

The standard errors of the estimated coefficient in all these regressions are clustered by counties and states. The coefficients β_j yield the effect of the intensity of the treatment by displaying the differences between responses of high-TFE and low-TFE counties and states to the Covid-19 shock relative to pre-pandemic. Finally, conventional diff-in-diff analogs to equations (1) and (2) are also included to summarize the event-study results.

4. EMPIRICAL RESULTS

This section shows that frontier culture has triggered structural changes in labor-supply decisions in response to Covid-19 growing frustration. TFE is positively related to entrepreneurial activity and quits-separations during the Great Resignation period, with both state-level and county-level estimates confirming this finding.

4.1 Business Applications

Using the event study specification in (2), a substantial increase in business applications is found in high TFE counties after the pandemic declaration, compared to low TFE counties. By contrast, the effects of TFE on applications in pre-pandemic periods do not exhibit any pre-trends. It is worth noting that the findings diverge from earlier research conducted by Barrios et al. (2021), where a positive relationship between frontier culture and entrepreneurship is found before the pandemic. This reinforces the main claim of this paper, namely, that the pandemic shock has had a greater impact on individuals residing in higher TFE counties, without any noticeable effects previously.

Figure 3 shows that TFE has a big positive effect on business applications after 2019. The results suggest that, relative to 2019, each additional decade of TFE in a given county is associated with 150 more business applications in 2021. Note that this is a sizeable effect given that, within the pre-treatment period, the cross-county annual mean business applications is 930. Figure 3b also suggest robust results when state-by-year fixed effects are included, a specification that is much more demanding.

Figure 4 provides a dynamic understanding of the point estimates of weighted average TFE measures from the event study specification in (1). Since the level of analysis at the state level and the aggregate TFE measures are not the same as at the county level, the coefficients should be interpreted cautiously. However, the pattern of the coefficients and their statistical significance yield support to the main results in Figure 3, capturing the dynamic pattern of the point estimates as well as providing detailed information about the exact time period (month) in which the jumps take place. The effect of frontier culture relative to February 2020 shows a sharp break in the business applications patterns starting from June 2020 which remain at high levels. Figure 5 presents the state-level results of equation (1) for other measures of TFE aggregation. Although they are noisier and interpretations are different, the results support the general conclusion.

4.2 Job Separations and Quits

The estimates from the event-study application in regression (2) for total separations are displayed in Figure 6, where the regression equation includes the same set of controls as before. According to the results, each additional decade of TFE in a given county is associated with a rise of 900 extra job separations in 2021 relative to the pre-pandemic year (2019Q3). This impact is substantial once more given that, within a county, pre-pandemic mean job separations are 7705. Furthermore, as shown in Figure 6b, adding state-by-year fixed effects does not seem to change the previous conclusions.

Figure 10b presents even-study coefficient from regression (1) for weighted average TFE on Quits. The results suggest consistent conclusions with county-level analysis. The positive jump of the impact of on Quits starts to appear after 12 months from the shock. Figure 8 shows the result also for alternative measures The standard errors are larger than before as the sample consists of 49 states in the U.S., while the county-level regressions incorporate 2040 baseline counties. Nevertheless, the dynamic paths displayed in all illustrate once more a sharp jump in the point estimates starting from March 2020. Furthermore, although the immediate impact initially suggested that individuals in high-TFE states were less likely to quit their jobs, there was a great surge in the effect of quits during the Great Resignation period, which occurred ten months after the start of the pandemic.

Overall, the results suggest that people from states with greater frontier culture have become more likely to quit their jobs after late 2020 relative to the pre-pandemic declaration. Both results indicates no pre-trends before the pandemic declaration in March 2020. This is clearer in business applications, as the point estimates exhibit a sharp jump just after the pandemic starts, than in the number of quits, but even in this case a jump is detected soon after the pandemic declaration. Therefore, the previous results can be considered as generally promising in explaining job quits and separations.

5. ROBUSTNESS CHECKS

This section considers additional time-invariant controls that may affect the labor responses to Covid-19. They are related to the frontier culture to check whether other county and state-specific confounding effects related to the infection risks for the main results can be ruled out. Second, the possibility of heterogeneous impacts by gender is discussed. Finally, conventional diff-in-diff analogs of equations (1) and (2) are also presented as well as estimated elasticities based on logged specifications of the regression.

5.1 Confirmed Covid Cases

Figures 9 and 10 display the point estimates controlling for Covid-19 confirmed cases and deaths. Note that, controlling for covid cases in the main results may create simultaneity bias. In effect, though a high level of quits could capture a reaction to high infection rates, the low infection rates could also be the result of the high level of quits. Therefore, one must be careful in interpreting the model when controlling for this variable. However, the new results do not seem to alter the previous main findings. In fact, controlling for this variable improves the estimated effects of TFE on the outcome variables in terms of statistical significance and magnitudes of the estimate. Further, this stronger evidence being also supported by the diff-diff analogs in the appendix. Appendix Tables 1-2 both document that, when the confirmed cases are included in the model, the impact of the TFE slightly increases.

5.2 Regressions in logs

As a final step, the main results from regression (2) with the dependent variables being reported in logged format (instead of levels) are presented to provide an alternative assessment of the estimated elasticities of TFE in terms of percentage changes rather than absolute changes.

According to Figure 11, each additional decade of TFE in a given county is associated with a 4% increase in business applications (Figure 11a) and 1.5 % more quits (Figure 11b). These are considerable impacts given that the within-year cross-county standard deviation is 17 % for business applications and 6.4% for quits. The results from equation (1) yield similar conclusions in Figures 12 although, as expected, they are noisier and should not be interpreted in the same magnitude. Each extra decade of average TFE for a given state is related to around 1 to 2% more business applications and 1% more quits.[10] Given that there are three decades of weighted TFE differences between first and fourth-quartile states, these effects are able to explain a considerable part of the gap displayed in Figure 2. State-level results have higher standard errors as expected. However, the dynamics of the effect support the main results.

5.3 Heterogenous Impacts of Gender on Quits

Gender studies showed that women have long faced challenges at work, including gender discrimination, income inequalities, and lack of equal opportunities. The pandemic has highlighted and exacerbated these difficulties, driving many women to consider more fulfilling and adaptable employment opportunities. Accordingly, women have been found to have quit their jobs more than men during the Great Resignation leading to even greater gender gaps in the labor market.Picchi (2021). While the pandemic has impacted women disproportionally, it has also been documented that the impact also differs by state U.S. Census Bureau (2023). Recently Bazzi et al. (2023) have shown that counties with higher TFE exhibit lower female labor force participation, signaling the importance of analyzing the Great Resignation from a gender perspective. Here I show that women in the counties with greater TFE have experienced even more quits during the Great Resignation. Figure 13 suggests slightly different impact rates for women. While each additional TFE is associated with a 1 to 1.5% increase in the male quits relative to pre-pandemic, this impact rises to 1.5-2% for women. Note that, by analyzing the quits samples differently across gender, I rule out errors caused by using the female share of the whole county in the main equation since quits female shares may differ from the population female shares.

6. CONCLUSION

The Covid-19 crisis has induced a different labor supply response than in previous recessions due to its focus on vital health care. The combination of confinement rules, mobility restrictions,

[10] Appendix Figure A.19 presents the results for also other measures.

and increasing remote job opportunities has prompted workers to realize the importance of work-life balance and their priorities. Consequently, many American workers have quit the workforce searching for better work-life balance and more satisfying career options outside of traditional salaried jobs. Accordingly, a record number of resignations accompanied a sudden jump in the number of new business applications due to increased frustration with the pandemic environment. Geographically, these jumps in quits and business applications have been fairly heterogeneous. This paper provides new empirical evidence about the crucial role that geographical-cultural orientation plays in understanding the new trends in labor supply decisions and rising entrepreneurial activities during the Great Resignation period. Particularly, our argument is that American individualism has induced new labor supply trends in response to the Covid-19 pandemic. Counties and states with higher frontier culture (more individualistic) have experienced more business applications and higher job resignations. Also, women in counties with greater TFE has been more responsive to the Great Resignation. As a result, I argue that frontier culture might be at the heart of this differential response in labor supply decisions.

The study comes with some drawbacks coming from the data sources. The available data from the U.S. Census Bureau does not directly identify how many of those quitters are the ones that applied to form a business. However, it could be argued that the increased applications and resignations occurred simultaneously due to the same covid-related frustration. Furthermore, the availability of more frequent data at the county level would also be welcome for future research as it would facilitate improving the knowledge of the dynamic evolution of the point estimates for county-level analysis.

All in all, the paper provides a significant contribution to both labor market studies on the great resignation and the cultural impacts of the frontier literature. As well as supporting long-term impacts of history, it illustrates how cultural orientations persist through generations and predict responses to unexpected events, such as pandemics.

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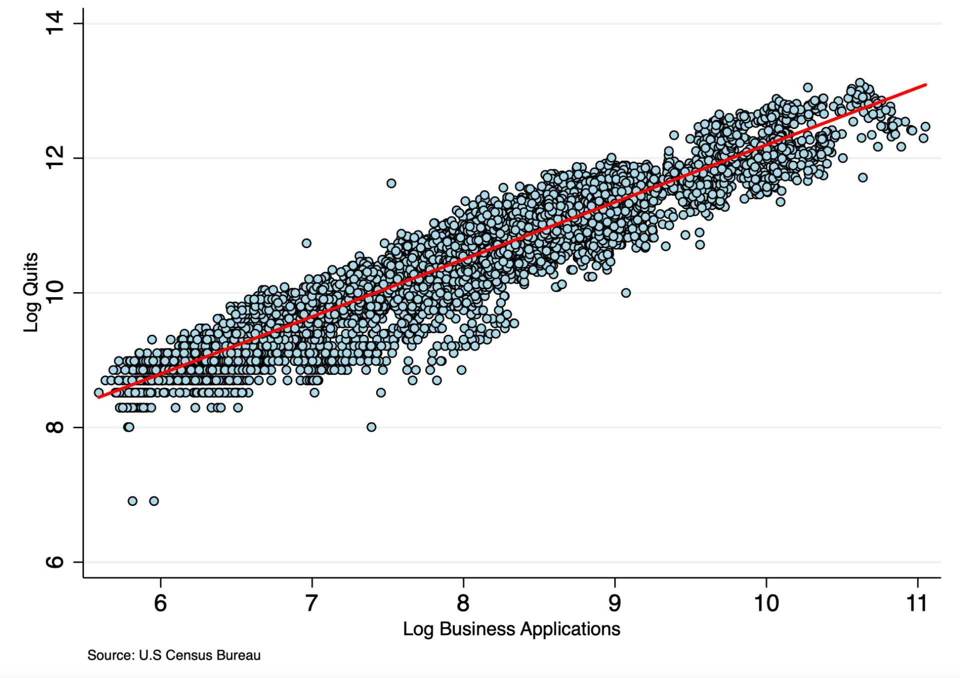
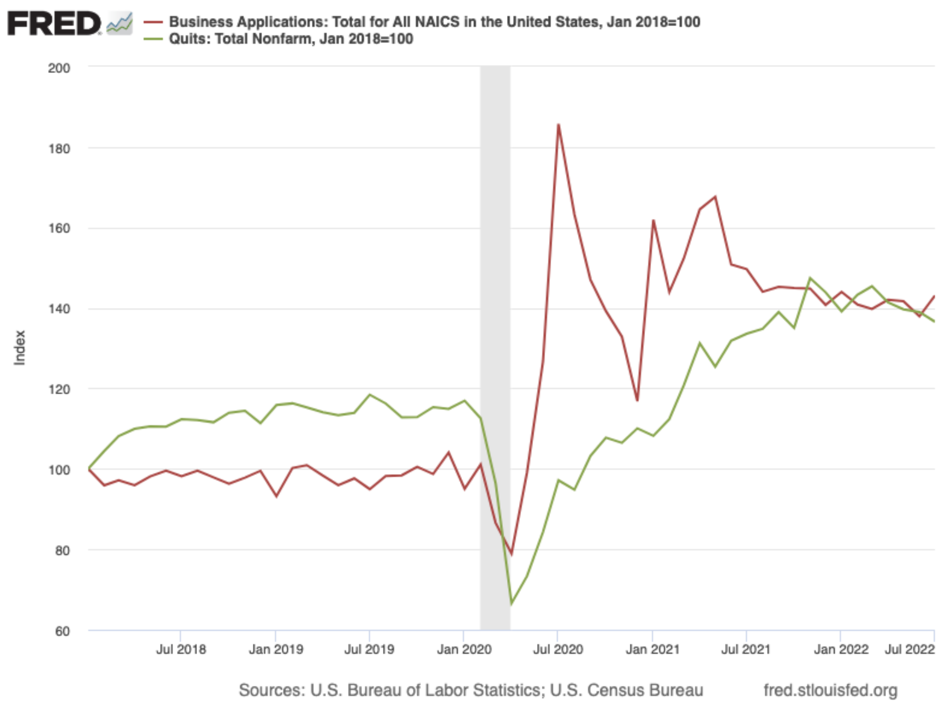


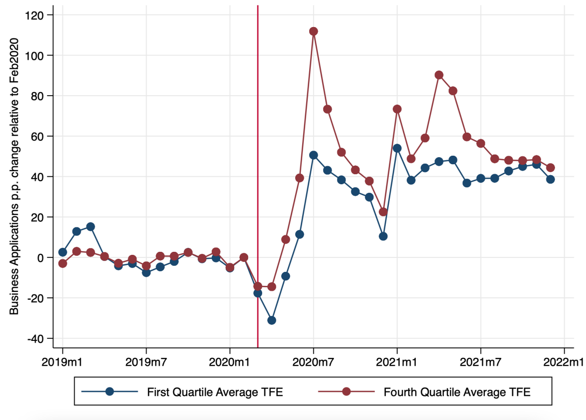
(a)



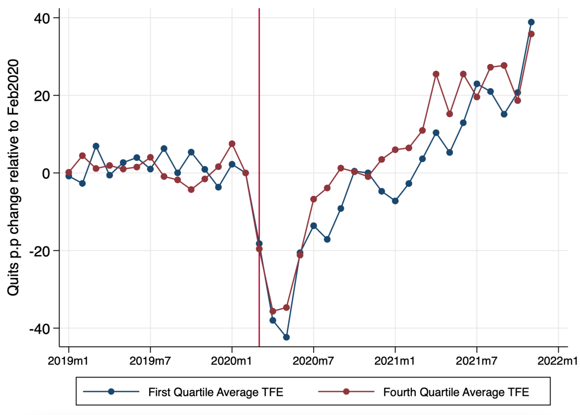
(b)

Figure 1: Co-movement of Business Applications and Quits

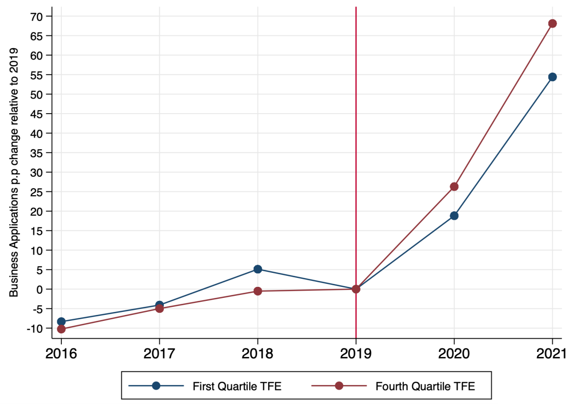
Notes: This figure illustrates the parallel rise in voluntary job quits and new business applications beginning in mid-2020. Figure from Panel (a) plots log monthly business applications against log monthly quits. Both series cover the period from 2015 to 2023. The fitted line represents a simple linear regression. Figure from Panel (b) plots their respective time trends. Both measures indicate strong co-movement during the pandemic recovery. Panel (b) shows the monthly index (January 2018 = 100) both outcomes. Business applications are reported by the U.S. Census Bureau's Business Formation Statistics (BFS), while quits are drawn from the Bureau of Labor Statistics' Job Openings and Labor Turnover Survey (JOLTS). The shaded area corresponds to the NBER-defined COVID-19 recession (February to April 2020). Data retrieved from FRED, Federal Reserve Bank of St. Louis.



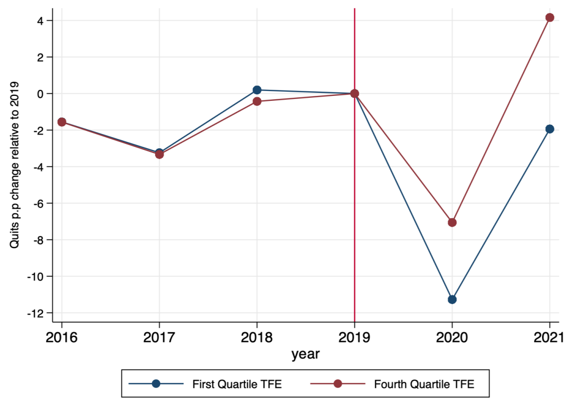
(a) Business Applications - State



(b) Quits - State



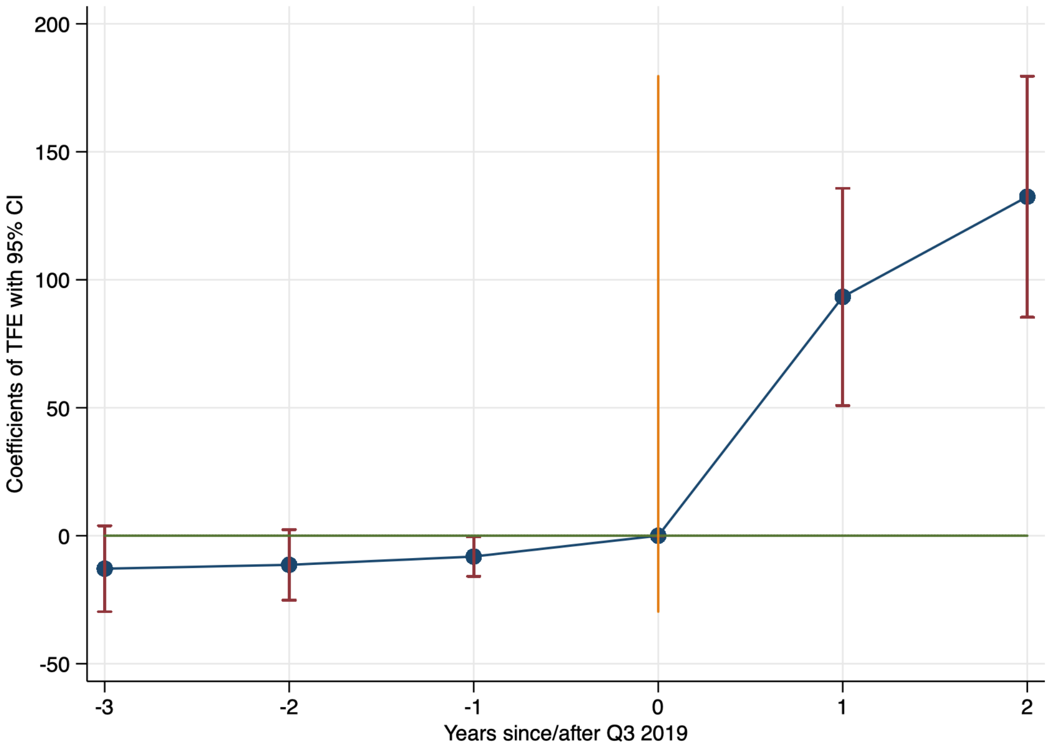
(c) Business Applications- County



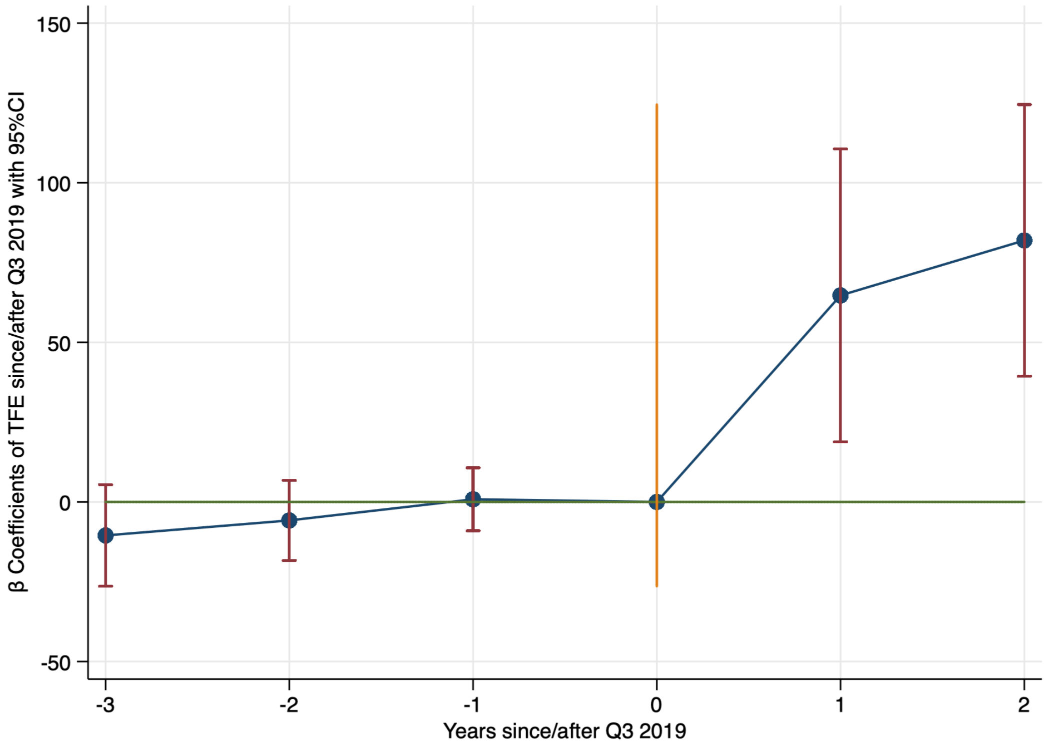
(d) Quits- County

Figure 2: Monthly State and Yearly County Basic Facts with TFE

Note: The graphs a and b show the evolution in business applications and quits in states from 2019 until January 2022. They represent the monthly p.p change relative to February 2020.The blue plot represents the percentage change relative to February 2020 for the first-quartile of states with average TFE, while the red line corresponds to the fourth-quartile states with average TFE. Figures c and d show the evolution of the same outcomes for counties in terms of yearly p.p change relative to 2019 pre-pandemic year.



(a) County and Year FE



(b) County and State by Year FE

Figure 3: Estimated Coefficients of TFE on Business Applications

Notes: The figures plot the estimated yearly coefficients from equation (2) of Total Frontier Experience (TFE) on business applications, relative to 2019, along with 95% confidence intervals. Panel (a) includes county and year fixed effects; Panel (b) adds state-by-year fixed effects. The specification controls for COVID-19 stimulus payments, personal income, demographics (age, gender, race, foreign-born share), education, and population density. Standard errors are clustered at the county level. The vertical line at event time 0 marks the beginning of the post-pandemic period.

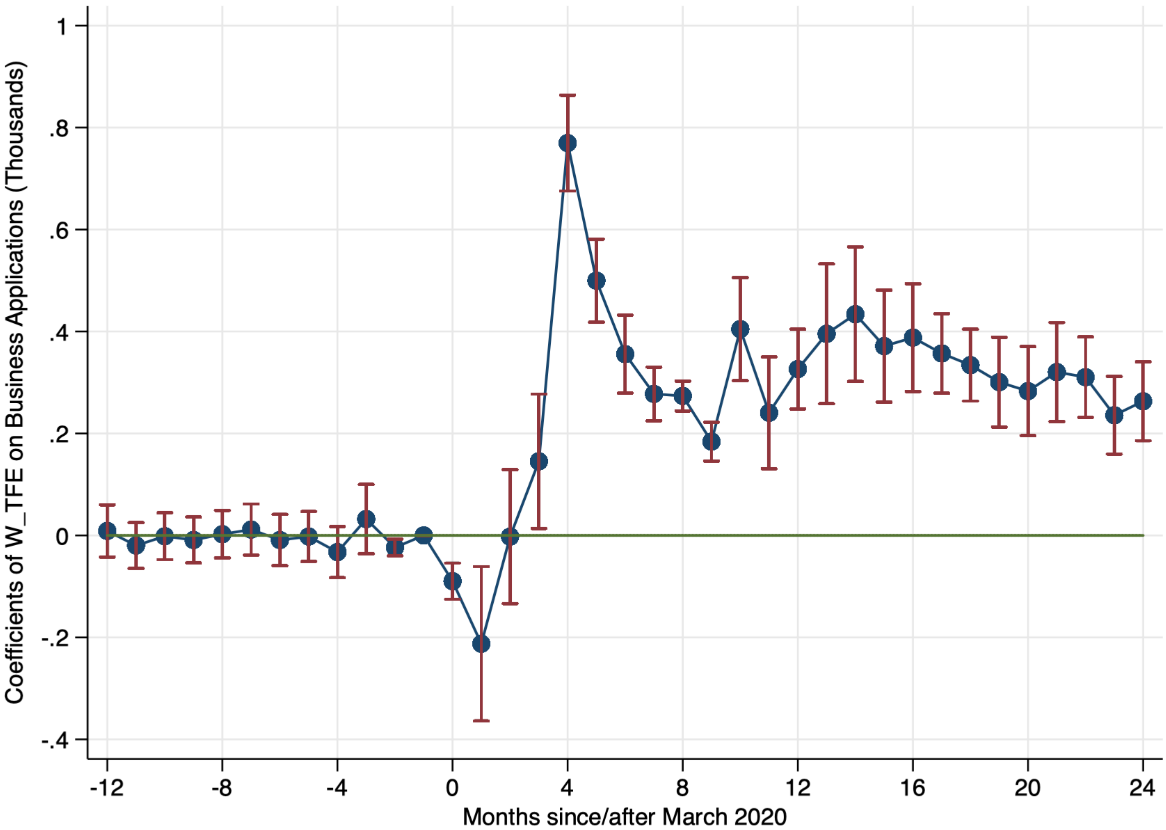
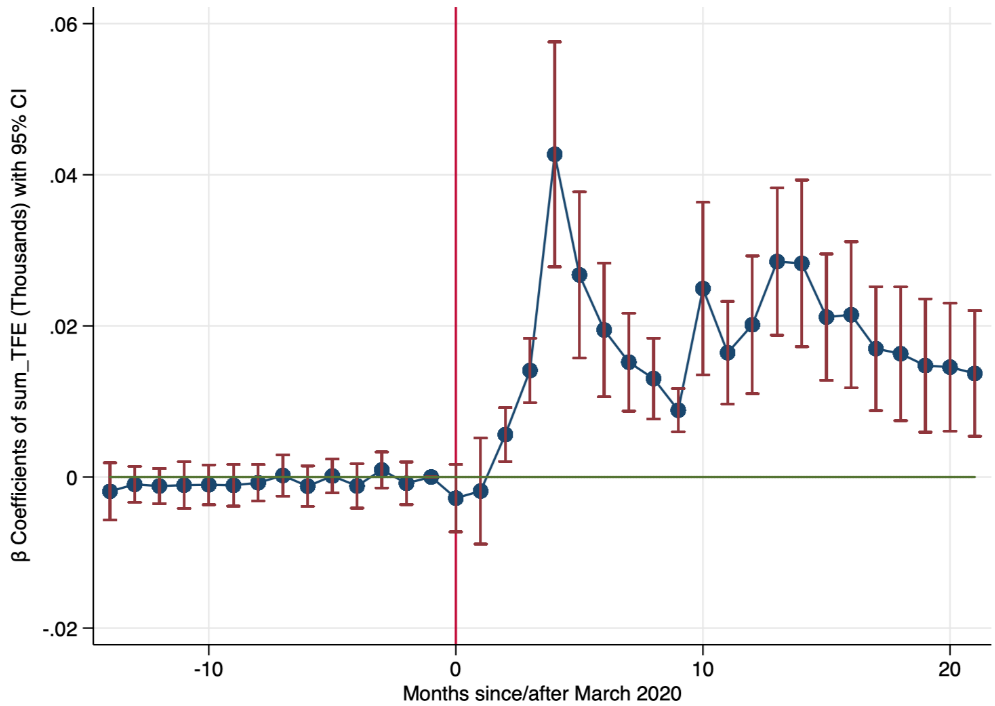
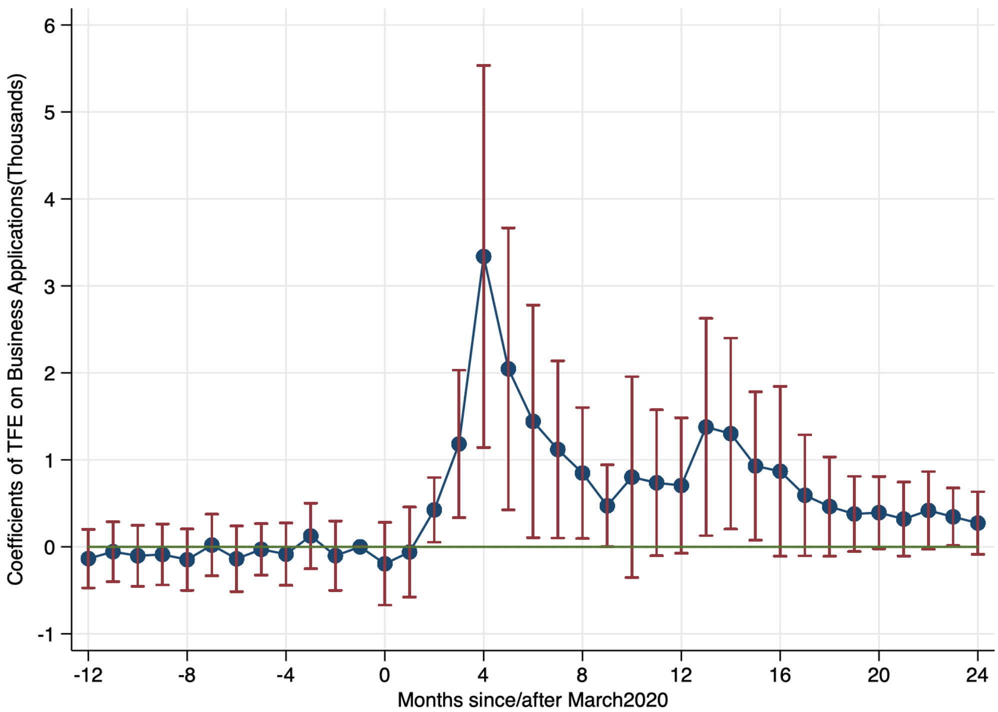


Figure 4: State Level Results on Business Applications

Notes: This Figure presents the estimated state level event-study coefficients from equation (1). The specification plots the effect of average frontier experience on monthly business applications of a state relative to February 2020, along with 95% confidence intervals. TFE measure is weighted average from main county-level frontier exposure by the population. The standard errors are clustered at the state level.



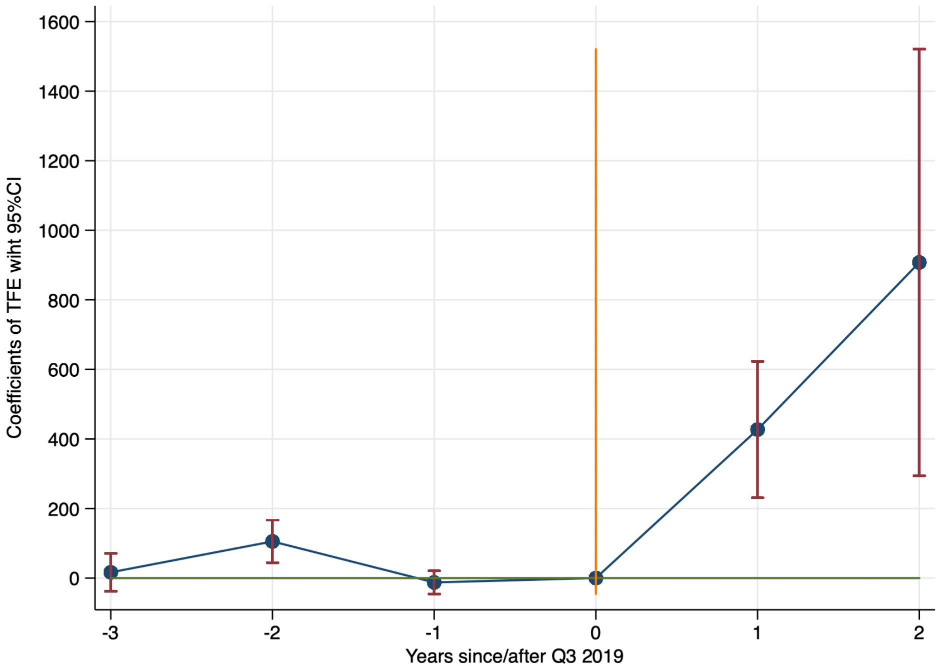
(a) Coefficients of Total TFE



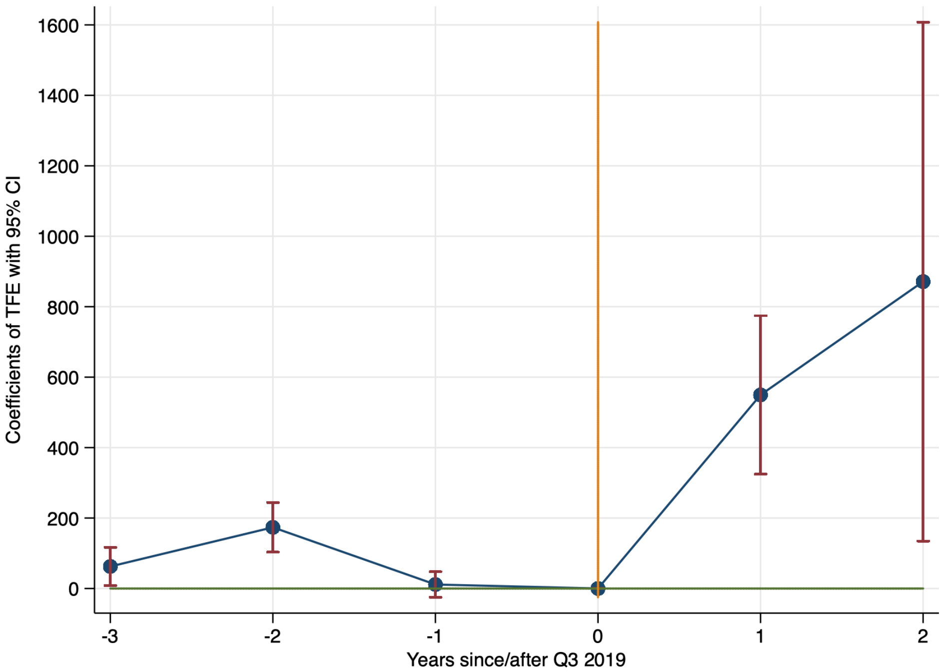
(b) Coefficients of Average TFE

Figure 5: State Level Results on Business Applications For Different TFE Measures

Notes: Figures present the estimated state level event-study coefficients from equation (2) for different ways of TFE aggregation. Figure in panel (a) plots the coefficients of total frontier exposure of of a state while Figure in panel (b) shows the effects of unweighted average TFE of a state relative to February 2020, along with 95% confidence intervals. The standard errors are clustered at the state level.



(a) County and Year Fixed Effects



(b) County and State by Year Fixed Effects

Figure 6: Estimated Coefficients of TFE on Separations

Notes: The figures plot the estimated yearly coefficients from equation (2) of Total Frontier Experience (TFE) on total separations, relative to 2019, along with 95% confidence intervals. Panel (a) includes county and year fixed effects; Panel (b) adds state-by-year fixed effects. The specification controls for COVID-19 stimulus payments, personal income, demographics (age, gender, race, foreign-born share), education, and population density. Standard errors are clustered at the county level. The vertical line at event time 0 marks the beginning of the post-pandemic period.

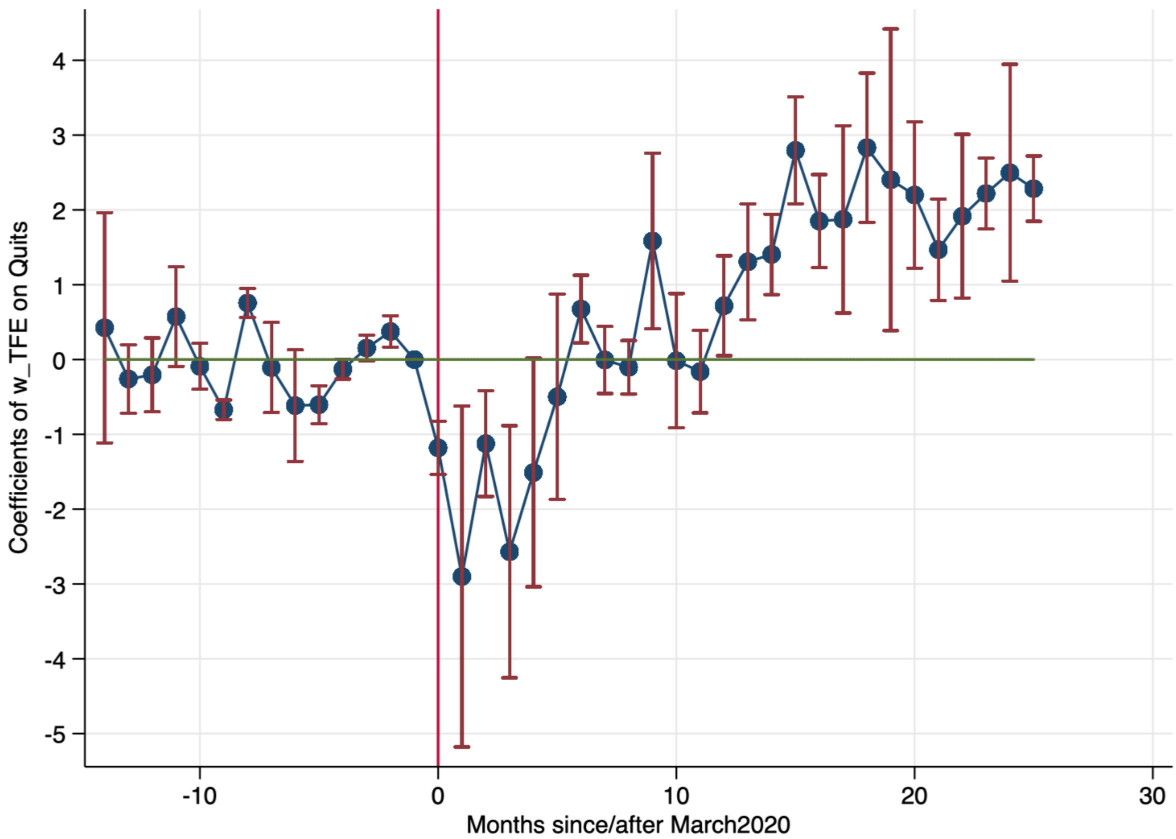
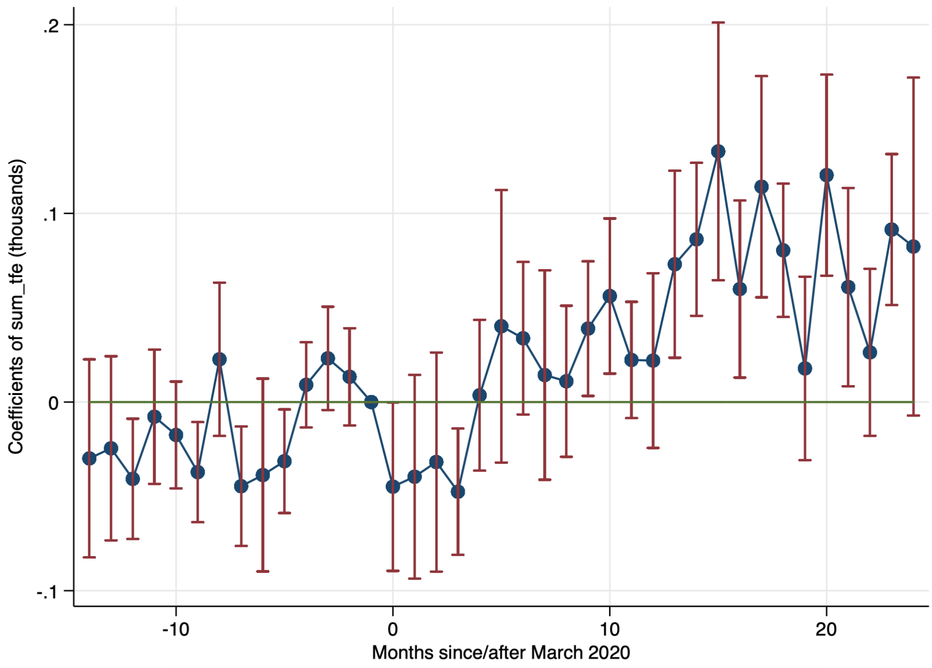
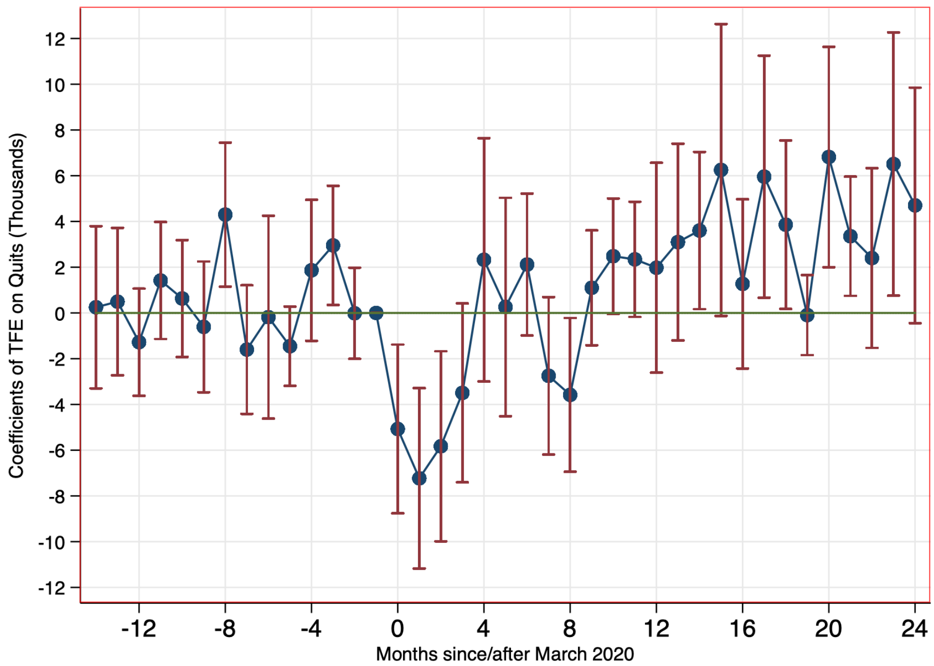


Figure 7: Coefficients of Weighted Average TFE - Quit

Notes: This Figure presents the estimated state level event-study coefficients from equation (1). The specification plots the effect of average frontier experience on monthly job quits of a state relative to February 2020, along with 95% confidence intervals. TFE measure is weighted average from main county-level frontier exposure by the population. The standard errors are clustered at the state level.



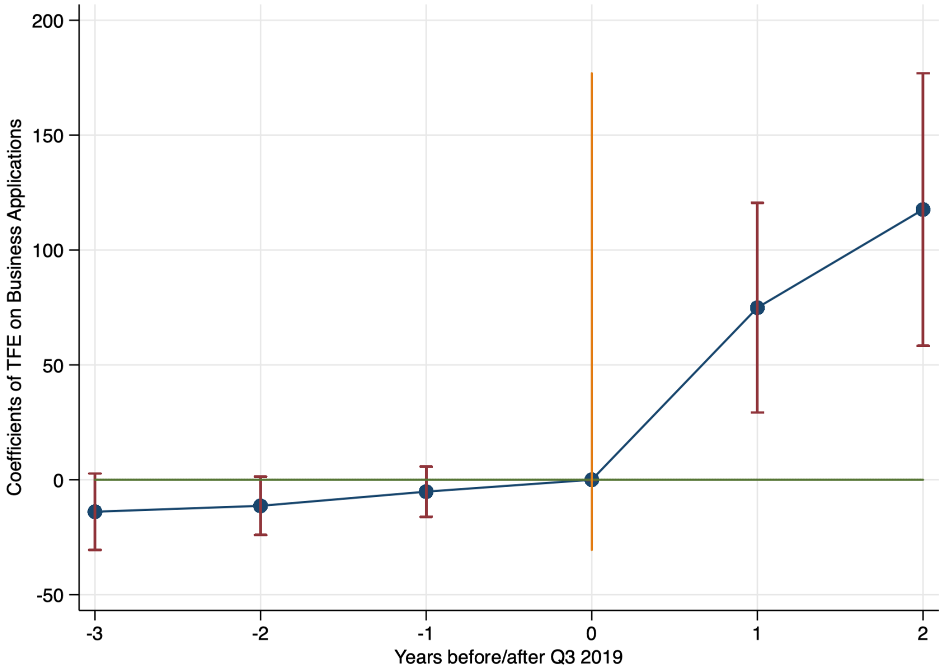
(a) Coefficients of Total TFE



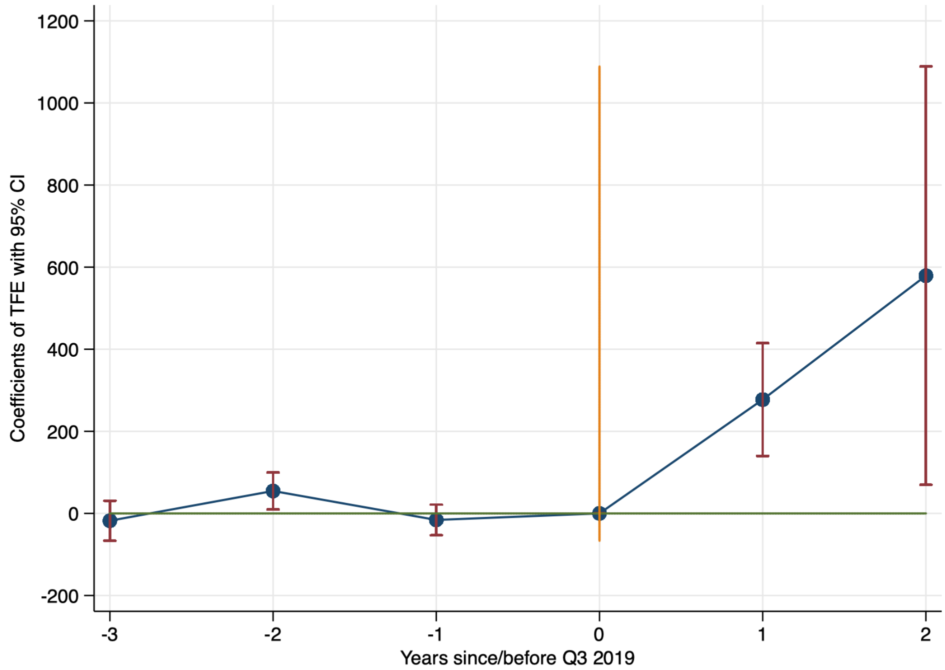
(b) Coefficients of Average TFE

Figure 8: State Level Results on Quits For Different TFE Measures

Notes: Figures present the estimated state level event-study coefficients from equation (1) for different ways of TFE aggregation. Figure in panel (a) plots the coefficients of total frontier exposure of of a state while Figure in panel (b) shows the effects of unweighted average TFE of a state relative to February 2020, along with 95% confidence intervals. The standard errors are clustered at the state level.



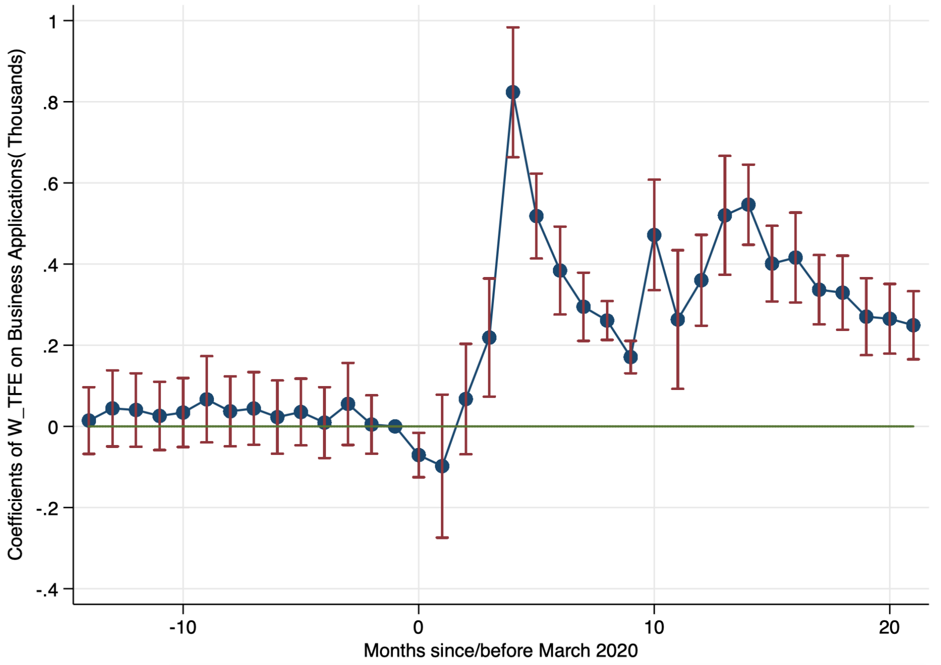
(a) Results for Business Applications



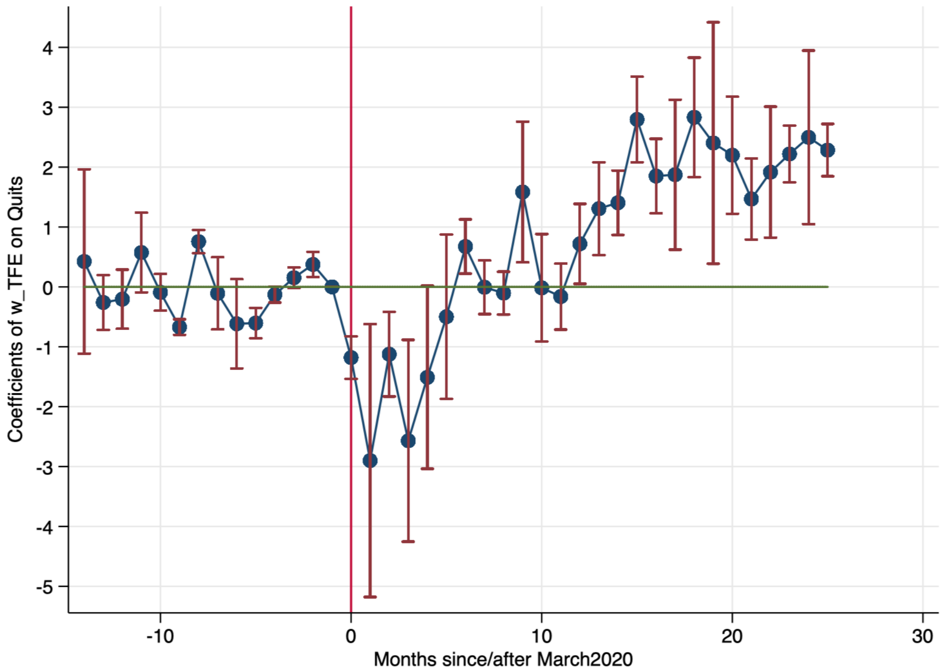
(b) Results for Total Separations

Figure 9: Estimated Coefficients of TFE - Controlling for Confirmed Cases and Deaths

Notes: Figures represent the yearly coefficient estimations from the equation (2) controlling for confirmed covid cases and deaths. Panel (a) presents the effects on business applications while Panel (b) on total separations. The standard errors are clustered by counties. Red lines show the 95% confidence intervals.



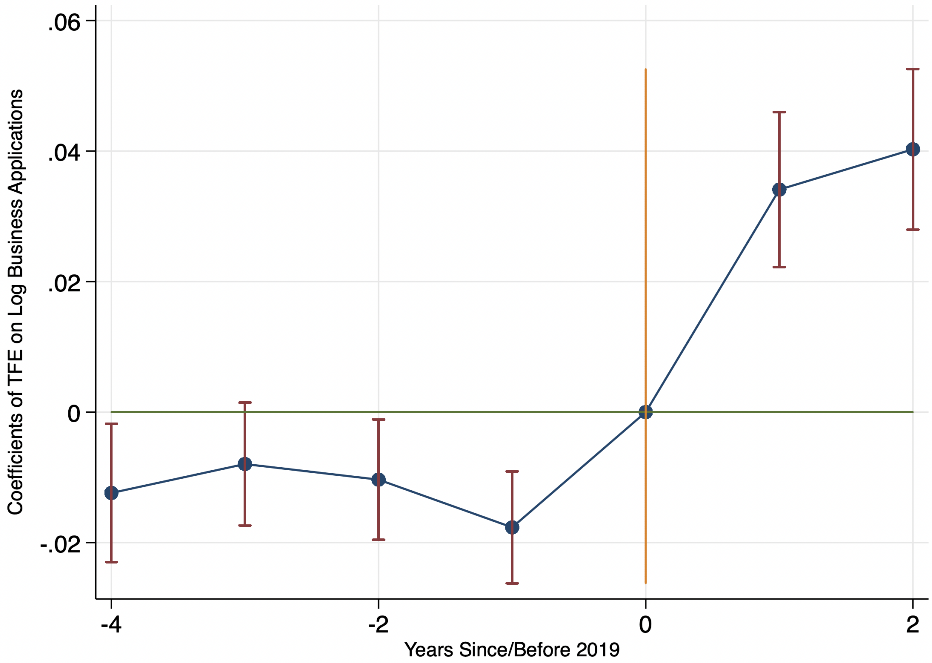
(a) Coefficients of Weighted Average TFE - BA



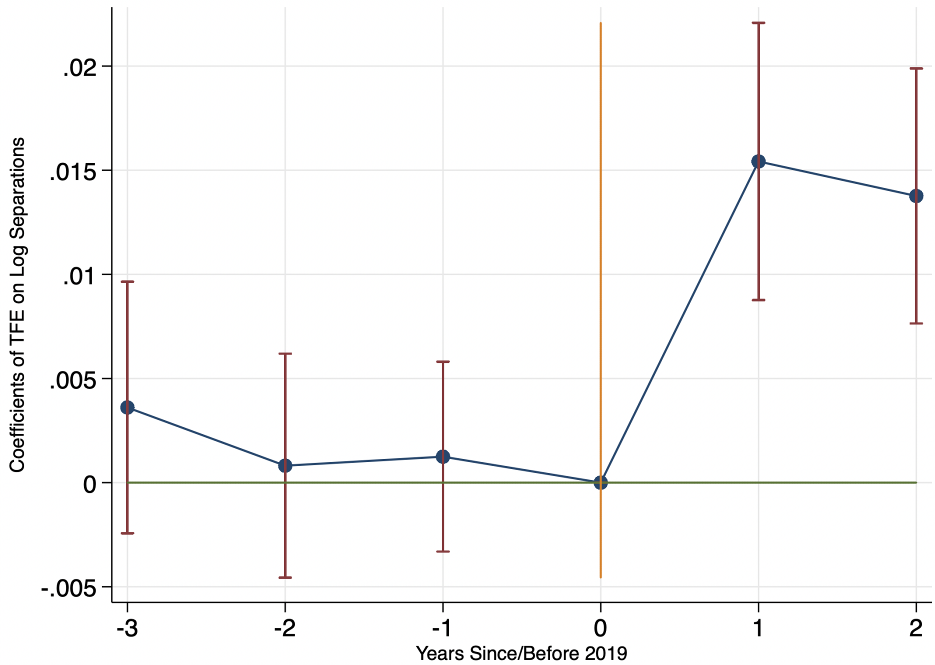
(b) Coefficients of Weighted Average TFE - Quit

Figure 10: State-Level Results on Business Applications and Quits - Controlling Covid Cases and Deaths

Note: Figures represent the monthly coefficient estimates from the equation (1) controlling for confirmed covid cases and deaths. Panel (a) presents the effects on business applications while Panel (b) on job quits. The standard errors are clustered by counties. Red lines show the 95% confidence intervals.



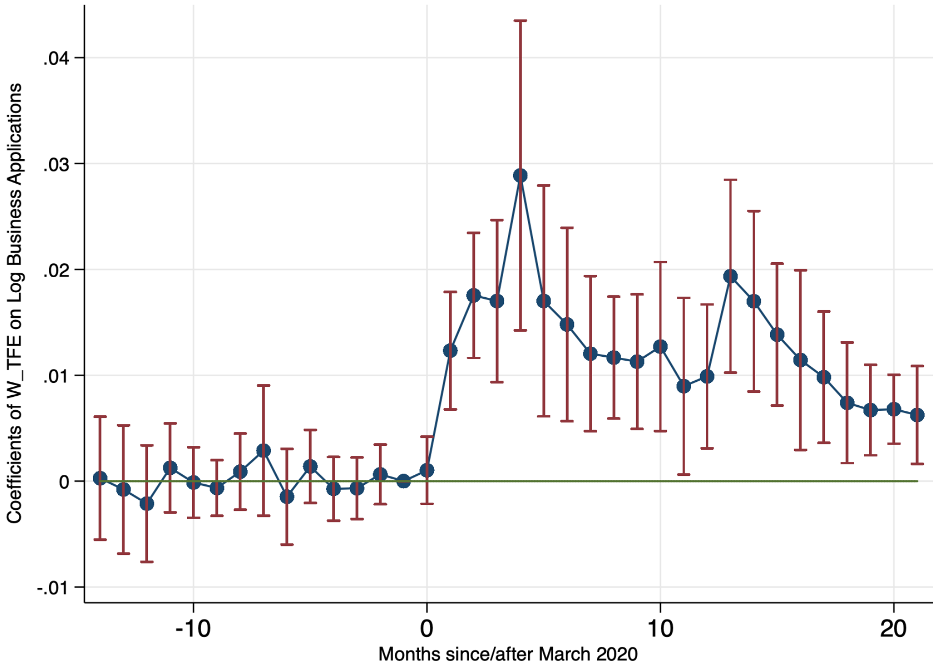
(a) Results for Log Business Applications



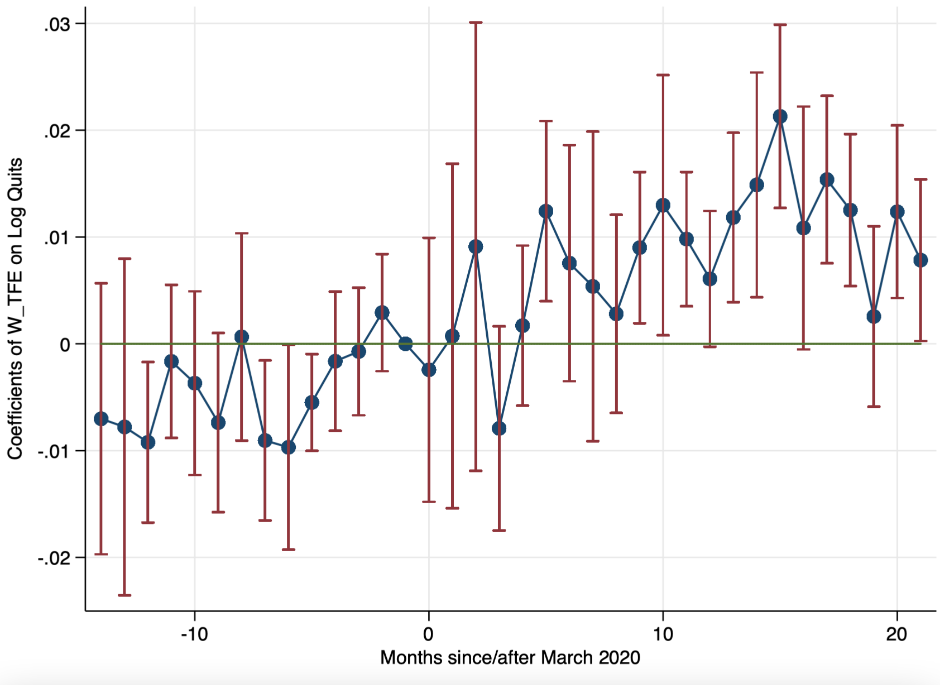
(b) Results for Log Total Separations

Figure 11: Estimated Coefficients of TFE

Note: Figures represent the event-study coefficient estimates from the equation (2) using logged outcomes. Panel (a) presents the effects on log business applications while Panel (b) on log job separations. The standard errors are clustered by counties. Red lines show the 95% confidence intervals.



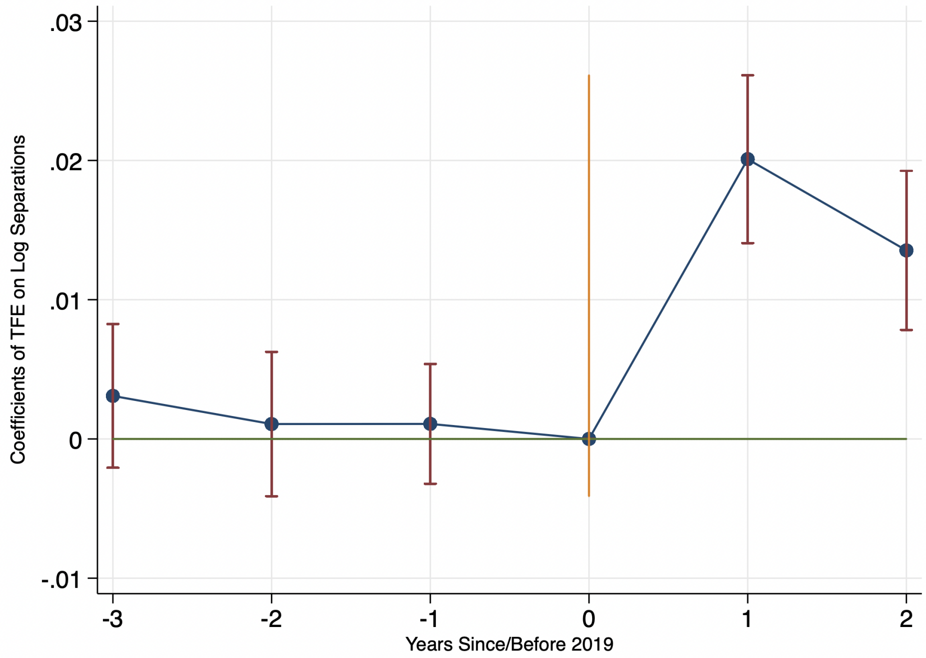
(a) Coefficients of Weighted Average TFE - Log BA



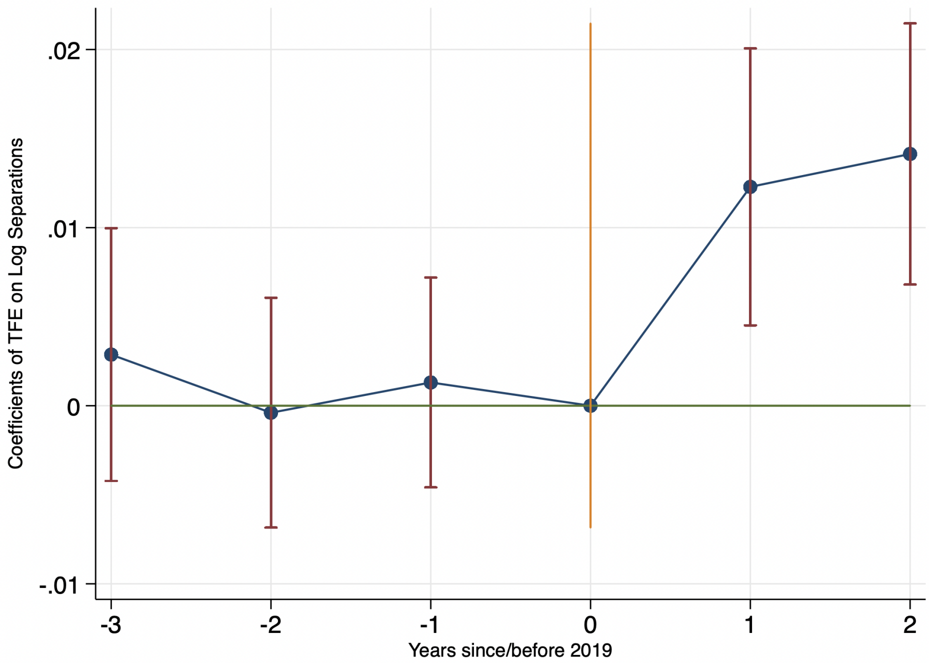
(b) Coefficients of Weighted Average TFE - Log Quit

Figure 12: Estimated Coefficients of TFE

Note: Figures represent the event-study coefficient estimates from the equation (1) using logged outcomes. Panel (a) presents the effects on log business applications while Panel (b) on log job quits. The standard errors are clustered by counties. Red lines show the 95% confidence intervals.



(a) TFE Impact for Female



(b) TFE Impact for Male

Figure 13: Estimated Coefficients of TFE on Separations By Gender

Notes: Figures represent the yearly coefficient estimations from the equation (2) controlling for government transfers and demographics by gender. The standard errors are clustered by counties. Red lines show the 95% confidence intervals.

Appendix A. Appendix

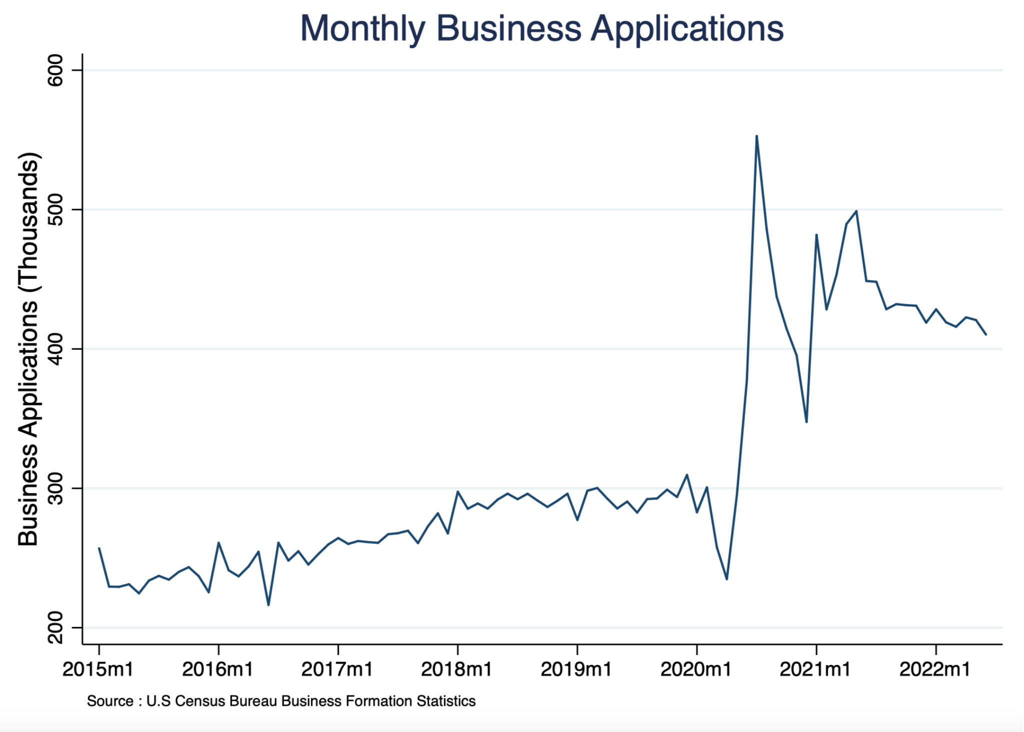


Figure A.15

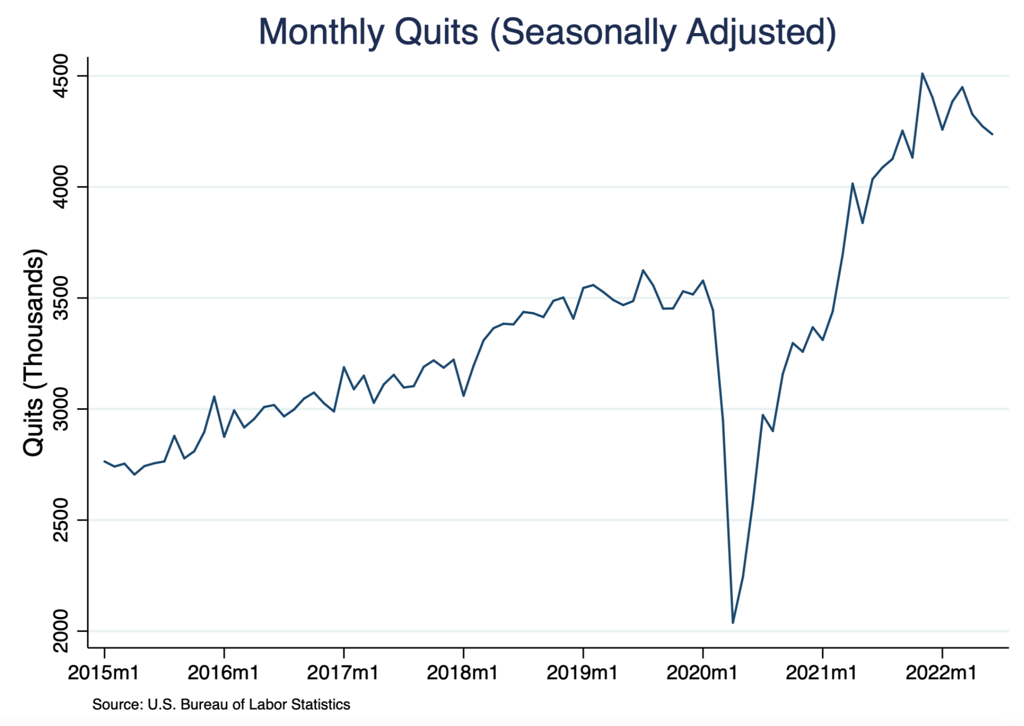


Figure A.16

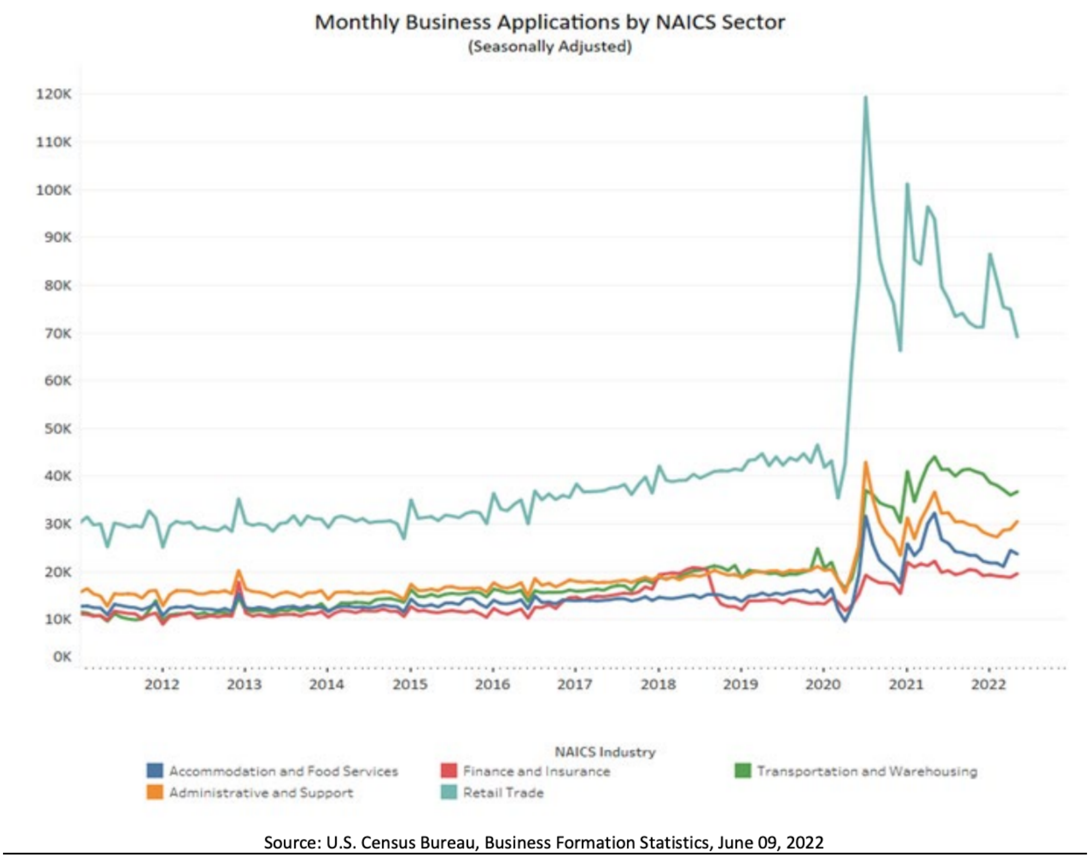


Figure A.14: Business Applications Jumps by Sector

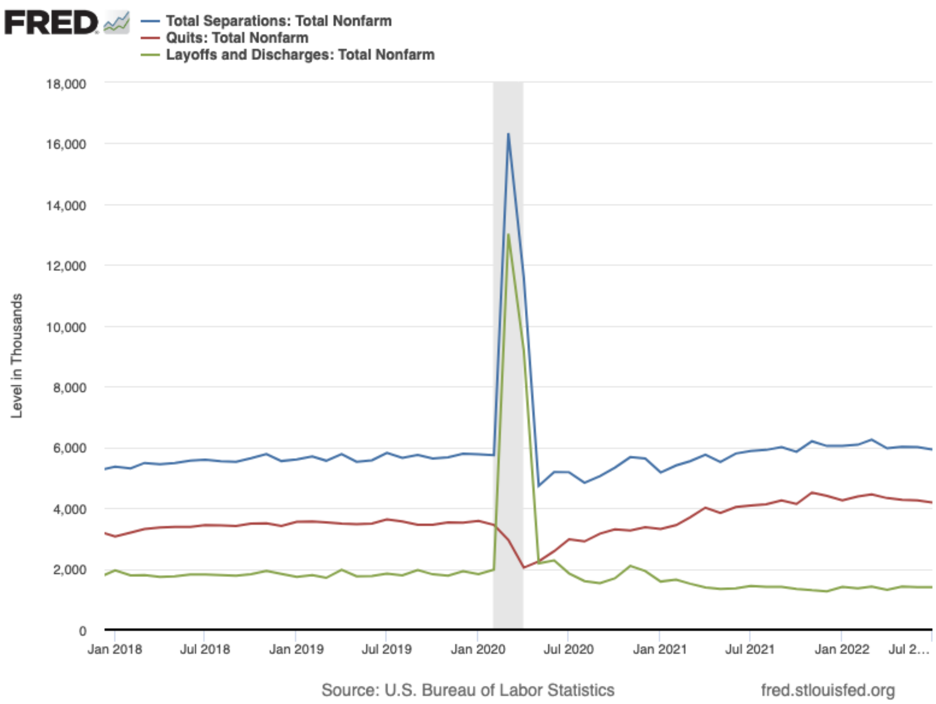


Figure A.17: U.S. Bureau of Labor Statistics, Total Separations,Quits & Layoffs, retrieved from FRED, Federal Reserve Bank of St. Louis

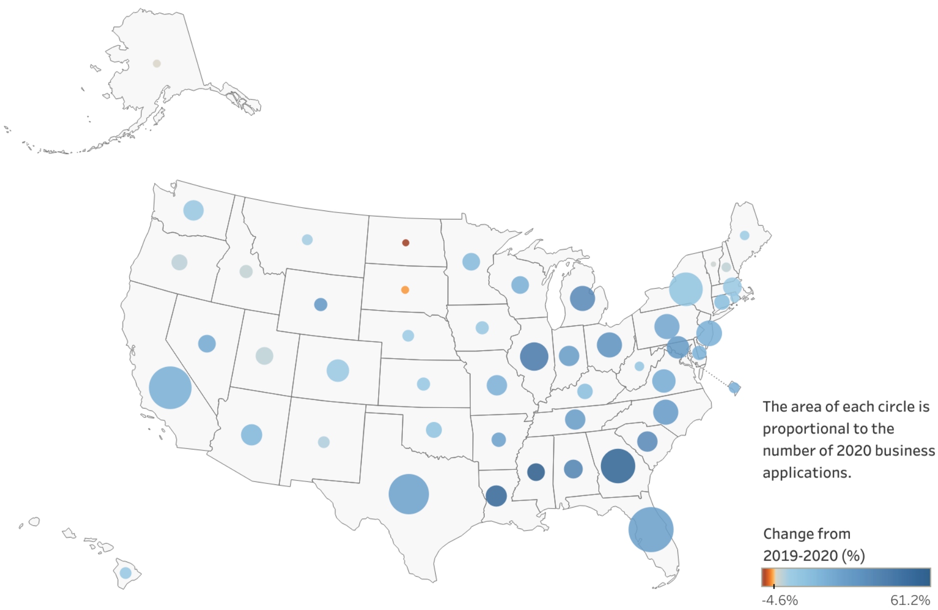
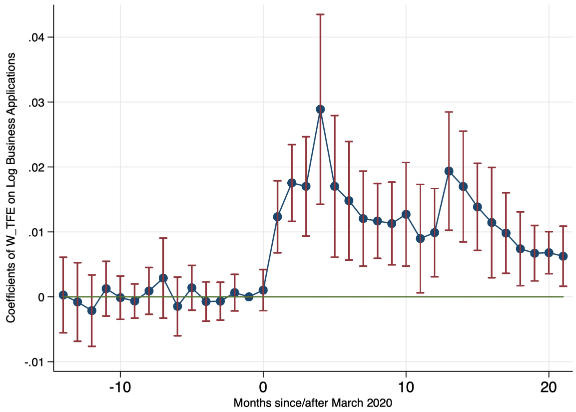
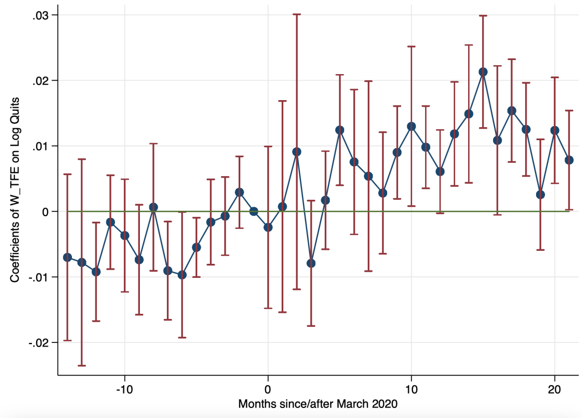


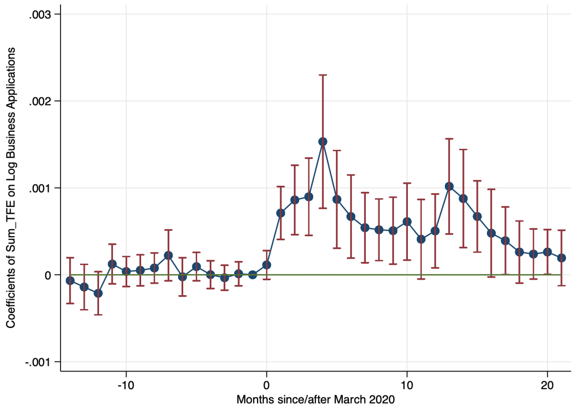
Figure A.18: Change of Business Applications by Geography by US Census Bureau



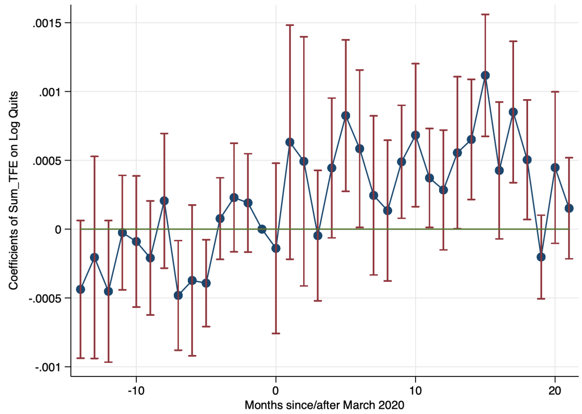
(a) Coefficients of Weighted Average TFE - Log BA



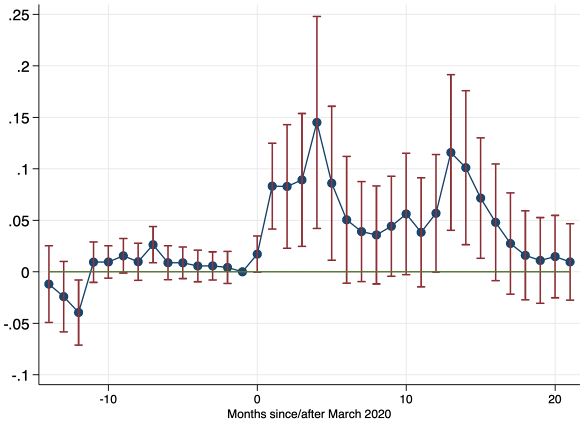
(b) Coefficients of Weighted Average TFE - Log Quit



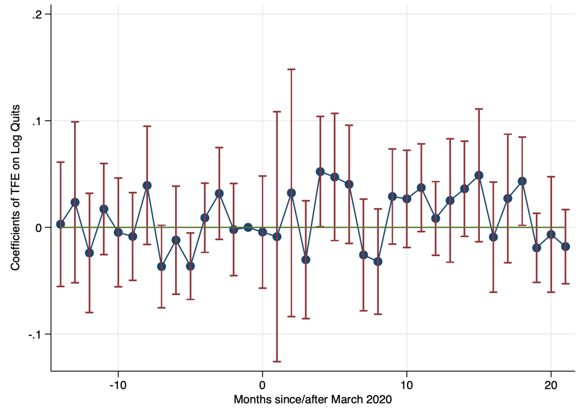
(c) Coefficients of Total TFE - Log BA



(d) Coefficients of Total TFE - Log Quit



(e) Coefficients of Average TFE - Log BA



(f) Coefficients of Average TFE - Log Quit

Figure A.19: State-month FE Results on Log Business Applications and Log Quits

Note: The figures represent the monthly coefficient estimates from the equation 2. The standard errors are clustered at the state level.

Geography	County	State	State	State
Statistics	TFE	Average TFE	Weighted Average TFE	Cumulative TFE
Mean	1,422646	1,11	3,063566	90,80439
Std	1,262793	0,8202334	5,2467	95,725
Min	0	0	0	0
Max	6,3	3,013836	27,81827	479,2
P25	0,3	0,2835821	0,1148	10,4
P50	1,2	1,235294	1,438919	61
P75	2,1	1,716667	4,142972	155,6

Table A.1: Descriptives of Total Frontier Experience

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	BA	BA	BA	BA	BA	BA	Log BA	Log BA
Post-2019=1	773.4***	-531.1***	-528.6***	-491.5***	-1460.2***	-989.1***	0.219***	0.320***
	(162.2324)	(70.8588)	(72.1438)	(57.7648)	(243.2917)	(245.1686)	(0.0111)	(0.0472)
Post-2019=1 × TFE	-157.9*	125.7***	125.3***	129.2***	130.8***	61.04**	0.0419***	0.0356***
	(68.6038)	(28.6353)	(28.6719)	(28.1934)	(28.4739)	(22.2474)	(0.0054)	(0.0051)
Post-2019=1 × Governmet Transfers		0.00360	0.00379	0.00761*	0.00696*	0.00723*		-0.000000206
		(0.0030)	(0.0033)	(0.0031)	(0.0029)	(0.0031)		(0.0000)
Post-2019=1 × Population Density			-0.0233	-0.177*	-0.165	-0.162		0.0000160*
			(0.0347)	(0.0861)	(0.0855)	(0.0879)		(0.0000)
Post-2019=1 × Income				0.00000199	0.00000136	0.000000834		-1.08e-09*
				(0.0000)	(0.0000)	(0.0000)		(0.0000)
Post-2019=1 × Race					-1126.2*	-948.2		-0.142*
					(470.5904)	(509.8583)		(0.0578)
Post-2019=1 × AGE 65+					22.68**	31.88***		-0.0179***
					(7.7038)	(7.4468)		(0.0018)
Post-2019=1 × Foreign Born					(19.0794)	(19.5796)		(0.0021)
Post-2019=1 × Collage Graduates					(5.3073)	(7.1305)		(0.0018)
Post-2019=1 × Retirement					(192.0724)	(191.4053)		(0.0449)
Post-2019=1 × Net Migration Rate					-10.68*	-15.36**		-0.000644
					(4.2472)	(5.1147)		(0.0011)
Confirmed cases					10.31***	12.62***		0.00614***
					(1.8763)	(2.0389)		(0.0002)
Mean_Dep_V	1013	1013	1013	1013	1013	1013	5	5
N	11669	11669	11663	11663	11663	11663	11658	11652
Number_of_County	2040	2040	2040	2040	2040	2040	2040	2040
State_Time_FE	No	No	No	No	No	Yes	No	No

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.2: County-Yearly Estimation of Business Applications

	(1) Sep	(2) Sep	(3) Quit	(4) Sep	(5) Sep	(6) Quit	(7) Sep	(8) log Sep	(9) Log Sep
Post-2019=1	-2152.4228***	-288.3751	-332.9970	-367.0378	-966.0708	2579.1380*	3293.1421**	-0.0564***	
	(394.1113)	(217.4777)	(210.9676)	(201.8107)	(573.3423)	(1135.0089)	(1236.8048)	(0.0068)	
Post-2019=1 × TFE	649.7338***	228.2825**	231.1123**	226.4277**	194.9439*	176.8267*	55.5132	0.0132***	0.0084**
	(167.7179)	(83.0932)	(81.4092)	(80.1518)	(86.2751)	(85.7670)	(90.0285)	(0.0034)	(0.0032)
Post-2019=1 × Governmet Transfers		-0.0652***	-0.0692***	-0.0739***	-0.0736***	-0.0729***	-0.0679***		0.0000
		(0.0099)	(0.0095)	(0.0104)	(0.0107)	(0.0106)	(0.0102)		(0.0000)
Post-2019=1 × Population Density			0.2399	0.3485	0.2747	0.1847	0.2303		-0.0000***
			(0.1678)	(0.3850)	(0.3952)	(0.4026)	(0.3797)		(0.0000)
Post-2019=1 × Income				0.0000	0.0000	0.0000	0.0000		0.0000
				(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)
Post-2019=1 × Race					2571.7667*	3667.0143**	-339.9158		-0.0715
					(1230.1097)	(1191.3469)	(1125.7737)		(0.0561)
Post-2019=1 × AGE 65+					-68.4439**	-63.4443**	-61.9024**		-0.0010
					(22.5839)	(21.8764)	(23.7717)		(0.0010)
Post-2019=1 × Foreign Born					(54.3811)	(53.7108)	(52.8185)		(0.0015)
Post-2019=1 × Collage Graduates					(17.2737)	(16.9083)	(23.1175)		(0.0009)
Post-2019=1 × Retirement					(1092.5700)	(1112.7121)	(1187.4148)		(0.0234)
Post-2019=1 × Net Migration Rate					36.3359**	37.1227**	32.6211*		0.0038***
					(13.8293)	(13.8107)	(16.6121)		(0.0005)
Confirmed cases						-9.6275	-10.2937		0.0036***
						(5.5941)	(5.7917)		(0.0001)
Mean_Dep_V	6324	6324	6324	6324	6324	6324	6324	7	7
N	11506	11506	11506	11506	11506	11506	11506	11506	11506
Number_of_County	2040	2040	2040	2040	2040	2040	2040	2040	2040
State_Time_FE	No	No	No	No	No	No	Yes	No	No

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: County-Yearly Estimation of Quits

	(1) BA	(2) BA	(3) BA	(4) BA	(5) BA	(6) BA	(7) BA	(8) BA	(9) BA	(10) LOGBA	(11) LOGBA	(12) LOGBA
Post-March2020=1 × w_TFE	0.386***	0.192*	0.240*							0.00878*		
	(10.95)	(2.04)	(2.48)							(2.65)		
Post-March2020=1 × Impact Payments		0.000000769***	0.000000438		0.00000146*	0.00000147*		0.000000850*	0.000000852*			
		(4.28)	(1.14)		(2.58)	(2.51)		(2.29)	(2.27)			
Post-March2020=1 × Foreign Rate			-0.217		-0.419*	-0.420*		-0.237	-0.237			
			(-1.81)		(-2.29)	(-2.26)		(-1.60)	(-1.60)			
Post-March2020=1 × Population Density			0.00000513		0.00000899	0.00000900		0.00000829*	0.00000829*			
			(1.79)		(1.75)	(1.74)		(2.10)	(2.08)			
Post-March2020=1 × White			-0.000868		-0.000302	-0.000262		-0.000802	-0.000779			
			(-0.53)		(-0.25)	(-0.18)		(-0.58)	(-0.48)			
Post-March2020=1 × Age 65+			0.608		-0.522	-0.528		0.0572	0.0541			
			(1.16)		(-0.65)	(-0.64)		(0.11)	(0.10)			
Covid Cases/pop			0.0000352			-0.0000157			-0.00000879			
			(0.17)			(-0.09)			(-0.05)			
Post-March2020=1 × TFE				1.365*	0.515	0.515					0.0552*	
				(2.23)	(1.22)	(1.22)					(2.25)	
Post-March2020=1 × sum_TFE							0.0190***	0.0101*	0.0101*			0.000595***
							(4.22)	(2.02)	(2.02)			(4.02)
N	1,728	1,728	1,644	1,728	1,644	1,644	1,728	1,644	1,644	1,728	1,728	1,728
Mean_Dep_Variable	7.6	7.6	7.6	7.6	7.6	7.6	7.6	7.6	7.6	8.3	8.3	8.3

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4: State-Monthly Estimation of Business Applications

	(1) Quit	(2) Quit	(3) Quit	(4) Quit	(5) Quit	(6) Quit	(7) Quit	(8) Quit	(9) Quit	(10) Log Quit	(11) Log Quit	(12) Log Quit
Post-March2020	-0.5297	-0.4191	-1.2974	-0.9182	-3.9834	-3.0464	-1.9487	-3.5226	-2.7900	-0.0255	-0.0270	-0.0409**
	(1.0237)	(1.1474)	(1.4989)	(1.2949)	(2.4351)	(2.0182)	(1.0878)	(1.8610)	(1.5725)	(0.0134)	(0.0185)	(0.0151)
Post-March2020=1 × w_TFE	0.6746*	0.6859	0.9041*							0.0059		
	(0.3185)	(0.3504)	(0.3488)							(0.0031)		
Post-March2020=1 × Impact Payments		0.0000	0.0000		0.0000	0.0000		0.0000	0.0000			
		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)			
Post-March2020=1 × Foreign Rate			-0.9836		-1.0829	-1.0043		-0.7636	-0.7425			
			(0.8799)		(1.1545)	(0.9114)		(1.2005)	(0.9406)			
Post-March2020=1 × Population Density			0.0000*		0.0001*	0.0000*		0.0001**	0.0000**			
			(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)			
Post-March2020=1 × White			-0.0403*		0.0176	-0.0347*		0.0112	-0.0393*			
			(0.0154)		(0.0090)	(0.0145)		(0.0089)	(0.0155)			
Post-March2020=1 × Age 65+			-3.7083		-5.3093	-3.6697		-5.8905	-4.1883			
			(2.7784)		(3.5694)	(2.9414)		(3.3981)	(2.8596)			
Covid Cases/pop			0.0184***			0.0187***			0.0184***			
			(0.0049)			(0.0047)			(0.0047)			
Post-March2020=1 × TFE				2.1872	2.0563	1.5184					0.0173	
				(1.6311)	(1.6833)	(1.2919)					(0.0164)	
Post-March2020=1 × sum_TFE							0.0381**	0.0500***	0.0404***			0.0004**
							(0.0122)	(0.0142)	(0.0114)			(0.0001)
N	1,764	1,764	1,680	1,764	1,680	1,680	1,764	1,680	1,680	1,764	1,764	1,764
Mean_Dep_Variable	71	71	71	71	71	71	71	71	71	11	11	11

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.5: State-Monthly Estimation of Quits