HUSTLING FROM HOME? WORK FROM HOME FLEXIBILITY AND ENTREPRENEURIAL ENTRY*

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First Version: April 14, 2024

This Version: March 1, 2025

We examine the influence of the growing trend of work-from-home (WFH) on new business formation, with a particular focus on the period surrounding the COVID-19 pandemic. At baseline, local new business entry is positively associated with the proportion of occupations amenable to telework in the region. Utilizing the advent of the COVID-19 pandemic and the implementation of stay-at-home mandates as an exogenous shock, we examine the effects of realized flexibility for WFH on entrepreneurial entry. While overall new business registrations increased following pandemic stay-at-home mandates, areas with an occupational mix that has higher potential for telework demonstrate less pronounced growth in new business formation, particularly in regions with lower economic demand factors. Survey evidence highlights how flexibility provided by traditional employment reduces entrepreneurial intent, especially for workers seeking non-pecuniary benefits such as autonomy or flexibility. Consistent with this substitution effect, we observe significant gender disparities, with a notable decline in women-led startups in areas with greater telework potential. Our results suggest a nuanced tension between the attractiveness of flexibility in traditional employment and the autonomy provided by entrepreneurial entry.

JEL Codes: J22, L26, M13, J10

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*We thank numerous colleagues for their thoughtful feedback and comments. We are grateful to the Startup Cartography Project for the provision of data used in this project. All errors are our own. Corresponding Author: John M Barrios (john.m.barrios@yale.edu), Yale SOM, Washington University in St Louis Olin School of Business & NBER.

1. INTRODUCTION

Labor markets have undergone transformative changes in recent years. Work-from-home (WFH) has emerged as a pivotal feature in contemporary workplace dynamics, with the potential to fundamentally reshape employment and business practices (Barrero, Bloom, and Davis, 2023). The shift to flexible WFH arrangements, fueled in part by technological advancements, and dramatically accelerated by the COVID-19 pandemic (Hansen, et. al., 2023), marks a significant paradigm shift in the conceptualization and execution of work. The flexibility inherent in WFH arrangements not only effects traditional business models and workforce management, but may also have potential implications for entrepreneurial dynamics.

Predictions regarding how the availability of WFH affects motivations for entrepreneurial entry point in multiple directions. On one hand, increased flexibility in traditional employment might encourage some individuals to engage in entrepreneurship. Greater control over work schedules resulting from WFH may allow would-be entrepreneurs to invest time in developing business ideas while still being employed or allow them to engage in entrepreneurship as a "side hustle," thus empowering more individuals to experiment with entrepreneurial activities (Barrios et al., 2022). On the other hand, this same flexibility could lead to a decrease in entrepreneurial activity. Traditionally, one of the primary motivators for entrepreneurship has been its promise of greater autonomy, including the flexibility to set one's own hours and work environment (Hurst and Pugsley, 2011). The rise of WFH availability in traditional employment, however, may offer similar benefits of flexibility and autonomy, potentially reducing the comparative advantage of entrepreneurship from a non-pecuniary benefit perspective. As a result, the incentive to undertake the risks associated with starting a new business in pursuit of flexibility may be reduced. The transition to widespread WFH post-pandemic thus raises an important yet nuanced economic question: How does the increased flexibility afforded by WFH influence the landscape of new business formation?

To explore this question, we leverage a measure of pre-pandemic WFH potential developed by Dingel and Neiman (2020) and further disaggregated by Gupta, Mittal, Peeters, and Van Nieuwerburgh (2022), which classifies the feasibility of teleworking across various occupations and merges this classification with occupational employment counts in different US regions. This

measure serves as our main proxy for the ex ante regional feasibility of WFH.[1] We combine this measure with a detailed, census-like database of new business registrations across the US, sourced from the Startup Cartography Project (Guzman and Stern, 2020). To capture the individual motivations and decision-making processes behind entrepreneurial entry during the WFH shift, we augment our archival data analysis with a survey targeting individuals who faced WFH opportunities during the pandemic. The survey responses offer valuable insights into how flexibility in traditional employment influenced their decisions to pursue entrepreneurship.

The onset of the COVID-19 pandemic and the subsequent enactment of stay-at-home mandates offer a unique natural experiment that enables us to shift focus from the theoretical *potential* of teleworking to its practical, real-world application and consequences (Barrero, Bloom, and Davis, 2023b). We investigate how the sudden, widespread adoption of WFH practices resulting from stay-at-home mandates influenced entrepreneurial entry, particularly in regions with varying degrees of pre-pandemic telework potential. The combination of our datasets and survey responses allows us to establish both a pre-pandemic baseline of the relation between potential for WFH activity and entrepreneurial entry, and to explore how individual-level factors interact with these broader regional trends over time. Overall, the exogenous shock to WFH brought about by pandemic mandates leads to a *reduction* in new business activity in regions with the greatest pre-pandemic feasibility for WFH. Put differently, areas that had high pre-existing potential for WFH—and thus were more likely to see actual implementation of WFH practices during to COVID-19—experience lower growth in new business starts.

Importantly, the economic impact of these shifts is unlikely to be uniform across different demographics and regions. The motivations and opportunities for entrepreneurship can vary significantly based on factors such as income levels, employment status, and gender, as well as regional economic conditions (Hessels, et al., 2008; Allen and Curington, 2014). We next investigate whether the decrease in entrepreneurial entry in regions with realized WFH practices is influenced by the level of financial incentives for entrepreneurship, given the increased flexibility in conventional employment. If our hypothesis holds true, we would expect the negative effect of increased WFH availability on entrepreneurial activity to be more pronounced in areas

[1] Code used to reproduce this measure is downloaded from https://data.mendeley.com/datasets/jjcckss4mn/1 (accessed October 2022).

where the financial benefits of entrepreneurship are already low. If the pecuniary benefits of entrepreneurial entry are already low, and we reduce the non-pecuniary benefits, this should have a larger dampening effect than a similar reduction in areas where high pecuniary benefits still exist. To explore this, we examine variation in local economic opportunities prior to the pandemic. Consistent with our hypothesis, we find that in areas marked by lower income levels and higher unemployment rates before the pandemic, the decline in new business startups due to the WFH shift induced by the pandemic was more significant. For example, in areas with low economic opportunity, a one standard deviation increase in teleworkable share is associated with an incremental 3.5% decrease in new business registrations. The limited economic opportunities in these areas (which suggest lower pecuniary returns from entrepreneurial activities) appear to exacerbate the impact of WFH flexibility in traditional jobs on new business formation.

Additionally, the non-pecuniary benefits of entrepreneurial activity may differ across gender. This may be particularly true given the disproportionate tendency of household duties to be borne by women (Lachance-Grzela and Bouchard, 2010; Bertrand et al., 2015; Kleven et al., 2019). Notably, women appear to have borne a larger burden of additional childcare responsibilities during the pandemic, especially with the closure of schools (Hutchinson et al., 2023). As a result, the increased flexibility offered by traditional employers may be especially valuable to women, who may have otherwise have pursued entrepreneurship as a means to achieve similar flexibility.

Examining data from five major U.S. states where the gender of new business registrants can be identified, we observe a distinctive trend post-pandemic. Regions with a higher potential for WFH, as measured by the teleworkable share, exhibit a significantly marked decrease in new business formation among women entrepreneurs. This is notable, considering that there were no significant gender differences in the trends of new business formation between male and women entrepreneurs before the pandemic stay at home mandates. This finding aligns with the observation that social norms that often place a greater share of household and caregiving responsibilities on women in the labor force (Lachance-Grzela and Bouchard, 2010; Bertrand et al., 2015; Kleven et al., 2019).

Finally, we show that our key finding is further supported by responses to a short survey we administered to a representative panel on Prolific, revealing how flexibility in traditional employment interacts with entrepreneurial motivations. Respondents who highly value flexibility are significantly more likely to express entrepreneurial intent. However, this relationship weakens

substantially when flexibility is already available in their current jobs. This substitution effect highlights how traditional employment's ability to replicate the non-pecuniary benefits of entrepreneurship, such as autonomy, reduces the incentive to undertake the risks of starting a new business.

The study makes a number of contributions to the literature. First, our findings contribute to the ongoing discussion on modern work dynamics, especially in terms of the evolving relationship between traditional employment and entrepreneurship. Entrepreneurial activity is widely recognized as a primary contributor to economic and employment growth (Davis and Haltiwanger, 1992, Jovanovic and MacDonald, 1994, Haltiwanger, Jarmin, and Miranda, 2013, and Guzman and Stern, 2020). Consequently, understanding what drives individuals to embark on entrepreneurial ventures is of paramount interest to both researchers and policymakers. Our study adds to existing literature on pecuniary motivations for entrepreneurial entry by providing empirical evidence on how employer-provided work flexibility—traditionally a distinctive feature of entrepreneurial activity—affects new business formation as workplace flexibility is increasingly incorporated into conventional employment models. The integration of such flexibility has complex ramifications for entrepreneurial activity and business dynamism.

Our study also provides valuable insights into the differential impacts of the pandemic-induced WFH shift. The COVID-19 pandemic allows us to observe the effects of a sudden and widespread transition to teleworking. Crucial for policymakers, our findings reveal differing effects on entrepreneurship depending on regional economic conditions and for would-be entrepreneurs of different genders. The shift towards flexible work arrangements in traditional employment appears to have a disproportionately negative impact on female entrepreneurship, highlighting the need for exploration of targeted policies and support mechanisms that can address the unique challenges faced by would-be women entrepreneurs. By shedding light on these disparities, our study contributes to a more inclusive understanding of entrepreneurship, emphasizing the need for diversity and equality in the entrepreneurial ecosystem (Lachance-Grzela and Bouchard, 2010; Allen and Curington, 2014; Ewens, 2022).

In addition to these contributions, our study opens avenues for future research and policy development. By highlighting the nuanced tradeoff between flexibility in traditional employment and entrepreneurial entry, we underscore the complexity of motivations behind starting new ventures. This understanding can inform the development of policies and programs that effectively

support aspiring entrepreneurs, taking into account the changing dynamics of the workforce. Furthermore, our findings on regional and demographic variations in the impact of WFH provide a basis for more localized and targeted approaches to fostering entrepreneurship.

2. SAMPLE AND DATA

Our primary dependent variables of interest are measures of new entrepreneurial activity at the local level. More specifically, we are interested in the quantity of new businesses launched at the zipcode level over time.

2.1. New Business Formation

Our first outcome variable is the quantity of new business launches, measured using business registrations by location and time period. For this purpose, we utilize data on new for-profit business registrations from the Startup Cartography Project (SCP, Guzman and Stern, 2020).[2] The SCP leverages business registration records, which are public records created when an individual registers a new business as a corporation, LLC or partnership. Importantly, as noted by Guzman and Stern (2020), while it is possible to found a new business without business registration (e.g., a sole proprietorship), the benefits of registration are substantial, and include limited liability, various tax benefits, the ability to issue and trade ownership shares, and credibility with potential customers. Furthermore, all corporations, partnerships, and limited liability companies must register with a Secretary of State or equivalent to take advantage of these benefits. The act of registering the firm triggers the company's legal creation. As such, these records reflect the population of incorporated businesses operating in a location that take a form that is a practical prerequisite for growth.

The SCP dataset provided to us includes records on the complete population of firms satisfying one of the following two conditions: (i) a for-profit firm physically located in the local jurisdiction, or (ii) a for-profit firm whose jurisdiction is in Delaware but whose principal office address is in the local state. The SCP dataset provides a number of variables of interest to entrepreneurship researchers. We focus here on the primary measure: the quantity of new business registrations in a zip code in a given year-quarter, which we designate as New Business Registration ($\mathrm{NBR}_{i,t}$). The SCP data is available starting from the year 1988. Our analysis utilizes quarterly data collected

[2] See http://www.startupcartography.com.

from 2011 to 2018 for 42 available U.S. states and the District of Columbia, and monthly data collected from January 2019 to February 2021 for seven available U.S. states (FL, GA, KY, NY, TN, TX, VT, and WA). Only limited data has been collected and processed to date by SCP for the period from April 2021 onwards, and as such, we end our sample in March 2021.

2.2. Remote Work Measures

We use two measures of remote work. First, we use the measure of zip-level share of potentially teleworkable workforce constructed in Gupta, Mittal, Peeters, and Van Nieuwerburgh (2022).[3] This measure is cross-sectional, and combines the occupational composition of the zip code and the occupation-specific potential for remote work measured by Dingle and Neiman (2020). Second, we use the measure of prevalence of remote work provided by Hansen, et. al. (2023). The monthly time series measure is generated as the share of new job vacancy postings explicitly offering hybrid or fully remote options in large US cities. Their method quantifies hybrid and remote work opportunities by using natural language processing techniques to categorize and classify over 250 million job vacancy postings based on the extent to which these jobs can be performed in a hybrid or fully remote manner. We manually look up the list of zip codes located within each city to create a city-to-zip mapping.[4]

2.3. Survey Data

In addition to the administrative data, we conducted a survey through Prolific to capture individual-level insights regarding the influence of work flexibility on employment and entrepreneurial decisions. The survey, titled "Work-From-Home and Job Flexibility," was designed to understand how the availability of WFH options and flexible work arrangements impact individuals' choices to remain in traditional employment or pursue self-employment.

Our survey was administered during July 2024 and targeted individuals who were currently employed or considering changes in employment status, with a focus on flexibility in work schedules. A total of 1,000 participants completed the survey. Approximately 60% of respondents rated job flexibility as "important" or "very important" in their employment decisions. Among respondents, 35% expressed a high likelihood of leaving their current job for one offering greater

[3] The measure is reproduced using codes downloaded from https://data.mendeley.com/datasets/jjcckss4mn/1 (accessed October 2022).
[4] We looked up city names on www.zip-codes.com.

flexibility, while 25% indicated a high interest in starting a new business to achieve greater autonomy.

The survey addressed topics such as the importance of flexibility in choosing a job, the likelihood of leaving a current job for one with greater flexibility, and the likelihood of starting a new business. Respondents ranked their reasons for valuing flexibility, with work-life balance and reduced commute time emerging as the most significant factors, cited by 72% and 65% of respondents, respectively. Family responsibilities were particularly prominent for female respondents, with 40% identifying this as a major driver of their need for flexibility, compared to 25% of male respondents.

2.4. Other Data

To classify founder's genders, we use the raw business registration data underlying SCP for five available states during the Covid-19 pandemic for which names are available to classify gender: FL, GA, KY, TN, and TX. We use the Social Security Administration (SSA)'s Baby Names dataset to identify the frequency at which a certain name is given to male versus female children. We then sum over the period spanning 1940 through 2005 to calculate name frequency by gender. We focus on founder names that are "strongly gendered", which means that above 90% of the occurrences of those names are associated with a single gender. Among the founder names that we match to the SSA database, 94% are "strongly gendered". Using this classification, we then calculate two measures: the proportion of newly registered businesses containing exclusively women founders and the proportion containing at least one woman founder. Because we are calculating shares of businesses in a zipcode that have women founders, we require our zipcode-month observations to contain at least ten newly registered businesses.[5]

We also obtain annual data on the population and average adjusted gross income (AGI) by zipcode from the IRS Statistics of Income (SOI) database from 2011 to 2020. For the first three months in 2021 included in our sample, we carry over the 2020 values. We use the same database to collect data on the number of tax filings with unemployment compensation, and calculate the unemployed share in a given year. Additionally, we obtain data on county-level new Covid-19 case rates from the New York Times, and the implementation of state and local stay-at-home

[5] These ratios are better measured in places with more new businesses. If there are only a few new businesses, the ratio can easily be 0 or 1 but may not well-represent the region. The results are robust to different cutoffs such as 0, 5, and 20.

mandates from the Goolsbee et al. (2020) updated database. To assign zipcodes to counties, we use the combination of a zip-to-ZCTA crosswalk and a ZCTA-to-county crosswalk provided by the Census. In cases where a zipcode spans multiple counties, we map it to the county containing the largest population share of that zipcode. For the vast majority (~97%) of the zipcodes in the sample, stay-at-home mandates were implemented in March 2020. The remaining 3% implemented stay-at-home mandates in April 2020. Accordingly, we define our $POST_{i,t}$ variable as taking a value of zero prior to March 2020 and one thereafter.

3. EMPIRICAL ANALYSIS

3.1. Telework potential and entry

We begin our analysis by establishing a pre-pandemic baseline association between telework potential and new business formation in the local area. There are a number of reasons we may expect a positive relation between new business registrations and share of jobs with telework potential in the zip code. Regions with a high potential for telework may boast more advanced technological infrastructure and a workforce that is not only tech-savvy but also adaptable and highly educated. These areas could also foster a supportive culture of innovation and entrepreneurial risk-taking. Moreover, these areas may already have higher shares of realized WFH, potentially enabling more "side hustle" entrepreneurial experimentation.

Panel A of Table 1 presents summary statistics for the pre-pandemic sample. We utilize the quarterly SCP data from 2011 to 2018 due to the larger number of states covered. The merged sample includes all states with available data on the measure of telework potential, and consists of 248,409 observations covering 9,029 zipcodes in the United States from 2011 to 2018.

Figure 1 graphs the relationship between the teleworkable share of jobs in a zip code and new business registrations, both in the raw data (Panel A) and controlling for time trends, population and income (Panel B). We observe a positive correlation between the share of potential teleworkable workers in a ZIP code and the number of new business registrations in that zip code.

In Table 2, we present estimates modeling this baseline relation using a simple OLS regression. The dependent variable is the natural logarithm of the number of new business registrations, and the right hand side variables are the standardized teleworkable workforce share and controls for population and income levels. Standard errors are clustered at the zipcode level. Column (1) presents estimates from a regression of log new business registrations on standardized

teleworkable share alone, column (2) adds control variables, and column (3) further adds state-by-year fixed effects. Across all three specifications, zip codes with a higher proportion of teleworkable occupations also have more entrepreneurial activity in the pre-pandemic environment. Using the strictest specification, a one standard deviation increase in the share of teleworkable employment is associated with a ~16% increase in new business registrations.

3.2. Pandemic Effects: Realizing work from home potential

Next, we utilize the COVID-19 pandemic as a natural experiment that provided an exogenous shift to work from home activity, which allows us to capture the effects of realized WFH—stay-at-home mandates which push the WFH potential to be realized—on entrepreneurial entry. Importantly, stay-at-home mandates had a variety of effects on local economic conditions, in addition to driving many jobs characterized by potential for WFH to be realized WFH (Goolsbee and Syverson, 2021). Additionally, COVID case rates varied widely across counties and cities, further affecting behavior and choices.

Our COVID-19 pandemic sample consists of the seven states for which SCP has collected business registration data during the pandemic. The sample consists of 63,434 observations covering 2,666 zip codes from 2019 to 2021. Summary statistics for the sample are presented in Panel B of Table 1. Figure 2 plots the overall trends in new business registrations immediately preceding and during the COVID-19 pandemic. The plot shows a boost in entrepreneurial activity following the pandemic onset, with some cyclicality, consistent with that found in prior work (Decker and Haltiwanger, 2023). While the aggregate pattern is consistent with previous findings, our interest lies in understanding the extent to which trends in new business formation change as a result of WFH potential and stay-at home mandates.

To explore the effects of the pandemic and its associated stay-at-home mandates, we estimate models of the following form:

$$\log(NBR_{i,t}) = \beta\, POST_t * TWShare_i + X_{i,t} + \gamma_t + \theta_i + \varepsilon_{i,t}, \quad (1)$$

where $Post_t$ is an indicator variable taking a value of one from March 2020 onwards. $TWShare_i$ is the share of potentially teleworkable workforce in the zip code from Gupta et al. (2022), standardized to have a mean of zero and standard deviation of one for ease of interpretation. $X_{i,t}$ is a vector of time-varying controls including income, population, and new COVID case rate, intended to control for consumer activity factors previously identified by the literature (Goolsbee

and Syverson, 2021). γ_t are year-month fixed effects, and θ_i are zip code fixed effects. Standard errors are clustered at the zip code level. The lower order terms for $Post_t$ and $TWShare_i$ are absorbed in the fixed effects structure.

The estimates are presented in Table 3. Column (1) presents estimates from a model with no fixed effects. Column (2) adds fixed effects for state and year-month. Column (3) replaces the state fixed effects with zip code fixed effects (resulting in the absorption of the teleworkable share lower order term), and column (4) replaces the year-month fixed effects with year-month-by-state fixed effects. Overall, the estimates suggest that pandemic stay-at-home mandates led to a less pronounced increase in new business registrations in areas that had higher telework capacity. Across specifications, a one standard deviation increase in potential telework share following the enactment of stay-at-home mandates translates into 7-8% fewer new business registrations relative to baseline.

Figure 3 presents a plot of the dynamic effects of teleworkability, in the form of the continuous share effects over the sample period (telework share interacted with the month fixed effect). February 2020, the month prior to stay-at-home mandate implementation, is used as the baseline month. Prior to the beginning of the pandemic, zip codes with different shares of teleworkability did not seem to experience differential *changes* in new business registrations. Post-February 2020, new business registrations drop relatively for zipcodes with higher values of teleworkability. The empirical patterns are consistent with two potential, non-exclusive channels. First, in areas with low teleworkability, stay-at-home mandates may have left large segments of the workforce in the region unemployed or on forced leave, leading to either economic incentives to find income from entrepreneurial activities or to sufficient time to explore latent entrepreneurial ideas. At the same time, areas that had high levels of teleworkability may have translated into higher levels of WFH when stay-at-home mandates are enacted, and this flexibility within traditional employment reduces the non-pecuniary benefit of entrepreneurial entry.

Up until now, we have employed a measure of *potential* for teleworkability. To further explore the WFH channel, we turn to our measure of realized WFH from Hansen, et al. (2023). Specifically, we employ telework potential as an instrument for actual WFH in a two stage least square (2SLS) approach using a similar specification as in equation (1). Table 4 presents estimates from three models. First, in columns (1) and (2), we regress the natural logarithm of the number of new business starts in a county and month on the realized WFH share and controls. Consistent with our

prior findings, we observe a negative relationship between realized WFH share and new business starts. A one standard deviation increase in WFH share is associated with a 4.5% decrease in new business registrations.

In columns (3) through (6), we use telework potential as an instrumental variable for the realized work from home share. Columns (3) and (4) present first stage models, while columns (5) and (6) present the second stage. Standard errors are clustered at the zip code level. In the first stage, we observe a strong and significant positive relationship between $POST_{i,t} * TWShare_i$ and realized $WFH\ Share_{i,t}$. The first stage F-statistics are 371 and 227 in Columns (3) and (4), respectively. The second stage reveals a similar pattern to that observed when estimating our original models with telework potential: In cities with higher realized WFH under traditional employment, we observe less of an increase in new business registrations. A one standard deviation increase in instrumented *realized* WFH share is associated with a roughly 45% lower bump in new business registrations post pandemic stay-at-home mandates. The findings reinforce our proposed flexibility tradeoff channel, whereby increased flexibility provided by WFH allows would-be-entrepreneurs who were entering entrepreneurship primarily for the non-pecuniary benefit of work flexibility to instead remain within traditional employment frameworks.

3.3. Treatment Heterogeneity and Outside Options

If the channel for reduced entrepreneurial entry in areas with realized WFH is driven by the reduced pecuniary benefits to entrepreneurship brought about by the increased flexibility in traditional employment, then we should expect that the effect will be magnified if the pecuniary benefits of entrepreneurship in the area are also low. We explore this by utilizing heterogeneity in pre-pandemic local levels of economic opportunity. We estimate models similar to equation (1), with the addition of triple interaction with pre-pandemic average AGI (logged) and unemployment share.

The estimates are presented in Panel A of Table 5. Columns (1) and (2) estimate models with the interaction of $POST_t$, $TWShare_i$ and $Log\ Average\ AGI_{i,2019}$, while columns (3) and (4) present estimates of models with the interaction of $POST_t$, $TWShare_i$ and $\%\ Unemployment_{i,2019}$. The first of each pair of models includes year-month and zip code fixed effects, while the second of each pair includes state-by-year-month and zip code fixed effects. Consistent with the hypothesized channel, as the pecuniary benefits of entrepreneurial activity

diminish (AGI decreases or unemployment increases), the moderating effect of telework potential is further magnified.

To get a sense of the economic magnitude of the effects, we generate an indicator for low economic opportunity in the area, defined as being below median in pre-pandemic average AGI and above median in pre-pandemic unemployment share. In Panel B, we re-estimate a stricter specification of the models in Panel A, substituting the indicator for low economic opportunity for the continuous measures and including year-month-by-state and zip-by-year fixed effects. In areas with low economic opportunity, a one standard deviation increase in teleworkable share is associated with an incremental 3.8% decrease in new business registrations.

3.4. Variation by Gender

Presumably however, the non-pecuniary benefits of entrepreneurial activity may differ across gender, particularly given the disproportionate tendency of household duties to be borne by women (Lachance-Grzela and Bouchard, 2010; Bertrand et al., 2015; Kleven et al., 2019). Given that women appear to have disproportionately born the costs of additional childcare responsibilities due to school closings during the pandemic (Hutchinson et al., 2023), it is possible that the increased flexibility offered by employer firms being of particular value to women who might otherwise have entered into entrepreneurship in pursuit of such flexibility.

To explore this further, we estimate models similar to those in equation (1), replacing the dependent variable with the percentage of women-led new business registrations based our two measures of founder gender: the proportion of newly registered businesses containing exclusively women founders and the proportion containing at least one woman founder. The estimates are presented in Table 6. Column (1) calculates the percentage of women-led new businesses using businesses based on exclusively women founded companies, while column (2) uses the percentage of new businesses containing at least one woman founder. Post stay-at-home mandates, a one standard deviation increase in the teleworkable share of jobs in the zip code is associated with a 0.9 to 1.6 percentage point decrease in the share of new business starts with women founders, relative an unconditional mean percentage of 29.6% (all woman founders) or 65.7% (at least one woman), representing a 3% drop in all-women founder businesses and a 2.4% drop in at least one women founder businesses.

Panel A of Figure 4 plots the dynamics for the percentage of women-led businesses (relative to the level in January 2020) using our two measures of founder gender. We interact teleworkable share with the year-month fixed effect and model the coefficient over time relative to February 2020. Prior to the advent of stay-at-home mandates, we observe no statistical trend. Afterwards, we observe a negative relationship between teleworkable share and the share of women-led businesses, for both measures.

In Panel B, we present the plot for a continuous difference-in-differences estimation comparing the effect of teleworkability on the change in the number of businesses founded by women to the effect on the change in the number of new businesses founded by men. February 2020 serves as the reference point. Pre-pandemic, the trends in new business starts by men and women as a function of teleworkability are indistinguishable from zero. From the figure, however, it is apparent that post pandemic, there was a drop in both businesses founded by and businesses founded by women as the share of teleworkable jobs increases. This drop was more pronounced for women-led businesses, consistent with the hypothesis that the additional flexibility provided by realization of WFH reduces the non-pecuniary benefit of entry into entrepreneurship, which is more valuable for women given the disproportionate household production burden.

4. SURVEY RESULTS

To complement our empirical analysis, we conducted a short survey titled "Work-From-Home and Job Flexibility" through Prolific in July 2024. The survey aimed to capture individual-level views on the tradeoff between work flexibility and entrepreneurial activity, to supplement our topline finding. A total of 1,000 participants, representative of employed individuals and those considering employment changes, completed the survey. Summary statistics for the survey sample are presented in Panel C of Table 1.

Participants were asked about the importance of job flexibility in their employment choices, the likelihood of pursuing entrepreneurship to achieve greater flexibility, Figure 5 (Panel A) illustrates the strong positive relationship between the importance of job flexibility and entrepreneurial intent. Respondents who rated flexibility as "very important" (score of 5) were over three times more likely to express high entrepreneurial interest compared to those assigning flexibility a low importance rating. The predicted probabilities in the figure highlight a sharp gradient: as the perceived importance of flexibility increases, so does the share of individuals with

a high likelihood of leaving their current job to pursue a business venture. These findings underscore the centrality of flexibility as a driver of entrepreneurial aspirations.

The regression results in Table 7 further quantify this relationship, revealing the nuanced trade-offs between valuing flexibility and its availability in current jobs. Across all models, individuals who place high importance on flexibility are significantly more likely to express a high likelihood of leaving their current job to start a business. In Column (7), which includes demographic controls, state fixed effects, and household income decile fixed effects, we find that individuals who highly value flexibility are 21.6 percentage points more likely to consider leaving their jobs to pursue entrepreneurship. This result is consistent with the theoretical view that flexibility proxies for autonomy, a critical driver of entrepreneurial entry (Hamilton, 2000).

Flexibility that is provided in current employment serves as a significant retention mechanism, however, reducing the likelihood of individuals leaving for entrepreneurship. Across specifications, the availability of job flexibility consistently dampens the pull of entrepreneurial opportunities, even as additional controls are included. While the direct effect of job flexibility loses statistical significance in the fully controlled model, its persistent negative sign suggests that offering flexibility in the current position helps to retain individuals by satisfying their primary motivation for considering entrepreneurship.

The interaction term in Columns (6) and (7) reveals a critical nuance: the availability of flexibility in current jobs substantially weakens the positive relationship between valuing flexibility and entrepreneurial intent. In Column (7), the negative and statistically significant interaction coefficient of -0.204 suggests that when individuals perceive their current jobs as already meeting their flexibility needs, the marginal benefit of leaving for entrepreneurship diminishes sharply. This finding is consistent with the intuition that traditional employment can substitute for the autonomy traditionally associated with entrepreneurship by providing similar non-pecuniary benefits.

Figure 5 (Panel B) visually reinforces this dynamic, showing that individuals in flexible jobs are significantly less likely to leave for entrepreneurship than those in non-flexible roles, even among those who highly value flexibility. This highlights a clear substitution effect: as flexibility becomes more accessible within traditional employment, the comparative advantage of entrepreneurship as a pathway to autonomy erodes. The ability of firms to replicate the non-pecuniary benefits of entrepreneurship through flexible arrangements—such as remote work or

adjustable hours—reduces the incentive for workers to take on the risks associated with starting their own businesses.

Our survey results reinforce our main finding, suggesting that traditional employment's growing ability to offer flexibility—particularly through work-from-home arrangements—is reshaping entrepreneurial decision-making. By providing benefits such as autonomy and flexibility, once exclusive to entrepreneurship, work-from-home policies reduce the relative appeal of starting a business for workers primarily seeking flexibility. This shift in labor markets has the potential to alter the composition of entrepreneurs, with broader implications for labor allocation and innovation.

5. CONCLUSION

Our study examines the intricate relationship between WFH and entrepreneurship, with a particular focus on the context of the COVID-19 pandemic. Our results yield several significant insights. Before the pandemic, regions with higher telework potential exhibited a positive relationship with new business starts, indicating that teleworkability facilitated entrepreneurial activity. However, the shift to widespread WFH during the pandemic unveils a complex dynamic. In the post-pandemic landscape, regions with high telework potential experience a comparatively lower increase in new business registrations. These empirical suggests that the increased flexibility offered by traditional employment may have reduced the non-pecuniary benefits of entrepreneurship, such as autonomy, thereby altering the calculus of entrepreneurial entry.

Survey results reinforce this interpretation, highlighting how flexibility in traditional employment settings diminishes the comparative advantage of entrepreneurship for workers seeking work-life balance or autonomy. Respondents who highly value flexibility expressed strong entrepreneurial interest, but this interest waned when flexibility was already provided in their current jobs. These findings underscore the evolving competition between traditional employment and entrepreneurship as employers adapt to meet workers' non-pecuniary demands.

A particularly salient aspect of our findings pertains to the impact on female entrepreneurship. The shift to WFH during the pandemic has disproportionately affected women-led entrepreneurship, particularly in areas with substantial telework potential. This trend may be attributed to the pandemic's disproportionate burden on women, exacerbated by factors such as school closures and increased household responsibilities. To the extent that women are more likely

to enter into entrepreneurship activity in pursuit of flexibility, the emergence of WFH in less risky traditional employment frameworks may offer an alternative that reduces women's participation in entrepreneurial activity. These results underscore the pressing need for policies and support mechanisms tailored to the unique challenges women face in balancing work and family responsibilities, and, in particular, for women entrepreneurs.

Overall, our study offers valuable insights for policymakers and scholars seeking to understand how WFH reshapes entrepreneurial activity in a post-pandemic world. By providing benefits such as autonomy and flexibility—once exclusive to entrepreneurship—WFH policies reduce the relative appeal of starting a business for workers primarily motivated by flexibility. This shift in labor markets may not only suppresses necessity-driven entrepreneurial entry but also alters the composition of entrepreneurs, with broader implications for labor allocation and innovation dynamics. By illustrating how WFH policies of traditional employment can substitute for the non-pecuniary benefits of entrepreneurship, we provide a nuanced perspective on the shifting motivations behind entrepreneurial entry. As we move toward a more flexible labor market, these insights are critical for fostering a resilient, dynamic, and inclusive entrepreneurial ecosystem.

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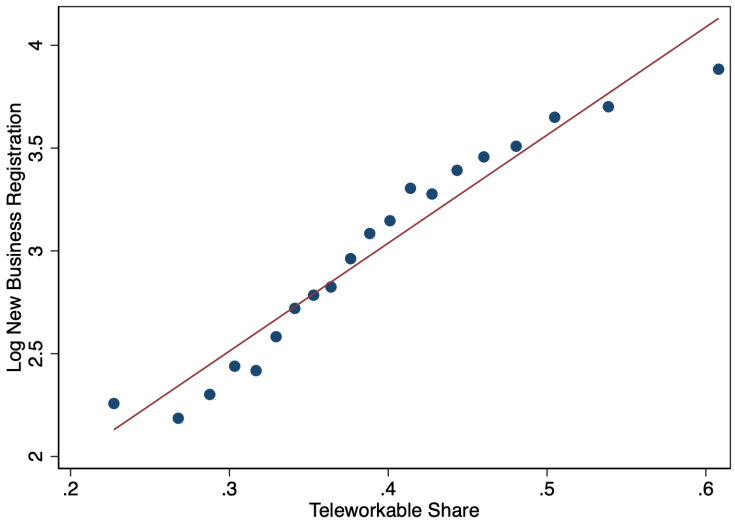
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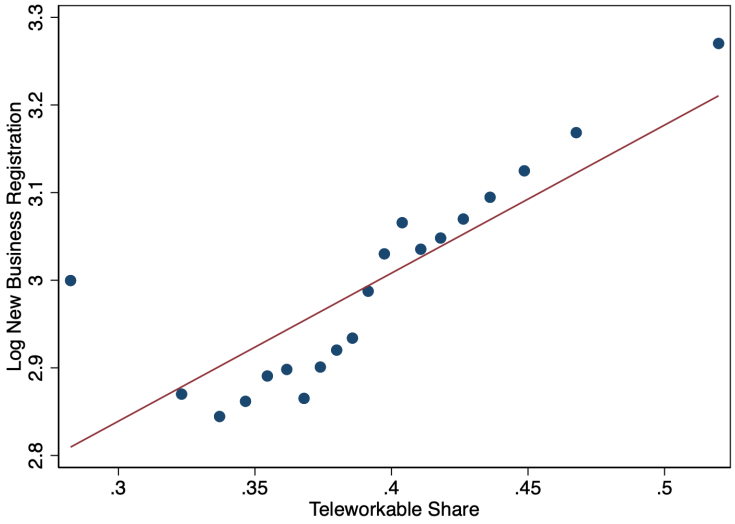
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Panel A: Raw Data



Panel B: Controlling for Time Trends, Population, and Income

Figure 1. Pre-Pandemic Relation between Teleworkable Share and New Business Registration

Notes: This figure displays the binscatter plot of the teleworkable share and the natural logarithm of the number of new business registrations. The sample period spans 2011Q1-2018Q4 and include 42 available U.S. states and the District of Columbia. The level of observation is a zipcode-quarter. In Panel A, no control variables are included. In Panel B, we control for year-quarter fixed effects and time-varying zipcode characteristics, including the natural logarithm of population and AGI.

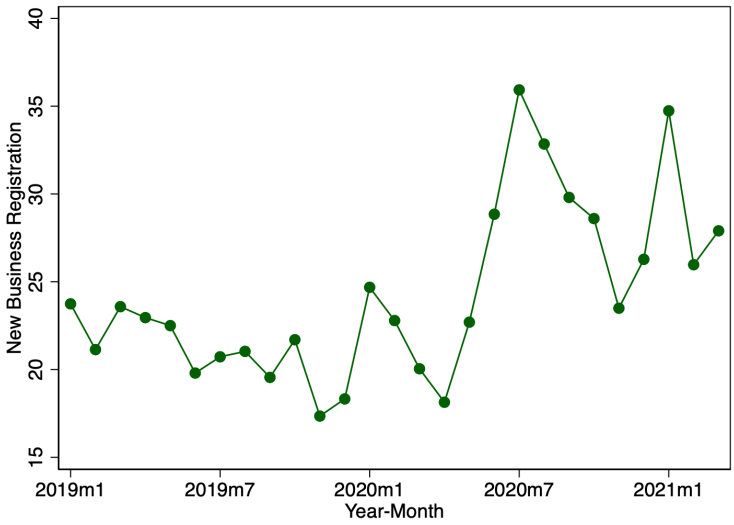


Figure 2. Trends in New Business Registration Surrounding the Covid-19 Pandemic

Notes: This figure displays average monthly number of new business registrations over time from January 2019 to March 2021. The sample include the 8 U.S. states: AK, FL, GA, KY, NY, TN, TX, VT, and WA. The number of new business registrations is measured at the zipcode level.

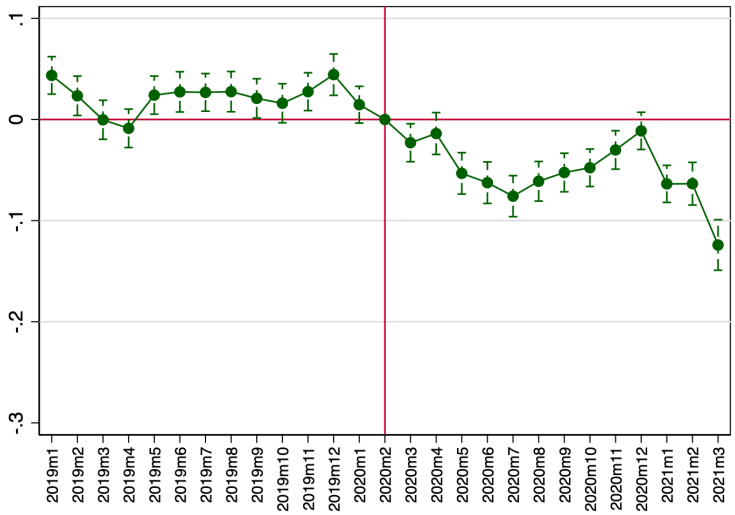
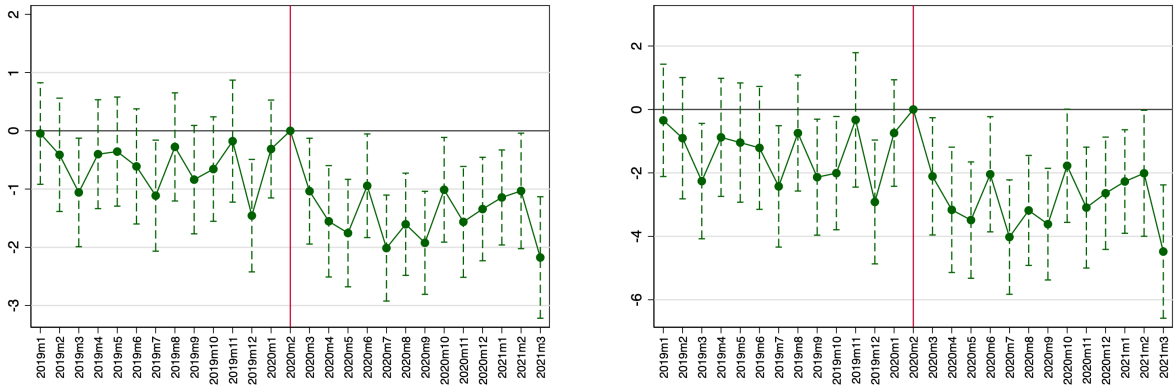


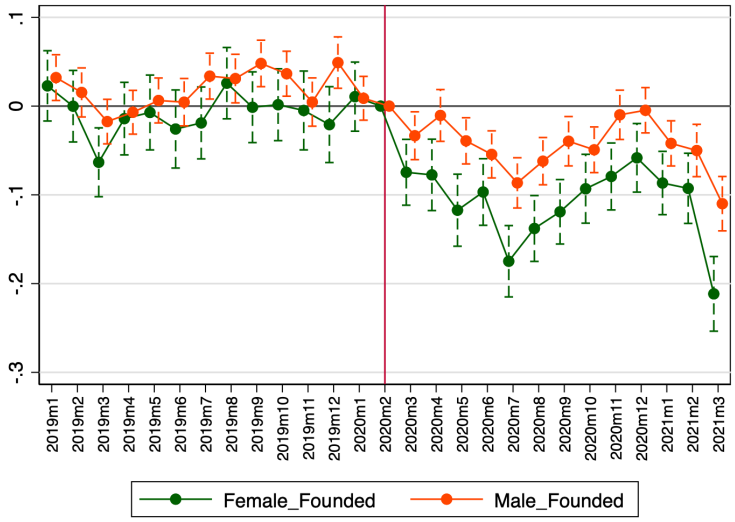
Figure 3. Dynamic Difference-in-Difference Estimates of the Effect of Telework on Entrepreneurship During the Pandemic

Notes: This figure displays the dynamic difference-in-difference coefficient estimates on the interaction of year-month indicators and *Teleworkable Share,* and their 95% confidence intervals. *Teleworkable Share* is standardized to have a mean of zero and a standard deviation of one. The sample period includes months from January 2019 to March 2021. The sample include the 8 U.S. states: AK, FL, GA, KY, NY, TN, TX, VT, and WA. Given that the vast majority of the sample implemented stay-at-home mandates in March 2020, February 2020 is used as the baseline year in all estimations. The level of observation is a zipcode-month. The regression controls for the natural logarithm of population and AGI, new Covid case rate, zipcode fixed effects, and state-by-month fixed effects.



Y = All Female Share *Y = Some Female Share*

Panel A: Share of Newly Registered Businesses with All and Some Female Founders

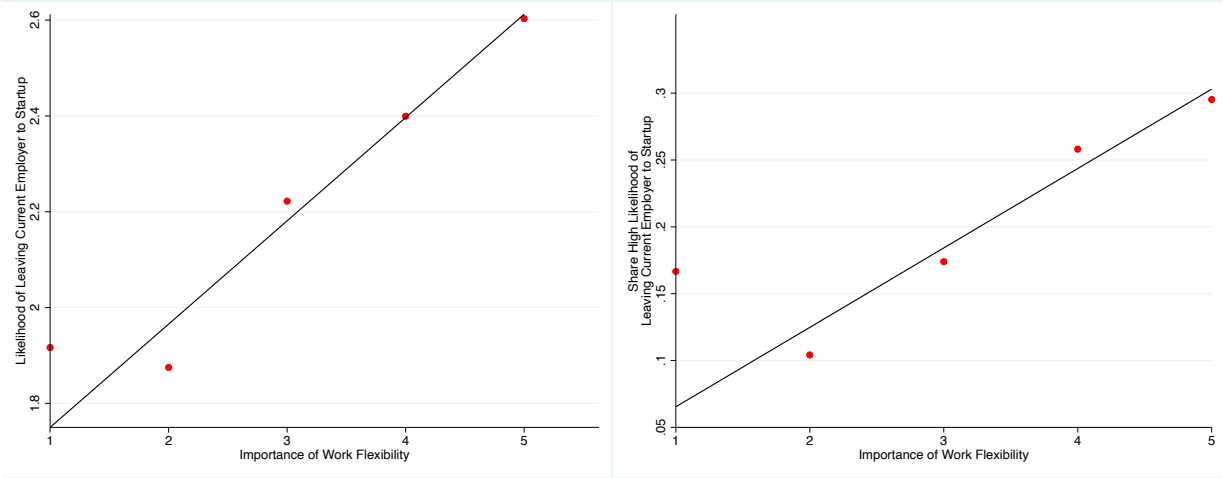


Panel B: Log New Business Registration with Female and Male Founders

Figure 4. Dynamic Difference-in-Difference Estimates of the Effect of Telework on the Founder Gender Composition During the Pandemic

Notes: This figure displays the dynamic difference-in-difference coefficient estimates on the interaction of year-month indicators and *Teleworkable Share,* and their 95% confidence intervals. The outcome variable for the left graph of Panel A is *All Female Share*, share of newly registered businesses with exclusively female founders. The outcome variable for the right graph of Panel A is *Some Female Share*, the share of newly registered businesses with at least one female co-founder. The outcome variable in Panel B is the natural logarithm of new business registrations with exclusively female (green line) and male (orange line) founders. *Teleworkable Share* is standardized to have a mean of zero and a standard deviation of one. The sample covers January 2019 to March 2021 and includes monthly new business registration data from five U.S. states for which we have the underlying raw data: FL, GA, KY, TN, and TX. Given that the vast majority of the sample implemented stay-at-home mandates in March 2020, February 2020 is used as the baseline year in all estimations. The level of observation is a zipcode-month. The regression controls for the natural logarithm of population and AGI, new Covid case rate, zipcode fixed effects, and state-by-month fixed effects.

Panel A: The Influence of Flexibility Preferences on the Likelihood of Leaving a Job to Start a Business



Panel B: The Impact of Current Job Flexibility on Entrepreneurial Intent as a Function of the Perceived Importance of Flexibility

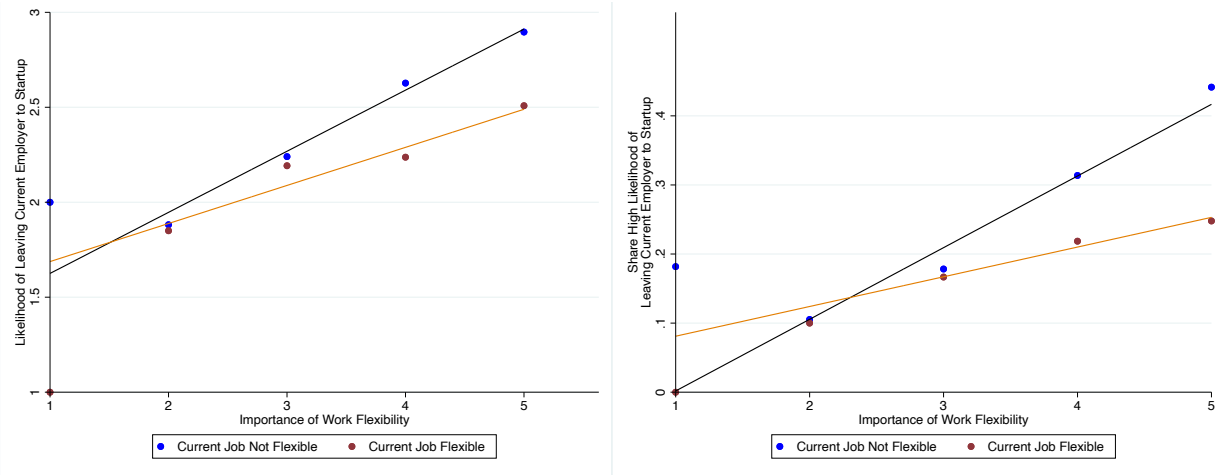


Figure 5. The Role of Work Flexibility in Entrepreneurial Intent

Notes: This figure illustrates the role of work flexibility in shaping entrepreneurial intent. Panel A examines how the perceived importance of work flexibility influences the likelihood of leaving a current job to start a business, with the left subplot showing predicted probabilities and the right subplot depicting the share of individuals with a high likelihood of leaving. Panel B explores how current job flexibility interacts with these preferences, comparing the likelihood of leaving for individuals in flexible versus non-flexible jobs. The x-axis represents the importance of flexibility (low to high), and the y-axis captures measures of entrepreneurial intent, demonstrating how flexibility preferences and job conditions jointly drive entrepreneurial transitions.

Panel A: Pre-Pandemic Sample

Variable	Mean	SD	P5	Median	P95
Teleworkable Share	0.39	0.09	0.26	0.38	0.56
New Business Registrations	44.32	59.66	1	25	150
Population	20372.85	17001.09	1330	16620	52590
Average AGI	42.99	44.36	14.92	32.36	102.23

Panel B: Pandemic Sample

Variable	Mean	SD	P5	Median	P95
Teleworkable Share	38.41	9.16	25.28	37.47	55.7
New Business Registrations	34.62	44.18	1	20	117
Population	24677.93	18511.21	2320	21580	60910
Average AGI	54.15	78.03	17.76	36.84	143.62
WFH Share	6.41	3.73	2.11	5.09	14.14
New Case Rate	346.07	614.64	0	0	1699.3
Post	0.48	0.5	0	0	1
All Female Share	32.39	11.4	14.29	31.91	51.52
Some Female Share	70.37	21.94	36.07	69.44	107.96

Panel C: Survey Sample

Variable	Mean	SD	P5	Median	P95
Interest in starting own business/entrepreneurial venture	2.97	1.42	1.00	3.00	5.00
Very interested in entrepreneurship	0.16	0.36	0.00	0.00	1.00
Likelihood of Pursuing Entrepreneurship	2.37	1.30	1.00	2.00	5.00
Likelihood of leaving for a startup	0.24	0.43	0.00	0.00	1.00
Women	0.55	0.50	0.00	1.00	1.00
Age	36.46	9.91	22.00	35.00	55.00

Table 1. Summary Statistics

Notes: This table reports summary statistics of the variables used in the paper. In Panel A, the sample spans years 2011 through 2018 and covers 42 available U.S. states and the District of Columbia. The level of observation is a zipcode-quarter. In Panel B, the sample covers January 2019 to March 2021 and includes monthly new business registration data from 8 U.S. states: AK, FL, GA, KY, NY, TN, TX, VT, and WA. The level of observation is a zipcode-month. We exclude months on and after April 2021 due to missing data from several large states after that, such as NY and TX. *Teleworkable Share* measures the share of jobs amenable to remote work in a zipcode, produced in Gupta, et. al. (2022). *New Business Registrations* is the number of new business registrations in a zipcode measured in the SCP database. *Population* is the number of individuals in the zip. *Average AGI* is the average individual adjusted gross income in the zipcode. Population and AGI data are obtained from the IRS SOI database. *WFH share* is the percent of remote or hybrid workforce measured constructed in Hansen, et. al. (2024). *New Case rate* is the number of new Covid cases per 100,000 population. *Post* is an indicator variable that takes the value of one from March 2020 onwards. *All Female Share* is the share of newly registered businesses with exclusively female founders. *Some Female Share* is the share of newly registered businesses with one or more female co-founders. Panel C presents summary statistics from a July 2024 survey of 998 employed individuals considering changes in their employment status. Key variables include interest in entrepreneurship, measured on a 5-point scale, and a binary indicator for being very interested in entrepreneurship. The likelihood of leaving for a startup is captured as a binary variable. Preferences for job flexibility are represented by a binary variable (defined as a response of "3" or higher to a question about the importance of flexibility), and current job flexibility is indicated by a binary variable (where "1" represents jobs that offer flexibility). Demographic variables include gender and age.

	(1) Log New Business Registration	(2) Log New Business Registration	(3) Log New Business Registration
Teleworkable Share (std)	0.494***	0.131***	0.167***
	(0.013)	(0.014)	(0.013)
Log Population		0.967***	0.956***
		(0.007)	(0.006)
Log Average AGI		0.557***	0.562***
		(0.025)	(0.025)
State-by-Quarter FE	N	N	Y
Observations	248,409	248,409	248,373
R-squared	0.120	0.694	0.819

Table 2. Relation between Teleworkable Share and New Business Registrations before the Pandemic

This table presents the results from panel OLS regressions of log new business registration on teleworkable share. Teleworkable Share is standardized to have a mean of zero and a standard deviation of one. The sample spans years 2011 through 2018 and covers 42 available U.S. states and the District of Columbia. The level of observation is a zipcode-quarter. In Column (1), no control variables or fixed effects are included. In Column (2), we control for the number of people and average income in a zipcode. In Column (3), we additionally control for state-by-year quarter fixed effects. Other variable definitions can be found in Table 1 legend. Standard errors are reported in parenthesis and are clustered at the zipcode level.

	(1) Log New Business Registration	(2) Log New Business Registration	(3) Log New Business Registration	(4) Log New Business Registration
Post X Teleworkable Share (std)	-0.080***	-0.079***	-0.080***	-0.072***
	(0.005)	(0.005)	(0.005)	(0.004)
Post	0.053***			
	(0.008)			
Teleworkable Share (std)	0.079***	0.176***		
	(0.024)	(0.020)		
Log Population	1.037***	0.978***	0.852***	-0.019
	(0.017)	(0.015)	(0.132)	(0.124)
Log Average AGI	0.501***	0.411***	0.191***	0.011
	(0.040)	(0.034)	(0.071)	(0.054)
New Case Rate	0.000***	0.000***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
State FE	N	Y	N	N
Year-Month FE	N	Y	Y	N
Zip FE	N	N	Y	Y
State-by-Month FE	N	N	N	Y
Observations	63,434	63,434	63,429	63,429
R-squared	0.625	0.757	0.904	0.935

Table 3. Difference-in-Difference Estimates of the Effects of Telework and Stay-at-Home Mandates on Entrepreneurship during the Pandemic

This table presents the results from Difference-in-Difference regressions. *Teleworkable Share* measures the share of jobs amenable to remote work in a zipcode, produced in Gupta, et. al. (2022). *Teleworkable Share* is standardized to have a mean of zero and a standard deviation of one. *Post* is an indicator variable that takes the value of one from March 2020 onwards. The sample covers January 2019 to March 2021 and includes monthly new business registration data from 8 U.S. states: AK, FL, GA, KY, NY, TN, TX, VT, and WA. The level of observation is a zipcode-month. We exclude months on and after April 2021 due to missing data from several large states after that. We vary the type of fixed effects included in the columns, as indicated at the bottom of the table. Other variable definitions can be found in Table 1 legend. Standard errors are reported in parenthesis and are clustered at the zipcode level.

	OLS		2SLS: First Stage		2SLS: Second Stage	
	(1) Log New Business Registration	(2) Log New Business Registration	(3) WFH Share (std)	(4) WFH Share (std)	(5) Log New Business Registration	(6) Log New Business Registration
WFH Share (std)	-0.095***	-0.045***			-0.447***	-0.627***
	(0.014)	(0.011)			(0.042)	(0.056)
Post X Teleworkable Share (std)			0.196***	0.168***		
			(0.011)	(0.011)		
Log Population	1.045***	0.212	-1.890***	-1.302***	0.174	-1.027***
	(0.268)	(0.161)	(0.494)	(0.430)	(0.285)	(0.301)
Log Average AGI	0.106	-0.066	0.227	0.332**	0.226	0.266*
	(0.110)	(0.077)	(0.157)	(0.154)	(0.149)	(0.144)
New Case Rate	0.000***	-0.000	-0.000***	-0.000***	-0.000*	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year-Month FE	Y	N	Y	N	Y	N
Zip FE	Y	Y	Y	Y	Y	Y
State-by-Month FE	N	Y	N	Y	N	Y
Observations	30,403	30,403	25,326	25,326	24,910	24,910
R-squared	0.881	0.929	0.912	0.931		

Table 4. 2SLS Estimates of the Effects of Telework on Entrepreneurship during the Pandemic

This table presents the results from panel 2SLS regressions of the effects of telework on entrepreneurship during the Pandemic. The sample covers January 2019 to March 2021 and includes monthly new business registration data from 8 U.S. states for which the Hansen, et. al. (2023) measure of WFH is available. The level of observation is a zipcode-month. *WFH share* is the percent of remote or hybrid workforce measured constructed in Hansen, et. al. (2024). *Teleworkable Share* measures the share of jobs amenable to remote work in a zipcode produced in Gupta, et. al. (2022). Both *WFH share* and *Teleworkable Share* are standardized to have a mean of zero and a standard deviation of one. *Post* is an indicator variable that takes the value of one from March 2020 onwards. Columns (1) and (2) report estimates from OLS regressions to test the relationship between WFH Share and new business registrations during the Pandemic. Columns (3) and (4) report estimates from the first stage of two-stage least square (2SLS) regressions, where we use telework potential and its interaction with stay-at-home mandates to instrument for the share of remote workforce. Column (5) and (6) report second stage estimates from 2SLS. Other variable definitions can be found in Table 1 legend. Standard errors are reported in parenthesis and are clustered at the zipcode level.

Panel A: Continuous Interactions

	(1) Log New Business Registration	(2) Log New Business Registration	(3) Log New Business Registration	(4) Log New Business Registration
Post X Teleworkable Share	-0.009	-0.008	-0.059***	-0.038***
	(0.009)	(0.007)	(0.008)	(0.007)
Post X Teleworkable Share X Log Average AGI	0.010***	0.013***		
	(0.004)	(0.003)		
Post X Teleworkable Share X % Unemp			-0.014*	-0.018**
			(0.008)	(0.007)
Controls and Other Lower Order Terms	Y	Y	Y	Y
Year-Month FE	Y	N	Y	N
Zip FE	Y	Y	Y	Y
State-by-Month FE	N	Y	N	Y
Observations	63,429	63,429	63,429	63,429
R-squared	0.904	0.936	0.904	0.935

Panel B: High/Low Indicators

	(1) Log New Business Registration	(2) Log New Business Registration	(3) Log New Business Registration
Post X High Log Average AGI	0.064***		
	(0.017)		
Post X Teleworkable Share X Low Average AGI	-0.035**		
	(0.018)		
Post X High % Unemp		0.022	
		(0.034)	
Post X Teleworkable Share X High % Unemp		-0.032*	
		(0.019)	
Post X Low Economic Condition			0.068***
			(0.016)
Post X Teleworkable Share X Low Economic Condition			-0.038**
			(0.018)
Controls and Other Lower Order Terms	Y	Y	Y
Zip FE	Y	Y	Y
State-by-Month FE	Y	Y	Y
Observations	63,250	63,250	63,250
R-squared	0.943	0.943	0.943

Table 5. Variation in Pecuniary Benefits

This table estimates heterogeneous effects of the effect of telework potential during the Pandemic. *Teleworkable Share* measures the share of jobs amenable to remote work in a zipcode produced in Gupta, et. al. (2022). *Post* is an indicator variable that takes the value of one from March 2020 onwards. *Log Average AGI* is the natural logarithm of the average individual adjusted gross income in the zipcode. *% Unemp* is the fraction of tax filings with unemployment compensation reported in the IRS data in the zipcode. *Teleworkable Share, Log Average AGI,* and *% Unemp* are standardized to have a mean of zero and a standard deviation of one. In Panel B, *Low Average AGI (High % Unemp)* is an indicator variable that takes the value of one if *Log Average AGI (% Unemp)* is below (above) median in the state. *Low Economic Condition* is an indicator variable that takes the value of one if both *Low Average AGI* and *High % Unemp* are equal to one. The sample covers January 2019 to March 2021 and includes monthly new business registration data from 8 U.S. states: AK, FL, GA, KY, NY, TN, TX, VT, and WA. The level of observation is a zipcode-month. We exclude months on and after April 2021 due to missing data from several large states after that. Standard errors are reported in parenthesis and are clustered at the zipcode level.

	(1) All Female Share	(2) Some Female Share
Post X Teleworkable Share (std)	-0.911***	-1.611***
	(0.144)	(0.291)
Log Population	-13.218***	-26.638***
	(4.208)	(8.622)
Log Average AGI	-2.660*	-6.434**
	(1.489)	(3.219)
New Case Rate	-0.000	-0.000
	(0.000)	(0.001)
Zip FE	Y	Y
State-by-Month FE	Y	Y
Observations	26,687	26,687
R-squared	0.376	0.339

Table 6. The Effects of Telework and Stay-at-Home Mandates on the Share of Female-Led Entrepreneurship during the Pandemic

This table presents the results from Difference-in-Difference regressions. *All Female Share* is the share of newly registered businesses with exclusively female founders. *Some Female Share* is the share of newly registered businesses with one or more female co-founders. *Teleworkable Share* measures the share of jobs amenable to remote work in a zipcode produced in Gupta, et. al. (2022). *Teleworkable Share* is standardized to have a mean of zero and a standard deviation of one. *Post* is an indicator variable that takes the value of one from March 2020 onwards. The sample covers January 2019 to March 2021 and includes monthly new business registration data from five U.S. states for which we have the underlying raw data: FL, GA, KY, TN, and TX. The level of observation is a zipcode-month. Other variable definitions can be found in Table 1 legend. Standard errors are reported in parenthesis and are clustered at the zipcode level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Likelihood of Leaving for Startup						
High Importance of flexibility in work schedule	0.086**		0.105***	0.102**	0.092**	0.210***	0.216**
	(0.030)		(0.031)	(0.032)	(0.033)	(0.063)	(0.069)
Current Job Offers flexibility		-0.039	-0.066*	-0.065*	-0.053	-0.008	-0.001
		(0.027)	(0.028)	(0.029)	(0.030)	(0.033)	(0.037)
High Importance of flexibility in work schedule X Current Job Offers flexibility						-0.174*	-0.204*
						(0.074)	(0.082)
Controls	N	N	N	Y	Y	Y	Y
State FE	N	N	N	N	Y	Y	Y
Household Income Decile FE	N	N	N	N	Y	Y	Y
Observations	998	998	998	998	994	994	758
Adjusted R-squared	0.008	0.001	0.012	0.012	0.015	0.021	0.025

Table 7. The Relation Between Flexibility Preferences and Current Job Flexibility on the Likelihood of Leaving to Start a Business

This table presents regression results examining how preferences for work flexibility and current job flexibility influence the likelihood of leaving a current job to start a business. The sample is drawn from a survey conducted in July 2024, targeting employed individuals considering changes in their employment status with a focus on job flexibility and entrepreneurial intent. Columns (1) to (3) progressively include flexibility preferences and current job flexibility as predictors. Column (4) adds controls for gender and age (log-transformed). Columns (5) and (6) incorporate fixed effects for state of residence and income level, with Column (6) including interaction terms between flexibility preferences and current job flexibility. Column (7) restricts the sample to full-time employees with fixed effects included. Robust standard errors are reported in parentheses. Interaction terms and control variables are noted where applicable.