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SPECIAL ISSUE PAPER

Digital exposure, age, and entrepreneurship

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Abstract
This study focuses on age and digital exposure as factors driving individuals to be (1) *employees* or *entrepreneurs*, (2) *full-time* or *part-time*, or (3) *opportunity* or *necessity* entrepreneurs. It extends occupational choice models, relying on a utility maximization framework, to entrepreneur types incorporating age and digital exposure effects. Using 132 months of Current Population Survey data and multilevel modelling with individuals' fixed effects and metropolitan area random effects, the study finds that (1) workers with low- and high- digital exposure are more likely to become entrepreneurs than peers with medium digital exposure, mirroring digitization's "push" and "pull" mechanisms on entrepreneurship; (2) age strengthens digitization's "pull" mechanism to be *entrepreneurs* (versus *employees*) and *opportunity* (versus *necessity*) entrepreneurs; (3) digital exposure has a weak marginal potential to increase workers' odds to be *part-time* (versus *full-time*) entrepreneurs. The study also notes the importance of location and concludes with discussion and implications.

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1 Introduction

Digitization converts analogue information to digital form so that the information can be processed, stored, and transmitted by computers (McQuail 2000). For workers, digitization is reflected by their digital exposure in the industry sectors where they work. Digital exposure is much broader than digital skills; it integrates elements of the agglomeration (Marshall 1890; Arrow 1962; Romer 1986) of digital ecosystems (Sussan and Acs 2017), including digital platforms, digital tools, digital technology, digital usage, and digital skills in their jobs.

Digitization is seen as a precondition for growth in today's economy; however, concerns about the fate of workers in a digitized economy seem legitimate. Acemoglu and Restrepo (2017) provide evidence justifying workers' concerns. While digitization *replaces* routine-task jobs and "pushes" those employees towards entrepreneurship (Autor 2003; Frey and Osborne 2017); there may also be a "pull" effect. Digitization *facilitates* new entrepreneurial opportunities with openness, affordances, and generativity (Nambisan et al. 2019). Digitization's dual roles—replacement and facilitation effect of employment—align well with literature on occupational choice and entrepreneurship determinants.

While digitization intersects population ageing,[1] the "push" and "pull" effects could be both particularly applicable to older workers (often of age 55 or above) and provide a more nuanced understanding of the relationship between age and entrepreneurship. On the one hand, older workers are particularly vulnerable to being pushed out of employment due to perceived skill obsolescence (Crown and Longino 2000) or a lack of job-hunting skills (Hooyman and Kiyak 2005). On the other hand, Zhang (2008) argues that reduced physical constraints in economic activities and a greater reliance on knowledge and information could help "pull" older workers into entrepreneurship. As a result of the "push" and "pull" effects, consistent empirical evidence shows that the self-employment rate is higher among older workers than that among younger workers (Zissimopoulos and Karoly 2007; Hipple and Hammond 2016).

Not only digital exposure is a concept related to environment and space, entrepreneurship is also related to geography, as Sternberg (2021) suggested. This study fits into this paradigm and incorporates spatial influences. Our empirical analysis first relies on multilevel mixed-effects logistic models to model spatial as well as temporal dependencies (Baayen et al. 2008) across different metropolitan areas. Metropolitan areas reflect local transportation, commuting, and demand patterns (vom Berge 2013). We also control for local unemployment rate variations that capture local labour market conditions (Bilal 2021). Further, we control for central city area or not to reflect the very core of economic spatial patterns. From Friedmann (1966)'s core–periphery model to Krugman (1991)'s new economic geography, central city areas have always been economic highlights, notwithstanding suburbanization of

[1] According to the 2020 U.S. Census, 17% of the US population was over 65 years; projected to be 21% in 2030. Bureau of Labour Statistics data indicate that the share of the labour force aged 55 or over is expected to increase from 23.4% in 2019 to 25.2% in.2029.

jobs and maturation of "edge cities" (Garreau 1991). Local labour market conditions and central city locations are part of the social capital construct in our occupational choice modelling.

Incorporating metropolitan area-level random effects and individual worker level fixed effects and controlling for local labour market conditions, social capital, and other attributes, this study investigates the impact of digital exposure and the age modification effect on being entrepreneurs or different types of entrepreneurs. It contributes to the literature on digitation and entrepreneurship by (1) identifying the age modification effects on the digitization–entrepreneurship dynamics, (2) extending occupational choice literature to propensities for *opportunity* (versus *necessity)* and *full-time* (versus *part-time*) entrepreneurs, (3) adopting a digital exposure measure to capture digital ecosystem effects, instead of just digital skills, and (4) integrating digitization's labour replacement and facilitation effects. Relying on 132 months' Current Population Survey data and a set of multilevel mixed-effects logistic regression models and other models to test four hypotheses, the study finds that (1) workers with low- and high- digital exposure are more likely to become entrepreneurs than peers with medium digital exposure, mirroring digitization's "push" and "pull" mechanisms on entrepreneurship; (2) age increasingly strengthens digitization's "pull" mechanism to be *entrepreneurs* (versus *employees*) and *opportunity* (versus *necessity*) entrepreneurs; (3) high digital exposure has a weak marginal potential to increase workers' odds to be *part-time* (versus *full-time*) entrepreneurs. The study also notes the importance of location.

The study therefore first emphasizes the importance of lifelong learning and digital exposure for workers with medium and low digital exposure, not just digital skills, to reduce their replacement risk and for workers who want to be entrepreneurs later in life. The high (*opportunity) entrepreneur* propensity among older workers with high digital exposure helps challenge the stereotype that older workers are typically technologically obsolete or become mostly *necessity* entrepreneurs. The study also calls for policy support to help accommodate and incubate entrepreneurship as the last and needed resort for workers with low digital exposure, particularly older workers with low digital exposure, and brings attention to potential work paradigm change for more *part-time* entrepreneurship with rising digital exposure.

The next section reviews the key literature, followed by four research hypotheses. Then, after explaining research methodology, we present descriptive statistics, findings with robustness checks, and limitations of the study. Lastly, we present topics due further discussion, summarize conclusions, and consider implications of our findings.

2 Literature review

Digitization's *replacement* and *facilitation* effects for workers are reflected in "push" and "pull" effects in entrepreneurship with different mechanisms. The different mechanisms could manifest in propensities for different entrepreneur types across the age spectrum. Prior literature has not addressed the age effect on the digitization–entrepreneurship relationship, neither on multiple different entrepreneur types.

We review the literature on four related areas: the determinants of entrepreneurship, digitization's role on entrepreneurship, age and entrepreneurship, and types of entrepreneurs.

2.1 Determinants of entrepreneurship

Utility theory and occupation choice models have been used to characterize workers' decisions regarding employment, self-employment, and leisure (e.g. Blanchflower 2000); for older workers' decisions, it is the trade-off between employment, self-employment, retirement, and leisure (e.g. Lévesque and Minniti 2006). Jafari-Sadeghi (2020) argues for the importance of the "push"- or "pull"- factors in guiding behaviour. The "push" to start a business is generated by the need for income; the "pull" is generated by grasping new entrepreneurial opportunities. Prior literature has addressed many factors influencing the likelihood of starting a new business. Horisch et al. (2017) focus on occupational choice through the prism of gender, while Friedline and West (2016) focus on race. Lee and Vouchilas (2016) and Zhang and Acs (2018) highlight and contextualize the relationship between entrepreneurial activity and age, particularly of older workers. Other identified factors driving entrepreneurial propensity include education (Parker 2009; Velilla and Ortega 2017), unemployment rates (Fairlie and Fossen 2017), prior (quasi-) entrepreneurial experience (Hsu et al. 2017), urban residence (Glaeser 2007), responsibility for family care (Walker et al. 2007), local economic settings (Fairlie and Fossen 2017), wealth or liquidity constraints (Schmalz et al. 2017) and health (Zhang and Carr 2014). Recently, digitization has also been identified as a source for entrepreneurship because it facilitates entrepreneurship (Nambisan et al. 2019) or because it replaces jobs (Frey and Osborne 2017; Fossen and Sorgner 2019). In addition to the determinants of entrepreneurship, a review of the relationship between digitization and entrepreneurship can help contextualize the current study.

2.2 Digitation and entrepreneurship

According to McQuail (2000), digitization converts analogue information to digital form so that the information can be processed, stored, and transmitted by computers. The impacts of digitization on the propensity to start businesses are addressed in Frey and Osborne (2017) and Fossen and Sorgner (2018). Sussan and Acs (2017) extended the inquiry to consider starting new ventures within a "digital ecosystem".

Since the creation of personal computers, digitization has facilitated new entrepreneurial opportunities with openness, affordances, and generativity (Nambisan et al. 2019). For the openness, digital technology has expanded the scope of who can participate (actors), what can be contributed (inputs), how to contribute (process), and to what ends (outcomes) (Nambisan et al. 2019). Digital technologies are broadening the visibility of businesses (Isaksson and Wennberg 2016), offering more and increasingly efficient communication channels for marketing, sales, financing, human resources, and social networking, allowing easier and cheaper access to market research information (Goldfarb et al. 2013), and providing access to financing via crowdfunding (Haddad and Hornuf 2018). For the affordances, digitalization reduces search, communication, and monitoring costs (Goldfarb et al. 2013), lowers barriers to funding, marketing, sales and distribution, and allows for rapid and seamless information sharing (Isaksson and Wennberg 2016). For generativity, digital technologies produce unprompted change through "blending" or recombining various potentially unrelated and uncoordinated entities. For example, digitization has brought new entrepreneurial opportunities in shared economy (Richter et al. 2017) and digital entrepreneurship (Sussan and Acs 2017). This propels the facilitating "pull" effect for becoming entrepreneur. This "pull" effect can be particularly valuable for older workers by posting fewer physical constraints in the digitalized and knowledge-based world (Zhang 2008).

In the meantime, digitization has replaced many workers' jobs, which "push" many unemployed workers into entrepreneurship (Sorgner 2017), while also putting certain entrepreneur jobs at risk. As artificial intelligence becomes more and more efficient at simulating and replacing human tasks, Frey and Osborne (2017) rely on expert judgments since 2013 on occupation-specific tasks and conclude that about 47 per cent of the US labour force currently in jobs is very likely to be replaced by machines in the next decade or so. This result has largely been confirmed by other studies (e.g. Acemoglu and Restrepo 2017), though the average risk of automation varies across countries (see, e.g. Arntz et al. 2017).

2.3 Age and entrepreneurship

Theoretically and empirically, the willingness and intention to start a business decrease with age (Van Praag and Van Ophem 1995), due to the increasing opportunity cost of time with age, and thus there is a higher discount rate of wage utility in the future (Lévesque and Minniti 2006). However, the opportunity to start a business increases with age because of higher or increased accumulated physical, social, and human capital (Lee and Vouchilas 2016).

With those two opposite forces, some prior literature observed a nonlinear age trend on entrepreneurship, peaking in ages of 35–44 (Parker 2009), some studies even show a more pronounced self-employment rate among older workers (Zissimopoulos and Karoly 2007[2]). Newer and different data sources from the U.S. Census Bureau[3] echoes that older adults over age 65 have higher rates of self-employment (approximately 15.5%) than younger adults (Hipple and Hammond 2016), while only 1.4% of adults in the youngest working age category (16–24) were self-employed.

Part of the complex age effects in entrepreneurship could be related to entrepreneur types (Zhang and Acs 2018). Kautonen et al. (2014) empirically demonstrated that entrepreneurial activity increases almost linearly with age for sole proprietors but increases till late 40 s and then decreases for people who aspire

[2] Using Health and Retirement Study data.

[3] The data source is the Current Population Survey.

to hire workers (owner-managers) using European samples. Block and Wagner (2010) noted *opportunity* and *necessity* entrepreneur differ in age structure. Zhang and Acs (2018) showed that propensity of *novice* (versus *non-novice*) and *unincorporated* (versus *incorporated*) entrepreneurs has a U-shaped age trend dipping around age 60, while the propensity of *full-time* (versus *part-time*) declines since age 30 s.

Gielnik et al. (2018) approach the relationship between age and decision to be an entrepreneur from a transnational, life-cycle perspective. Entrepreneur efforts are the result of a three-stage transformation—opportunity identification, opportunity evaluation, and finally engagement in entrepreneurial activity: younger people are more likely to make the first transformation, while older workers are more likely to make the second transformation because of fewer future time perspectives at older ages. They also emphasize prior entrepreneurial experience as increasing with age and encouraging the second transformation.

2.4 Types of entrepreneurs

Prior literature has examined different entrepreneur types, but very limited literature has addressed the relationship between digitization and entrepreneur types. Fossen and Sorgner (2018) explored digitization's role on *incorporated* versus *unincorporated* entrepreneurship and found that digitization's labour replacement (or job automation) increased the likelihood of becoming *unincorporated* entrepreneurs, while digitization's human–machine interaction (or collaboration) increased the likelihood of becoming *incorporated* entrepreneurs. This is an interesting empirical finding; however, interpreting the distinction between incorporated and *unincorporated* entrepreneurship in self-reported survey data could prove difficult. Zhang and Acs (2018) also measured other entrepreneur types, including *opportunity* versus *necessity* entrepreneurs and *full-time* versus *part-time* entrepreneurs.

The most prominent difference between *opportunity* and *necessity* entrepreneurs is their motivation for starting a business (Block and Wagner 2010). *Opportunity* entrepreneurs start a new venture to pursue a business opportunity, i.e. have an interest in financial success (Weber and Schaper 2004) or in self-realization (Kautonen et al. 2017), whereas *necessity* entrepreneurs are pushed to start a business often facing unsatisfactory alternatives (Bergmann and Sternberg 2007), i.e. unemployment or limited wages. Block and Wagner (2010) thus call for different policies because the two groups vary in age, gender, region, and perceived risk.

Working more hours, *full-time* entrepreneurs have a stronger commitment and bear more risks than their *part-time* counterparts: *Part-time* entrepreneurs usually test a business opportunity without making an irrevocable investment (Wennberg et al. 2006), need fewer physical and financial resources as they support lower marginal costs (Folta et al. 2010) and have more flexibility and time for themselves or family commitments (Block and Landgraf 2013). *Full-time* entrepreneurs are therefore expected to have higher earnings and be healthier (Fig. 1).

3 Hypotheses

As mentioned earlier, digitization has helped develop entrepreneurship in two different ways—the "push" and "pull" mechanisms. For the "pull" mechanism, digitization facilitates new entrepreneurial opportunities with openness, affordances, and generativity (Nambisan et al. 2019); this mechanism would not be effective unless people who intend to run business are familiar with digital platforms, digital tools, digital technology, and skills, i.e. with high digital exposure. Therefore, workers with high digital exposure are potentially more likely than workers with low digital exposure to benefit from the "pull" mechanism and become *entrepreneurs*, instead of being wage-and-salary *employees* who work for others.

From the "push" mechanism, digitization is known to push workers who do routine tasks out of jobs (Frey and Osborne 2017) and replace those jobs. Workers with limited digital exposure could be the ones to be replaced and have limited employment alternatives. For those workers, being self-employed or running their own business could be a potential employment alterative. Therefore, workers with low digital exposure are more likely to be "pushed" into entrepreneurship. Combining those two mechanisms, we hypothesize.

Hypothesis 1: *Workers with medium, not high or low, digital exposure is least likely to be entrepreneurs (versus wage-and-salary employees).*

Digitization's catalysing function for entrepreneurship could be particularly strong for older workers. While our world is being digitized, empirical evidence has consistently demonstrated a larger and increasing share of self-employment among older workers (Fairlie et al. 2016; Hipple and Hammond 2016; Zissimopoulos and Karoly 2007; Zhang and Acs 2018). Digitization facilitates knowledge-based jobs and entrepreneurship opportunities that could be more age friendly: digitization offers (1) easy access to information without having to commute, (2) automation to support routine and manual labour-intensive tasks, and (3) assisted technology to accommodate reading information, communication, mobility, and health care needs. All of those factors could especially benefit relatively physically constrained older workers (Zhang 2008), particularly those with high digital exposure. We therefore hypothesize.

Hypothesis 2: *Older workers with higher digital exposure, compared to those with lower digital exposure, are more likely to become entrepreneurs (versus wage-and-salary employees).*

Hypotheses 1 and 2 apply to and are tested across all working individuals in the labour force, including both *entrepreneurs* or *wage-and-salary employees*. Hypotheses 3 and 4, motivated and defined below, apply to entrepreneurs only, including *full-time* versus *part-time* entrepreneurs and *opportunity* versus *necessity entrepreneurs*.

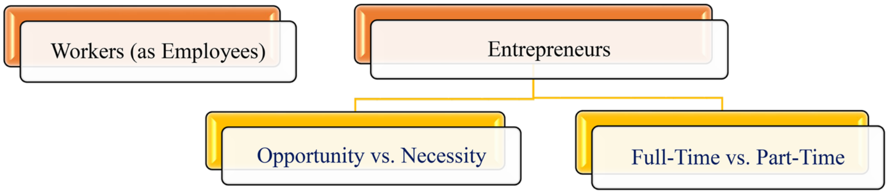

Fig. 1 Four (two pairs of) entrepreneur types

As digitization offers more communication channels, easier access to information (Goldfarb et al. 2013), and rapid and seamless information sharing (Isaksson and Wennberg 2016) over the Internet, this facilitates entrepreneurship from almost anywhere and anytime with access to computers and Internet. Digital technologies have made work more flexible and have blurred the borders between work and free time (Grönlund and Öun 2018). Digitization makes physical mobility less needed, which brings about convenience and flexibility to become *part-time* (versus *full-time*) entrepreneurs. Rising with digitization at the same time includes a trend of non-traditional work arrangement such as *part-time* or hybrid entrepreneurs (Folta 2007; Schulz et al. 2016) who are entrepreneurs on a *part-time* basis and might even have another job. While holding another job or commitment or being retired, one can in the meantime run a *part-time* side-line business, either to test a business opportunity with a lower resource investment (Wennberg et al. 2006; Folta et al. 2010) or to have more flexibility with other commitments (Block and Landgraf 2013), different from *full-time* entrepreneurs. In this context, we hypothesize.

Hypothesis 3*: Workers with higher digital exposure are more likely to be part-time (versus full-time) entrepreneurs than those with lower digital exposure.*

As mentioned earlier, digitization "pushes" workers out of wage-and-salary employment and potentially into entrepreneurship. Like machines replacing physical human labourers, digitization further automates routine tasks that continue to replace workers and jobs. From 1990 to 2007, deployment of industrial robots reduced the employment to population ratio in the United States (Acemoglu and Restrepo 2017). This enlarges the pool for those who have no alternative employment options and thus, being potentially "pushed" into entrepreneurship.

However, as time goes by, the "push" mechanism of digitization could be overridden by digitization's "pull" mechanism. First, digital exposure and its effect in facilitating entrepreneurship take some time; second, the accumulated working experience and wealth at older ages increase one's physical, human, and social capital thus elevating entrepreneurial opportunities (Lee and Vouchilas 2016; Zhang and Acs 2018). However, Zhang and Acs (2018) found no significant empirical evidence on a higher propensity for *opportunity* versus *necessity* entrepreneurs as people age. With better communication and information access, digitization's facilitating "pull" mechanism can catalyse spillovers and acquisition of human and social capital, elevating entrepreneurial opportunities. Possessing potentially more human and social capital than younger workers, older workers may have a comparative advantage in pursuing self-employment; an advantage that is further leveraged by less physical constraints owing to digitization. We therefore hypothesize.

Hypothesis 4*: As age increases, higher digital exposure increases workers' propensity for opportunity (versus necessity) entrepreneurship, compared to lower digital exposure.*

4 Data

The study relies on the longitudinally linked U.S. Current Population Survey (CPS) data compiled by Flood et al. (2015),[4] as well as the U.S. Bureau of Labor Statistics (BLS) metropolitan area unemployment rate for local economic conditions,[5] for the years 2006–2016. To measure the transition between not employed to different entrepreneur types, a nationally well-represented dataset that captures month-to-month employment transitions over multiple years with individual-level demographic and socioeconomic details is the best. The CPS data become appropriate for multiple reasons:

1. Since our analysis parses the sample population by entrepreneur type, age, and industrial sector, there is a risk of having limited observations in some categorical groupings. To minimize this risk, a large, reliable national sample is necessary. The CPS dataset covers the noninstitutionalized US civilian population aged 16 and above and includes extensive longitudinal demographic and socioeconomic information. It also has one of the highest response rates, 90%, among government household surveys (U.S. BLS and US Census Bureau 2006).
2. The monthly CPS data allow identification of employment status change and different entrepreneur types. Most importantly, it provides the reasons for unemployment (*voluntary* of *involuntary*), enabling the separation of *opportunity* and *necessity* entrepreneurs, respectively.[6]
3. The CPS is the best source for self-employment information, as it reports on self-employed individuals not covered in the Current Employment Statistics and is the source of official statistics on the status of US self-employment (Zissimopoulos and Karoly 2007).

[4] See the Integrated Public Use Microdata Series, https://cps.ipums.org/cps/.

[5] See https://www.bls.gov/lau/.

[6] We defined opportunity versus necessity entrepreneurs based on three survey questions in the CPS: (1) whether a respondent was self-employed, was an employee in private industry or the public sector, was in the armed forces, or worked without pay in a family business or farm; (2) whether persons were part of the labour force—working or seeking work—and, if so, whether they were currently unemployed; and (3) why respondents were unemployed—either actively seeking work or on temporary layoff from a job—during the previous week.

4. The CPS provides microdata at the individual level and with reliable estimates at the metropolitan statistical area levels. The metropolitan area affiliation allows for controlling individual workers' macroeconomic environments.

Households in the CPS are interviewed according to a 4-8-4 rotation pattern: that is, households are interviewed for four consecutive months, dropped out of the sample for the next eight months, and interviewed again in the next four months, after which they leave the sample permanently.[7] The 4-8-4 rotation has the added benefit of allowing the sample to be constantly replenished, with continuity and without an excessive burden on respondents (U.S. BLS and U.S. Census Bureau 2006), though it only tracks a person for eight sampling months in total.

Although the CPS data contains self-identified information that can cause common method bias (Podsakoff et al. 2003), this is not a major concern in this study. The data cover 132 monthly data points with eight monthly measures for each worker; the constantly replenishing data, therefore, avoid the problem of using a single response at a single point in time. In addition, using the well-represented, large-scale, multipurpose CPS national survey data reduces the effects of social desirability bias typically seen in small, single-purpose surveys (Binder and Coad 2013).

5 Empirical models and variables

To test digitization effect on entrepreneur and entrepreneur type propensities, we extended the occupational choice model in prior literature to include entrepreneur type propensities. To address the modifying age effects through digitization on entrepreneurship, we adopted an interaction term between digitization and age. Empirically, we adopt a series of binomial multilevel mixed-effects logistic regression models as well as other logit models.

Considering our data structure and local labour market locational effects, multilevel mixed-effects logistic regression models have benefits over several other often-used modelling approaches. Our hierarchical data, at both metropolitan and individual levels, as in Hörisch et al. (2017), allows for the luxury to adopt multilevel modelling. With the longitudinal and panel data, a fixed-effects logistic regression could be a possible option to model the temporal changes fixed onto a specific individual, rather than just using a simple logistic regression. However, entrepreneurial behaviour is an employment behaviour subject to local market conditions and the labour pool. Therefore, individual workers are interdependent in an area where knowledge, information, labour, and social networks flow easily and affect individual workers. In this case, worker fixed-effect logistic regression is limited, as the assumption of independent and identical distribution between individual workers is violated (McCoach and Adelson 2010) and it does not allow for necessary random effects in local areas.

[7] For example, individuals who are interviewed in January, February, March, and April of one year are interviewed again in the next January, February, March, and April.

If we only wish to adjust the logistic regression for non-independence, we could choose a logistic regression with metropolitan area fixed-effect logistic regression or logistic regression with clustered standard errors. However, neither of those potential alternative methods addresses the random effects in local areas. This is particularly an issue when there are many clusters (metropolitan areas) in studies like this one. Multilevel modelling also has an advantage of allowing for unbalanced sample size across local areas (Raudenbush 1993) shown in this study, compared to modelling with metropolitan area fixed-effects or clustered standard errors.

A metropolitan area typically includes one or more urban centres that form an employment-based commuting circle. For our models, this serves well as our socioeconomic area control. We want to observe not only variations across specific entrepreneurs (fixed individual effects) but also random variations across metropolitan areas (random metropolitan area effects). In longitudinal or panel data, random effects are useful for modelling intra-metropolitan area correlation; that is, entrepreneurs in the same metropolitan area are correlated because they share common metropolitan area-level random effects. Mixed-effects logistic regression contains both fixed effects and random effects.

Multilevel mixed-effects logistic regressions have been used extensively in social science studies, such as Ng et al. (2006), which analyses a Bangladeshi fertility survey, and Rabe-Hesketh and Skrondal (2012), which analyses school data from Scotland. As StataCorp (2015) notes, log likelihood calculations for fitting any generalized mixed-effects model require integrating out the random effects. A widely used method is to directly estimate the integral required to calculate the log likelihood by Gauss–Hermite quadrature or some variation thereof. The estimation method we use is a multi-coefficient and multilevel extension of one of these quadrature types, an adaptive Gaussian quadrature based on conditional modes using Stata (StataCorp 2015), with a multi-coefficient extension from Pinheiro and Bates (1995) and a multilevel extension from Pinheiro and Chao (2006). This rest of this section explains further methodological details.

5.1 Binomial multilevel mixed-effects logistic regression model specification

To estimate the utility-maximization-theory-based occupational choice models, logistic regressions are adopted to test the various factors affecting the propensity to be entrepreneurs or specific entrepreneur types. Our outcome variables are binary. An appropriate model is a logistic regression, with the dependent variable capturing the log odds of the binary outcomes modelled as a linear combination of the independent variables, as shown in Model (1). Model (1) is the base logistic cumulative distribution function with the linear binary predictor of the probability that $Y=1$, that is, for entrepreneurs to be a certain type in a contrasting pair: *entrepreneur* (versus *wage-and-salary employees*), *opportunity* (versus *necessity*) entrepreneurs, and *full-time* (versus *part-time*) entrepreneurs:

$$P(Y_{itj} = 1|u_{tjj}) = \frac{\exp(\alpha_0 + \sum \beta_k X_{kitj} + Z_{itj}u_{tj})}{1 + \exp(\alpha_0 + \sum \beta_k X_{kitj} + Z_{itj}u_{tj})}. \tag{1}$$

In our two-level mixed-effects logistic regression model, a series of m metropolitan areas are conditional on a set of random effects u_{tj}, for $j=1$, …. m metropolitan areas, with metropolitan area j consisting of $i=1$, …., n_j workers in metropolitan area j across time periods (months) t. $\sum X_{kitj}$ measures k factors affecting individual workers, such as human and social capital, demographic and socioeconomic attributes, and local market conditions. Each vector X_{itj} is a covariate for the fixed effects, analogous to the covariates in a standard logistic regression model, with regression coefficients (fixed effects) β. Vector Z_{itj} is the covariate corresponding to the random effects. The random effects u_{tj} are m realizations from a multivariate normal distribution, with mean 0 and variance δ. The random effects are not directly estimated as model parameters but are instead summarized according to the unique elements of variance.[8]

To test digitization and age effects on entrepreneur and entrepreneur type propensities, we extended the widely used occupational choice model in prior literature and Model (1) into Model (2) to include entrepreneur type propensities (i.e. *E-Propensity*). In order to address the effect of digitization and age on entrepreneurship, we adopted an interaction term between digitization (*DigitalExposure*) and age (*Age*):

$$\begin{aligned}&\text{logit(E-Propensity}_{\text{ijt}}) = \text{g}(\textbf{DigitalExposure}_{\text{ijt}}, \textbf{Age}_{\text{ijt}}, \textbf{DigitalExposure}_{\text{ijt}}{*}\textbf{Age}_{\text{ijt}},\\ &\text{Unemployment}_{\text{ijt}}\ \text{Reside}_{\text{ijt}}, \text{FamilyE}_{\text{ijt}}, \text{Exp}_{\text{ijt}}, \text{Edu}_{\text{ijt}}, \text{Health}_{\text{ijt}}, \text{Capital}_{\text{ijt}}, \text{Demographics}_{\text{ijt}},\\ &\text{Marital}_{\text{ijt}}, \text{Child}_{\text{ijt}},) \quad \boxed{\text{Social Capital}} \quad \boxed{\text{Human Capital}} \quad \boxed{\text{Physical Capital}}\end{aligned} \tag{2}$$

Workers' *E-Propensity* relies on individuals' *age*, *marital* status, *child* responsibility, and three main capitals—physical capital; human capital represented by education attainment (*Edu*) and *health* status; and social capital represented by family members' entrepreneur propensity (*FamilyE*), prior working experience (*Exp*), where the individual *resides*, and local business cycles represented by local *unemployment* rates. All these vary by individual i, location j, and time t. The following sections explain our detailed variable measurements in Model (2).

[8] Considering the fact that the local economic condition might have spatial influence or autocorrelation from contiguous local areas' economic conditions, as addressed in Santarelli et al. (2009), spatial econometrics were initially considered. However, for five reasons we did not think it necessary in this study: (1) we adopted multilevel modelling at metropolitan area level and individual levels in the study already; (2) we controlled for local unemployment rates and central city status to capture local socioeconomic influence; (3) our cluster-level unit is in metropolitan areas, which are not mostly contiguous geographically. Without contiguity, the spatial interdependence is limited. (2) A metropolitan area is a commuting circle in which residents and commuters share the urban centres and socioeconomic atmosphere, rather than sharing those in another metropolitan area some distance away. This differs from other geographic units that are arbitrarily determined by political (such as county) or population size boundaries (such as census blocks). (3) When facing a non-contiguous geographic unit, one needs to use a distance matrix to measure spatial associations that typically assume Euclidian distance between centroids of metropolitan areas. This hypothetical centroid approximation is not a good representation of the urban core, and the distance-based measure of influence from another metropolitan area is further compromised by size of the metropolitan areas. (4) Our basic unit of analysis is fixed at individual level and the majority of variation across our observations is at the individual level, not at a geographic area level, thus spatial interdependence is less of a concern.

5.2 Dependent variables

The dependent variables capture the propensity to be an *entrepreneur* (versus a *wage-and-salary employee*), *opportunity* (versus *necessity)*, and *full-time* (versus *part-time)* entrepreneurs. They are binary variables with value 1 for *entrepreneurs*, *opportunity* entrepreneurs*, and full-time* entrepreneurs and value 0, respectively, for *employees*, *necessity* entrepreneurs*, and part-time* entrepreneurs.

5.2.1 Measure of entrepreneurs

Self-employment is a measure often used for entrepreneurship (Fairlie and Fossen 2017[9]). In this study, we define entrepreneurs as those who own incorporated or unincorporated businesses and those who are employers or non-employers[10] in the *non-agricultural knowledge-based* sectors. To avoid the drawbacks of using self-employment to measure entrepreneurship and address perspectives of innovation and knowledge spillovers (Acs et al. 2010), this study defines entrepreneurs as *knowledge-based non-agricultural* self-employment, consistent with Zhang (2008). The *knowledge-based* occupations follow the definition used in Florida's (2004) "creative class".[11] Three CPS questions are used to extract this data: (a) whether a respondent was self-employed, was an employee in private industry or the public sector, was in the armed forces, or worked without pay in a family business or farm; (b) what type of industry in which the person performed his or her primary occupation; (c) what occupation in which the person worked. This study includes both incorporated and unincorporated self-employment to measure beyond sole proprietors. Alternative entrepreneurship measures include R&D expenditures and number of start-ups; however, the former tends to underestimate small-business entrepreneurship (Acs and Audretsch 1990) and the latter (Audretsch and Keilbach 2004) does not fully capture sustainability issues.

5.2.2 Measures of the four entrepreneur types

We measure *opportunity* versus *necessity* entrepreneurs based on two survey questions in the CPS, in addition to the above three survey questions defining entrepreneurs[12]: (d) whether persons were part of the labour force (working or seeking work)

[9] Among others, including Evans and Leighton (1989), Kautonen et al. (2014), and Zissimopoulos and Karoly (2007).

[10] According to Fairlie et al. (2016), the U.S. Census Bureau notes that the definitions of non-employers and self-employed business owners are not the same; although most self-employed business owners are non-employers, about a million self-employed business owners are classified as employer businesses.

[11] Florida's (2004) "creative class" occupations include sectors of management, business and financial operations, computer and mathematical, architecture and engineering, science, law, education, arts and media, health-care practitioners, and high-level sales management.

[12] i.e. (a) whether a respondent was self-employed, was an employee in private industry or the public sector, was in the armed forces, or worked without pay in a family business or farm; (b) what type of industry in which the person performed his or her primary occupation; (c) what occupation in which the person worked.

and, if so, whether they were currently unemployed; and (e) why respondents were unemployed (either actively seeking work or on temporary layoff from a job) during the previous week.

Considering that the CPS data follows the aforementioned 4–8-4 rotation pattern, *necessity* entrepreneurs are measured as entrepreneurs[13] who were unemployed workers[14] because they were unable to work, unpaid workers, or unemployed for involuntary reasons [based on answers from above CPS question (e)] in any of the previous eight sampled months.

Correspondingly, *opportunity* entrepreneurs are measured as entrepreneurs[15] who had a job [including in the armed forces, based on answers from above CPS question (d)] or left a job voluntarily [based on answers from above CPS question (e)] in the eight previous sampled months for that individual. Note that not all entrepreneurs are classified as either *necessity* or *opportunity* entrepreneurs. This measure of *necessity* versus *opportunity* coincides somewhat with Fairlie and Fossen (2017) but is more nuanced in terms of whether a job loss is voluntary or not.

We measure *full-time* entrepreneurs as those who reported having worked for 35 + hours weekly during the reference months, otherwise *part-time*. Those are defined using the following CPS questions: (f) whether they have part-time or full-time (35 + hours) employment status, in addition to the above three CPS questions (a) through (c) that we used to define *entrepreneurs*.

5.3 Independent variables

Our key independent variables include *Age* and *DigitalExposure*. The former is a continuous numerical variable, and the latter is an ordinal categorical variable. *Age* includes all working ages in the data, though our highest cut-off age is 85, enough to cover all effective working ages.

To measure digital exposure, we adopted McKinsey Global Institute (MGI)'s Industry Digitization Index (McKinsey Global Institute 2015) which provides a snapshot of activity at the sector level. Workers in a more digitized industry sector have higher digital exposure. Because the digital frontier is expanding on many fronts simultaneously, it is impossible to pin down the extent of digitization in the US economy with any single metric (McKinsey Global Institute 2015). MGI's Industry Digitization Index offers an extensive measure of workers' digitization environment. The index compiles 27 indicators to measure the digital assets, digital usage, and digital workers in each sector and examines sectors across the economy. According to McKinsey Global Institute (2015), to measure digital assets, for instance, the index incorporates business spending on computers, software, and telecom equipment, as well as the stock of ICT assets, the share of assets such as robots

[13] That is self-employed in the knowledge-based sectors, based on answers from above CPS questions (a) through (c).

[14] Based on answers from above CPS question (d).

[15] Based on answers from above CPS questions (a) through (c).

and cars that are digitally connected, and total data storage. Usage metrics include an industry's use of digital payments, digital marketing, and socializing technologies, as well as the use of software to manage both back-office operations and customer relationships. On the workforce side, the index evaluates more than 12,000 detailed task descriptions to identify those associated with digital technologies and skills (such as database administration). This index also includes the share of workers in each sector in technology-related occupations that did not exist 25 years ago and also determines digital spending and assets on a per-worker basis.

To be more specific, we classified the industry sectors into 6 ordinal digitization levels, based on the overall digitization for MGI's Industry Digitization Index, as shown below in descending order of digitalization:

1. Knowledge-intensive sectors that are highly digitized across most dimensions, including sectors of *information and communications technology*.
2. Capital-intensive sectors with the potential to further digitize their physical assets, including sectors of *Media, Professional Services, Finance, and Insurance.*
3. 4. Service sectors with a long tail of small firms having room to digitize customer transactions, including sectors of *Oil and Gas, Utility, Advanced Manufacturing,* and *Wholesale Trade.*
4. Business-to-business sectors with the potential to digitally engage and interact with their customers, including sectors of *Retail Trade, Real Estate, Education,* and *Public Administration.*
5. Labour-intensive sectors with the potential to provide digital tools to their workforce including sectors of *Basic Goods Manufacturing, Transportation and Warehousing,* and *Health.*
6. Quasi-public and/or highly localized sectors that lag across most dimensions, including sectors of *Agriculture, Mining, Construction, Arts, and Entertainment.*

In this study, we used both 6-level and 3-level measures for digital exposure. The advantage of using the 3-level measure is that we can label and visualize them easily as high-, medium-, and low-level digital exposure, respectively, representing levels 5–6, 3–4, and 1–2.

This measure not only captures multiple dimensions of a digital ecosystem, it is also the best available measure to fully use the CPS samples and effectively measure digital context and access. Fossen and Sorgner (2018) used CPS data's occupation codes cross-walked with ONET's skill levels to measure automation occupations, relying on Frey and Osborne (2017)'s study. However, this measure relies on skills only and the occupational code crosswalk does not have a one-to-one match, resulting in occupation code approximation that affects data interpretation. More importantly, Frey and Osborne (2017) and Fossen and Sorgner (2018)'s measure can only use a limited part of the CPS samples; many occupational codes cannot be classified based on that measure, thus potentially compromising the representativeness of the CPS data.

5.4 Control variables

Following prior occupational choice literature on entrepreneurship, Model (2) includes the following control variables: local *unemployment rate*, and individual *residence* location, *family* entrepreneur propensity, employment *experience*, race, gender, *marital* status, *health*, *education*, and *child* responsibility.

First, local economic setting offers important background for entrepreneurship (Fairlie and Fossen 2017). We include metropolitan *unemployment rates* as a control variable for macroeconomic conditions. Unemployment rates are also directly associated with our definition of *necessity* entrepreneurship.

Urban residence has been another contributing factor for entrepreneurship (Glaeser 2007). Considering the importance of social network in central cities where knowledge and information agglomerate, we include the variable *central city* to measure whether the individual is residing in the central city or in more rural/suburban areas. While there are often advantages to urban areas, there may be disadvantages, such as higher living costs for younger workers, traffic, crime, or lower environmental quality (Sternberg 2021).

To measure social capital, we also used the personal network of entrepreneurs among family members, i.e. entrepreneur propensity of family members (*family entrepreneur*), consistent with Bourdieu (1986), Dubini and Aldrich (1991), and Putnam (1993). Since we do not have data on other social network measures such as friends or business contacts that an entrepreneur connects to or has indirect relationship to, we could not capture those social network elements. We added workers' prior industrial experience, as well as urban residence (*central city*) to capture other elements of workers' social networking context. Prior (quasi-)entrepreneurial experience offers a valuable asset to entrepreneurship (Hsu et al. 2017) because it shows how attached an individual is to the labour market; it contributes to one's motivation, social capital, and choice of entrepreneurship as an occupation. The CPS data allows us to track work experience. When extracting the data across all the variables needed in this study, several other work experience variables were dropped because of limited observations with estimable values. As a result, we were only able to use the *hours worked on the main job* to measure work history.

Health, as a human capital measure, affects entrepreneurial propensity (Zhang and Carr 2014). We use a dummy variable *any difficulty* as a proxy for individuals' health status to indicate whether an individual has any physical or cognitive difficulties.[16]

As the other human capital measure, a higher educational attainment is expected to enhance individuals' entrepreneur propensity (see Velilla and Ortega 2017).

[16] CPS does not offer detailed information on an individual's health status. Although Health and Retirement Studies offer detailed information on health, this dataset lacks information on monthly employment that is key to this study.

We therefore include dummy variables *high school, some college, bachelor's,* and *advanced degrees*.[17]

For physical capital, previous literature indicated the role of liquidity constraints (Schmalz et al. 2017) in entrepreneurial propensity. However, the CPS data captures income but not cumulative wealth. With too many missing values, we had to drop the income measures.

This study measures gender using dummy variable *male*, measures race using the dummy variables *White* and *African American*,[18] and measures marital status using dummy variables *never married* and *widowed, divorced, or separated*.[19] *Child* responsibility requires time and commitment to be entrepreneurs; we therefore use binary variable capturing responsibility for *child*(ren) *under 16* to measure this. To better control other unobserved time varying factors, we included *year* dummy variables for pre-, in-, and post-recession years.[20]

5.5 Robustness check methods

To check the robustness of our findings and make sure our findings are not just data or model artefacts, we ran the same models based on different data samples and ran different models with different specifications. We also examine corresponding model diagnostic statistics, such as log likelihood and the log likelihood ratio tests, to further check our model robustness.

Considering the fact that older workers aged 70 or above could have different entrepreneur propensities with limited entrepreneur intention (Van Praag and Van Ophem 1995) and older adults aged 70 or above are much less likely to be in the labour force, we ran multilevel mixed-effects logistic regression models with data limited to only those less than 70 years old. This would help remove the modelling noise from relatively few observations from those at more advanced ages over 70 that might behave differently. We expect the findings after this treatment would not change.

Although we already explained the advantage of multilevel mixed-effects logistic models, we also ran more widely known and typically adopted logistic models—simple logit models, logit models with robust standard errors, and logit models with fixed metropolitan area effects. We do not expect the major findings would differ using those models, though multilevel mixed-effects logistic models would best capture not only the individual-level fixed effects but also metropolitan area-level random effects that help capture the regional heterogeneity and dependence.

[17] Those who did not report their educational attainment information or attained less than high school degrees were the omitted category.

[18] *Other race* is the item omitted for comparisons with the above race dummy variables.

[19] Being *married* is the item omitted for comparisons with the marital status dummy variables.

[20] The better economic years including the pre-recession 2006 and 2007 and growth year 2016 are the omitted.

6 Descriptive statistics

Our descriptive statistics start with different types of entrepreneur rates by age (shown in Fig. 2). The entrepreneur rates include the percentages of (1) *entrepreneurs* (among non-agricultural knowledge-based wage-and-salary workers, hereafter called "*workers*"); (2) *opportunity* (among the sum of *opportunity* and *necessity* entrepreneurs) entrepreneurs; and (3) *full-time* (among the sum of *full-time* and *part-time entrepreneurs*) entrepreneurs.

Overall, without controlling for other variables, the entrepreneur rate among workers rises with age: as age increases, a worker is more likely to work for themselves than for others. *Full-time* (versus *part-time*) entrepreneur rate has a concaved quadratic age trend that peaks around age 50, slightly later than entrepreneur peak age mentioned in Parker (2009). The *opportunity* (versus *necessity*) entrepreneur rate is lower for ages before 25 but higher for ages after 60, consistent with our expectation.

Across all the 1,550,531 records shown in Table 1, 8.6% of the workers are entrepreneurs.[21] Most entrepreneurs are *full-time* (71%, versus 29% for *part-time*) and *opportunity* (69.9%, versus 30.1% for *necessity*) entrepreneurs. Note that the number of observations for *opportunity* versus *necessity* entrepreneurs (27,507) is smaller than the sum of *full-time* and *part-time* entrepreneurs (127,554). Not all entrepreneurs can be clearly classified into just *opportunity* or just *necessity* entrepreneurs.

The average age among our observed workers[22] is 43. The majority of them are women (57%), White (81%), married (61%), have attained college education or above (83.5%), have no young children (67%), work around 40 h weekly, have no physical or mental difficulties (97%), and come from areas with a mean unemployment rate of 7% in 2006–2016.

For our digital exposure measure, the mean for the *6-Level Digital Exposure* is 3.11 out of 6, while the mean for the 3-level variable *3-Level Digital Exposure* is 1.88 out of 3. Different categorizations can result in slightly different mean digital exposure levels.

Table 2 presents the industry sector distribution for the 6 digitization levels. Overall, fewer workers have high digital exposure (level 6 and 5 combined) than medium (level 4 and 3 combined) or low digital exposure (level 2 and 1 combined). According to the MGI Industry Digitization Index (McKinsey Global Institute 2015), workers with high digital exposure already have the needed familiarity with digital tasks and their jobs tend to require more analytic skills that can better guide digitization to a higher productivity level. The low-level digitized industry sectors still have much to be digitized and typically concentrated with workers with more manual job skills.

Table 9 in the "Appendix" presents the correlation matrix for pair-wise correlation coefficients between all variables. According to the mostly weak and some

[21] Please note that our definition of entrepreneurs is a subset of self-employment using the CPS data because our definition limits to knowledge-based non-agricultural self-employment.

[22] Note we only study knowledge-based non-agricultural sector workers, including entrepreneurs.

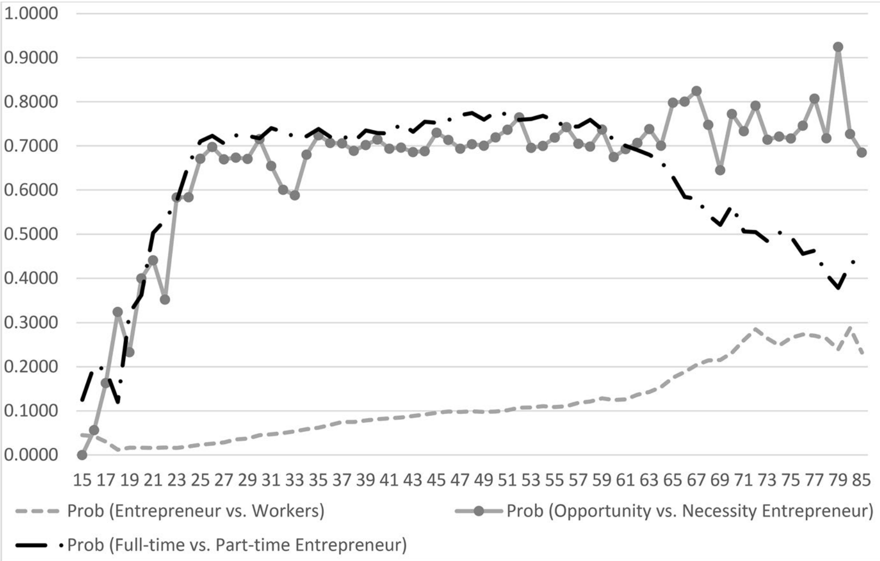

Fig. 2 Entrepreneur rates by age and entrepreneur type, CPS data of 2006–2016

Table 1 Summary statistics for variables used to test hypotheses

Variable	Obs	Mean	Std. dev.	Min	Max
Entrepreneur vs. workers	1,550,531	0.086	0.281	0	1
Opportunity vs necessity entrepreneur	27,507	0.699	0.459	0	1
Full-time vs. part-time entrepreneur	127,554	0.710	0.454	0	1
6-level digital exposure	1,550,531	3.110	1.286	1	6
3-level digital exposure	1,550,531	1.877	0.744	1	3
Age	1,550,531	43.34	13.20	15	85
Central city	1,550,531	0.375	0.484	0	1
Unemployment rate	1,550,531	7.131	2.259	2	20
Family entrepreneur	1,550,531	0.089	0.284	0	1
Hours (hrs) worked at main job	1,550,531	39.73	10.69	0	99
Male	1,550,531	0.433	0.495	0	1
Race: African American	1,550,531	0.101	0.301	0	1
Race: White	1,550,531	0.812	0.391	0	1
Education: high School	1,550,531	0.145	0.352	0	1
Education: some college	1,550,531	0.254	0.435	0	1
Education: bachelor’s	1,550,531	0.341	0.474	0	1
Education: advanced	1,550,531	0.240	0.427	0	1
Any difficulty	1,550,531	0.028	0.165	0	1
Marital: separated divorced widowed	1,550,531	0.139	0.346	0	1
Marital: never married	1,550,531	0.251	0.433	0	1
Child under 16	1,550,531	0.332	0.471	0	1

Table 2 Number of workers by six digital exposure levels and industry sectors

Industry sectors	Digital exposure with 6 or 3 levels						Total
	Low		Medium		High		
	1.Agriculture, Mining construction	2.MFG, transportation	3.Retail RE education	4.Wholesale Trade, utilities	5. FI, Prof.Svcs.	6. ICT	
Mining	4,897	0	0	1,002	0	0	5,899
Utility	0	0	0	13,150	0	0	13,150
Construction	51,798	0	0	0	0	0	51,798
MFG	0	73,510	0	59,736	0	0	133,246
Wholesale trade	0	0	0	30,321	0	0	30,321
Retail trade	0	0	91,082	0	0	0	91,082
Transport and warehousing	0	48,310	0	0	0	0	48,310
Information	0	0	0	0	16,209	37,082	53,291
FIRE	0	0	171,328	0	0	0	171,328
Professional services	0	0	0	0	291,956	0	291,956
Education	0	0	249,595	0	0	0	249,595
Health	0	288,767	0	0	0	0	288,767
Art and entertainment	68,987	0	0	0	0	0	68,987
Other services	0	0	52,801	0	0	0	52,801
Total	125,682	410,587	564,806	104,209	308,165	37,082	1,550,531

Table 3 Multilevel mixed-effects logistic regressions model results with three digital exposure levels

Mixed-effects logistic regression models (all ages)	Model 1: entrepreneur vs. worker			Model 2: full-time vs. part-time E			Model 3: opportunity vs. necessity E		
	Odds ratio	Std. err.		Odds ratio	Std. err.		Odds ratio	Std. err.	
Independent variables									
3-level digital exposure									
Medium	0.263	0.008	***	0.870	0.096		0.655	0.093	***
High	0.858	0.023	***	0.860	0.076	*	0.659	0.080	***
Age	1.039	0.000	***	0.990	0.001	***	1.007	0.002	***
3-level digital exposure* age									
Medium	1.004	0.001	***	1.003	0.002	*	1.007	0.003	**
High	1.011	0.001	***	1.002	0.002		1.007	0.002	***
Social capital									
Unemployment rate	1.010	0.003	***	0.990	0.009		0.991	0.014	
Central city	1.038	0.007	***	1.042	0.023	*	0.954	0.030	
Family entrepreneur	0.316	0.005	***	1.005	0.054		0.871	0.034	***
Hrs worked at main job	0.986	0.000	***	1.241	0.002	***	1.040	0.001	***
Human capital									
Edu: HS	0.621	0.013	***	1.357	0.090	***	1.826	0.158	***
Edu: some college	0.549	0.011	***	1.339	0.086	***	2.044	0.172	***
Edu: bachelors	0.628	0.013	***	1.329	0.084	***	2.352	0.195	***
Edu: advanced	0.794	0.016	***	1.296	0.082	***	3.223	0.271	***
Any difficulty	1.105	0.018	***	0.926	0.048		0.627	0.044	***
Demographics and socioeconomic attributes									
Male	2.206	0.014	***	1.190	0.024	***	1.437	0.044	***
Race: African Ame	0.774	0.013	***	0.930	0.054		1.012	0.075	
Race: White	1.402	0.017	***	0.783	0.031	***	1.268	0.067	***

Table 3 (continued)

Mixed-effects logistic regression models (all ages)	Model 1: entrepreneur vs. worker			Model 2: full-time vs. part-time E			Model 3: opportunity vs. necessity E		
	Odds ratio	Std. err.		Odds ratio	Std. err.		Odds ratio	Std. err.	
Marital: sep div wid	0.802	0.007	***	1.030	0.030		0.827	0.036	***
Marital: never married	0.708	0.007	***	0.995	0.033		0.806	0.037	***
Child < 16	1.220	0.009	***	0.907	0.023	***	0.978	0.034	
Year FE	Yes			Yes			Yes		
_cons	0.030	0.002	***	0.002	0.000	***	0.213	0.047	***
Metropolitan Area RE var(_cons)	0.082	0.010	**	0.026	0.007	**	0.164	0.033	**
LR test vs. logistic model: chibar2(01) = 5119.04 Prob > = chibar2 = 0.0000	5119.04	***		117.44	***		235.68	***	
Number of obs	1,550,531			127,554			27,507		
Number of groups	144			144			144		
Obs per group:									
min	403			15			1		
avg	10,767.6			885.8			191		
max	119,364			10,094			2370		
Log likelihood	− 393,442.12			− 34,846.1			− 14,956.5		
Wald chi2(28)	98,780.33	***		26,754.7	***		2895.74	***	

1. The integration method used is mvaghermite with 7 integration points

2. * indicates statistical significance at 0.1 level, ** indicates statistical significance at 0.05 level, and *** indicates statistical significance at 0.01 level

moderate correlation coefficients, we are not concerned about potential multicollinearity for multivariate analysis.

7 Findings from empirical models

Table 3 presents our empirical findings. We first used the *3-Level Digital Exposure* measure, as shown in Table 2*:* high, medium, and low. Model 1 in Table 3 shows the findings testing Hypotheses 1 and 2: controlling for all other factors, it is the workers with medium digital exposure that are least likely to be *entrepreneurs* (versus *employees*), compared to workers with both low and high digital exposure; the odds for workers with medium digital exposure to be *entrepreneurs* (versus *employees*) is only 26% of that for workers with low digital exposure. While workers with high digital exposure are also slightly less likely to be *entrepreneurs* (versus *employees*) than that for workers with low digital exposure (about 86% of the odds), their odds to be *entrepreneurs* (versus *employees*) are still about 60 percentage points higher than that for workers with medium digital exposure. This is consistent with Hypothesis 1. For workers with low digital exposure, they are often replaced by digitization and "pushed" to entrepreneurship as a potential last resort for employment. This largely reflects digitization's "push" mechanism. Workers with high digital exposure can take advantage of digitization's facilitation effect and become entrepreneurs. This largely reflects digitization's "pull" mechanism.

As age increases, the effect of digital divide on entrepreneur propensity becomes more evident and the entrepreneur propensity gaps between workers with high, low, and medium exposures in turn become wider and wider, controlling for all other variables. Starting around mid- 20 s, workers with high digital exposure jump to have higher odds to be *entrepreneurs* (versus *employees*) than workers with low digital exposure; the gaps in turn between high, low, and medium digital exposure are widening with age since then; workers with medium digital exposure always have the lowest odds to be *entrepreneurs* (versus *employees*). Figure 3 illustrates those.

As mentioned earlier, for relatively older workers who are more physically constrained due to declining physical strength, health conditions, or mobility, digitization's "pull" mechanism that reinforces the value of "footloose" human capital could be particularly important for their entrepreneurial propensity (Zhang 2008). Figure 3, mirrored in Table 3 Model 1, demonstrates that older workers with higher digital exposure are more likely to become *entrepreneurs* (versus *employees*). Controlling for all other variables, for workers with medium digital exposure, one additional year of age increases their odds of being *entrepreneurs* (versus *employees*) by 0.004; for workers with high digital exposure, one additional year in age increases the odds for their propensity for *entrepreneurs* (versus *employees*) even more, by 0.011. This is consistent with Hypothesis 2.

The Models 2 and 3 in Table 3 test Hypotheses 3 and 4, respectively. As expected in Hypothesis 3, workers with high digital exposure are slightly more likely to be *part-time* (versus *full-time*) entrepreneurs in Model 2, compared to workers with low or medium digital exposure and controlling for all other factors. This reflects digitization's facilitation effect (or "pull" mechanism) that facilitates easier part-time entrepreneurs, though the evidence is weak (at $p <= 0.1$). Compared to workers with low digital exposure, the odds for workers with high digital exposure to be *full-time* (versus *part-time*) entrepreneurs is 0.14 lower, while the effects for low or medium digital exposure do not show statistical difference at $p = 0.1$.

Compared to younger workers, older workers with high or medium digital exposure are more likely to be *opportunity* (versus *necessity)* entrepreneurs in Model 3 of Table 3. Compared to workers with low digital exposure, for workers with high and medium digital exposure, one additional year in age elevates their odds to be *opportunity* (versus *necessity*) entrepreneurs by 0.007, ceteris paribus. This is consistent with our Hypothesis 4.

Workers' accumulated human, social, and physical capital increase with age; this results in rising entrepreneur opportunities and thus a rising potential for *opportunity* (versus *necessity*) entrepreneurship (Lee and Vouchilas 2016; Zhang and Acs 2018), though Zhang and Acs (2018) was not able to find empirical evidence to verify the relationship between age and *opportunity* (versus *necessity*) entrepreneurship. The older ages strengthen the digitization's facilitation effect and therefore facilitate older workers who have strong human and social capitals to become *opportunity* (versus *necessity*) entrepreneurs.

Figure 4 illustrates the age-digitization interaction effect on *opportunity* (versus *necessity*) entrepreneur propensity using the *3-Level Digital Exposure* measure. Although at the start of the working age, high and medium digital exposure is associated with lower odds to be *opportunity* (versus *necessity*) entrepreneurs than low digital exposure, after the tipping point around the age of mid-50, this situation is reversed.

To further investigate into the impact of different levels of digital exposure, we also estimated the multilevel mixed-effects logistic models using *6-Level Digital Exposure* measures.[23] The model estimates are presented in Table 4.

The findings of Table 4 are basically consistent with the findings from Table 3, except that at six levels of digital exposure, we see a more continuous measure of digitation effects, instead of directly contrasting high, medium, and low digital exposure. As is seen in Model 4, workers employed in more digitized industry sectors overall have lower odds to be *entrepreneurs* (versus e*mployees*). Combining the estimates of Models 4 and 6 with that in Models 1 and 3, respectively, we find low digital exposure is overall associated with the highest odds to be *entrepreneurs* (versus e*mployees*) and *opportunity* (versus *necessity*) entrepreneurs. As digitization occurs, workers with low digital exposure are replaced by technology and pushed out of wage-and-salary employment into entrepreneurship, though many of them could also grasp entrepreneur opportunities to become *opportunity* entrepreneurs at a certain point. Holding all other factors constant, moving up along the six-level digital exposure index by 1 reduces the odds for workers to be *entrepreneurs* (versus *employees*) by 0.14.

[23] As defined in Table 2.

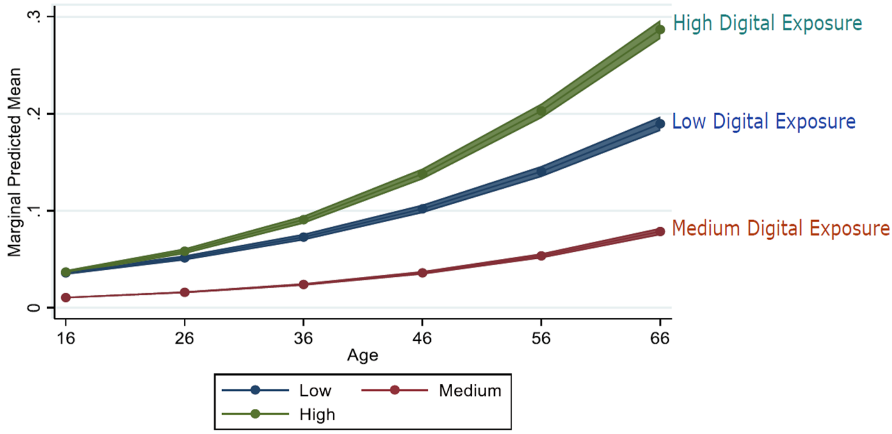

Fig. 3 *Entrepreneurs* (vs. *employees*) propensity by digital exposure level and age

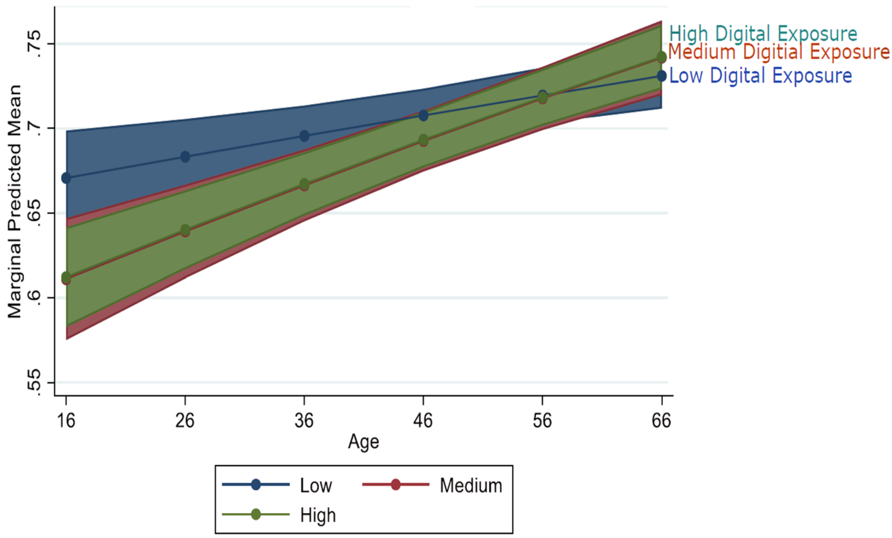

Fig. 4 *Opportunity* (vs. *necessity*) entrepreneur propensity by digital exposure level and age

However, as age increases, older workers with higher digital exposure still have higher odds to be *entrepreneurs* (versus e*mployees*); this age effect strengthens with each additional year of age. This is consistent with Hypothesis 2. With each year's increase in age, the odds to be *entrepreneurs* increase by 0.004, ceteris paribus.

For the *full-time* (versus *part-time*) entrepreneur propensity in Model 5, the digital exposure effects are not statistically significant in Table 4, though marginally significant ($p < = 0.1$) in Table 3. This means Hypothesis 3 is only marginally supported by Model 2 and it only shows up on high digital exposure. Model 6 estimates are basically consistent with Model 3: higher digital exposure is first associated with

Table 4 Multilevel mixed-effects logistic regressions model estimates with six digital exposure levels

Mixed-effects logistic regression models (all ages)	Model 4: entrepreneur vs. worker			Model 5: full-time vs. part-time E			Model 6: opportunity vs. necessity E		
	Odds ratio	Std. err.		Odds ratio	Std. err.		Odds ratio	Std. err.	
Independent variables									
Digital exposure	0.851	0.008	***	0.969	0.023		0.879	0.029	***
Age	1.030	0.001	***	0.991	0.002	***	1.002	0.003	
Digital exposure * age	1.004	0.000	***	1.000	0.000		1.003	0.001	***
Social capital									
Unemployment rate	1.010	0.003	***	0.990	0.009		0.991	0.014	
Central city	1.059	0.007	***	1.041	0.023	*	0.955	0.030	
Family entrepreneur	0.322	0.005	***	1.006	0.054		0.873	0.034	***
Hrs worked at main job	0.988	0.000	***	1.241	0.002	***	1.041	0.001	***
Human capital									
Edu: HS	0.640	0.014	***	1.362	0.090	***	1.826	0.157	***
Edu: some college	0.595	0.012	***	1.344	0.086	***	2.013	0.169	***
Edu: bachelors	0.656	0.013	***	1.332	0.084	***	2.291	0.189	***
Edu: advanced	0.781	0.016	***	1.294	0.082	***	3.157	0.266	***
Any difficulty	1.086	0.017	***	0.927	0.048		0.627	0.044	***
Demographics and socioeconomic attributes									
Male	2.361	0.015	***	1.188	0.024	***	1.440	0.044	***
Race: African Ame	0.709	0.012	***	0.929	0.054		1.011	0.075	
Race: White	1.326	0.015	***	0.782	0.031	***	1.264	0.067	***
Marital: sep div wid	0.824	0.007	***	1.030	0.030		0.825	0.036	***
Marital: never married	0.707	0.007	***	0.996	0.033		0.803	0.037	***
Child < 16	1.228	0.009	***	0.908	0.023	***	0.978	0.034	
Year FE	Yes			Yes			Yes		

Table 4 (continued)

Mixed-effects logistic regression models (all ages)	Model 4: entrepreneur vs. worker			Model 5: full-time vs. part-time E			Model 6: opportunity vs. necessity E		
	Odds ratio	Std. err.		Odds ratio	Std. err.		Odds ratio	Std. err.	
_cons	0.028	0.002	***	0.002	0.000	***	0.252	0.059	***
Metropolitan area RE var(_cons)	0.086	0.011	**	0.026	0.007	**	0.165	0.033	**
LR test vs. logistic model: chibar2(01)	6014.04	***		118.49	***		236.01	***	
Number of obs	1,550,531			127,554			27,507		
Number of groups	144			144			144		
Obs per group:									
Min	403			15			1		
Avg	10,767.6			885.8			191		
Max	119,364			10,094			2370		
Integration pts	7			7			7		
Log likelihood	− 413,571			− 34,850.65			− 14,955.83		
Wald chi2(26)	69,921.19	***		26,749.71	***		2897.78	***	

The integration method used is mvaghermite with 7 integration points

* indicates statistical significance at 0.1 level, ** indicates statistical significance at 0.05 level, and *** indicates statistical significance at 0.01 level

Table 5 Robustness check 1: multilevel mixed-effects logistic regressions model estimates for ages of 15–69

Mixed-effects logistic regression models (age < = 70)	Model 7: entrepreneur vs. worker			Model 8: full-time vs. part-time E			Model 9: opportunity vs. necessity E		
SE	Odds ratio	Std. err.		Odds ratio	Std. err.		Odds ratio	Std. err.	
Independent variables									
Digital exposure	0.847	0.008	***	0.956	0.025	*	0.872	0.030	***
Age	1.031	0.001	***	0.990	0.002	***	1.001	0.003	
Digital exposure * age	1.004	0.000	***	1.001	0.001		1.003	0.001	***
Social capital									
Unemployment rate	1.010	0.003	***	0.983	0.009	*	0.990	0.014	
Central city	1.066	0.007	***	1.035	0.023		0.964	0.031	
Family entrepreneur	0.320	0.005	***	1.007	0.055		0.880	0.035	***
Hrs worked at main job	0.988	0.000	***	1.239	0.002	***	1.041	0.001	***
Human capital									
Edu: HS	0.624	0.013	***	1.390	0.094	***	1.826	0.160	***
Edu: some college	0.573	0.012	***	1.350	0.088	***	2.042	0.173	***
Edu: bachelors	0.630	0.013	***	1.352	0.087	***	2.313	0.194	***
Edu: advanced	0.746	0.016	***	1.302	0.084	***	3.147	0.269	***
Any difficulty	1.066	0.018	***	0.905	0.051	*	0.617	0.045	***
Demographics and socioeconomic attributes									
Male	2.356	0.015	***	1.209	0.025	***	1.421	0.044	***
Race: African Ame	0.707	0.012	***	0.905	0.053	*	0.998	0.074	
Race: White	1.311	0.015	***	0.772	0.031	***	1.277	0.068	***
Marital: sep div wid	0.822	0.008	***	1.011	0.031		0.846	0.039	***
Marital: never married	0.726	0.007	***	0.988	0.034		0.799	0.037	***
Child < 16	1.254	0.009	***	0.902	0.023	***	0.983	0.035	
Year FE	Yes			Yes			Yes		

Table 5 (continued)

Mixed-effects logistic regression models (age < = 70)	Model 7: entrepreneur vs. worker			Model 8: full-time vs. part-time E			Model 9: opportunity vs. necessity E		
SE	Odds ratio	Std. err.		Odds ratio	Std. err.		Odds ratio	Std. err.	
_cons	0.028	0.002	***	0.002	0.000	***	0.257	0.062	***
Metropolitan Area RE var(_cons)	0.086	0.011	**	0.028	0.007	**	0.169	0.033	**
LR test vs. logistic model: chibar2(01)	5837.57	***		131.7	***		239.84	***	
Number of obs	1,524,113			121,015			26,453		
Number of groups	144			144			144		
Obs per group:									
min	401			15			1		
avg	10,584.1			840.4			183.7		
max	116,770			9489			2252		
Integration pts	7			7			7		
Log likelihood	− 399,303.1			− 33,114.13			− 14,409.12		
Wald chi2(26)	61,297.51	***		24,981.5	***		2803.62	***	

* indicates statistical significance at 0.1 level, ** indicates statistical significance at 0.05 level, and *** indicates statistical significance at 0.01 level

lower odds to be *opportunity* (versus *necessity*) entrepreneurs, but each additional year of age increases the odds by 0.003; at older ages, higher digital exposure is associated with higher odds to be *opportunity* (versus *necessity*) entrepreneurs. This is consistent with Fig. 4 and Hypothesis 4.

Location also matters to entrepreneurship. First, residing in *central cities* and a higher local *unemployment rate* both increase the odds of being *entrepreneurs* (versus *employees*) and, with weak evidence, *necessity* (versus *opportunity*) entrepreneurs across all models, ceteris paribus. Second, across all models in Tables 3 and 4, the random effects at the metropolitan areas level are statistically significant at $p < 0.05$. Also, the log likelihood ratio tests against simple logistic regression models are statistically significant for almost all multilevel mixed-effects logistic regression models. Therefore, capturing those random metropolitan area location effects, conducting multilevel mixed-effects modelling, and controlling for central cities and local unemployment rates are necessary.

8 Results from robustness checks

Our robustness checks rely on different data samples, different model specifications, and model diagnostics statistics. Considering the fact that older workers at more advanced ages could have different entrepreneur propensities (Van Praag and Van Ophem 1995), we conducted robustness check first among those less than 70 years old with the same multilevel mixed-effects logistic regression models. As shown in Table 10 in the "Appendix", the number of working individuals drop sharply and become relatively small after age 69. Table 5 presents the estimates mirroring Table 4, but only with workers aged less than 70. We found no evident differences between the findings in Tables 4 and 5. In the more digitized world that are less physically constrained and thus more age friendly for those with digital exposure, even older workers aged over 70 can run businesses; however, Table 10 in the "Appendix" shows that many older workers stop working after 60 s.

To further conduct robustness check, we also ran several sets of logistic models, including simple logistic models (see Models 10–12 in Table 6), logit models with robust standard errors (see Models 13–15 in Table 7), and logit models with fixed metropolitan area effects (see Models 16–18 in Table 8). All the three sets of models reflect the same findings as in Models 4–9 in Tables 4 and 5: although higher digital exposure is first associated with lower odds to be *entrepreneurs* (versus *employees*) and *opportunity* (versus *necessity*) entrepreneurs, each additional year of age increases those odds, respectively, by 0.004 and 0.003; at older ages, higher digital exposure is associated with higher odds to be *entrepreneurs* (versus *employees*) and *opportunity* (versus *necessity*) entrepreneurs, ceteris paribus. The same findings across Models 4–18 further demonstrate our model robustness.

Our model log likelihoods across all the above multilevel mixed-effects models are high, indicating good overall model fits. The random effects across the metropolitan areas are statistically significant across all models, indicating the necessity of capturing those random metropolitan area effects. The log likelihood ratio tests against simple logistic regression models are statistically significant for eight out

Table 6 Robustness check 2: logistic regressions model estimates

Logit models	Model 10: entrepreneur vs. worker			Model 11: full-time vs. part-time E			Model 12: Opportunity vs. necessity E		
	Odds ratio	Std. err.		Odds ratio	Std. err.		Odds ratio	Std. err.	
Independent variables									
Digital exposure	0.860	0.008	***	0.964	0.023		0.878	0.028	***
Age	1.031	0.001	***	0.990	0.002	***	1.002	0.002	
Digital exposure * age	1.004	0.000	***	1.000	0.000		1.003	0.001	***
Social capital									
Unemployment rate	1.010	0.002	***	1.016	0.006	**	0.981	0.008	**
Central city	1.107	0.007	***	1.024	0.021		0.948	0.028	*
Family entrepreneur	0.334	0.005	***	1.010	0.054		0.863	0.033	***
Hrs worked at main job	0.988	0.000	***	1.241	0.002	***	1.040	0.001	***
Human capital									
Edu: HS	0.626	0.013	***	1.360	0.089	***	1.846	0.156	***
Edu: some college	0.589	0.012	***	1.335	0.085	***	2.003	0.165	***
Edu: bachelors	0.653	0.013	***	1.326	0.083	***	2.312	0.188	***
Edu: advanced	0.779	0.016	***	1.284	0.081	***	3.168	0.262	***
Any difficulty	1.086	0.017	***	0.917	0.047	*	0.621	0.043	***
Demographics and socioeconomic attributes									
Male	2.377	0.015	***	1.193	0.024	***	1.420	0.043	***
Race: African Ame	0.670	0.011	***	0.925	0.053		1.032	0.074	

Table 6 (continued)

Logit models	Model 10: entrepreneur vs. worker			Model 11: full-time vs. part-time E			Model 12: Opportunity vs. necessity E		
	Odds ratio	Std. err.		Odds ratio	Std. err.		Odds ratio	Std. err.	
Race: White	1.249	0.014	***	0.785	0.031	***	1.263	0.065	***
Marital: sep div wid	0.833	0.007	***	1.032	0.030		0.820	0.036	***
Marital: never married	0.723	0.007	***	0.998	0.033		0.808	0.036	***
Child < 16	1.233	0.009	***	0.905	0.022	***	0.976	0.034	
Year FE	Yes			Yes			Yes		
_cons	0.030	0.002	***	0.001	0.000	***	0.266	0.058	***
Number of obs	1,550,531			127,554			27,507		
LR chi2(26)	79,304.41	***		83,810.64	***		3503.89	***	
Log likelihood	− 416,578.2			− 34,909.9			− 15,073.83		
Pseudo-R2	0.0869			0.5455			0.1041		

Table 7 Robustness check 3: logistic regressions model with robust standard error estimates

Logit models with robust standard errors	Model 13: entrepreneur vs. worker			Model 14: full-time vs. part-time E			Model 15: opportunity vs. necessity E		
	Odds ratio	Std. err.		Odds ratio	Std. err.		Odds ratio	Std. err.	
Independent variables									
Digital exposure	0.860	0.009	***	0.964	0.022		0.878	0.028	***
Age	1.031	0.001	***	0.990	0.002	***	1.002	0.003	
Digital exposure * age	1.004	0.000	***	1.000	0.000		1.003	0.001	***
Social capital									
Unemployment rate	1.010	0.002	***	1.016	0.006	***	0.981	0.008	**
Central city	1.107	0.007	***	1.024	0.020		0.948	0.028	*
Family entrepreneur	0.334	0.005	***	1.010	0.048		0.863	0.033	***
Hrs worked at main job	0.988	0.000	***	1.241	0.002	***	1.040	0.001	***
Human capital									
Edu: HS	0.626	0.013	***	1.360	0.083	***	1.846	0.160	***
Edu: some college	0.589	0.012	***	1.335	0.079	***	2.003	0.169	***
Edu: bachelors	0.653	0.013	***	1.326	0.077	***	2.312	0.192	***
Edu: advanced	0.779	0.016	***	1.284	0.075	***	3.168	0.269	***
Any difficulty	1.086	0.017	***	0.917	0.048	*	0.621	0.044	***
Demographics and socioeconomic attributes									
Male	2.377	0.015	***	1.193	0.023	***	1.420	0.042	***
Race: African Ame	0.670	0.011	***	0.925	0.048		1.032	0.074	

Table 7 (continued)

Logit models with robust standard errors	Model 13: entrepreneur vs. worker			Model 14: full-time vs. part-time E			Model 15: opportunity vs. necessity E		
	Odds ratio	Std. err.		Odds ratio	Std. err.		Odds ratio	Std. err.	
Race: White	1.249	0.014	***	0.785	0.028	***	1.263	0.065	***
Marital: sep div wid	0.833	0.007	***	1.032	0.029		0.820	0.037	***
Marital: never married	0.723	0.007	***	0.998	0.031		0.808	0.037	***
Child < 16	1.233	0.009	***	0.905	0.021	***	0.976	0.033	
Year FE	Yes			Yes			Yes		
_cons	0.030	0.002	***	0.001	0.000	***	0.266	0.057	***
Number of obs	1,550,531			127,554			27,507		
Wald chi2(26)	71,406.17	***		15,241.49	***		2733.37	***	
Log pseudo-likelihood	− 416,578.2			− 34,909.9			− 15,073.83		
Pseudo-R2	0.0869			0.5455			0.1041		

Table 8 Logistic Regressions Model with Fixed Metropolitan Area Effects, Robustness Check 4

Logit models with metropolitan area fixed effects	Model 16: entrepreneur vs. worker			Model 17: full-time vs. part-time E			Model 18: opportunity vs. necessity E		
	Odds ratio	Std. err.		Odds ratio	Std. err.		Odds ratio	Std. err.	
Independent variables									
Digital exposure	0.851	0.008	***	0.971	0.023		0.879	0.029	***
Age	1.030	0.001	***	0.991	0.002	***	1.002	0.003	
Digital exposure * age	1.004	0.000	***	1.000	0.000		1.003	0.001	***
Social capital									
Unemployment rate	1.011	0.003	***	0.964	0.011	***	0.983	0.017	
Central city	1.059	0.007	***	1.040	0.023	*	0.951	0.030	
Family entrepreneur	0.322	0.005	***	1.004	0.054		0.877	0.034	***
Hrs worked at main job	0.988	0.000	***	1.241	0.002	***	1.041	0.001	***
Human capital									
Edu: HS	0.641	0.014	***	1.376	0.091	***	1.811	0.157	***
Edu: Some College	0.595	0.012	***	1.363	0.088	***	2.008	0.169	***
Edu: bachelors	0.656	0.013	***	1.353	0.086	***	2.278	0.189	***
Edu: advanced	0.781	0.016	***	1.312	0.084	***	3.130	0.265	***
Any difficulty	1.086	0.017	***	0.934	0.049		0.622	0.044	***
Demographics and socioeconomic attributes									
Male	2.361	0.015	***	1.189	0.025	***	1.445	0.044	***
Race: African Ame	0.710	0.012	***	0.921	0.054		1.005	0.075	

Table 8 (continued)

Logit models with metropolitan area fixed effects	Model 16: entrepreneur vs. worker			Model 17: full-time vs. part-time E			Model 18: opportunity vs. necessity E		
	Odds ratio	Std. err.		Odds ratio	Std. err.		Odds ratio	Std. err.	
Race: white	1.327	0.015	***	0.778	0.031	***	1.269	0.068	***
Marital: sep div wid	0.824	0.007	***	1.030	0.030		0.826	0.037	***
Marital: never married	0.707	0.007	***	0.995	0.033		0.804	0.037	***
Child < 16	1.228	0.009	***	0.908	0.023	***	0.980	0.035	
Metropolitan area FE									
Year FE	Yes			Yes			Yes		
_cons	0.022	0.002	***	0.003	0.001	***	0.251	0.102	***
Number of obs	1,550,531			127,554			27,479		
LR chi2(169)	85,976.56	***		84,224.96	***		4099.24	***	
Log likelihood	− 413,242.1			− 34,702.74			− 14,766.12		
Pseudo-R2	0.0942			0.5482			0.1219		

of the nine multilevel mixed-effects logistic regression models, indicating the difference and superiority of the multilevel hierarchical model over the simple logistic regression for those models.

9 Limitations of the study

As the first study exploring the age effect on the digitization–entrepreneurship relationship, on different entrepreneur types, and integrating digitization's replacement and facilitation effects, this study is not without flaws. Although our data offer extensive information on individual workers, our data does not measure individual worker motivations or intentions; this limits our ability to make inferences about individual preferences.

Our use of the MGI Industry Digitization Index to measure digital exposure is appropriate, yet it is less than a perfect measure. We defined digital exposure using industry sectors that workers working in, not just individual workers' skills. Given the stated strengths of this empirical measure, and its more direct tie to the CPS data set, the relative advantages are strong. However, higher digital exposure does not necessarily mean that all individuals in the more digitalized industry have higher digitization skills. Instead, working in a more digitized industry gives workers more exposures to digital platforms, tools, technologies, and skills, and thus more digital readiness. It provides a broader measure than digital skills.

There might be other ways to measure digitization, such as using occupational skills instead of industry sectors; however, working in a specific occupation does not always mean a worker has a certain level of digital skills. Frey and Osborne (2017)'s measure also has a limitation to rely on expert judgments from the year 2013 concerning the technological possibilities to perform occupation-specific tasks automatically in the near future; this is though very helpful to define digitalized occupations, does not always reflect the actual workers' digital skills in those occupations, either. Plus, as mentioned earlier, our digital exposure measure can allow us to use all observations in the CPS data without compromising the data representativeness, and it is relatively straightforward to interpret and replicate.

We have also explored the possibilities of computer and internet usage to measure digitization at the individual worker level. However, those variables have considerable missing values that also resulted in largely compromised representativeness of the initially well-sampled national dataset.

10 Discussion

Prior literature has identified and discussed the destructive role of digitization—employment replacement (Frey and Osborne 2017; Fossen and Sorgner 2018) and on facilitation role of digitization for entrepreneurship and innovation (Nambisan et al. 2019). Those two different perspectives are infrequently put together to discuss their shaping of entrepreneurship. This study bridges that gap and investigates how digitization's replacement effect and facilitation effect work together on entrepreneurship by first examining different levels of digital exposure and then by different types of entrepreneurs. Further, this study contributes to the literature by identifying the modifier effect of age on digitization's role in entrepreneurship, which is particularly relevant in our ageing and digitizing world.

This study's contribution to the literature is not just on the different levels of digital exposure, on digitization's role on different types of entrepreneur propensities, but also particularly on the age effects. Fossen and Sorgner (2018) started the exploration on digitization's role on *incorporated* versus *unincorporated* entrepreneurship, but they did not explore on digitization's role on *opportunity* versus *necessity* or *full-time* versus *part-time* entrepreneurship defined by Zhang and Acs (2018) using the same CPS dataset. Age effects were not previously studied in the relationship between digitization and entrepreneurship.

This study sets digitization at the historical intersection with ageing and for the first time explores how age modifies digitization effect in shaping entrepreneur and entrepreneur type propensities. The study finds that older ages strengthen digitization's "pull" mechanism for workers with a higher digital exposure more likely to be *entrepreneurs* (versus *employees*) and to be *opportunity* (versus *necessity*) entrepreneurs. Zhang and Acs (2018) expected to see older workers have a greater propensity to be *opportunity* versus *necessity* entrepreneurs, but they failed to find empirical evidence. This study using the same data identifies that it is the age effect interacted with digitization that makes the difference between the *opportunity* and *necessity* entrepreneurship at older ages; it is digital exposure that makes *opportunity entrepreneurship* more evident among *older* workers.

The study also finds weak empirical evidence that high digital exposure is marginally associated with a high likelihood of *part-time* (versus *full-time*) entrepreneurship. Digital exposure facilitates openness, affordances, and generativity (Nambisan et al. 2019): running a business becomes easier due to broadened visibility of a business (Isaksson and Wennberg 2016), reduced search, communication, and monitoring costs (Goldfarb et al. 2013), easier access to market research information (Goldfarb et al. 2013), loans, and funds through crowdfunding (Haddad and Hornuf 2018), and new entrepreneurial opportunities in a shared economy (Richter et al. 2017). With those advantages, one can be an entrepreneur while having other commitments. This is consistent with Folta (2007) and Schulz et al. (2016)'s observations on the rise of *part-time* or hybrid entrepreneurship. Although this finding is not verified when using a more continuous measure of digital exposure, this digital exposure's "pull" effect on *part-time* (versus *full-time*) entrepreneurship might only occur to high digital exposure. It also reflects that the digitization's "pull" effect on *part-time* entrepreneurship is a relatively new phenomenon and yet to manifest itself with more empirical evidence. This is worth further analysis.

As entrepreneurial behaviour is an employment behaviour subject to local market conditions, metropolitan areas are important units of analysis in this study. Economic behaviour often occurs within their own metropolitan areas, seldom from other metropolitan areas (Schwartz 1993).

In order to address the influence of location and region, the study first adopted multilevel mixed-effects logistic models. Since variation and dependence over space will induce correlations among observations and thus complicate simple regression-based models, mixed-effect modelling is an important solution to non-independence caused by geographic locations (Thorson and Minto 2015); multi-level mixed-effect models improve modelling of spatial and temporal dependencies (Baayen et al. 2008). Our consistently significant metropolitan random effects and the superiority of multilevel modelling shown via the likelihood ratio tests echo the importance of multilevel mixed-effects models.

Secondly, we controlled for local unemployment rates in all our models and find it elevates the *entrepreneur* (versus *employee*) and, to a lesser extent, *necessity* (versus *opportunity*) entrepreneur propensity. Employment conditions, such as unemployment rate, are particularly spatially dependent with spatial disparities. On the one hand, nearby regions tend to share similar outcomes due to spatially related changes in labour demand (Mitchell and Bill 2004). On the other hand, unemployment rates differ widely across local labour markets (Bilal 2021). Regional wage differentials do not only influence migration decisions of mobile workers, but also affect the bargaining process on local labour markets, leading to differences in vacancies and unemployment as well, depending on transport costs and the elasticity of substitution (vom Berge 2013). It is therefore particularly important to control for local unemployment rate.

Third, as central city is another key concept in regional science, we also controlled for central cities in all models and find a higher odd to be *entrepreneurs* (versus *employees*) and, to a much lesser extent, *full-time* (versus *part-time*) and *necessity* (versus *opportunity*) entrepreneurs in central cities. From Friedmann (1966)'s core–periphery model to Krugman (1991)'s new economic geography, "place" variation between central city and other locations has always been pronounced. As Alves (2012) demonstrated using Geographic Information System that the urban structure and related social geography affect and interact with not only the way people interact, but also their chances of social and economic integration; this includes employment and occupational choice. It is for this reason that our location variables also contribute to our social capital construct.

Although some studies see the suburbs as economically autonomous areas minimally or not at all dependent on the central cities (Fishman 1987) due to suburbanization of jobs and people and maturation of "edge cities" (Garreau 1991); Schwartz (1993) demonstrates that suburban places continue to lack the agglomeration economies necessary for high-level corporate services and suburban companies rely mostly on service firms located either in their own central city or in the central city of another metropolitan region. After examining fourteen large metropolitan economies since 1970 with broadening the composition of employment, increasing commuting from areas outside the suburbs, developing major new centres of business, consumer, and social services, Stanback (1991) showed that agglomeration economies make cities increasingly dependent on commuting suburbanites for their experienced and educated labour force and posing new challenges to the social and economic structure of the central city.

11 Conclusion and implications

Standing at the historical junction of digitization and ageing, facing two conflicting effects from digitization mentioned in the literature—facilitation effects (i.e. "pull" mechanism) and replacement effects (i.e. "push" mechanism)—it is important to understand how digitization and ageing together transform our workforce and shape entrepreneurship and tomorrow's labour market. This study for the first time examines the role of digital exposure on propensities for *entrepreneurs* (versus *employees*), *full-time* (versus *part-time*) entrepreneurs, and *opportunity* (versus *necessity*) entrepreneurs, for the first time examines the age modification effect on the role of digitization, and for the first time integrating digitization's replacement effects and facilitating effects in employment with the "push" and "pull" mechanisms in entrepreneurship.

Relying on 11 years (132 months)'s Current Population Survey Data and multilevel mixed-effects logistic regression models and another variety of logit models, the study tests and supports most of the stated hypotheses. It finds that (1) workers with low- and high- digital exposure are more likely to become entrepreneurs than peers with medium digital exposure, mirroring digitization's "push" and "pull" mechanisms on entrepreneurship; (2) high digital exposure has the potential, with weak evidence, to increase workers' odds to be *part-time* (versus *full-time*) entrepreneurs; (3) although workers with low digital exposure are overall most likely to be *entrepreneurs* (versus *employees*), an older age increasingly strengthens digitization's "pull" mechanism to be *entrepreneurs* (versus *employees*) and *opportunity* (versus *necessity*) entrepreneurs.

Our study shows a bridge exists between the replacement effect (Frey and Osborne 2017) and the facilitation effect (Nambisan et al. 2019) impacting our workforce. Both effects are at work but have different mechanisms. While the replacement effect results in the "push" mechanism into entrepreneurship from workers with low digital exposure, the facilitation effect results in the "pull" mechanism into entrepreneurship from workers with high digital exposure. Both ends result in higher entrepreneur propensity, compared to workers with medium digital exposure. In the sense of "misfits" for entrepreneurs, being in the middle typically represents the norm and mainstream of a society. To stay comfortable in employment without much risk to be replaced, one needs to have a certain level of digital exposure. That is why most jobs now require certain levels of digital skills. The entrenched middle, however, still needs to maintain certain levels of digital exposure to stay employed comfortably without facing too much pressure or risk of being replaced. We are in the world of lifelong learning. Digitization helps facilitates and calls for such learning.

Workers with low digital exposure, often replaced in the wage-and-salary employment, are most likely to be "pushed" to be *entrepreneurs* (versus *employees*) or to embrace the "misfits" and become *opportunity* (versus *necessity*) entrepreneurs. This suggests a higher tolerance or inclusiveness of entrepreneurship than wage-and-salary employment, facing the destructive job-replacement role of digitization. Entrepreneurship, probably particularly self-employment, often offers the last resort to help offer workers at the bottom of skill spectrum a hope and opportunity for employment and income. This often contributes to the beauty of entrepreneurs' "misfit", in addition to entrepreneurship's role in innovation and job creation. This gives an important reason to support entrepreneurship and self-employment. Therefore, it is important for public policy to support, facilitate, and help accommodate and incubate entrepreneurship, particularly for those with low digital exposure.

The role of age in this mix must also be recognized. Overall, at younger ages, low digital exposure "pushes" workers to be *entrepreneurs* (versus *employees*), but older ages increasingly strengthen the "pull" mechanism into *entrepreneurship* (versus being *employees*) and into *opportunity* (versus *necessity*) entrepreneurship. This challenges the stereotypes that older workers are typically digitally obsolete or can only be *necessity* entrepreneurs. Instead, older ages with high digital exposure enjoy both the elevated entrepreneurial opportunity rising with age and digitization's facilitation effects on entrepreneurship.

Although at younger ages, low digital exposure can still push workers to become *entrepreneurs* or even *opportunity* entrepreneurs; with age increases, the digital divide is widening the gap for workers' propensity between *entrepreneurs* and *employees* and between *opportunity* and *necessity* entrepreneurs. Workers with high digital exposure are more familiar with digital technology, skills, and platforms and thus could better take advantage of digitization's facilitation role in entrepreneurship and innovation.

What is more powerful in this study is that this digital divide does not even necessarily mean digital skills one possesses or has acquired, but the exposure to digital ecosystems, or environment and access. This shows the importance of digital exposure to our future entrepreneurs in this increasingly digitalized world. For workers who want to be *entrepreneurs* (versus *employees*) and *opportunity* (versus *necessity*) entrepreneurs at later ages, strengthening their digital exposure could be particularly helpful.

With the *opportunity* entrepreneurship among older workers is typically concentrated into those with high exposures to digitization, only those high digital exposure, older workers can take advantage of the digitization's facilitation effect on entrepreneurship. This leaves those older low-digital-exposure workers the weakest link—they are not only pushed out of employment due to digitization's replacement effect, but also, due to digital divide, do not benefit from digitization's accommodation for physical conditions or digitization's facilitation effects on entrepreneurship. In the ageing society, many of those older workers still have many years to live for a decent living standard—they need income or a job. Public policy therefore needs to target on training older workers who need a job but with low digital exposure to update their skills. Strengthening digital exposure is thus bridging between the digitization's replacement and facilitation effects, and the "push" and "pull" mechanisms into entrepreneurship. Measures suggested by Zhang (2019) suggest on training methods for older workers (aged 50 and above) using programmes including federally funded workforce training programmes might be a start.

This study also identifies a potential facilitation effect from digitization on *part-time* versus *full-time* entrepreneurship, consistent with the literature's observation on a rising trend of non-traditional work arrangement, including *part-time* or hybrid entrepreneurs (Folta 2007; Schulz et al. 2016). For many, one job for the whole life is not possible anymore and non-traditional work arrangement might become the new norm in our increasingly digitized world. This could imply a paradigm shift in how, where, when people work and what people work on. As Grönlund and Öun (2018) noted, digitization has made work more flexible and has blurred the borders between work and free time. This, again, requires more lifelong learning and adaptation from almost everyone in the society. Therefore, not only labour policies need to accommodate this potential change, but our education system might also need to have a paradigm shift as well.

This study only identified a weak marginal evidence on digitization's effect on *part-time* versus *full-time* entrepreneurship. With digitization and *part-time* entrepreneurship becoming more and more prevalent, this is worth future studies with newer data on further nuances related to *part-time* entrepreneurship, digitization, and non-transitional work arrangements. In the current COVID-19 pandemic, our society is further expedited into a much more digitalized world. Therefore, the trends identified in this study, but using the newest data throughout the pandemic, could reveal more nuances with the natural digitization experiment.

This study also shows that location matters to the age and digitization effects on entrepreneurship. First, central city locations and local unemployment rates elevate the odds to be *entrepreneurs* (versus *employees*) and, with weak evidence, *necessity* (versus *opportunity*) entrepreneurs; second, the random effects in different metropolitan areas are also statistically significant and multilevel logistic models show advantage over simple logistic models. By revealing the vulnerability for central city residents, it shows that not only employment and entrepreneurship policy need to be localized, enhancing digital exposure needs to incorporate local economic conditions and best agglomerate local resources. This would not only help younger workers but also older ones. As digital exposure integrates digital ecosystem, location and its geographic agglomeration would be a natural, integral part of digital exposure. Therefore, investigating into how regional policies can effectively enhance workers' digital exposure at different locations with different industry mix and scales could be a key to unlock regional innovation, spur better knowledge and entrepreneurship spillovers, and bridge the digital divide. Our future study plans include adding spatial nuances to the measure of digital exposure to enrich our work on entrepreneurship.

Appendix

See Tables 9 and 10.

Table 9 Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Opportunity vs necessity E	1.00																		
2	Full-time vs. part-time E	0.26	1.00																	
3	Digitized industry	0.01	− 0.02	1.00																
4	Digitized industry Group	− 0.01	− 0.02	0.97	1.00															
5	Age	0.09	− 0.03	0.01	0.00	1.00														
6	African American	− 0.02	0.03	0.01	0.00	− 0.04	1.00													
7	White	0.03	− 0.04	0.00	0.01	0.08	− 0.65	1.00												
8	HS	− 0.03	0.04	− 0.19	− 0.17	− 0.01	0.00	0.02	1.00											
9	Some College	− 0.05	− 0.04	− 0.05	− 0.04	− 0.04	0.06	− 0.02	− 0.21	1.00										
10	Bachelors	0.00	− 0.01	0.11	0.13	− 0.06	− 0.04	0.03	− 0.28	− 0.36	1.00									
11	Advanced	0.10	0.03	0.11	0.07	0.14	0.00	− 0.02	− 0.26	− 0.33	− 0.45	1.00								
12	Any difficulty	− 0.06	− 0.06	0.00	0.00	0.11	0.01	0.00	0.00	0.04	− 0.03	− 0.02	1.00							
13	Sep div wid	− 0.02	0.01	0.01	0.01	0.14	0.04	0.00	0.02	0.02	− 0.02	− 0.02	0.05	1.00						
14	Never married	− 0.06	0.00	0.00	0.02	− 0.37	0.09	− 0.07	0.00	0.03	0.01	− 0.05	− 0.01	− 0.17	1.00					
15	Child < 16	− 0.01	0.00	0.01	0.00	− 0.29	− 0.02	0.00	− 0.04	− 0.03	0.04	0.02	− 0.08	− 0.12	− 0.25	1.00				
16	Hrs work Mn job	0.29	0.72	− 0.04	− 0.04	− 0.01	0.02	− 0.03	0.03	− 0.05	− 0.01	0.04	− 0.07	0.00	− 0.02	0.00	1.00			

Table 9 (continued)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
17	Family entre-preneur	− 0.06	− 0.07	− 0.05	− 0.04	0.01	− 0.05	0.01	0.05	0.04	− 0.03	− 0.05	0.01	− 0.09	− 0.04	0.02	− 0.07	1.00		
18	Central city	− 0.02	− 0.01	0.04	0.05	− 0.09	0.08	− 0.08	− 0.08	− 0.03	0.04	0.05	0.00	0.03	0.18	− 0.07	− 0.01	− 0.03	1.00	
19	Unemploy Rt	− 0.04	− 0.01	− 0.02	− 0.02	0.00	− 0.01	0.03	0.05	0.03	− 0.03	− 0.04	0.02	0.00	− 0.03	0.01	− 0.01	0.04	− 0.04	1.00

Table 10 Frequency of working individuals and probabilities of entrepreneur types by age

Age	Obs in working individuals	Prob (entrepreneur vs. workers)	Prob (opportunity vs. necessity entrepreneur)	Prob (full-time vs. part-time entrepreneur)
15	785	0.0446	0.0000	0.1250
16	1731	0.0422	0.0566	0.2029
17	3034	0.0297	0.1633	0.1928
18	4947	0.0117	0.3243	0.1200
19	7602	0.0163	0.2333	0.3217
20	10,289	0.0165	0.4000	0.3625
21	12,716	0.0158	0.4409	0.5026
22	17,636	0.0168	0.3525	0.5321
23	23,741	0.0158	0.5833	0.5750
24	27,215	0.0194	0.5838	0.6587
25	30,992	0.0230	0.6711	0.7106
26	32,381	0.0254	0.6977	0.7227
27	33,480	0.0285	0.6697	0.7056
28	35,054	0.0351	0.6736	0.7241
29	35,814	0.0372	0.6706	0.7227
30	36,879	0.0448	0.7159	0.7172
31	36,967	0.0469	0.6549	0.7401
32	36,433	0.0496	0.6009	0.7317
33	36,343	0.0535	0.5882	0.7210
34	36,457	0.0583	0.6802	0.7217
35	36,659	0.0618	0.7245	0.7383
36	36,140	0.0682	0.7068	0.7207
37	35,545	0.0749	0.7061	0.7229
38	35,861	0.0748	0.6889	0.7100
39	36,494	0.0779	0.7021	0.7351
40	37,328	0.0809	0.7145	0.7293
41	37,587	0.0829	0.6942	0.7283
42	37,402	0.0851	0.6961	0.7502
43	36,644	0.0884	0.6861	0.7320
44	37,099	0.0917	0.6881	0.7546
45	38,129	0.0956	0.7303	0.7523
46	37,186	0.0986	0.7135	0.7587
47	37,145	0.0973	0.6937	0.7699
48	37,092	0.0991	0.7043	0.7745
49	36,930	0.0972	0.7009	0.7596
50	38,678	0.0984	0.7195	0.7770
51	38,090	0.1014	0.7369	0.7711
52	37,592	0.1070	0.7651	0.7589
53	37,373	0.1077	0.6958	0.7612
54	35,912	0.1103	0.7003	0.7682
55	35,288	0.1087	0.7191	0.7574

Table 10 (continued)

Age	Obs in working individuals	Prob (entrepreneur vs. workers)	Prob (opportunity vs. necessity entrepreneur)	Prob (full-time vs. part-time entrepreneur)
56	34,218	0.1106	0.7427	0.7427
57	32,354	0.1181	0.7051	0.7442
58	31,025	0.1210	0.6988	0.7593
59	28,273	0.1285	0.7376	0.7373
60	26,735	0.1246	0.6753	0.7139
61	24,766	0.1259	0.6927	0.7000
62	22,126	0.1364	0.7069	0.6908
63	18,950	0.1430	0.7382	0.6797
64	16,008	0.1537	0.7007	0.6647
65	13,671	0.1751	0.7985	0.6292
66	10,913	0.1883	0.8006	0.5845
67	9277	0.2041	0.8247	0.5798
68	7974	0.2142	0.7479	0.5431
69	6159	0.2151	0.6450	0.5209
70	4994	0.2315	0.7725	0.5661
71	4064	0.2603	0.7333	0.5061
72	3450	0.2849	0.7914	0.5044
73	2870	0.2641	0.7143	0.4839
74	2477	0.2483	0.7215	0.5034
75	2197	0.2654	0.7170	0.4944
76	1830	0.2732	0.7463	0.4551
77	1565	0.2703	0.8072	0.4625
78	1309	0.2636	0.7174	0.4084
79	1140	0.2395	0.9250	0.3780
80	3645	0.2878	0.7273	0.4337
85	1871	0.2320	0.6852	0.4455

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