The Effect of Unemployment on the Importance of Digital Income

By Carolyn Carswell-Freestone

(6838924)

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Supervisor: Professor Pierre Brochu

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Abstract

This paper puts forth two separate contributions. First, it examines the importance of digital income considering age and gender. Second, this paper delineates the relationship between the importance of digital income and unemployment, defined at a sub-regional level. This investigation involves the use of the newly released 2018 Digital Economy Survey, as well as the confidential master files of the 2017 and 2018 monthly Labour Force Survey. I find that a change in the unemployment rate does not seem to affect the average dollar value of digital income earned, although it does appear to affect the probability of generating digital income. Furthermore, I find that there are substantial gender differences considering both the importance of digital income and its relationship to unemployment. This finding is consistent for all forms of digital income generation, including the use of sharing economy platforms.

1. Introduction

An era of rapid technological advancement has been accompanied by the disruption of economic markets through the rise of the digital economy. The digital economy is entirely borderless. It allows individuals to buy and sell/provide goods and services through the use of digital platforms on the internet and in the form of applications (apps). The digital economy does not adhere to traditional business models, nor is it subject to stringent market regulations (hence efficiency is maximized). It eliminates market inefficiencies by allowing supply and demand to govern prices, as exemplified by surge pricing on digital platforms such as Uber. The avoidance of costly regulations which hotels, condominiums, and taxis are forced to adhere to allows these companies built on digital platforms such as Airbnb and Uber to charge lower prices than traditional market hotel prices or taxi fares.

This paper will put forth two separate contributions. First, this paper outlines the importance of digital income and the various demographic considerations which may affect this. Until now, there has been a lack of data surrounding this topic, so we currently know nothing about this importance for Canada.[1] My next contribution illustrates the relationship between unemployment rates and the importance of digital income. This study will allow us to answer questions such as: What role does the digital economy play at different points in the business cycle? Does digital income complement current income or serve as a supplement during economic downturns?[2] I examine the importance of digital income for various ages and genders in order to determine whether business cycle fluctuations affect its importance.

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[1] Statistics Canada (2018a) puts forth a brief paper on key findings of the Digital Economy Survey. However, there are only a few findings listed with respect to the generation of digital income. From this, we know that the most common way of generating digital income is through online bulletin boards. Furthermore, the average Canadian who generates money from selling goods on online bulletin boards earns $722 (on average). Not much is known regarding demographic considerations such as gender or age and these statistics.

[2] The link between alternative work arrangements and unemployment has been evaluated in Katz and Krueger (2017). This is the closest contribution to mine. From Katz and Krueger (2017), we know that there is a small relationship

To investigate these pressing questions, this study relies on a recently released dataset: The 2018 Digital Economy Survey (DES). The 2018 DES provides a rich specification describing various forms of digital income generated by a sample of 5,666 Canadians from June 2017 to July 2018. The DES is the only public survey to provide Canadian data surrounding the generation of digital income. There exist several American studies which utilize private data to examine the importance of digital income. However, none of these surveys utilize data with as rich of a specification of digital income sources. This richness in specification is unique to the DES and therefore, unique to Canada.

My data shows three things. First, there is an economically large relationship between the unemployment rate and the probability of generating digital income on online bulletin boards. However, there does not appear to be a relationship between unemployment and the average quantity of digital income earned in dollars. Second, there are significant differences in the importance of digital income between men and women, and the link between unemployment and the importance of digital income is unique to each gender. Lastly, despite the fact that significantly more men utilize peer-to-peer ridesharing platforms, income from these platforms does not appear to be significantly more important to men. Women, on the other hand, may have a tendency to utilize home-sharing platforms to generate additional income in recessions.

The rest of the paper is structured as follows: Section 2 provides a review of the literature, Section 3 describes the two datasets used in this paper, and Section 4 provides summary statistics. In Section 5, I present the Econometric Equation. Section 6 evaluates the results of this study. In Section 7, I conduct robustness checks. Finally, Section 8 concludes the paper.

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between weak labour markets and the pursuit of alternative work arrangements. However, Katz and Krueger's (2017) definition of alternative work arrangements is too broad to pin down the relationship between digital income and unemployment.

2. Literature Review

2.1 Review of the Literature

There exists a substantial body of literature surrounding the importance of nonstandard employment, or alternative work arrangements.[3] This body of literature is not new and provides evidence that non-traditional income has been growing for quite some time. These studies, however, classify nonstandard employment very broadly. Katz and Krueger (2019a) examine the growth in the prevalence of alternative work arrangements in the United States from 2005 to 2015. They define alternative work arrangements as individuals who are "temporary help agency workers, on-call workers, contract workers, and independent contractors or freelancers." Katz and Krueger (2019a) conduct the RAND-Princeton Contingent Worker Survey (RPCWS) in October and November 2015, and compare the results of this survey with the Bureau of Labour Statistics (BLS) Contingent Worker Supplement (CWS) in 2005. In Katz and Krueger (2019b), after comparing these results to the newly released 2018 Current Population Survey Contingent Worker Supplement (CPS-CWS), they conclude that the percentage of workers who engage in alternative work arrangements increased by 1% or 2% from February 2005 to the end of 2015. Katz and Krueger (2019b) further conclude that only 0.5% of American workers use an online intermediary to engage in direct selling.

Kostyshyna and Luu (2019) use the Bank of Canada's Canadian Survey of Consumer Expectations (CSCE)[4] to examine the prevalence of non-standard or informal work arrangements as a potential explanation for an unusual lack of underlying wage growth in the Canadian labour market, since this additional supply of labour may impede wage growth. Kostyshyna and Luu

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[3] Alternative work arrangements are classified as non-standard or non-traditional work arrangements such as independent contract workers, on-call workers, temporary health agency workers, and workers provided by contract firms (Katz and Krueger, 2019a).

[4] The CSCE is a quarterly Canadian nationally-representative household survey conducted online.

(2019) find that approximately 18% of Canadians participate in informal work, excluding those who do so as a hobby. Manyika et al. (2016) report the findings of a 2016 McKinsey Global Institute survey, in which individuals in the United States, France, the United Kingdom, Germany, Sweden, and Spain are surveyed from June to July 2016 in order to examine demographic characteristics of "the gig economy," where individuals pursue independent work. According to Anani (2018), the "gig economy" involves participating in "gigs" or single tasks/projects to generate income.[5] Manyika et al. (2016) find that individuals under 25 years of age represented a quarter of the independent workforce or less. They also find that low-income households make up only 25% of independent workers in all countries except Spain, despite the fact that approximately half of low-income households are independent workers. The fact that Spain deviates from this finding is notable given the fact that unemployment rates in Spain are consistently higher than the other European countries surveyed.

Goldschmidt and Schmieder (2017) use the Integrated Employment Biographies (IEB) data, which provides social security data in Germany, to determine the effect that this progression towards "domestic outsourcing," or contracting out labour (domestically), has on the German wage structure.[6] They find that that businesses who "domestically outsource" workers have likely been incentivized to do so as a cost-cutting measure. This agrees with Weil (2014)'s assertion in *The Fissured Workplace* that businesses are able to outsource activities which prove inessential to operations, since with technological change comes diminished costs associated with coordination

[5] The term "gig economy" is very broad and may encompass tasks related to digital income, but also encompasses a vast array of additional independent tasks that cannot be classified as digital. Literature relating to income associated with the "gig economy" is best described as literature describing non-standard income, since this economic classification is so broad.

[6] Social Security Data in Germany through International Employment Biographies (IEB) provides information surrounding "duration of employment, the total pay over that period, the employment type, alongside demographic variables (age, gender, education, and nationality).

of activities. An earlier American study, Abraham and Taylor (1996), arrives at the same conclusion using a standard probit model and data from the Industry Wage Surveys by the BLS from June 1986 to September 1987. They also find that this practice of contracting out low-skilled labour is more prevalent in larger metropolitan centres.

In addition to the significant existing body of literature surrounding the proliferation of nonstandard employment, there is a small but growing body of very recent literature surrounding the importance of digital income. The greatest hindrance to the development of this literature has been data limitations, since this data is so new and has been, up until now, quite scarce.

Farrell and Greig (2016a) study the receipt of income from thirty digital platforms and its relation to income volatility, while focusing on the dichotomy between labour income and capital income platforms. To do so, they use a private dataset that includes a random sample of one million JPMorgan Chase Institute customers in the United States who held a chequing account for a three-year period, from October 2012 to September 2015. Farrell and Greig (2016a) find that workers tend to use labour platforms to smooth income over time and mitigate against volatilities. When traditional non-platform income diminishes by 14% in a given month, labour platform earnings increase by 15%, which almost directly offsets traditional income volatilities. However, capital platforms are not used to smooth income volatilities over the three-year period. Farrell and Greig (2016b) find that three in six workers who enter the digital economy in a given month will exit within a year. Furthermore, younger workers, and those with higher incomes or employment that is considered more stable are more likely to exit the digital economy within a year. These findings lend credence to the notion that digital income is used to smooth income volatilities during periods where income "dips" or in transitional periods between jobs. Farrell and Greig (2016a) also examine labour market characteristics such as age, gender, and geographic location and the generation of income through the platform economy. They find that in comparison to the average labour force, those who participate in the platform economy tend to be younger, have lower than average incomes, and are more likely to be male and live in the Western United States when compared to other geographic regions in the U.S..

Hall and Krueger (2018) also make use of private data to examine pressing questions regarding demographic characteristics in the labour market for a specific platform in the digital economy: Uber.[7] Hall and Krueger's (2018) study uses data obtained privately from Uber's partnership with the Benenson Strategy Group through two surveys conducted in December 2014 and November 2015 to examine hours of work, income, and the motivations behind drivers partnering with Uber as well as demographic characteristics of Uber drivers. Hall and Krueger (2018) find that Uber drivers tend to occupy a younger demographic than taxi-drivers and chauffeurs. When considering gender, there are more female Uber drivers than taxi drivers, but women are still a minority in this industry. Hall and Krueger (2018) also analyze Uber's monthly growth rate by U.S. city, and find that the growth rate in the number of Uber drivers in each city increases exponentially with each additional month Uber operates in that city. This implies that business cycle fluctuations and unemployment spells in various American cities do not appear to affect changes in the number of drivers partnering with Uber.

Smith (2016) uses survey data from the Pew Research Center, a nonpartisan fact tank based out of Washington DC to examine demographic characteristics and their relationship to digital platform income.[8] From July 12th to August 8th 2016, the Pew Research Center surveyed 4,567 American adults on alternative work arrangements grounded in the Sharing Economy. The survey

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[7] The Uber platform involves matching drivers and passengers through the internet and imposes surge pricing, meaning that when demand for an Uber is higher, passengers pay more.

[8] Pew Research Center is a non-profit organization, a subsidiary of The Pew Charitable Trusts, which serves as its primary source of funding.

looked into Americans' generation of income through the use of digital platforms which Pew Research Center refer to as "gig work" platforms. The results of the survey indicate that young adults are more inclined to generate income from these online platforms. Furthermore, 23% of individuals who generate income from these gig work platforms are students, which is likely in part due to the fact that gig work platforms allow individuals to moderate their schedules.

Aside from the aforementioned privately-sponsored studies, there has been a recent instance of publicly-funded analysis with respect to the digital economy. In March 2018 the United States Bureau of Economic Analysis (BEA) released a preliminary measure of the size and growth of the digital economy's contribution to GDP. The BEA's statistics, however, only include goods and services that are classified as primarily digital because of measurement issues associated with measuring "partially digital" services carried out through the sharing economy.[9] In an accompanying report, Barefoot et al. (2018) conclude that the digital economy grew at a much faster rate annually than the U.S. economy as a whole. Since the BEA only includes goods/services which are primarily digital, it excludes digital income generated from peer-to-peer accommodation and peer-to-peer ridesharing and may also exclude the provision of freelance services among other categories of income outlined in the DES. This means that it is not possible to compare the results of the BEA data with that of the DES in this study, since the composition of these samples varies substantially. Since the BEA's data is the closest American counterpart to the Canadian DES, these limitations of the BEA survey emphasize that the DES released by Statistics Canada is extremely

[9] The BEA classifies primarily digital goods/services on the basis of three distinct categories: digital-enabling infrastructure necessary for computer networks, e-commerce transactions which use computer networks, and digital media. For example, this includes computer hardware such as Apple laptops and software such as OSX in the first category, the sale and purchase of Bitcoin in the second category, and Netflix subscriptions in the third category. Peer-to-Peer transactions which take place through digital intermediaries such as home-sharing on Airbnb and ride-sharing on Uber are "partially digital" since the good rented/service provided is not digital, even though the transaction itself is processed through a digital intermediary.

progressive in nature. Not only does the DES include the Sharing Economy (and does not focus exclusively on goods/services which are entirely digital in nature), it provides demographic data considering age and gender, as well as sub-regional geographical information.

Statistics Canada (2018a) published a report accompanying the release of the Digital Economy Survey, as well as an infographic which provides a summary of the survey's findings. The data indicates that over the reference period, from July 2017 to June 2018, just over one-quarter of Canadian adults (18 years of age and older) generated money online through the use of digital platforms.[10] The most commonly used method of generating online income was through the use of online bulletin boards which include platforms such as Kijiji, eBay, and Etsy to sell new or used products. Statistics Canada (2018a) reports that the average Canadian who generates income through online bulletin boards earns $722. Despite the fact that earnings from the sale of products on online bulletin boards did not vary on the basis of age or personal income among those who did participate, Statistics Canada finds that the practice of selling goods on online bulletin boards tends to be more popular among younger demographics, specifically those younger than 44 years of age, as well as those who have an annual personal income above $100,000.

Aside from these findings, Statistics Canada's (2018a) report accompanying the DES provides little information on the generation of income through digital platforms both in general and considering specific platforms. There is an absence of necessary information surrounding both demographic characteristics associated with digital earnings and whether geographical factors play a role. Since the DES has been released very recently, there is very little literature which summarizes what we know about these various sources of digital income in Canada. My first contribution will be the presentation of summary statistics which aims to fill in these gaps.

[10] In this study, I find that just under a quarter of Canadians generate digital income. I conclude that sub-regional sample restrictions perpetuate this minor discrepancy.

There exists a body of literature which has looked into how the digital economy is linked with economic outcomes of interest considering specific digital platforms. Cramer and Krueger (2019) compare the capacity utilization rate of UberX drivers and taxi drivers to assess the theory that occupational licensing perpetuates market inefficiencies and distortion. The capacity utilization rate is defined as either the amount of time or the number of miles for which a driver has a passenger in the car. They find that UberX drivers had a passenger 50% of the time on average, whereas taxi drivers had a passenger between 30 and 50% of the time. These findings suggest that occupational licensing can, in fact, reduce efficiencies and distort markets. Furthermore, Brodeur and Nield (2016) examine both the effects of surge pricing and the effect that Uber has on the taxi industry. They find that there is a correlation between the number of Uber rides per hour in New York and whether it is raining, as the number of rides increases by 25% in this inclement weather, which exemplifies surge pricing at work. In contrast, the number of taxi rides in New York increases by only 4% when it is raining.[11] They also find that the number of taxi rides in New York decreased overall by 25% once Uber entered the market.

Barron et al. (2018) use public data from Airbnb's website from 2011 to 2016 to examine whether the proliferation of home-sharing platforms increased housing prices and rental rates for locals in the United States.[12] They find that there is a positive correlation between the number of short-term rentals in a given community and housing prices and rental rates. Specifically, they find that, on average, a 1% increase in the number of Airbnb listings perpetuates a 0.018% increase in

[11] Brodeur and Nield (2016) arrive at this figure using data for Uber and taxi rides in New York City from April to September 2014, and January to June 2015, as well as using National Weather Service Observatory data.

[12] Barron et al. (2018) also use data from Zillow, an American platform for long-term rentals matching landlord with prospective tenants to determine corresponding local rental rates to the zip code-year-month-level data obtained from Airbnb. They complement this dataset with data obtained from the U.S. Census Bureau's American Community Survey to determine median household income and population among other demographic characteristics in these communities where short-term rentals are listed.

rental rates and a 0.026% increase in house prices. Furthermore, Barron et al. (2018) find that an increase in the owner-occupancy rate will lead to a decrease in the effect of Airbnb listings on housing prices and rental rates, which is to be expected. Lee (2016) examines the proliferation of Airbnb in Los Angeles and its effect on the affordable housing crisis in this city. According to Lee (2016), 64% of Airbnb listings in Los Angeles are year-round short-term rentals in which the owners never live. Lee finds that in Los Angeles, a 1% decrease in the housing supply corresponds to a 0.2% increase in rental prices.

The closest contribution to that of this study is Katz and Krueger (2017), which investigates the relationship between alternative work arrangements and unemployment. However, this study is especially broad and considers nonstandard employment income rather than digital income. Katz and Krueger (2017) aim to determine whether weak labour markets and high joblessness play a role in the rise in alternative work arrangements and the increase in self-employment income. In order to determine the effect that weak labour markets and high joblessness play with respect to alternative work arrangements and self-employment income, Katz and Krueger (2017) match identical individuals in two separate survey years to determine whether a relationship exists between unemployment in the initial survey year and the participation in alternative work arrangements in the second survey year. They do so prior to and following the Great Recession, in order to determine whether this event perpetuated a change in the relationship between unemployment and the tendency to pursue alternative work arrangements.[13]

Despite the fact that Katz and Krueger (2017) find that unemployment has a positive, statistically significant effect on participating in alternative work arrangements, they conclude that

[13] Katz and Krueger (2017) match 14,090 individuals surveyed in the 2005 CPS-CWS to the February 2004 CPS. They also linked 1,203 participants in the October-November 2015 RAND-CWS to the Financial Crisis survey, conducted in February, March, and April of 2013.

this effect, in itself, is too small in magnitude to account for the proliferation of alternative work in the past decade. They find that accounting for the percentage increase in unemployment along with the increase in the likelihood of participation in alternative work, the share of individuals participating in alternative work would be predicted to rise by 0.4 percentage points from 2005 to 2015. In actuality, there is a 5 percentage point increase in the share of workers who pursue alternative work over the course of the decade examined. This means that the increase in unemployment by the Great Recession could only account for a 1.2 percentage point rise in workers pursuing alternative work.

Upon examining schedule C income, or self-employment income, Katz and Krueger (2017) conclude that the increase in unemployment following the great recession does not sufficiently account for the vast increase in schedule C income and temporary help services employment over the same period. [14] They find that self-employment income increased from 8.7% to 16.5% from 1979 to 2014. It can be concluded that both weak labour markets and high joblessness have played a role in the rise in alternative work arrangements and the increase in self-employment income. However, the magnitude of this role is very small and insignificant considering the immense growth of the prevalence of alternative work arrangements.

2.2 Summary

In sum, there exists a large body of literature which examines the importance of nonstandard employment income. However, 'nonstandard employment' is extremely broad and does not provide any insight into the importance of digital income. Recently, there has been some development into this analysis into the importance of digital income, but the body of literature is small and extremely new due to data limitations. In addition to this, there has been the emergence

[14] Katz and Krueger (2017) examine US annual time-series data from the Internal Revenue Service (IRS), which considers self-employed filers and employees working in temporary help service positions ("temp workers").

of recent literature which discusses the link between digital income and important economic outcomes. But, none of these studies consider unemployment. The closest contribution to mine is Katz and Krueger (2017), but they consider an extremely broad definition of 'nonstandard employment.'

3. Data

In what follows subsequently, I outline the datasets used in this paper including the 2018 Digital Economy Survey (DES) and the Labour Force Survey (LFS) master files from July 2017 to June 2018.[15]

3.1 The 2018 Digital Economy Survey

The 2018 DES is the first Canadian survey to inquire into Canadians' engagement in the sharing economy, or "peer-to-peer e-commerce" through both the sale/provision and purchase of goods and services through the use of digital platforms. The DES is a cross-sectional household survey whose population of interest consists of the general population of Canadian adults, 18 years of age and older, who reside in the 10 Canadian provinces, excluding institutionalized individuals.[16] The DES is comprised of a twelve-month reference period, from July 2017 to June 2018, with the collection period taking place from June 15th to July 12th, 2018.[17] Statistics Canada

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[15] These confidential data sets were accessed at the Carleton Ottawa, Outaouais Local (COOL) Research Data Centre (RDC).

[16] The DES sampling frame is stratified on the basis of province. Households are independently selected within each strata (province) in the first stage of data collection.

[17] The reference period for the household information section of the DES (including number of individuals living in a household, the number of those in the household over the age of 18, gender, age group, and geographic region) is the collection period (for example, an individual's age group would be determined based on their age as of the day upon which they were surveyed). Similar to the Census, the reference period in the questionnaire for all income/earnings related data covers a twelve-month period as of the prior year. But contrary to the census, for which income-related questions are asked of the calendar year prior to the Census, the DES asks questions as of the past 12-months. The exception to this twelve-month reference period is the last question in the survey in which the DES asks for an estimate of total personal income from all sources, before taxes and deductions, with the reference period being the calendar year ending December 31st, 2017.

initially selected 12,000 households to participate in the DES. The response rate was 50.48%. The sample size of the DES includes 5,666 observations.

The key richness of the DES is captured by a series of questions which ask, "over the past 12 months," how much money have you personally raised through the platform/digital economy? Most importantly, it provides a detailed breakdown (i.e. the dollar amount) for seven distinct categories of digital income. These include: total digital income, digital income generated through crowdfunding platforms, online bulletin boards, income generated through selling/posting creative content online, digital income generated through peer-to-peer accommodation, peer-to-peer ride-sharing or delivery services, freelance digital income, or other digital income not previously mentioned.[18] The DES is the only Canadian survey which explicitly quantifies these sources of income exclusively and separately from other traditional sources of income. Furthermore, the DES includes data pertaining to demographic considerations including gender, age group, and geographical identifiers (i.e. province and postal code).[19] However, traditional labour market variables such as labour force status are not available in this data set.[20] This is why this study necessitates the use of the LFS.

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[18] Crowdfunding consists of raising capital online from a large pool of contributors who typically donate smaller sums of money. Examples of crowdfunding platforms provided by the DES include: GoFundMe and Kickstarter. GoFundMe is more often associated with charitable donations, while Kickstarter is a platform most commonly used by entrepreneurs. Examples of online bulletin boards provided by the DES include Craigslist, StubHub, Kijiji, Ebay, and Facebook. Creative content can be posted or sold online using platforms such as Youtube for video blogging or "vlogging," as well as Tumblr, Weebly, and WordPress for traditional blogs, among others.
Examples of peer-to-peer accommodation services include Airbnb, HomeAway, and VRBO, among others. Peer-to-peer ride-sharing and delivery services include Uber, Lyft, UberEats, and SkiptheDishes.
Lastly, Upwork and Freelancer platforms, as outlined in the DES, serve as examples of platforms which allow individuals to provide specialized services online. Both Upwork and Freelancr match individuals and companies looking to hire for a short-term task with workers with specialized skills. There are a variety of platforms utilized for the provision of services which do not fit into the aforementioned categories. For example, the app TaskRabbit connects workers (with more general skills, rather than specialized) with individuals looking to have tasks around the house completed such as assembling furniture, mounting and installation, and moving and packing.

[19] There are six distinct age groups classified in the survey: "18 to 24 years," "25 to 24 years," "35 to 44 years," "45 to 54 years," "55 to 64 years," and "65 years and over." The DES also includes a variable for total income. Unfortunately, this variable is expressed in fairly large intervals and therefore could not be used in this study.

[20] Unfortunately, this dataset also does not provide information surrounding educational attainment.

3.2 The 2017 and 2018 Labour Force Survey master files

The second data source utilized in this investigation is the LFS master files from July 2017 through June 2018. The LFS is a monthly household survey which generates employment-related data and serves as basis for official statistics including the unemployment rate. LFS data is extracted from the general population aged 15 and over excluding institutionalized individuals, members of the armed forces, those who live in remote areas, and those who live on reserves.[21] The LFS samples approximately 56,000 households per month.[22]

Examining the relationship between the importance of digital income and labour market outcomes requires unemployment rate information at a sub-regional level. Although many Canadian surveys provide data on labour force status, I rely on the LFS and do so for two important reasons. First, the LFS is the only Canadian survey which provides monthly data surrounding labour force status. This is important because I need to construct an annual unemployment rate over the July 2017 to June 2018 period to match with the DES data. Second, the LFS has been created for the purpose of conveying employment information at the sub-regional level. This is important because this study aims to explore how local labour market conditions affect digital income.

3.3 Merging the DES & the LFS datasets

Given that the DES provides sub-regional geographical information by postal code, whereas the LFS only provides it at the CMA/CA level,[23] I require the use of Statistics Canada's

[21] The LFS does provide data from the ten Canadian provinces, as well as from the three Canadian territories. For the purposes of consistency across my dataset, I only include LFS observations from the ten Canadian provinces, as the DES excludes the Canadian territories from its sample.

[22] Approximately 100,000 individuals are sampled per month within this sample of 56,000 households.

[23] Both a CMA and a CA are defined as a geographical area which consists of one or more "neighbouring municipalities" surrounding the urban core. A CMA has a total urban population of at least 100,000, where 50,000 must live around the core. A CA, on the other hand, has a core population of at least 10,000 but does not need to have a total population of 100,000 to be classified as a CA. There can be two types of urban cores in a CMA or CA. The

Postal Code Conversion File (PCCF) to make the two files compatible. Once merged, all individuals that live in the same CMA/CA share the same local unemployment rate. For example, all individuals in the DES that live in Toronto over the period from July 2017 to June 2019 will have the same unemployment rate. See the appendix for more detail on how this merge was carried out.

3.4 Sample Restrictions

For the purpose of my study, I focus on adults aged 18 and over residing in a CMA or CA as defined in the LFS. The lower bound is due to the fact that the DES only includes adults 18 years of age and over. Contrary to other studies, I do not impose an upper bound to my age restriction, since little is understood surrounding the importance of digital income. An additional sample restriction is the omission of individuals who are unable to be identified at the CMA/CA level.[24]

4. Summary Statistics

Table (1) exhibits the incidence of each digital income earning category in Canada.[25] I find that 24.1% of Canadians generate digital income. Most (23%) of this is accounted for by Canadians who generate income through online bulletin boards. The remaining 0.9% of digital income is divided amongst the remaining six categories. The percentage of Canadians who generate digital

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core is the primary population centre with the greatest amount of people. As mentioned previously, in a CMA, the core must have a population of 50,000. In a CA, this core population must be 10,000. The secondary core is a population centre within a CMA in addition to the core which has at least 10,000 people, and was therefore previously a CA that has merged with the CMA. Within the SGC, the term 'fringe' is used to describe population centres within a CMA or CA that have less than 10,000 people and are not adjacent to the core or secondary core.
It should be noted that the LFS also includes data at the Economic Region (ER) level, but this study uses CMA-level data because it is coarser.

[24] Individuals who do not reside in one of the 34 CMAs and 34 CAs classified in the LFS are all amalgamated into one category in the LFS: non-CMA. This category may include those living in strong metropolitan influenced zones, moderate metropolitan influenced zones, weak metropolitan influenced zones, no metropolitan influenced zones, or those living in one of the 63 CAs which are included in the 2016 Standard Geographical Classification but not included in the 2017 or 2018 monthly LFS. See the Appendix for more detail.

[25] All means are weighted using individual person weights (the WTMP variable) as defined in the DES.

income through the use of peer-to-peer accommodation platforms and peer-to-peer ridesharing/delivery services is especially interesting. Despite the fact that so many Canadians use the services/accommodations provided by platforms such as Uber and Airbnb, only 0.04% of the Canadian population generates income through peer-to-peer ridesharing/delivery platforms and 0.03% generate income through peer-to-peer accommodation platforms respectively. These small proportions justify the small magnitude of the average Canadian dollar value of digital incomes in Table (2), which will be discussed subsequently.

Table (2) depicts means and standard deviations of each category of digital income outlined in the DES for the population as a whole, as well as for gender-specific demographics and age-specific cohorts. The most notable finding is the fact that there appears to be a difference across gender.[26] Overall, men generated significantly more digital income than women, on average. The average digital income generated by males in Canada across all platforms was \$290.74, whereas women only generated just over half of that value, \$167.18. Men generated more digital income across all platforms/methods, with the exception being income generated from creative content online, as well as income associated with peer-to-peer accommodation. Women generated over five times as much digital income through creative content than men. There are also significant differences across crowdfunding income, online bulletin income, and "other" (not otherwise specified) digital income.

[26] Despite the fact that the standard errors are relatively large compared to the estimated means, these average earnings are in fact statistically different across gender. To determine this, I regress the variable for total digital income (in dollars) on the female indicator variable alone. The female indicator variable is a binary variable which equals one if individual i is female and zero otherwise (see Section 5.). The model for this experiment takes the following form: $y_i = \beta_0 + \beta_1 female_i$.
Since β_1 is actually a very large negative coefficient, it is obvious that average earnings differ between males and females (β_1 is not remotely close to zero). Furthermore, the corresponding p-value is statistically significant at the 5% level, meaning that I can confidently ascertain that the average earnings are different between genders.

Upon examining various age cohorts, individuals aged 45 to 54 generated the most digital income, followed by those aged 25 to 34. Unsurprisingly, the oldest cohort generated the least digital income. The second smallest digital income earning category was the youngest age group, including those 18 to 24 years of age. A potential explanation for this is the fact that many young adults are still in school and therefore, may not generate any income (traditional or digital). Online bulletin board income is the most popular form of digital income across all age cohorts and genders. Individuals aged 35 to 44 generated the most income on online bulletin boards. The cohort of ages 25 to 34 generated the most income in the peer-to-peer rideshare category. Lastly, those 45 to 54 earned the most digital freelance income.

The average values in Table (2) appear small. This is because the proportion of Canadians who generate digital income in these eight categories is extremely small (see Table (1)). To ensure that sample size restrictions do not significantly affect the average values of digital income, all summary statistics are first calculated with an unrestricted sample. I restrict my sample size using a three step process, observing averages for every sample size. First, I consider the entire DES sample. Next, I eliminate those individuals from my sample who are missing observations for at least one category of digital income. Lastly, I eliminate those who did not reside in one of the 34 CMAs or 32 CAs for which the LFS provides data over the sample period. All of my summary statistics are essentially the same across the three aforementioned specifications. The only exception to this rule was peer-to-peer accommodation income, for which eliminating those from CMAs that I could not match to the LFS significantly affected average income.[27] Table (2) only includes means from the last specification, since eliminating these groups does not affect my results.

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[27] The results associated with income earned through peer-to-peer accommodation were still economically important. See Section 6. Results.

5. Econometric Model

The econometric model takes the following form:

$$y_i = \alpha_0 + \alpha_1 ur_r + \alpha_2\, female_i + \alpha_3 age18to24_i + \alpha_4\, age35to44_i + \alpha_5\, age45to54_i + \alpha_6\, age55to64_i + \alpha_7\, age65plus_i + \varepsilon_i \qquad (1)$$

where the dependent variable y_i measures the importance of digital income for individual i. In this study, y_i is measured in two ways. First, it is measured as the amount (dollar value) of digital income generated in the past year (i.e. July 2017 to June 2018). Second, it is measured as a binary variable equal to one if individual i generates digital income in the reference period and 0 otherwise. ur_r is the unemployment rate (on a scale of 0 to 100) in region *r.* Every individual in the CMA/CA region will therefore have the same unemployment rate. Finally, my control variables include a female indicator variable, and five age dummies (i.e. 18 to 25, 35 to 44, 45 to 54, 55 to 64, and 65 and up), with individuals 25 to 34 years of age as the reference group.

I estimate equation (1) examining both total digital income and sub categories of digital income. For example, in the case of crowdfunding income, the two measures of digital income would be defined as follows. First, y_i represents the total dollar value of digital income generated on crowdfunding platforms from July 2017 to June 2018 by individual i. Second, In the binary case, y_i is equal to one only if individual i has generated digital income online using crowdfunding platforms during the reference period.[28]

6. Results

6.1 General Discussion

[28] There are 8 possible definitions of y_i in each econometric model. These definitions are listed as follows: total digital income, digital income generated through crowdfunding platforms, online bulletin boards, income generated through selling/posting creative content online, digital income generated through peer-to-peer accommodation, peer-to-peer ride-sharing or delivery services, freelance digital income, or other digital income not previously mentioned.

In Table (3), I present my estimates for the OLS regression where the dependent variable is a binary variable that equals one if the individual has earned digital income in the past year.[29] Columns (1) through (7) focus on sub-categories of digital income, whereas column (8) is for all sources of digital income.[30] Given that the dependent variable is binary, the estimated coefficient represents the marginal effect (i.e. how a change in the explanatory variable affects the probability of generating digital income).

From column (8) one can see that a 1 percentage point increase in the unemployment rate is associated with a 1.3 percentage point decrease in total digital income. Given that in a typical recession the unemployment rises by 4 percentage points, such a finding implies that in a recession, the probability of having digital income in the past year would decrease by 5.2 percentage points, to put this finding in perspective.[31] Considering the fact that 24% of Canadians generate digital income, this change is not economically insignificant. It is not, however, statistically significant, even at the 10% level. Furthermore, when focusing on the incidence of digital income within various subcategories, it becomes evident that income generated through online bulletin boards is

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[29] The regression results in Table (3) and all subsequent tables are weighted using individual person weights (the WTMP variable) as defined in the DES. They are clustered at the CMA/CA level, given that unemployment varies substantially from sub-region to sub-region, to deal with the Molten effect.

[30] For example, in the case of Column (2), which represents one of the sub-categories of digital income, i.e. online bulletin board income, the binary variable equals one if the individual had any income over the past year from online bulletin boards.

[31] Despite the fact that from July 2017 to June 2018, the Canadian unemployment rate was very low, there is significant variability in the unemployment rate across different sub-regions There are substantial differences among CMAs and CAs, and in the Maritimes and Newfoundland especially, the unemployment rates are quite high.

Since the DES is very new and only includes data from July 2017 to June 2018, I do not have data from any recessionary periods in my dataset. This means that I must use an interpretation of the unemployment coefficient (ur_r) to put the effect of a recession on digital income generation into perspective. In a typical recession, the unemployment rate increases by four percentage points on average. Therefore, the change in digital income generation corresponding to a four percentage point increase in the unemployment rate serves as a proxy for the effect of a recession on digital income generation in this study. The recessionary effects discussed in this paper rely heavily on this proxy, as this is the best approximation currently possible due to limitations in the availability of historical data.

the driving force of the changes in the probability of generating digital income, as it is the only category which appears economically large. However, it is still statistically insignificant.

In Table (4), I present the OLS results where the dependent variable is now the dollar amount of digital income. The structure of the columns is very similar to that of Table (3). Columns (1) through (7) are for subgroups of digital income and Column (8) is for total digital income. Examining total digital income in Column (8), it is the case that a 1 percentage point increase in the unemployment rate causes the average value of digital income generated (from all sources) to decrease by \$3.64 (a drop of \$14.56 in a recession). This effect is both economically and statistically insignificant. Upon examining the various categories of digital income, the effect typically remains negative (except for digital income generated through peer-to-peer accommodation or crowdfunding platforms), however, the effect remains both economically small and statistically insignificant. These findings are especially interesting considering the fact that higher unemployment rates seem to diminish the incidence of digital income generation, but the magnitude of the change in digital income earnings in dollars is negligible.

6.2 Gender Differences

In the existing body of literature there have been multiple reports of gender differences with respect to digital income earnings. Farrell and Greig (2016a) report that males are more likely to generate digital income. Furthermore, Hall and Kreuger (2018), report that men are more likely to generate income through Uber. My existing model includes a binary variable for gender which allows me to illustrate the difference in digital earnings between males and females. However, the second contribution of this study is an analysis of the relationship between unemployment and digital income earnings. The dummy variable does not allow for gender-specific unemployment rates, so I am unable to interpret the relationship between unemployment and digital income generation separately for men and women. Therefore, I drop the dummy variable and repeat my analysis for the relationship between unemployment and digital income by gender.

Table (5) shows the OLS results from the linear probability model for men, where the dependent variable is a binary variable. As exhibited in Column (8), the overall effect of the unemployment rate on the probability of generating digital income is quite small. Furthermore, upon examining columns (1) through (7), it becomes evident that there is no relationship between unemployment and the probability of generating digital income for men, with the exception being online bulletin board income, which accounts for the 0.7 percentage point increase shown in Column (8). Table (6) shows the OLS results from the regression where the dependent variable is the dollar value of digital income for males. As exhibited in Column (8) of this table, the unemployment rate does appear to have an effect on the generation of digital income for men in terms of average dollars generated. During a recession, one could expect to see the incidence of digital income for men increase by $69 based on these findings.

The OLS results from the linear probability model for women are found in Table (7). Column (8) shows that a 1 percentage point increase in the unemployment rate corresponds with a 2.98 percentage point decrease in the probability of generating digital income for women. This figure suggests nearly a 12 percentage point decrease in total income in the context of a typical recession, which is very substantial considering the fact that this means that during an average recession the percentage of Canadian females generating digital income would decrease by half, hypothetically. Here, the decrease is almost entirely driven by online bulletin board income. This result is both economically and statistically significant at the 5% level. Table (8) shows the OLS results where the dependent variable is the dollar value of digital income for females. When the unemployment rate increases by 1%, women earn $24.78 less in terms of digital income (this would correspond to $100 less in a recession). Despite the fact that this number is not particularly large, the magnitude of the decrease in average digital income is more substantial for women than for men. However, none of these results are statistically significant.

Returning to Table (5), Column (4) outlines the probability of generating peer-to-peer accommodation income for males, following a 1 percentage point increase in the unemployment rate. The probability of generating peer-to-peer accommodation income does not vary with the unemployment rate for males. Column (5) shows that a 1 percentage point increase in the unemployment rate is associated with a 0.1 percentage point increase in the use of ridesharing/delivery applications to generate digital income. Since only 0.04% of the population generates digital income through the use of these apps, this means that this increase is not insignificant in terms of magnitude.

In Table (7), Column (4) shows that for females, peer-to-peer accommodation income would increase by 0.4 percentage points during the average recession. While this number may sound entirely irrelevant, when paired with the fact that only 0.03% of the Canadian population generates digital income through peer-to-peer accommodation, this means that this form of income would more than double in a recession, hypothetically speaking. The magnitude of the effect of the unemployment rate on the probability of generating ride-sharing income is the same for women as men, however, the direction of the response varies for men and women. When unemployment increases, men are 0.1 percentage points more likely to generate digital income through the use of ride-sharing/delivery apps, whereas women are 0.1 percentage points less likely to do so. It is documented that more men generate digital income through ridesharing/delivery apps than women. This is consistent with the fact that in times of higher unemployment, more men would be predicted to utilize these platforms to generate digital income meanwhile the number of women using these apps would decrease. It is also particularly interesting that women would seem to be increasingly more likely to use home-sharing platforms such as Airbnb to generate some income during recessions. I do not see an effect for men.

In sum, it becomes evident that there is a significant difference in the link between unemployment and digital income for both men and women. In times of increased unemployment, the incidence of digital income generation among men is much less affected. Furthermore, the magnitude of any changes in digital earnings for men are much smaller than changes in incidence of digital income generation among women. Despite the fact that the relationship between the unemployment rate and average digital income generated (in dollars) is not economically significant in magnitude, the relationship between the unemployment rate and the probability of generating digital income is economically important. However, these results are not statistically significant. Furthermore, based on the regression results, there is a substantial difference between the predicted outcomes of men and women in typical recessions, especially considering the magnitude of the changes in digital income.

7. Robustness Checks

In order to evaluate the stability of my results, I repeat my two regressions (the standard OLS and the linear probability model) for men and women, exclusively considering those between 24 and 54 years of age, since this group generates the most digital income. Tables (9) and (10) report regression results for the linear probability model, where the dependent variable is binary, for men and women respectively. Tables (11) represent the regression results where the dependent variable represents the dollar amount of digital income for men. Table (12) does the same for women.

My three key findings are consistent across this smaller sample. First, the average quantity of digital income earned remains quite small during recessions. Second, there are significant gender differences. The response of male and female digital income to surges in the unemployment rate vary in both direction and magnitude. Females are always more significantly affected. Lastly, the probability of generating income on peer-to-peer accommodation platforms is consistent but magnified. This is not surprising, seeing as these specific age cohorts have the greatest concentration of digital income.

8. Conclusion

Using the 2018 DES and 2017 and 2018 LFS master files, I look at two things: first, I examine the importance of digital income and assess whether demographic characteristics affect its generation. Second, I determine the relationship between the unemployment rate and the probability of generating digital income, as well as the link between the unemployment rate and the dollar value of digital income earned.

There are three main conclusions. First, there does not appear to be a significant relationship between the unemployment rate and the dollar value of digital income earned. There does, however, appear to be an economically important relationship between the unemployment rate and the probability of generating digital income, especially amongst females. The second conclusion I draw is the fact that there are distinct gender differences in both the generation of digital income and how it responds to unemployment. Lastly, with respect to the sharing economy, I find that despite the fact that ridesharing/delivery platforms do not appear to be differently affected in a recession when considering gender, the probability of using peer-to-peer accommodation platforms to generate digital income in a typical recession appears to increase substantially for women. The release of new Canadian data has been critical for this investigation in allowing Canadians to answer pressing questions surrounding the importance of digital income and its relationship to business cycle fluctuations. Despite the fact that I have been able to identify significant gender differences in digital income's importance, this study has been limited by the fact that data is still not available to determine whether this importance is affected by educational attainment. Once such data becomes available to Canadians, such an investigation is certainly warranted as a next step.

Appendix A1: Census Metropolitan Areas (CMAs) and Census Agglomerations (CAs)

This appendix explains how I merge the two datasets at the sub-regional level, more precisely, at the CMA/CA level.

The LFS classifies CMAs and CAs according to the 2011 Standard Geographical Classification (SGC). The DES, however, only has geographical identifiers either at the province level or postal code level. This necessitates the use of Statistics Canada's Postal Code Conversion File (PCCF) to convert postal codes to the CMA/CA-level in the DES.[32] Once carried out, sub-regional geographical classification will be common across the DES and LFS (at the CMA/CA level).

The first difficulty I face is the fact that the RDC, where I access the confidential data used in this paper, only provides the PCCF that relies on the 2016 SGC, rather than that of 2011.[33] Fortunately, the two SGCs are very similar, and a crosswalk between the two can be easily created. In what follows, I provide an explanation of this crosswalk. The 2016 SGC includes 36 CMAs and 117 CAs. Two new CMAs were created in 2016, which were previously listed as CAs in 2011. This is not of concern for my analysis, as I do not make a distinction between CMAs and CAs. However, eight new CAs have been created in 2016. All of these CAs are omitted to ensure compatibility with the 2011 SGC. Lastly, two CAs included in the 2011 SGC were dropped in 2016 as the population of their cores dropped below 10,000. These are part of the "non-CMA" category in the LFS. Furthermore, despite the fact that the CMAs are all identified by the same names, in the LFS, Ottawa is identified by the name "Ottawa," and Gatineau is identified by the name "Gatineau." In the 2016 Census of Population, there are two CMAs by the name of "Ottawa-Gatineau," with each CMA specifying which province the individual resides in. For example, "Ottawa-Gatineau (Ontario part)" from the 2016 Census of Population corresponds to "Ottawa" in the LFS classified by the 2011 SGC. Similarly, "Ottawa-Gatineau (partie du Québec)" corresponds to "Gatineau" in the LFS. Since these two cities are clearly distinct in both classifications, this discrepancy does not prove problematic. Furthermore, three additional CAs have different names in the LFS (2011 SGC) and the 2016 Census of Population. "Sarnia" in the Census is referred to as "Sarnia-Clearwater" in the LFS, and "Chilliwack" in the Census is

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expressed as “Chilliwack-Hope.” Neither “Clearwater” nor “Hope” are separate CAs in the Census, and upon examination of 2016 SGC maps and the 2011 SGC maps, the boundaries do not appear to be different. The last CA discrepancy is “Rouyn-Noranda/Val-d’Or-Malartic” in the LFS, which corresponds with two separate neighbouring CAs in the 2016 Census of Population, “Rouyn-Noranda,” and “Val-d’Or.” For this investigation, I generate an unemployment rate based on the CA Rouyn-Noranda/Val-d’Or-Malartic, as expressed in the LFS.

According to the 2011 SGC there are 34 CMAs and 114 CAs, as well as 4 categories of Census Metropolitan Influenced Zones (MIZs). MIZs are defined as regions in which the core population is below 10,000. There are four MIZ categories: Strong Metropolitan Influenced Zones, Moderate Metropolitan Influenced Zones, Weak Metropolitan Influenced Zones, and No Metropolitan Influenced Zones. The LFS, however, only identifies 34 CMAs and 32 CAs. [32] The remaining regions which are unaccounted for (i.e. 79 CAs, and 4 MIZs) all fall under the “Non-CMA” category in the LFS. The geographical regions included in “non-CMA” are all distinct and their locations within Canada vary drastically. Therefore, I cannot calculate a meaningful unemployment rate for the “non-CMA” category, so these regions cannot be included. In the end, I am left with data covering the 34 CMAs and 32 CAs.[34]

[32] All of the 34 CMAs and 32 CAs correspond to CMAs and CAs in the 2011 SGC. The exception is Rouyn-Noranda/Val-d’Or-Malartic, which I account for previously.

[34] The 34 CMAs include: St. John’s (NB), Halifax (NS), Moncton (NB), Saint John (NB), Saguenay (QC), Québec (QC), Sherbrooke (QC), Trois Rivières (QC), Montréal (QC), Gatineau (QC), Ottawa (ON), Kingston (ON), Peterborough (ON), Oshawa (ON), Toronto (ON), Hamilton (ON), St. Catharines-Niagara (ON), Kitchener-Cambridge-Waterloo (ON), Brantford (ON), Guelph (ON), London (ON). Windsor (ON), Barrie (ON), Greater Sudbury (ON), Thunder Bay (ON), Winnipeg (MB), Regina (SK), Saskatoon (SK), Calgary (AB), Edmonton (AB), Kelowna (BC), Abbotsford-Mission (BC), Vancouver (BC), and Victoria (BC). The 32 CAs include: Charlottetown (PEI), Cape Breton (NS), Fredericton (NB), Granby (QC), Cornwall (ON), Norfolk (ON), Chatham-Kent (ON), Sarnia-Clearwater (ON), North Bay (ON), Sault Ste. Marie (ON), Medicine Hat (AB), Lethbridge (AB), Red Deer (AB), Chilliwack-Hope (BC), Nanaimo (BC), Prince George (BC), Corner Brook-Deer Lake (BC), Summerside (PEI), Truro (NS), New Glasgow (NS). Bathurst (NB), Miramichi (NB), Rouyn-Noranda/Val-d’Or-Malartic (QC), Brandon (MB), Moose Jaw (SK), Prince Albert (SK), Leamington (ON), Timmins (ON), Wood Buffalo (AB), Saint Georges (QC), Thompson (MB), Fort St John (BC).

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Table 1. Proportion of Canadians who Generate Digital Income:
Means and Standard Deviations in Brackets

	Proportion
Total Digital Income	0.241 (0.428)
Online Bulletin Income	0.230 (0.421)
Crowdfunding Income	0.002 (0.047)
Creative Content Digital Income	0.007 (0.083)
Peer-to-Peer Accommodation Income	0.003 (0.051)
Peer-to-Peer Rideshare/ Delivery Income	0.004 (0.067)
Freelance Digital Income	0.004 (0.063)
“Other” Digital Income	0.009 (0.095)
Observations	3,763

NOTES: All summary statistics are calculated using weights. Standard deviations in brackets. Each specification is restricted to individuals 18 years of age and older who live in one of the 34 CMAs or 32 CAs found in the LFS. The “Proportion” column represents the proportion of the Canadian population who generates the specified form of digital income.

Table 2. Average Digital Income by Gender: Means and Standard Deviations in Brackets

	Total	Males	Females	Ages 18-24	Ages 25-34	Ages 35-44	Ages 45-54	Ages 55-64	Ages 65+
Crowdfunding Income	3.17 (109.409)	6.26 (155.25)	0.14 (5.044)	1.05 (22.100)	13.53 (230.222)	0.01 (1.050)	0 (0)	0.17 (3.671)	0 (0)
Online Bulletin Income	156.76 (1065.651)	201.87 (1329.558)	112.39 (714.523)	80.49 (454.754)	238.14 (1548.556)	289.13 (1402.096)	94.17 (327.116)	150.69 (1045.699)	42.18 (520.207)
Creative Content Digital Income	12.98 (289.593)	4.18 (190.334)	21.63 (361.400)	0 (0)	27.42 (382.191)	0.86 (18.498)	40.56 (562.190)	0.98 (19.818)	0 (0)
Peer-to-Peer Accommodation Income	5.19 (289.672)	4.97 (347.616)	5.42 (218.256)	0 (0)	0.36 (6.036)	14.64 (596.781)	1.15 (22.867)	15.88 (392.556)	0 (0)
Peer-to-Peer Rideshare/ Delivery Income	3.95 (117.491)	7.51 (165.582)	0.45 (19.943)	1.44 (44.263)	11.12 (223.526)	5.10 (94.917)	2.75 (73.711)	0.03 (0.518)	0.01 (0.461)
Freelance Digital Income	18.88963 (748.7301)	19.70413 (985.4725)	18.09 (396.352)	0.20 (2.664)	33.40 (560.120)	9.76 (190.163)	55.60 (1726.712)	1.86 (136.352)	2.59 (112.387)
"Other" Digital Income	27.51 (1294.798)	46.25 (1832.796)	9.08 (147.562)	35.35 (403.020)	5.15 (68.354)	3.10 (38.615)	138.58 (3213.179)	0.37 (27.201)	0.09 (6.715)
Total Digital Income	228.45 (1889.022)	290.74 (2511.319)	167.18 (932.470)	118.53 (636.880)	329.12 (1712.273)	322.60 (1544.949)	332.83 (3698.629)	169.98 (1126.413)	44.87 (577.550)
Observations	3,763	1,722	2,041	163	492	636	599	773	1,100

NOTES: All summary statistics are calculated using weights. Standard deviations in brackets. Each specification is restricted to individuals 18 years of age and older who live in one of the 34 CMAs or 32 CAs found in the LFS. The "Total" column represents the average quantity of digital income for both genders and all age groups. The "Males" column represents the average quantity of digital income for males of all age groups. The "Female" column represents the average quantity of digital income for females of all age groups. The "Ages 18-24" column and every subsequent column represents the average quantity of income for both genders who fall into the specified age category.

Table 3. OLS Regression Results for Linear Probability Model Both Genders (marginal effects reported)

Explanatory Variables	Probability of Generating Crowdfunding Income (1)	Probability of Generating Online Bulletin Income (2)	Probability of Generating Creative Content Digital Income (3)	Probability of Generating Peer-to-Peer Accommodation Income (4)	Probability of Generating Peer-to-Peer Rideshare/ Delivery Income (5)	Probability of Generating Freelance Digital Income (6)	Probability of Generating Other Digital Income (7)	Probability of Generating Digital Income (All Sources) (8)
Unemployment Rate	-0.0001 (0.001)	-0.013 (0.013)	-0.000 (0.001)	0.001* (0.000)	-0.000 (0.001)	-0.001 (0.001)	-0.002 (0.001)	-0.013 (0.012)
Female	-0.002 (0.002)	0.000 (0.024)	0.005 (0.004)	0.002 (0.002)	-0.002 (0.003)	0.003 (0.003)	0.006 (0.005)	0.001 (0.023)
Age 18 to 24	-0.005 (0.005)	-0.068 (0.051)	-0.020*** (0.007)	-0.004 (0.003)	0.001 (0.008)	-0.002 (0.007)	0.012 (0.017)	-0.090* (0.051)
Age 35 to 44	-0.007 (0.004)	0.031 (0.0422)	-0.015** (0.007)	0.001 (0.005)	0.001 (0.006)	-0.003 (0.004)	-0.001 (0.005)	0.018 (0.041)
Age 45 to 54	-0.007 (0.004)	-0.072** (0.036)	-0.015 (0.009)	0.001 (0.005)	-0.004 (0.004)	-0.006 (0.004)	0.001 (0.008)	-0.078** (0.035)
Age 55 to 64	-0.004 (0.005)	-0.184*** (0.043)	-0.018*** (0.006)	-0.002 (0.004)	-0.004 (0.005)	-0.008** (0.004)	-0.012*** (0.004)	-0.196*** (0.042)
Age 65 and up	-0.007 (0.005)	-0.240*** (0.034)	-0.021*** (0.007)	-0.004 (0.003)	-0.007* (0.004)	-0.008* (0.004)	-0.012*** (0.004)	-0.262*** (0.037)
Constant	0.008 (0.006)	0.389*** (0.087)	0.019** (0.009)	-0.002 (0.003)	0.009** (0.004)	0.011** (0.005)	0.019* (0.010)	0.409*** (0.083)
Observations	3,763	3,763	3,763	3,763	3,763	3,763	3,763	3,763

NOTES: The dependent variables are binary for having digital income (from a specified source). This sample is restricted to those over 18 years of age who live in the 34 CMAs and 32 CAs found in the LFS. The unemployment variable represents the mean unemployment rate in which an individual *i* resides. All individuals living in the same CMA/CA have the same unemployment rate. All regressions are weighted. Standard errors clustered at the sub-regional (CMA/CA) level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4. OLS Regression Results for Both Genders

Explanatory Variables	Total Crowdfunding Income	Total Online Bulletin Income	Total Creative Content Digital Income	Total Peer-to-Peer Accommodation Income	Total Peer-to-Peer Rideshare/ Delivery Income	Total Freelance Digital Income	Total Other Digital Income	Total Digital Income (All Sources)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	0.569 (0.774)	-4.354 (17.49)	-6.963 (5.683)	5.117* (2.950)	-2.005 (1.607)	-8.202 (5.920)	12.20 (16.73)	-3.635 (26.32)
Female	-6.269 (6.328)	-91.55 (68.22)	17.27 (12.97)	0.472 (6.581)	-7.201 (4.469)	-1.864 (20.39)	-35.51 (41.14)	-124.6 (80.00)
Age 18 to 24	-12.92 (14.01)	-163.9 (124.1)	-26.15 (21.40)	-0.388 (0.761)	-10.16 (10.03)	-33.23 (25.28)	27.63 (25.79)	-219.1 (146.0)
Age 35 to 44	-13.60 (13.72)	49.98 (153.6)	-26.19 (22.60)	14.16 (12.08)	-6.063 (10.80)	-23.47 (25.53)	-2.754 (5.486)	-7.938 (171.9)
Age 45 to 54	-13.73 (13.84)	-145.7 (113.2)	14.24 (45.66)	0.292 (0.883)	-8.348 (9.970)	22.96 (56.19)	131.4 (125.4)	1.167 (200.1)
Age 55 to 64	-13.47 (13.76)	-87.94 (116.7)	-25.56 (22.02)	15.01 (14.95)	-10.97 (9.344)	-30.73 (25.92)	-6.359 (5.086)	-160.0 (141.3)
Age 65 and up	-13.52 (13.63)	-195.8 (118.3)	-27.35 (22.77)	-0.436 (0.562)	-11.08 (9.502)	-30.70 (26.16)	-5.180 (4.752)	-284.0** (140.2)
Constant	13.64 (13.94)	309.5 (205.7)	56.81* (28.92)	-28.05 (17.84)	25.89 (19.75)	79.52* (45.22)	-43.64 (73.38)	413.7* (234.4)
Observations	3,763	3,763	3,763	3,763	3,763	3,763	3,763	3,763

NOTES:. The reference age group is 24 to 35 years of age. This sample is restricted to those over 18 years of age who live in the 34 CMAs and 32 CAs found in the LFS. The unemployment variable represents the mean unemployment rate in which an individual *i* resides. All individuals living in the same CMA/CA have the same unemployment rate. All regressions are weighted. Standard errors clustered at the sub-regional (CMA/CA) level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5. OLS Regression Results for Linear Probability Model for Males (marginal effects reported)

Explanatory Variables	Probability of Generating Crowdfunding Income (1)	Probability of Generating Online Bulletin Income (2)	Probability of Generating Creative Content Digital Income (3)	Probability of Generating Peer-to-Peer Accommodation Income (4)	Probability of Generating Peer-to-Peer Rideshare/ Delivery Income (5)	Probability of Generating Freelance Digital Income (6)	Probability of Generating Other Digital Income (7)	Probability of Generating Digital Income (All Sources) (8)
Unemployment Rate	0.000 (0.001)	0.007 (0.014)	0.000 (0.002)	0.000 (0.000)	0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.007 (0.014)
Age 18 to 24	-0.007 (0.009)	-0.070 (0.064)	-0.012 (0.009)	-0.000 (0.000)	-0.007 (0.005)	-0.006 (0.005)	0.033 (0.026)	-0.086 (0.066)
Age 35 to 44	-0.011 (0.008)	0.0252 (0.053)	-0.008 (0.008)	0.010 (0.007)	0.009 (0.011)	-0.001 (0.003)	0.004* (0.002)	0.025 (0.054)
Age 45 to 54	-0.011 (0.008)	-0.007 (0.048)	-0.010 (0.009)	0.000 (0.000)	-0.001 (0.007)	-0.002 (0.004)	0.011* (0.007)	-0.007 (0.047)
Age 55 to 64	-0.008 (0.008)	-0.174*** (0.039)	-0.007 (0.010)	-0.000 (0.000)	-0.001 (0.007)	-0.006 (0.004)	0.000 (0.000)	-0.177*** (0.040)
Age 65 and up	-0.011 (0.008)	-0.206*** (0.041)	-0.012 (0.009)	-0.000 (0.000)	-0.007 (0.005)	-0.005 (0.005)	-0.012*** (0.004)	0.000 (0.000)
Constant	0.010 (0.009)	0.262*** (0.098)	0.010 (0.013)	-0.002 (0.002)	0.004 (0.009)	0.011 (0.011)	0.019* (0.010)	0.007 (0.007)
Observations	1,722	1,722	1,722	1,722	1,722	1,722	1,722	1,722

NOTES: The dependent variables are binary for having digital income (from a specified source). The reference age group is 24 to 35 years of age. This sample is restricted to those over 18 years of age who live in the 34 CMAs and 32 CAs found in the LFS. The unemployment variable represents the mean unemployment rate in which an individual *i* resides. All individuals living in the same CMA/CA have the same unemployment rate. All regressions are weighted. Standard errors clustered at the sub-regional (CMA/CA) level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6. OLS Regression Results for Males

Explanatory Variables	Total Crowdfunding Income	Total Online Bulletin Income	Total Creative Content Digital Income	Total Peer-to-Peer Accommodation Income	Total Peer-to-Peer Rideshare/ Delivery Income	Total Freelance Digital Income	Total Other Digital Income	Total Digital Income (All Sources)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	1.099	3.227	-3.849	3.991	-4.451	-15.60	32.80	17.22
	(1.472)	(30.87)	(3.130)	(4.020)	(3.599)	(14.14)	(34.58)	(48.83)
Age 18 to 24	-25.42	-353.2	-1.677	0.725	-23.13	-5.303	65.42	-342.5
	(27.74)	(241.9)	(1.131)	(0.924)	(20.90)	(4.616)	(48.47)	(241.0)
Age 35 to 44	-27.45	-91.25	-0.905	29.87	-12.27	-0.102	4.590	-97.51
	(27.92)	(298.9)	(0.913)	(24.77)	(22.92)	(4.326)	(4.618)	(299.3)
Age 45 to 54	-27.62	-296.4	21.43	-0.388	-16.45	106.7	236.7	23.89
	(28.10)	(226.5)	(21.69)	(0.484)	(20.76)	(94.61)	(247.9)	(341.3)
Age 55 to 64	-27.34	-232.8	1.285	-0.275	-21.96	-1.397	-2.258	-284.8
	(28.06)	(239.3)	(2.030)	(0.550)	(19.72)	(2.382)	(4.555)	(242.2)
Age 65 and up	-27.48	-337.6	-1.111	0.138	-22.48	2.239	1.317	-385.0
	(27.96)	(240.6)	(0.781)	(0.487)	(20.24)	(6.091)	(4.065)	(241.6)
Constant	21.40	385.3	22.39	-22.20	47.08	89.23	-182.4	360.8
	(22.86)	(361.1)	(16.79)	(22.28)	(38.47)	(77.60)	(191.8)	(402.9)
Observations	1,722	1,722	1,722	1,722	1,722	1,722	1,722	1,722

NOTES: The reference age group is 24 to 35 years of age. This sample is restricted to those over 18 years of age who live in the 34 CMAs and 32 CAs found in the LFS. The unemployment variable represents the mean unemployment rate in which an individual *i* resides. All individuals living in the same CMA/CA have the same unemployment rate. All regressions are weighted. Standard errors clustered at the sub-regional (CMA/CA) level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7. OLS Regression Results for Linear Probability Model for Females (marginal effects reported)

Explanatory Variables	Probability of Generating Crowdfunding Income	Probability of Generating Online Bulletin Income	Probability of Generating Creative Content Digital Income	Probability of Generating Peer-to-Peer Accommodation Income	Probability of Generating Peer-to-Peer Rideshare/ Delivery Income	Probability of Generating Freelance Digital Income	Probability of Generating Other Digital Income	Probability of Generating Digital Income (All Sources)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	-0.000 (0.001)	-0.031** (0.013)	-0.000 (0.002)	0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.00194 (0.00223)	-0.0298** (0.0132)
Age 18 to 24	-0.003 (0.002)	-0.051 (0.069)	-0.028** (0.013)	-0.007 (0.006)	0.011 (0.018)	0.002 (0.015)	-0.010 (0.011)	-0.078 (0.071)
Age 35 to 44	-0.003 (0.002)	0.040 (0.068)	-0.021* (0.012)	-0.007 (0.006)	-0.007 (0.006)	-0.004 (0.007)	-0.005 (0.008)	0.016 (0.064)
Age 45 to 54	-0.003 (0.002)	-0.137** (0.054)	-0.019 (0.018)	0.002 (0.010)	-0.007 (0.006)	-0.009 (0.008)	-0.009 (0.011)	-0.149*** (0.048)
Age 55 to 64	0.001 (0.004)	-0.192** (0.082)	-0.028** (0.013)	-0.004 (0.008)	-0.007 (0.006)	-0.010 (0.007)	-0.023*** (0.008)	-0.214*** (0.071)
Age 65 and up	-0.003 (0.002)	-0.270*** (0.071)	-0.028** (0.013)	-0.007 (0.006)	-0.007 (0.006)	-0.010 (0.007)	-0.024*** (0.008)	-0.298*** (0.062)
Constant	0.004 (0.005)	0.503*** (0.099)	0.030** (0.015)	-0.000 (0.007)	0.012 (0.009)	0.014 (0.009)	0.034* (0.017)	0.526*** (0.098)
Observations	2,041	2,041	2,041	2,041	2,041	2,041	2,041	2,041

NOTES: The dependent variables are binary for having digital income (from a specified source). The reference age group is 24 to 35 years of age. This sample is restricted to those over 18 years of age who live in the 34 CMAs and 32 CAs found in the LFS. The unemployment variable represents the mean unemployment rate in which an individual *i* resides. All individuals living in the same CMA/CA have the same unemployment rate. All regressions are weighted. Standard errors clustered at the sub-regional (CMA/CA) level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8. OLS Regression Results for Females

Explanatory Variables	Total Crowdfunding Income	Total Online Bulletin Income	Total Creative Content Digital Income	Total Peer-to-Peer Accommodation Income	Total Peer-to-Peer Rideshare/ Delivery Income	Total Freelance Digital Income	Total Other Digital Income	Total Digital Income (All Sources)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	-0.0487 (0.0669)	-13.77 (11.84)	-9.172 (10.95)	6.297 (5.196)	-0.058 (0.117)	-2.006 (3.885)	-6.023 (5.132)	-24.78 (19.66)
Female								
Age 18 to 24	-0.495 (0.411)	37.15 (92.06)	-49.91 (44.27)	-2.154* (1.272)	2.509 (3.183)	-61.26 (50.39)	-2.764 (9.141)	-76.93 (110.3)
Age 35 to 44	-0.480 (0.417)	183.9* (94.60)	-49.68 (44.32)	-1.352 (0.847)	-0.699 (0.643)	-45.94 (49.77)	-5.675 (7.770)	80.08 (121.2)
Age 45 to 54	-0.502 (0.419)	-2.284 (21.78)	8.339 (83.95)	1.027 (1.549)	-0.699 (0.643)	-59.53 (50.81)	25.77 (25.14)	-27.87 (104.1)
Age 55 to 64	-0.405 (0.420)	48.63 (52.31)	-50.85 (43.97)	29.75 (30.12)	-0.697 (0.643)	-58.25 (50.63)	-8.441 (7.246)	-40.26 (87.82)
Age 65 and up	-0.504 (0.420)	-63.11*** (22.42)	-51.48 (43.70)	-1.075 (0.814)	-0.691 (0.642)	-61.93 (50.86)	-9.585 (7.617)	-188.4*** (55.12)
Constant	0.772 (0.734)	159.6** (67.58)	102.0 (67.62)	-33.63 (29.12)	1.021 (0.776)	73.11 (66.86)	42.78 (34.55)	345.6*** (128.4)
Observations	2,041	2,041	2,041	2,041	2,041	2,041	2,041	2,041

NOTES: The reference age group is 24 to 35 years of age. This sample is restricted to those over 18 years of age who live in the 34 CMAs and 32 CAs found in the LFS. The unemployment variable represents the mean unemployment rate in which an individual *i* resides. All individuals living in the same CMA/CA have the same unemployment rate. All regressions are weighted. Standard errors clustered at the sub-regional (CMA/CA) level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9. OLS Regression Results for Linear Probability Model for Males Aged 25-54 (marginal effects reported)

Explanatory Variables	Probability of Generating Crowdfunding Income	Probability of Generating Online Bulletin Income	Probability of Generating Creative Content Digital Income	Probability of Generating Peer-to-Peer Accommodation Income	Probability of Generating Peer-to-Peer Rideshare/ Delivery Income	Probability of Generating Freelance Digital Income	Probability of Generating Other Digital Income	Probability of Generating Digital Income (All Sources)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	-0.000 (0.001)	0.004 (0.020)	0.000 (0.003)	0.001 (0.001)	-0.001 (0.002)	-0.002 (0.003)	-0.002 (0.002)	0.002 (0.018)
Age 35 to 44	-0.011 (0.008)	0.025 (0.054)	-0.008 (0.008)	0.010 (0.007)	0.008 (0.010)	-0.001 (0.003)	0.004* (0.002)	0.024 (0.054)
Age 45 to 54	-0.011 (0.008)	-0.007 (0.048)	-0.010 (0.009)	-0.000 (0.000)	-0.001 (0.007)	-0.002 (0.004)	0.011 (0.007)	-0.006 (0.046)
Constant	0.012 (0.010)	0.275** (0.127)	0.010 (0.020)	-0.004 (0.004)	0.0125 (0.013)	0.016 (0.018)	0.009 (0.009)	0.307*** (0.115)
Observations	800	800	800	800	800	800	800	800

NOTES: The dependent variables are binary for having digital income (from a specified source). The reference age group is 24 to 35 years of age. This sample is restricted to males 25 to 54 years of age who live in the 34 CMAs and 32 CAs found in the LFS. The unemployment variable represents the mean unemployment rate in which an individual *i* resides. All individuals living in the same CMA/CA have the same unemployment rate. All regressions are weighted. Standard errors clustered at the sub-regional (CMA/CA) level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 10. OLS Regression Results for Linear Probability Model for Females Aged 25-54 (marginal effects reported)

Explanatory Variables	Probability of Generating Crowdfunding Income	Probability of Generating Online Bulletin Income	Probability of Generating Creative Content Digital Income	Probability of Generating Peer-to-Peer Accommodation Income	Probability of Generating Peer-to-Peer Rideshare/ Delivery Income	Probability of Generating Freelance Digital Income	Probability of Generating Other Digital Income	Probability of Generating Digital Income (All Sources)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	0.000 (0.001)	-0.057** (0.022)	-0.001 (0.004)	0.002 (0.001)	0.001 (0.001)	-0.0004 (0.002)	-0.005 (0.005)	-0.056*** (0.021)
Age 35 to 44	-0.003 (0.002)	0.043 (0.068)	-0.021* (0.012)	-0.007 (0.006)	-0.007 (0.006)	-0.004 (0.007)	-0.005 (0.008)	0.019 (0.0642)
Age 45 to 54	-0.003 (0.002)	-0.134** (0.054)	-0.019 (0.018)	0.002 (0.010)	-0.007 (0.006)	-0.009 (0.008)	-0.009 (0.011)	-0.147*** (0.048)
Constant	0.001 (0.006)	0.646*** 0.646***	0.032 (0.023)	-0.001 (0.006)	0.0015 (0.003)	0.013 (0.010)	0.048 (0.030)	0.670*** (0.132)
Observations	927	927	927	927	927	927	927	927

NOTES: The dependent variables are binary for having digital income (from a specified source). The reference age group is 24 to 35 years of age. This sample is restricted to females 25 to 54 years of age who live in the 34 CMAs and 32 CAs found in the LFS. The unemployment variable represents the mean unemployment rate in which an individual *i* resides. All individuals living in the same CMA/CA have the same unemployment rate. All regressions are weighted. Standard errors clustered at the sub-regional (CMA/CA) level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 11. OLS Regression Results for Males Aged 25-54

Explanatory Variables	Total Crowdfunding Income	Total Online Bulletin Income	Total Creative Content Digital Income	Total Peer-to-Peer Accommodation Income	Total Peer-to-Peer Rideshare/ Delivery Income	Total Freelance Digital Income	Total Other Digital Income	Total Digital Income (All Sources)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	1.989 (2.736)	-24.56 (58.76)	-7.422 (5.840)	7.622 (7.653)	-8.521 (6.682)	-30.34 (26.46)	62.62 (65.56)	1.393 (90.55)
Age 35 to 44	-27.39 (27.88)	-92.99 (299.7)	-1.129 (1.216)	30.10 (25.06)	-12.53 (23.20)	-1.026 (5.598)	6.460 (8.624)	-98.50 (300.2)
Age 45 to 54	-27.71 (28.21)	-293.7 (225.0)	21.78 (21.98)	-0.741 (0.921)	-16.05 (20.49)	108.1 (95.84)	233.8 (245.3)	25.43 (338.6)
Constant	16.45 (19.62)	539.9 (499.5)	42.26 (31.37)	-42.40 (42.44)	69.72 (54.79)	171.2 (144.1)	-348.3 (364.3)	448.8 (609.5)
Observations	800	800	800	800	800	800	800	800

NOTES: The reference age group is 24 to 35 years of age. This sample is restricted to males 25 to 54 years of age who live in the 34 CMAs and 32 CAs found in the LFS. The unemployment variable represents the mean unemployment rate in which an individual *i* resides. All individuals living in the same CMA/CA have the same unemployment rate. All regressions are weighted. Standard errors clustered at the sub-regional (CMA/CA) level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 12. OLS Regression Results for Females Aged 25-54

Explanatory Variables	Total Crowdfunding Income	Total Online Bulletin Income	Total Creative Content Digital Income	Total Peer-to-Peer Accommodation Income	Total Peer-to-Peer Rideshare/ Delivery Income	Total Freelance Digital Income	Total Other Digital Income	Total Digital Income (All Sources)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	-0.0757 (0.133)	-23.09* (12.63)	-18.95 (22.13)	0.697 (0.477)	0.101 (0.104)	-3.944 (7.884)	-12.99 (65.56)	-58.25** (24.94)
Age 35 to 44	-0.477 (0.412)	184.9* (95.28)	-48.67 (44.83)	-0.776 (0.636)	-0.715 (0.646)	-45.74 (49.49)	-4.958 (7.031)	83.52 (122.3)
Age 45 to 54	-0.500 (0.414)	-1.419 (22.26)	9.246 (84.84)	1.547 (1.910)	-0.714 (0.645)	-59.35 (50.59)	26.42 (25.95)	-24.77 (105.0)
Constant	0.919 (1.085)	210.4*** (60.11)	155.3 (120.8)	-3.098 (2.689)	0.152 (0.337)	83.68 (86.12)	80.77 (62.76)	528.1*** (153.2)
Observations	927	927	927	927	927	927	927	927

NOTES:. The reference age group is 24 to 35 years of age. This sample is restricted to females 25 to 54 years of age who live in the 34 CMAs and 32 CAs found in the LFS. The unemployment variable represents the mean unemployment rate in which an individual *i* resides. All individuals living in the same CMA/CA have the same unemployment rate. All regressions are weighted. Standard errors clustered at the sub-regional (CMA/CA) level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.