



The Impact of the Gig-Economy on U.S. Labor Markets: Understanding the Role of Non-Employer Firms using Econometric Models and the Example of Uber

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Abstract

In this work, I provide quantitative responses to the questions of how the size and the growth of the gig-economy can be measured and how labor markets respond to the exposure to online platforms using data on non-employer firms from the U.S. Census Bureau and on the staggered market entry of Uber in different U.S. metropolitan areas. I find that non-employer firms experienced a growth by 60 % between 1999 and 2014 adding almost 9 million non-employer firms to the U.S. economy. I show that non-employer firms are tightly linked to the rise of independent work and are highly effected by the emergence of online platforms. Uber triggers an increase of 20 percentage points in non-employer firms relative to employment in the transportation sector 4 years after entering local labor markets. Furthermore, Uber's market entry is associated with a 0.05 - 0.07 increase in non-employer share in the transportation sector. I demonstrate that the growth of non-employer firms between 2005 and 2014 is correlated with the growth in alternative work arrangements measured at the industry and state level by Katz and Krueger. I find that the rise of non-employer firms is not mechanically driven by differential industry or regional growth and that the number of gig-economy workers are at highest where unemployment is at highest. My results highlight the impact of the gig-economy on labor markets and provide evidence that the use of non-employer firms is relevant for measuring the gig-economy.

Keywords: Gig-Economy, Online Platform Economy, Labor Market, Non-Employer Firms, Uber

1. Introduction

“An approximate answer to the right question is worth a great deal more than a precise answer to the wrong question.” - John W. Tukey

Technology and the emergence of online platforms have changed the way in which people work, enabling a variety of on-demand services and creating new digital task marketplaces. Workers are able to earn income from their time, expertise or effort through platforms such as Uber, TaskRabbit, Handy or Lyft.

These online platforms facilitate matching and direct transactions between customers and labor force bringing birth to a major socio-economic trend falling into a range of activities known as the “gig-economy”. The gig-economy is a technology-influenced evolution of work that has called into question nations' core beliefs about the work place in society and how to best divide responsibility among workers, businesses, and government.¹ Understanding the prevalence

and implications of the gig-economy can help states and governments develop policies and support the communities, the businesses, and the workforce of tomorrow's labor markets. But the questions of how to measure the exact size and growth of the gig-economy have plagued researchers for years.

This work intends to provide quantitative response using information on non-employer firms combined with the case of Uber and state-of-the-art econometric techniques to help address certain shortcomings of administrative data and measure labor activity in the gig-economy. In the following introduction, I picture the origin of my motivation based on previous research, and describe my approach to address the hypotheses I drew up on the current issues related to the gig-economy.

1.1. Motivation and Related Work

A growing number of American workers earn income outside of traditional employee-employer relationships through self-employment and business ownership. According to the

¹Cf. Smith and Page (2016).

U.S. Department of Treasury, 16.8 million individuals reported having earned a profit and paid self-employment tax in 2014, representing a 32 percent increase from 2001.² The almost 17 million self-employed workers represented 12 percent of all tax filers with earnings. A study from [Farrell and Greig \(2016\)](#) shows that the number of individuals using online-labor platforms has increase 54-fold since 2012 reaching a 0.4 % of the U.S. workforce. These individuals derive one third of their income from online platforms, and even more so when their non-platform income drops.³ Why do individuals increasingly use these online platforms? Is this a structural trend? Are platforms increasing total labor supply and lowering unemployment, or simply shifting individuals from traditional jobs to online platform jobs? And how well suited is the existing tax records data to accommodate and measure this evolution, are all still open questions.

There has been much research on the rise of the so called “gig-economy”, a state of work enabled by online platforms and characterized by temporary positions filled by independent contractors on a short-term basis.⁴ However, existing observations provide little evidence of the true significance and manifestation of this alternative work arrangement on labor activity.⁵ Accurate measurement of the gig-economy is important for understanding current labor market trends. These trends have important implications for the income, health insurance coverage, and retirement security of self-employed workers. [Fox \(2014\)](#) argue that existing surveys and administrative data are not well suited to capture new forms of labor, and hence cannot be used to address these questions.

On the one hand, it is hard to clarify the sector and its meaning due to the changing nature of work, worker’s rights and the controversy about legal, fiscal and social aspects of services provided via online platforms.⁶ On the other hand, its size and impact has been difficult to measure due to the complexity of the concept, the relative recent developments and the limited amount of available data on employment of the gig-economy.⁷ Public institutions are not in a position to gather data and the U.S. government stopped surveying “contingent workers” after 2005, which means that no comprehensive database exists on workers in the gig-economy.⁸ [Katz and Krueger \(2016b\)](#) using a new dataset from the Census Bureau argue that all of the net employment growth in the U.S. economy between 2005 and 2015 can be attributed to the rise of independent work.⁹ This has resulted in a debate over the true significance of this new form of work re-

lationship. On one side, some critical claims utilizing aggregate self-employment statistics conclude that evidence of a revolution is hard to find and some proponents, on the other side, working with company data or proprietary information captured size and impact at a national level.¹⁰

It appears however that inconspicuous data made available by the Census Bureau on “non-employer firms“ in combination with self-employed statistics and company data can shed additional light on the gig-economy and how the entry of online platform influences labor markets.

1.2. Objectives and Approach

The objective of this thesis is to understand the origins of the rise of the gig-economy, its impact on labor markets, and the role of non-employer firms. In order to achieve these overarching objectives, this work is pursuing a subset of goals.

After unveiling the nature of the gig-economy and determining its stakeholders, characteristics, and the current implications in labor markets, the first goal is to provide record of the rise of non-employer firms as an integral part of the gig-economy and a clear testimony of their suitability to be considered a proxy for alternative work arrangements. This can be achieved with administrative data on non-employer firms made available by the U.S. Census Bureau, and data on contingent workers captured by the U.S. Bureau of Labor Statistics (BLS) as well as in a recent survey lead by [Katz and Krueger \(2016b\)](#). Comparing the rise of alternative work arrangements with non-employer firms using ordinary least squared methods will help identify the relevance of non-employer firms in the gig-economy.

The second goal of this work is to provide an understanding of the effect of online platforms on non-employer firms and extend findings to a relevant level for labor markets. The aim is not to quantify the precise evolution and growth of independent work inside the gig-economy, but rather deliver evidence of an apparent movement of non-employer firms in online gigging due to the exposure to online platforms. To do so, I use the paradigmatic case of Uber’s geographical expansion in the U.S. at commuting zone level and draw on data published in a company report. Estimating the change in non-employer firms with differences-in-differences techniques will aid understanding the role of non-employer firms and the impact of online labor-platforms by metropolitan area.

The final sub-goal of my thesis builds on the previous parts of my analysis on non-employer firms by measuring labor supply elasticities to changes in the exposure to online platforms. In particular, this is carried out in two stages: first, I investigate how the change in non-employer firms varies in state and industry by decomposing the growth accordingly. And secondly, I consider non-employer-firms and the staggered entry of Uber in different areas in the U.S. to estimate the associated employment response using data from

²Cf. [Jackson et al. \(2017\)](#).

³Cf. [Farrell and Greig \(2016\)](#).

⁴See among others [Hall and Krueger \(2015\)](#); [Katz and Krueger \(2016a\)](#); [Burtch et al. \(2016\)](#); [Gierten and Spiezia \(2016\)](#); [Hathaway and Muro \(2016\)](#); [Harrigan et al. \(2016\)](#); [Codagnone et al. \(2016\)](#); [Chen et al. \(2017\)](#); [Jackson et al. \(2017\)](#).

⁵Cf. [Codagnone et al. \(2016\)](#).

⁶Cf. [Codagnone et al. \(2016\)](#).

⁷Cf. [Hathaway and Muro \(2016\)](#).

⁸The Bureau of Labor Statistics (BLS) has announced to resume the survey of contingent workers to be published in 2017.

⁹Cf. [Katz and Krueger \(2016a\)](#).

¹⁰Cf. [Burtch et al. \(2016\)](#).

the Local Area Unemployment Statistics (LAUS). I perform this analysis for firms in industries that have been particularly impacted by online platforms, such as the taxi and the passenger ground transit industries.

This work also aims at providing evidence of the significance of non-employer firms to assessing further socio-economic issues arising from the evolution work in the gig-economy. It will, in turn, help understand the gig-economy's impact on labor market activity at geographical and industry specific levels. The purpose of these sets of analyses is to reflect on how future studies should be considering non-employer firms to assess how the dynamics in independent work relates with working relationship, contractors' situation, and other aspects of labor markets.

1.3. Indications and Hypotheses

As many studies have been dealing with the question how to measure the gig-economy, this work uses a sparsely tapped and valuable source of data to give an approximate but meaningful answer. Knowing that most non-employer firms are self-employed individuals reporting incomes from an unknown source irrespective of whether or not they hold a job, it appears the suspicion that they could shed light on the rise of the gig-economy. At this point, the research question that needs to be addressed is how to provide evidence that non-employer statistics is a suitable piece of data to compensate the scarcity of information on alternative work arrangements that represent the sole available element on labor supply in the gig-economy.

My first assumption states that non-employer firms can be used as a proxy for alternative work arrangements. In order to verify this assumption, I draw up the following hypothesis followed by the corresponding null hypothesis.

H1: Non-employer firms increase more in states/sectors where the increase is largest in alternative work data from 2015 Katz and Krueger compared to CPS CWS data from 2005.

H0: There is no increase in non-employer firms in states/sectors where alternative work arrangements' increase is the largest.

Before any further research utilizing non-employer statistics is carried out on the impact of the gig-economy, the question that one shall pose is how can be shown that the data is relevant and to what extent is it impacting gig-work. This is why the next essential part of this work is to test the relevance of non-employer firms for the gig-economy by assessing the effect of Uber as a practical example of an online gig-platform, which at the same time shall estimate the magnitude of impact on local labor markets. My assumption is that non-employer firms are a relevant proxy for alternative work arrangements and an integrated part of the gig-economy affected by the emergence of online labor-platforms.

H1: Non-employer firms increase more in metropolitan statistical areas or counties where Uber enters the market.

H0: There is no increase in non-employer firms after Uber's market entry

Having verified the relevance of non-employer firms as a proxy for alternative work arrangements and given evidence of alignment with other research, I would like to take advantage of this data to analyze the impact of the change in non-employer firms on labor market supply in the gig-economy.

My third presumption is that the gig-economy is cannibalizing jobs within same industries or within same states, which I wish to verify by testing the following hypothesis.

H1: The change in non-employer firms from the taxi industry is different from the change in non-employer firms from other industries after Uber comes into the market.

H0: The change in non-employer firms from the taxi industry is comparable to the change in other industries after Uber enters the market.

Finally, I expect the gig-economy to contribute to a decline in unemployment and not to take away jobs from employer firms. This can be investigated with the hypothesis stated below.

H1: The change in non-employer firms varies with the levels and changes in unemployment.

H0: The change in the share of non-employer firms has no effect on the unemployment rate

Testing these sets of hypotheses will help understand the role of non-employer firms as an integrated part of the gig-economy and the impact of online labor-platforms on labor market activity on geographical and industry specific levels.

2. Setting: The Rise of the Gig-Economy and Implications for U.S. Labor Markets

As indicated in the introduction, this thesis' setting addresses the labor implications of the so-called gig-economy also known as the sharing economy, the collaborative economy or the on-demand economy.¹¹ As it is often not clear what these terms refer to and what forms of working activities and entanglements are induced by this fairly new economic phenomenon, the following chapter has the major objective to put all relevant implications of labor activities into perspective of the gig-economy and demarcate the scope of this work.

2.1. The Online Platform Economy or the Gig-Economy?

Online platforms allow people to work and make money through the intermediary of a digital service handling issues such as customer matching and payment resolution. Despite

¹¹Cf. De Stefano (2016); Kessler (2015); Katz and Krueger (2016a).

outward similarities in how these services look and operate, they encompass a wide range of behaviors and characteristics. A young professional who occasionally smoothens his income by renting out his apartment on Airbnb is much different from a blue-collar who works for a ride-hailing service in between other obligations. And each of these examples is in turn vastly different from sites like Addeco that connects businesses with highly skilled freelance workers or eBay that offers an online-market for goods.¹² Ultimately, a clear distinction between online platform economy and gig-economy is necessary. An overview of selected online platforms is tabulated in appendix Table 1.

The online platform economy encompasses all economic activities involving an online intermediary that provides a platform by which independent workers or sellers can sell discrete services or goods to customers and facilitates peer-to-peer transactions.¹³ The literature distinguishes two sub-areas of the online platform economy.¹⁴ The first is characterized by capital platforms, such as eBay or Airbnb, which connect customers with individuals who rent assets or sell goods peer-to-peer. And the second subarea, which is understood as the gig-economy, is marked by labor platforms, such as Uber or TaskRabbit, connecting customers with freelance or contingent workers who perform discrete projects or assignments. This definition of labor platforms is consistent with the definition asserted by Harris and Krueger (2015) and the McKinsey Global Institute (2016), which describes the gig-economy “as an online marketplace for contingent work in which online platforms facilitate the sale of personal tasks”.¹⁵

The gig-economy is understood to include two types of work: “crowdwork” and “on-demand work”.¹⁶ Crowdwork is defined as work executed through the internet, connecting customers and workers, which both can either be organizations or individuals, on a global basis. It is also referred to as online labor markets (OLMs), which allow the remote delivery of electronically transmittable services such as the development of a website, the creation of a logo or various other tasks that can be crowdsourced.¹⁷ In on-demand work, jobs are assigned through a mobile application and are related to more traditional low skilled work activities such as transport, cleaning, or delivery. It is referred to as mobile labor markets (MLMs), where the matching and transaction processes are digital but the delivery of the services is physical and requires direct local interaction. One of the major differences among these two areas of the gig-economy is that crowdwork jobs can be executed anywhere in the world while on-demand work matches online supply and demand that are executed locally.¹⁸ Accordingly, considering these two parts together

in a common analysis can be perilous. Because the study object of this work implicates only local level labor market, the part of the gig-economy related to crowdwork is excluded.

The distinction between the gig-economy and sharing economy is that a gig-economy can encompass work that has nothing to do with digital applications or intermediary platforms, while the sharing economy exists within the virtual world. For example, a worker who holds several part-time jobs – possibly offering driving services through a digital application, working at a coffee shop, and playing in a band – is participating in the gig-economy but not necessarily in the sharing economy.¹⁹ They would be considered as participating in the sharing economy if any of these gigs were facilitated by a digital application provided by an intermediary platform.²⁰

2.2. Worker Classification and Labor Markets in the Gig-Economy

By definition, individuals earning money through online labor-platforms such as Uber are not employees of those companies and are not listed on official forms. The lines between employment classifications in the gig-economy are very blurry. In order to analyze its implications thoroughly, I must first settle on the definitions of gig workers and other types of independent workers.

At the highest level of classification, the Bureau of Labor Statistics (BLS) lumps non-traditional workers under the banner of contingent work which enclose all those who do not expect their current job to last, i.e. those who work on a non-permanent or temporary basis and those who have alternative work arrangements, i.e. those who do not have an implicit or explicit contract for ongoing employment.²¹ Additionally, the BLS includes the following as alternative employment arrangements: workers employed by a temporary help agency, by a contract company, on-call workers, freelancers or independent contractors. An employment arrangement may be defined as both contingent and alternative, but this is not automatically the case because contingency is defined separately from the four alternative work arrangements. Independent contractors are individuals who report they obtain customers on their own to provide a product or service as a contractor, independent consultant or freelancer.²² On-call workers report having certain days or hours in which they are not at work but on standby until called to work. Temporary help agency workers and contract firms workers are paid by help agencies and contract firms.

Other studies use broader definitions, like a 2015 paper published by the U.S. Government Accountability Office that included both self-employed individuals not included in

¹²Cf. Telles (2016).

¹³Cf. Becker & Rajwani (2016).

¹⁴Cf. Harris and Krueger (2015); McKinsey Global Institute (2016).

¹⁵This definition is used by Farrell and Greig (2016).

¹⁶Cf. De Stefano (2016).

¹⁷Cf. Codagnone et al. (2016).

¹⁸For more details on the dissimilarities and other features of the sub-areas of the gig-economy see De Stefano (2016).

¹⁹Cf. Becker & Rajwani (2016).

²⁰Cf. Farrell and Greig (2016).

²¹Cf. Bureau of Labor Statistics (2005).

²²Independent contractors and freelancers are synonyms. While the term independent contractor would be used to designate the tax and employment class of this type of worker, the term freelancing is most common in culture and creative industries.

the BLS surveys and part-time workers. The OECD refers to non-standard work (NSW), which excludes full-time permanent employment and includes self-employed, temporary and part-time workers.²³ Still other studies have included those people who utilize contingent work and freelancing to supplement their income from regular employment. This is a broader definition that indicates both independent and salary work without distinguishing, which job is primary and which is secondary.²⁴

Implicitly, these nontraditional workers are self-employed individuals all of which have existed long time before the rise of online service platforms. An individual is self-employed if the longest job held during the previous year was self-employment; or if the longest job held during the previous year was wage and salary and they report some self-employment income from other work.²⁵ They engage in a wide variety of economic activities, providing contract or consulting labor, earning non-platform-based or gig-economy income. Many earn income from both wages and self-employment work arrangement.²⁶

The BLS' preferred term, contingent worker, aligns well with that definition of the gig-economy. However, it refers to temporary forms of uncontracted employment that have existed long before the emergence of online platforms. To understand how the characteristics and activities of gig-workers have changed over time, I provide a categorization of individuals with earnings from non-standard work arrangements based on the source of earnings, and whether the individual engages on online-platforms. Using these criteria, I can identify selected groups of gig-economy workers with similar characteristics (see equations below).

$$\begin{aligned} \text{Gig Worker} &= \left\{ \begin{array}{c} \text{Temporary Contractors} \\ \vdots \\ \text{Independent Contractors} \end{array} \right\} + \left\{ \begin{array}{c} \text{Uber} \\ \vdots \\ \text{TaskRabbit} \end{array} \right\} \\ &+ \{\text{Local Customers}\} \\ &= \text{Alternative Work Arrangement} = \text{Intermediary Platform} \\ \text{Gig Worker} &= \text{Alternative Work Arrangement} + \text{Intermediary Platform} + \text{Local Customers} \end{aligned}$$

A different category of workers, which have not yet been often contemplated with regards to the gig-economy because they do not report as individual entities, is looming with similar characteristics as alternative workers. The category I refer to comprises non-employer firms. What the government calls businesses whose owners are the only employees are mostly run by one self-employed individual operating unincorporated businesses (known as proprietorships), which may or may not be the owner's principal source of income.²⁷

A non-employer business, as defined by the U.S. Census Bureau, is one that has no paid employees, has annual business receipts of \$1,000 or more (\$1 or more in the construction industries), and is subject to federal income taxes.

There is certainly a grey area between non-employer firms and gig-workers. However, both include alternative work arrangements and the majority of non-employer firms are self-employed individuals as are gig workers if not misclassified in tax reports. With this in mind it can be assumed that there may be some correlation between the two classifications of workers and the gig-economy.

2.3. Measuring the Gig-Economy

Accurate measurement of the magnitude and the growth of the gig-economy is important for understanding current labor market trends. These trends have extensive implications for the income, health insurance coverage, and retirement security of self-employed workers.²⁸ While self-employment offers certain advantages, workers turning away from traditional work arrangements will no longer receive substantial employee benefits, labor protections like overtime pay and minimum wages, training and skills development, and tax benefits that operate through the employee-employer relationship.²⁹ Hence, understanding the implications of the impact of the gig-economy on the changing workforce is an important step not only for workers wealth and benefit but also for administrations towards improving labor and tax policies.

Existing surveys and administrative data are not well suited to capture new forms of labor, and the new nature of work arrangements makes it difficult to monitor.³⁰ The data on the activities of self-employed is collected infrequently and is often incomplete. It is hard to clarify the sector and its meaning due to the changing nature of work, worker's rights and the controversy about legal, social and fiscal aspects of services provided via online platforms.³¹ The gig-economy is fragmented as each individual works on a contract or freelance basis, and thus may use several services, have many clients and work variable hours over time without clear affiliation to a company, a sector, a tax class or social security. It also spans multiple industries. Self-employers not only encompass gig workers but also other forms of self-employed workers. Another insecurity arises from the fact that individuals reporting self-employment income in surveys also file a tax return that report employee wages.³² In addition, some

²⁸ Administrations and public agencies rely on labor market information such as employment-population ratio, multiple jobholding rate, labor market dynamism, real wages and earnings distribution, and productive inputs to improve recommendations on labor policies.

²⁹ These benefits include, though are not limited to, health insurance and retirement coverage, tax compliance and administration, and protections under labor, occupational safety, and discrimination laws.

³⁰ Cf. Fox (2014), Abraham et al. (2016); Codagnone et al. (2016).

³¹ Cf. Codagnone et al. (2016).

³² Abraham et al. (2016) show that a large share of individuals who report being an employee in response to surveys also file a tax return that reports self-employment earnings rather than wages.

²³ Cf. Gierten and Spiezia (2016).

²⁴ For a good review of non-standard and contingent work arrangements see Bernhardt (2014), Jackson et al. (2017), Abraham et al. (2016) and Gierten and Spiezia (2016).

²⁵ Cf. Abraham et al. (2016).

²⁶ Cf. Jackson et al. (2017).

²⁷ <https://www.census.gov/epcd/non-employer/view/define.html>

workers earn income from both wages and self-employment, but do not report their self-employment status in surveys.³³

As online platforms - the digital marketplace-providers of the gig-economy - are private companies, they are not required to disclose employee numbers, or revenue. Public institutions are not in a position to gather data. The Bureau of Labor Statistics (BLS) used to release the Contingent Work Supplement (CWS) to the Current Population Survey (CPS), which provided periodically information on contingent workers and other self-employed contractors including gig employment.³⁴ However, they ceased surveying contingent workers after 2005, which means that no continuous database exists on workers in the gig-economy.³⁵ This has resulted in a race among researchers to find the most accurate measurement of the magnitude and growth of the gig-economy to compensate the poorly or incomplete data provided by households survey and federal statistics. In 2015 Katz and Krueger updated in a similar survey to the RAND American Life Panel (ALP) the data from the CPS CWS with additional information on workers' use of online platforms in the quest for customers.³⁶ This work became a prominent data collecting survey specifically designed to measure alternative work arrangements relevant for the gig-economy.

Gig workers might also show up in federal statistics, in household survey responses on self-employment activity and in administrative data from tax reports to the Internal Revenue Service (IRS) and the Social Security Administration (SSA) such as the 1040 Schedule C (sole proprietorship business), the 1040 Schedule SE (self-employment), and the 1099 MISC (box 7 non-employee compensation).³⁷ However, most of the past research using these sources struggled to prove the adequacy of the data to measure the gig-economy.³⁸ Abraham et al. (2016) show discrepancy between IRS and survey data and attempt to reconcile them. Chen et al. (2017) estimate the value of flexible work from Uber data. Mas and Pallais (2017) estimate the value of flexible work from survey data. Jackson et al. (2017) uses IRS data to show that all of the increase in self-employment is due to sole proprietors who have little or no business-related educations, and who therefor appear to almost exclusively provide labor services.

As mentioned in the introduction just a few studies have considered using non-employer firms for measuring the size of the gig-economy. Hathaway and Muro (2016) show the growth and geographical spread of non-employer firms in

the passenger ground transit and rooming industries.³⁹ In another paper published by The Future of Work Initiative, Holtz-Eakin et al. (2017) used non-employer establishment data to measure the overall growth of the gig-economy workforce. However, the insecurities in measuring the exact size of this labor pool have remained high and no evidence about the adequacy has been provided. This metric is not perfect. One reason is that non-employer firms include any self-employed person with no employees regardless of whether they earned income driving for Uber or mowing their neighbors' lawns and thereby creating a risk of misclassification. Furthermore the metric captures only those individuals who declared that income to the IRS.

2.4. The Rise of Alternative Work in the Gig-Economy

As described in the previous section, the different approaches found in literature to measure the size of the gig-economy are manifold. Some retrieve data on tax reports and other administrative information, other use statistical data captured by household surveys or company owned data, and others carry out their own surveys. While most studies provided estimations of the size of the gig-economy at one point in time, just a few were able to measure the evolution over time. Nevertheless, most of those who did estimate a trend found a considerable rise in self-employment workers or other alternative work arrangements.

The 2015 survey by Katz and Krueger (2016b) shows that the share of workers involved in alternative work arrangements increased from 10.7 % to 15.8 % from 2005 to 2015.⁴⁰ A striking implication of this estimate is that all of the net employment growth in the U.S. economy appears to have occurred in alternative work arrangements. In particular, the findings show that nearly 16 % of all workers are engaged in alternate work arrangements and that those who provide services through online intermediaries only account for 0.5 % of the total workforce. Even though, it appears that the level of individual workers using intermediary platforms to find customers is quite infinitesimal when compared to traditional contingent work, Katz and Krueger noted that the online intermediaries are growing at an impressive rate. They also discovered that alternative work arrangements increased in size in all of the four categories over the ten-year period between 2005 and 2015.⁴¹ Independent contractors, the largest subcategory of alternative work arrangements, grew from 6.9 % to 8.4 %. The percentage of on-call workers increased from 1.7 % to 2.6 %. Workers in temporary-help agencies comprised 1.6 %, up from 0.9 % in 2005. Finally, workers at contract firms accounted for 3.3 %, an increase from a 0.6 % share.

Another study conducted in late 2015 by JP Morgan Chase Institute show that the number of individuals using

³³Cf. Abraham et al. (2016).

³⁴See chapter 3.1.

³⁵Secretary of Labor Tom Perez announced in January 2016 that the Bureau of Labor Statistics (BLS) will resume the survey on contingent workers every two years starting in May 2017 including supplementary questions designed to capture technology-enabled gig work. See Donovan et al. (2016) and <https://blog.dol.gov/2016/01/25/innovation-and-the-contingent-workforce>.

³⁶Katz and Krueger (2016a).

³⁷Cf. Abraham et al. (2016).

³⁸For the following see Cf. Abraham et al. (2016).; Chen et al. (2017); Mas and Pallais (2017); Jackson et al. (2017).

³⁹Cf. Hathaway and Muro (2016).

⁴⁰For the following see Katz and Krueger (2016a).

⁴¹For a more detailed insights into the evolution of alternative work arrangements prior to 2005 see Bureau of Labor Statistics (2005).

online labor-platforms has increase 54-fold since 2012 reaching a 0.4 % of the U.S. workforce (which is in line with Katz and Krueger's 0.5 % of the total workforce).⁴² Interestingly, these individuals derive one third of their income from online platforms, and even more so when their non-platform income drops. Furthermore, the analysis estimated that 1 % actively earn income from some type of online platform in a given month and that 4 % had participated in one of these platforms over a three-year period. The findings also show that although labor platforms are growing more rapidly than capital platforms, the capital platform market is still significantly larger.

More recently, Abraham et al. (2016) has shown that estimates of self-employment from households survey and administrative data differ in both level and trend.⁴³ Data collected from tax reports by the IRS on self-employment are ranging between 12 % and 17 % with an upwards trend compared to a range of 6 % to 8 % and a downward trend with information gathered through household survey such as the Current Population Survey (CPS) and the American Community Survey (ACS). This discrepancy shows the importance for a more specific and adequate measure to understand changing work activities in the gig-economy.

Using non-employer statistics, Hathaway and Muro (2016) discover that over the past 20 years, the number of gig-economy workers measured with non-employer firms has increased by about 27 % more than payroll employees. The change is even more severe in certain industries, like ground transportation, where the number of gig-economy workers increased 44 % more than payroll employees. Hathaway and Muro (2016) found evidence of a change in the numbers, and the potential for a realignment of the role of non-employer firms in the gig-economy.

3. Data and Frameworks: Building Datasets and Frameworks with Non-Employer Statistics

The main analytical goal of the study is to assess the role of non-employer firms in the gig-economy by the mean of quantitative methods. This shall help to better understand the gig-economy's impact on labor markets and measure labor dynamics and other economic issues to change in the exposure to online labor-platforms. As a paradigmatic example of an online-platform, I chose the case of Uber's expansion in the U.S., which presents a quasi-natural treatment for single labor markets. To carry out this research, a comprehensive dataset is needed with historical data on gig-workers on the one hand and on the staggered entry of Uber on the other. This section details the construction of the longitudinal datasets and the econometric frameworks used in the statistical analyses of my thesis.

3.1. Data Sources and Construction of Datasets

Existing surveys and administrative data are not well suited to capture new forms of labor, and hence cannot be used to provide quantitative response.⁴⁴ The Bureau of Labor Statistics (BLS) offered the Contingent Work Supplement (CWS) to the Current Population Survey (CPS), which provided information on independent workers and other self-employed contractors including gig employment in the year 2005. This data was updated in 2015 by Katz and Krueger in a similar survey to the RAND American Life Panel (ALP). Drawing on raw data from multiple sources, I utilized data described in these subchapters in order to estimate and understand the influence of online intermediary-platforms on labor markets. My investigations rely on three types of data sources. First and foremost, administrative data which is extracted from tax reports or other declarations and made available by federal institutions such as the U.S. Census Bureau. Administrative data provides information that can help address certain shortcomings of survey-based measures, which appear to underestimate self-employment activity.⁴⁵ The second type of data source is survey data collected by government agencies such as the Bureau of Labor Statistics (BLS). And the third source stems from corporate statistics, in this case provided by Uber Technologies Inc in a statistical report. A detailed overview of all data sources can be found in appendix Table 2.

None of the raw data sets described above are in a form amenable to statistical analysis, which makes necessary purging, formatting, and recoding of the data before new variables can be defined. The raw data on non-employer firms, employer firms and alternative work arrangements, for instance, is not formatted in a one-to-one table. Indeed, some observations are tabled in form of aggregated data such as the number of established non-employer firms which are arranged on a county level, a state level and a national level in the same column. Furthermore, to be able to merge data from administrative sources and from surveys, I adapted the variables and their associated values to match within all data sets.

Unlike survey data, using administrative data, which does not ask specifically whether respondents are employees or contractors, is particularly challenging as information on individuals is limited and not as targeted. Federal institutions such as the Census Bureau doesn't publish these numbers in very user-friendly form, but I was able to get the raw data, utilizing the numbers in a beneficial manner from some other government surveys, and deliver a remarkably detailed picture of what activities the unincorporated self-employed are involved in.

3.1.1. Non-Employer Statistics

The starting point for my data construction and the key element in my primary analyses is the non-employer statistics which originates from statistical information obtained

⁴²Cf. Farrell and Greig (2016).

⁴³Cf. Abraham et al. (2016).

⁴⁴Cf. Fox (2014); Jackson et al. (2017).

⁴⁵Katz and Krueger (2016a); Abraham et al. (2016).

through business income tax records that the Internal Revenue Service (IRS) provides to the U.S. Census Bureau.⁴⁶ A non-employer firm is what the government refers to businesses whose owners are the only employees. Most are run by one self-employed individual but non-employer firms also comprise independent contractors, on-call workers, temporary help agency workers and workers provided by contract firms.

The non-employer statistics provides the only annual source of comprehensive data on the scope, nature, and activities of U.S. businesses with no paid employees at detailed industrial (NAICS codes) and geographical level (counties), which is the relevant level for labor markets.⁴⁷ The data is captured from 1999-2014 and is made available on the U.S. Census website.⁴⁸ It is worth mentioning that the comparability of the data over time may be affected by changes in industry classifications, methodology, and geographic definitions. However this issue in most part, especially given the scope of my work, is not relevant for the purposes of my research and, thus, was not addressed in the analysis.

The goal of extracting information from this source is to obtain a data set of non-employer firms by state and industry sector in the U.S. from 2005 to 2014 and use it to demonstrate the relevance of non-employer firms as a proxy for alternative work arrangements or independent work during this time span with constrained data availability.

The raw data set encompassing the number of non-employer firms was appended for the years between 1999 and 2014 and recoded in order to obtain a data set with the following variables: number of non-employer firms by state, industry, and year. I then created a state- and industry-specific identifier (state*industry) i.e. the Cartesian product of the variable state and industry, which is an indicator variable grouping state and sector and specifying each industry sector in each state with a single and defined indicator. This indicator variable is crucial to observe and run the analyses at within single industry sectors in each state.

The different industries are characterized with the 4-digit code from North American Industry Classification System (NAICS) and are fully included in the data set. This leaves the freedom of trimming it into a 2-digit code to cluster broader industry sectors or to subtract specific industries such as the taxi and limousine industry when creating new variables and considering Uber-driver specific labor markets. Duplicate industries in manufacturing, and transportation and warehousing looming in the data set were merged together to avoid double counting.

The resulting dataset consists of 5 variables comprising the number and total sales of non-employer firms between 1999 and 2004 and 3264 observations⁴⁹ corresponding to

each consolidated industry in each U.S. state. The information on non-employer establishments is the main subject of my analyses and is crucial for three steps of my research. First and foremost, it will help demonstrate its relevance as a proxy for independent workers and alternative work arrangements which represent the major piece of labor supply in the gig-economy. Secondly, this relevance will be underscored by using non-employer firms to show the impact of Uber's market entry, as an example for an intermediary gig-platform, on single metropolitan labor markets. And lastly, it will serve as a proxy for further investigations on the role of unemployment in the gig-economy and other labor economic questions.

The use of non-employer firms is a helpful proxy for self-employment and alternative work arrangements; however, as most administrative data this information is less useful for identifying the nature of work or the types of activities that people take on in self-employment.⁵⁰

3.1.2. Current Population Survey - Contingent Workers Supplement 2005

Another key source of data relevant for analyzing changes in the labor market due to exposure to online-platforms is the Contingent Workers Supplement (CWS). This is a supplement to the Current Population Survey (CPS) which in turn is a household survey conducted periodically by the Bureau of Labor Statistics.(BLS).⁵¹

The CWS collects data on contingent and alternative employment arrangements and provides information on the type of employment arrangement workers have on their current job and other characteristics of the current job. Contingent workers are persons who do not expect their jobs to last or who reported that their jobs are temporary. They do not have an implicit or explicit contract for ongoing employment. Alternative employment arrangements include persons self-employed as independent contractors, on-call workers, temporary help agency workers, and workers provided by contract firms. The raw data can be downloaded from the BLS website.⁵²

The BLS gets its self-employment aggregate data from a monthly survey of 60,000 American households conducted by the U.S. Census Bureau (which is the same survey that generates the unemployment rate). Respondents are asked, whether they were employed by government, by a private company, a nonprofit organization, or whether they were

tion should be exercised as the observations do not correspond to the number of non-employer firms but rather to the number of industries appended throughout all U.S. counties in which non-employer firms are counted.

⁵⁰Specifically, the wide range of self-employed activities includes consultants, real estate agents, construction workers, housekeeping services.

⁵¹The Current Population Survey is a monthly survey of about 60,000 households conducted by the for the Bureau of Labor Statistics.(BLS) and the primary source of labor force statistics for the population of the United States. It provides a comprehensive body of data on the labor force, employment, unemployment, persons not in the labor force, hours of work, earnings, and other demographic and labor force characteristics.

⁵²<https://catalog.data.gov/dataset/current-population-survey-contingent-worker-supplement>.

⁴⁶When the Census Bureau receives information through administrative records that a business has no paid employees, then the business becomes part of the potential non-employer universe.

⁴⁷Non-employer statistics use 2012 NAICS code.

⁴⁸Census (2016).

⁴⁹From an initial raw data set of 1,737,135 observations. However cau-

self-employed in the previous week.⁵³ In addition to contingent workers, the survey also identified those workers who have alternative work arrangements. An employment arrangement may be defined as both contingent and alternative, but this is not automatically the case because contingency is defined separately from the four alternative work arrangements (1) independent contractors, (2) on-call workers, (3) temporary help agency workers, (4) workers provided by contract firms.

The CWS is a relevant source of data in consideration of the changing nature of work and especially the gig-economy. Unfortunately the BLS has stopped collecting information on contingent and alternative work relationships in February 2005. In the absence of more recent data and in view of the rise of new labor economies the BLS has announced to resume the survey in 2017. Estimating the link between the change in non-employer firms and the rise of alternative work arrangements requires a longitudinal dataset with comparable historical information. This data from the 2005 survey on alternative work arrangements with 63,600 observations, however is cross-sectional and therefore provides only information at one point in time. This is why I built a dataset linking both CPS CWS data with the RPCWS from 2015 described in the next subsection. In order, to obtain matching information with the other sources, I recoded the industry nomenclature from Census code to NAICS code and consolidated the latter at a 2-digit level. I then merged duplicate industries occurring in the raw data to avoid divided and distorted results. In order to separately investigate the different subcategories of alternative work arrangements, I created separate variables from the respondents' responses on the number of self-employed contractor, on-call workers, contractors, and temporary workers filed by state and industry. These were consolidated into a variable yielding alternative work arrangements, which consists of all of the above.

To obtain more meaningful results, I created separate ratios for each single work arrangement mentioned above as a percentage to the total of observations by industry and state. The resulting dataset consists of eight variables reflecting ratios of work arrangements and 240 observations for each consolidated industry and in each U.S. state.

3.1.3. Rand-Princeton Contingent Worker Survey (Katz and Krueger 2015)

To fill the void created by the absence of recent data on contingent and alternative workers, Katz and Krueger have conducted the RAND-Princeton Contingent Worker Survey (RPCWS) in October and November 2015.⁵⁴ The RPCWS is a version of the BLS's CWS with additional inquiries to gather more information on work arrangements including questions on whether individuals worked through an intermediary such as Uber, Avon or TaskRabbit and whether they sold goods or

services.⁵⁵ The sample was collected randomly using a compilation of methods and has been aligned to the CPS through a set of survey weights.⁵⁶ The survey weights account for the fact that self-employed workers were over-represented in the RPCWS compared to the CPS CWS. I made use of this weighted dataset which has been made available for federal institutions and accredited researchers on the ALP website since November 2016.⁵⁷

This survey being a sequel of the CPS CWS, makes it an essential source of data for further research on alternative work arrangements. It provides a second set of data points in the year 2015 which will allow the observation of change in time and a comparison with the change of non-employer firms in the 10 years period between 2005 and 2015. This cross sectional data collected through random sampling in a national survey consists of 2,760 observations of individual workers restricted to those who did any work during the week prior to the survey.

To turn this raw data into valuable and ordered information, I proceeded analogous to the construction of the CPS CWS dataset, i.e. transforming survey data on individual workers into ratios of the different subcategories of work arrangements to total observations by industry and state obtaining 141 observations and 8 variables. Having a set of variables reflecting the same information (the ratios of work arrangements to total employed by industry and state) in 2015 as ten years earlier with the CPS CWS data, I merged both datasets adding up the number of observations to 315. I then, generated the indicator variable "state*industry", grouping state and sector into a single state- and industry identifier, as executed with the non-employer firms data. As a next step, I computed the change in share of alternative workers between 2005 and 2015 by state*industry for each subcategory respectively. With this, I have an identical observation variable and longitudinal data in both the dataset on non-employer firms and the one on alternative workers allowing me to make comparisons in change over time and across industries and states. If I can provide the evidence that the increase in non-employer firms between 2005 and 2015 is strongest in states and industries where it is strongest in alternative work arrangements, I will be able to show that non-employer firms are a good proxy for alternative workers and validate my assumption.

3.1.4. County Business Patterns

Using proportions in science, economics, and business as well as in other disciplines makes results more meaningful

⁵³A copy of the questionnaire is available online and can be downloaded from <https://alpdata.rand.org/index.php?page=data&page=howsurvey&syid=441>

⁵⁶The RPCWS sample is described here: <https://alpdata.rand.org/index.php?page=panelcomposition> and weighting procedures are described at: <https://alpdata.rand.org/index.php?page=weights>. See Katz and Krueger (2016a) for more details on the robustness of the survey.

⁵⁷<https://www.census.gov/data/datasets/2015/econ/cbp/2015-cbp.html>

⁵³Cf. Fox (2014).

⁵⁴Cf. Katz and Krueger (2016a).

as they offer more information than simple numbers and put the given information into perspective. In order to interpret results in a relative context but also to weight disproportional data and align it with previous work, it is essential to include further information on employer firms.

The County Business Patterns (CBP) is an annual series that provides subnational economic data by industry including the number of establishments with paid employees. The data items are extracted from the Business Register (BR), a database of all known single and multi-establishment employer companies maintained and updated by the U.S. Census Bureau. CBP covers more than 6 million single-unit establishments and 1.8 million multi-unit establishments.

Employer firms provided with the CBP needs to be included to balance out disproportions in non-employer firms and alternative work arrangements and to adjust the change for other trends in the labor market. It also allows to carry out regressions with ratios and relative numbers of employment characteristics and provide comparable results. In terms of dataset construction, I firstly appended the raw data encompassing the number of non-employer firms for each year between 1999 and 2014 and kept industry information on a 2-digit NAICS code level to maintain an adequate degree of clarity. Some industry values appearing twice were merged to avoid duplicates; NAICS code 31, 32, and 33 were merged as "manufacturing", 44 and 45 merged to "retail trade", and 48 and 49 to "Transportation and Warehousing". To focus on the relevant sectors for the gig-economy and put aside industries such as agriculture, mining, utilities, and construction which are not relevant or not element of the contingent workers survey, I also consolidated the industries "manufacturing = 1", "retail and wholesale trade = 2" and "Services"⁵⁸ = 3". As a result, I obtain a dataset of all U.S. establishments with paid employees by state, industry and year which enables me to generate new variables and apply weights on the regression estimates.

3.1.5. Uber Statistics Report

As a key part of my analysis, I use the case of Uber's expansion in the U.S. to test if and to what extent non-employer firms are relevant in the gig-economy and to estimate the impact of online platforms on labor markets. Founded in 2009, Uber is a mobile smartphone application that allows consumers to submit a trip request, which is then routed to Uber drivers who use their own cars to fulfill the request. In this work I refer to UberX, which is Uber's low-cost ride-hailing option and the first service offered when expanding into new areas. Estimating the link between the exposure of

non-employer firms to online-platforms, requires a longitudinal dataset with information on the time and place of Uber's market entry. Data on Uber's expansion by city are retrieved directly from a statistics report made public in 2016.⁵⁹ The data collected from the corporate owned website uber.com shows the launching of Uber's activity by city over the years since the first launch of their service UberX in San Francisco in 2010. The staggered entry of UberX in different Metropolitan Statistical Areas (MSAs) in the U.S. offers a quasi-natural experiment to instrument for local labor market's exposure to online platform, and study their impact not only on employment across sectors as in this work but other economic patterns.

Uber's data is not entirely precise, i.e. it is not clear what counties or geographical areas are included in the designated cities. Non-employer firms are not necessarily located in the city where they operate, i.e. an Uber driver can provide his or her service in the designated city but live in the nearby county.

In order to investigate the overall impact of Uber's entry and rule out the difference in years it is necessary to singularize the time of market entry into a unified scale variable. For the purpose of unifying Uber's market entry across the country, I converted the data relative to the year of launch in each respective city. This converted scale characterizes the year of entry with "year 0", the years prior to entry with the respective difference i.e. "year -1", "year -2", and the years following Uber's market entry with "year 1", "year 2".

The variables post and pre are dichotomous treatment variables indicating each relative year of Uber's entry in a given county. Consistent with prior studies examining the effect of Uber's entry on a local area, I focus on UberX, as opposed to other service, due to the significantly larger network of drivers.⁶⁰ As a next step, I generated a binary variable specifying whether Uber was present in a city (valued as "1") or not (valued as "0") to distinguish market places with Uber treatment from those without. I then associated the city with the county codes of the according metropolitan area which reflects adequately the commuting zone level of labor markets. This poses challenges in two cities, where the metropolitan area is not congruent with the county area from the administrative datasets.⁶¹ The revised dataset containing Uber's year of entry by metropolitan area with the according counties was merged with non-employer firms and employer firms (CBP) data. For the purpose of matching employer firms and non-employer firms operating within the same industry as Uber-drivers, I created a respective variable subtracting all firms that are not assigned to the industry of "Taxi and Limousine Service" classified with the NAICS code

⁵⁸The pool "services" comprises all of the following trades which are identified with a specific NAICS code "Transportation and Warehousing", "Information", "Finance and Insurance", "Real Estate and Rental and Leasing", "Professional Scientific, and Technical Services", "Management of Companies and Enterprises", "Admin, Support, Waste Management, and Remediation Services", "Educational Services", "Health Care and Social Assistance", "Arts, Entertainment, and Recreation", "Accommodation and Food Services", "Other Services and Public Administration".

⁵⁹Cf. Uber (2016); Burtch et al. (2016).

⁶⁰Cf. Burtch et al. (2016); Greenwood and Wattal (2017).

⁶¹While some cities illustrated in the data are distinctively distinguishable, others like Twin Cities and Rockies are not. Twin Cities is referring to the metropolitan area built around the cities of Minneapolis and Saint Paul. The designation "Rockies, CO" couldn't be associated to any county and was left out of the data.

"4853" and "Other Transit and Ground Passenger Transportation" classified with the NAICS code "4859". These two industry descriptions are assumed to be the most relevant for ride-hailing work enabled by Uber. Once having created this set of variables with firms and independent workers within the latter industries I refer to as the taxi or the Uber industry, I generated three new ratio variables; the first being the share of taxi-non-employer firms to all taxi employees, the second variable describes the taxi-non-employer firms as a share of all employees, and the last one indicates the share of non-employer firms to all firms. Similarly to the above mentioned unification of the differences in years, created a lagged variable of each of these ratios and a lagged logarithmic variable for the number of all employees which is supposed to respond to large difference in values in comparison to the other variables. For additional investigations, I created a pre entry and post entry variable aggregating all values before and after Uber's treatment of the economy. The dataset now consists of variables with values for the 3 years prior to Uber's market entry and the 4 years post market entry.

The final analysis dataset for the investigation on Uber's impact on non-employer firms contains 42.095 observations for each point in time between the years 2002 and 2014 and throughout states and counties with 14 variables on the number of employer and non-employer firms inside the taxi and ground passenger industry respectively. With this, I can carry out the analysis on the role of non-employer firms in the gig-economy and the impact of gig platforms on labor markets.

3.1.6. Local Area Unemployment Statistics

An important concern that stems from the rise of the gig-economy is whether online platforms have had a positive impact on unemployment. In order to investigate that question, I utilize unemployment data from federal statistics. The Local Area Unemployment Statistics (LAUS) program provides annual average estimates of labor force, employment, unemployment, and the unemployment rate for about 7,500 subnational areas. The concepts and definitions used by the LAUS program are the same as those used in the Current Population Survey (CPS). The areas include Census regions such as states, metropolitan areas, combined areas, small labor market areas, and counties.⁶²

These estimates are key indicators of local economic conditions and are used by various federal programs to help determine the distribution of funds to be allocated to each eligible area. In the context of my work, I will use the data to investigate the change in unemployment associated with the rise of non-employer firms to understand the impact of online gig-platforms on labor force. The raw data is composed of three main variables: the number of employed individuals, unemployed individuals and the labor force by FIPS code and year. Based on these variables, I computed the unemployment rate. Unfortunately, the data doesn't contain infor-

mation on unemployment across different industries which limits the possibilities of investigations.

3.2. Analysis Data, Specifications and Variable Definitions

The outcome of the data construction described in the previous chapter is a set of six separate panel data that can be merged into several constellations depending on the intended research application.⁶³ Based on these constructed sets, I created four new analysis datasets, each of them with a precise sequential purpose within my research approach. A summary of the final analysis datasets and their containing variables, which are created with data management techniques, is tabled in appendix Table 3.

The first set of panel data contains information on non-employer firms, alternative work arrangements from CPS CWS and RPCWS, and on employer firms sorted by state, industry, and years for 2005 and 2015. It aims at testing my first hypotheses - that non-employer firms increase more in states and industries where the increase is highest in alternative work - by estimating the correlation between non-employer firms and alternative work arrangements, and thereby filling the void of data shortage on self-employed and alternative workers between 2005 and 2015.

The second set of panel data comprises the staggered entry of Uber and the number of non-employer firms and employer firms sorted by county, industry, and year for the period between 2006 and 2014. This time frame not only allows investigating the effect of Uber in the years after its market entry in 2010 but also the prevailing conditions in the labor market 4 years prior to its launch. Showing the association between the rise of non-employer firms and Uber's expansion will help test my second hypothesis that non-employer firms are a relevant proxy for alternative work in the gig-economy and help estimate the magnitude of the gig-economy's impact on labor markets.

The objective of the third set of panel data is to understand the growth decomposition of non-employer firms, which can explain the dependence of the rise in non-employer firms on industry and labor supply dynamics. It is formed by merging non-employer firms and employer firms around a cluster of 23 industries sorted by state and years. With this dataset I aim to show that the gig-economy is cannibalizing jobs within same industries and within same states causing little to no spillover.

My last analysis dataset consists of a set of variables on unemployment, employer and non-employer firms, as well as time variables on Uber's local market entry sorted by county and year. The main purpose of this longitudinal dataset is to test my assumption that the rise of non-employer firms and thereby the gig-economy is contributing to a decline in unemployment and not taking away jobs from employer firms.

⁶²LAUS data can be downloaded online: <https://www.bls.gov/lau/data.htm>.

⁶³Panel data (also known as longitudinal or cross-sectional time-series data) is a dataset in which the behavior of entities are observed across time. Panel data allows to control for variables you cannot observe or measure like variables that change over time but not across entities. This is, it accounts for individual heterogeneity.

It also aims to assess the impact of the gig-economy on unemployment or vice-versa.

In all of the above datasets, I generated different types of variables such as observation variables, indicator variables, control variables, and dummy variables that are essential in the estimations described hereafter. For the purpose of putting non-employer firms in perspective to the entirety of employees, I created the variable non-employer share (NonempShare) which is defined as the ratio of the total number of non-employer firms to the total employment (sum of non-employer firms and employees) by each state and industry in a given year (in short: non-employer firms as a percent of all employees).

$$\text{NonempShare} = \frac{\text{Nonempfirms}}{\text{Nonempfirms} + \text{Employees}}$$

Considering this ratio enables the observation variable to be adjusted to externalities and global fluctuations in the labor market and makes non-employer share the key variable of my analysis.

I then created the variable state*industry i.e. the Cartesian product of the variable state and industry, which is an indicator variable grouping state and sector and specifying each industry sector in each state with a single and defined indicator. This indicator variable is crucial to observe and run the analyses within single industry sectors in each state. The share of alternative work arrangements computed with CPS and RPCWS data determines the ratio of alternative work arrangements to total employers. The share of non-employer firms is now computed as the number of establishments with no employees to the sum of non-employer firms and employer firms from the CBP data by state*industry from the Census data. The change of both ratios can now be determined by means of a lagged variable. The difference in the 10-year lagged variable and the corresponding ratio provides the change in share of non-employer firms.

In order to itemize my analysis, I also created different variants and different subcategories of non-employer share such as the share in alternative work arrangements, in self-employed contractors, in on-call workers, and in temporary agency workers. The breakdown of alternative work arrangements into its different subgroups for a separate estimation aims to answer the question which subgroup has the greater effect on the dependent variable.

The variables have been standardized so that the variances of dependent and independent variables are equal to 1. Therefore, standardized coefficients refer to how many standard deviations a dependent variable will change, per standard deviation increase in the predictor variable. For univariate regression, the absolute value of the standardized coefficient equals the correlation coefficient. Standardization of the coefficient is usually done to answer the question which of the independent variables has a greater effect on the dependent variable.⁶⁴

3.3. Econometric Frameworks

Each step of the analysis uses state-of-the-art econometric frameworks to test the hypotheses on the relevance of non-employer statistics for independent work in the gig-economy. My focus in the first step is on showing the correlation between non-employer statistics and alternative work arrangements (and self-employed contractors) which should indicate the suitability of the number of non-employer firms as a proxy for the extent of independent work. The second part of the analysis aims to underscore that hypothesis and, with a natural experiment, measure the magnitude of impact of Uber's staggered market entry in U.S. metropolitan statistical areas (MSA) on non-employer firms. In a third step, I decompose the change in non-employer firm prevalence between and within state and industry sector to estimate the impact the rise of independent workers on labor dynamics. Furthermore, to identify whether the rise of the gig-economy is driven by the availability of unemployed workers and thus new job allocation, I measure the correlation of unemployment dynamics and non-employer firm prevalence. This analysis addresses the proposition that by lowering barriers to entry in certain sectors, platforms allow people to work when they would otherwise be unemployed, thereby enabling them to smooth income.

3.3.1. Correlation between growth in non-employer firm prevalence and growth in alternative work

Starting with the first set of regressions I aim to measure the correlation between the change in non-employer firm prevalence and the change in alternative work arrangements captured by Katz and Krueger in the 2015 Rand-Princeton Contingent Work Survey (RPCWS) compared to the 2005 CPS. While many approaches in the research literature are applied to address the problem of the shortage of information on gig workers, just a few have considered using the number of non-employer firms to illustrate the labor effects of this new economy. The prior analyses cannot leverage the relevance of this data for filling the information gap between 2005 and 2015. Thus, the first part of my analysis is to show the relevance of non-employer firms as a proxy for independent workers.

Here, I use ordinary least squares (OLS) regression. The first set of regressions employ a panel dataset suitable for multivariate modeling (with and without fixed effects). The variables in question are by their standard deviation by year to equalize the range of data variability.⁶⁵ This is important for multivariate analysis and makes it easier to read and compare results from the regression ensuring that all variables are on the same scale.⁶⁶

In the first model, the dependent variable is the ratio of non-employer firms to total employees, referred as to non-employer share (cf. chapter 3.2). I introduce a weight on the

⁶⁵The standardization applies to the share and the difference in the following three variables: alternative workers, non-employer firms, and self-employed contractors.

⁶⁶Cf. Stock and Watson (2006).

⁶⁴Cf. Allen (1997).

total number of employees to balance for the disproportionate representation of the survey data and to be consistent with the prior research literature. This analytical weight is also applied to make statistics computed from the data more representative of the population since the datasets are built on administrative and survey data and to take into account that the outcome is an aggregated share. To check the robustness of the results I ran all the following regressions both with and without the weights.⁶⁷

The dependent variable is likely to be related to both current and lagged values of the independent variable that might change over time. Thus, using fixed-effects (FE) models on my panel data is appropriate in this setting because it is necessary to control for all time-invariant differences, so the estimated coefficients of the models cannot be biased because of omitted variables.⁶⁸ However, to stay prudent I ran the regressions with and without the fixed effects to verify the magnitude of the effect. Fixed effects are employed to take out heterogeneity among the states and to detrend all variables in time.

The econometric framework assuming correlation between non-employer share and labor force share engaged in alternative work by Katz and Krueger and CPS data is regression estimated as follows:

$$(NonempShare)_{s,j,t} = \beta_0^* + \beta_1^* X_{s,j,t} + \alpha_{s,j} + \gamma_t + \epsilon_{s,j,t} \quad (1)$$

where $(NonempShare)_{j,t}$ is the standardized dependent variable observed in time t (2005 or 2015) at the state*industry level j which in the model groups the variable industry and state into the single dimension state*industry.⁶⁹ This framework is applied to a set of individual regressions that are executed with a variation of fixed effects and weights and with two different variables separately. In one set of regressions the independent variable $X_{j,t}$ is defined as the share of alternative work arrangements $(AltWorkShare)_{j,t}$ and in the second set as the share of self-employed contractors $(SelfEmpShare)_{j,t}$. α_j are unobserved individual fixed effects⁷⁰ that help remove the bias caused by omitted time-invariant variables such as state and state*industry which are applied separately. γ_t represents time-period (yearly) fixed effects which is included in all regressions. β_0^* is the intercept, β_1^* the standardized regression coefficient, and $\epsilon_{j,t}$ is the standard error, which in this case equals the standard deviation of the sampling distribution of the coefficient.⁷¹ The

model uses robust standard errors, also known as White errors, to correct for biases introduced by heteroskedasticity.⁷² For the model-based interpretation, we must assume that $X_{j,t}$ and $\epsilon_{j,t}$ are uncorrelated ($E[X_{j,t}|\epsilon_{j,t}] = 0$) As the independent variable in the above regression equation, I employ, first, the labor force share of alternative workers and, second, the share of self-employed contractors. Self-employed contractors are a large subset of alternative workers. The described framework is a regression that by analogy estimates for the same dependent variable the individual effect of both the share in alternative workers and the share in self-employed contractors as a major subset of alternative workers. The latter measures the effect of the share of workers who claim to be self-employed in the CPS and Katz-Krueger surveys on the prevalence of non-employer firms in a state*industry. This multivariate framework allows variations in the regression models on weights and fixed effects in order to check the robustness of the analysis.

The last set of regressions aim to show that non-employer firms can be used as a proxy for the extent of independent work. They estimate the relationship between the change in non-employer share from 2005 to 2015 and the change in the number of alternative workers, as well as the change in the number of self-employed contractors in that same time period. This framework addresses my first hypothesis, that the number of non-employer firms increases more in states and sectors where the increase is largest in the 2015 Katz and Krueger data compared to the outcome data from the 2005 Contingent Work Supplement. The corresponding linear regression with fixed effects is modelled as follows:

$$(\Delta NonempShare)_{s,t} = \beta_0^* + \beta_1^* X_{s,t} + \alpha_s + \gamma_t + \epsilon_{s,t} \quad (2)$$

where the independent variable $(\Delta NonempShare)_{s,t}$ is the difference in non-employment share between 2005 and 2015, the dependent variable $X_{s,t}$ is, in one case, the difference in alternative workers from 2005 to 2015 $(\Delta AltWorkShare)_{s,t}$ and, in the other case, the difference in self-employed contractors $(\Delta SelfEmpShare)_{s,t}$ in that same timeframe. Both sets of regressions are estimated with and without a fixed effect α_s for state s and with a time fixed effect γ_t .

A subset of additional analyses have been carried out on other categories of alternative work arrangements such as on-call workers, temporary agency workers, and contractors. The underlying frameworks are not further specified since these categories of workers are not relevant for the scope of my work.

⁶⁷Weights on the number of employees are only included in the model whenever fixed effects of state*industry are applied.

⁶⁸When using FE, I assume that something within the industry or state*industry may impact or bias the outcome variables and it is necessary to control for this. FE remove the effect of those time-invariant characteristics so I can assess the net effect of the independent on the outcome variable.

⁶⁹The state*industry variable is a Cartesian product of the variable state and industry which serves as an identification variable giving each industry in each state an specific value.

⁷⁰Characteristics of state and industry that do not change over time.

⁷¹In order to avoid confusion, the standardized regression coefficients are denoted with an asterisk in order to distinguish them from unstandardized coefficients.

⁷²The traditional approach would be to test for the presence of heteroscedasticity using, for example, White's test. If heteroscedasticity is found then one would report robust SE, usually White SE which has become common practice in economics. Robust SE are typically larger than non-robust standard errors, so the practice can be viewed as an effort to be conservative. See <http://www.anderson.ucla.edu/faculty/jason.snyder/the-intuition-of-robust> and Dougherty (2011).

3.3.2. Pre and post effects of Uber's market entry on non-employer share

Aiming to understand the effects that online intermediary platforms have on independent work and test the relevance of non-employer firms for measuring the gig-economy's impact on labor markets, I developed a set of econometric frameworks that uses the example of Uber's staggered market entry in the U.S. These frameworks address the underlying hypothesis that non-employer firm prevalence increases more in counties where Uber comes in.

The primary econometric specification I employ is a multi-site entry differences-in-differences (DID) relative time model. Intuitively, this regression model allows to conduct a quasi-natural experiment using secondary data since the treatment, i.e. the entry of Uber X , is applied in different locations at different times, in plausibly exogenous manner. The strategy behind the DID method amounts to comparing the change in non-employer firms before and after the entry of Uber in counties where Uber is providing services and other counties where not.⁷³

The longitudinal nature of the data allows me to examine the existence of pre-treatment trends in non-employer firms activity. This data structure further enables to include location (county) and time (relative years) fixed effects, which effectively control for static heterogeneity across counties, as well as any unobserved temporal trends (e.g. seasonality) or shocks (e.g. change in regulations). Acknowledging that correlations between independent variables and residuals exists, I clustered counties making the estimate of the standard error more conservative. I employ a relative time model, as opposed to a traditional DID estimation, because it enables to evaluate the parallel trends assumption. The key assumption of the DID estimation is that there is no pre-treatment heterogeneity in the trends of treated and untreated groups. If trends in the dependent variable differ across the two groups, this presents a problem, as it implies that the untreated group cannot serve as a valid control, i.e. reflection of what would have happened in the absence of treatment. Extensively used in literature, this estimation incorporates a second set of time dummies that indicate the chronological distance between an observation period t , and a timing of treatment in county c .⁷⁴ Thus, this approach not only allows to ensure that there is no pretreatment heterogeneity (in trends) between the treated and untreated counties, it also helps determine how long it takes for significant effects to manifest following treatment. The econometric framework measuring the effect of Uber's market entry on non-employer firms is a DID regression estimated as stated below which was run both with

post-treatment control variables and without

$$\begin{aligned}
 Y_{c,t} = & \beta_0 + \beta_1(Post)_{c,t} + \beta_2(Post * 2010NonEmpShare)_{c,t} \\
 & + \beta_3(Post * EmpGrowth0610)_{c,t} \\
 & + \beta_4(Post * NonEmpGrowth0610)_{c,t} \\
 & + \alpha_c + \gamma_t + \epsilon_{c,t}
 \end{aligned} \tag{3}$$

where the dependent variable $Y_{c,t}$ is the share of taxi non-employer firms in all taxi employees in county c and time t ; $(Post)_{c,t}$ is a post-treatment dummy which is equal to "1" if the observation is in a county where Uber is active and "0" if not; and where the post treatment control variables 2010NonEmpShare are the share of non-employer firms in 2010; EmpGrowth0610 the logarithm of the employment growth from 2006 to 2010; and NonEmpGrowth0610 the logarithm of the non-employer firm growth from 2006 to 2010. These treatment dummy variables have the beneficial effect of controlling for the change in employment that is unrelated to Uber's entry in the economic model. α_c is the county fixed effect, γ_t is the time fixed effect, $\epsilon_{c,t}$ is the error term, and β_0 to β_4 are the regression coefficients.

To gain more insight in the way non-employer firms have been affected by Uber in single years before and after their market entry, I developed a second difference-in-differences (DID) regression model. The underlying economic frameworks assuming pre- and post-effects of Uber's market entry is a difference-in-differences regression estimated as follows:

$$\begin{aligned}
 Y_{c,t} = & \beta_0 + \sum_{t=-3}^{t=-1} \beta_{t+4}(Pre)_{c,t} + \sum_{t=0}^{t=4} \beta_{t+4}(Post)_{c,t} \\
 & + \beta_2(Post * 2010NonEmpShare)_{c,t} \\
 & + \beta_3(Post * EmpGrowth0610)_{c,t} \\
 & + \beta_4(Post * NonEmpGrowth0610)_{c,t} \\
 & + \alpha_c + \gamma_t + \epsilon_{c,t}
 \end{aligned} \tag{4}$$

where all variables and subscripts remain the same as in the previous framework except for the treatment dummy which is now divided into a pre-treatment dummy—equal to "1" if the observation is prior to Uber's entry in counties Uber has later entered and to "0" otherwise—and a post-treatment dummy, equal to "1" if the observation is after Uber has entered a county and equal to "0" otherwise. This estimation was carried out both with and without post-treatment effects.

To ensure comparability of the pre- and post-entry effects and investigate more dependent variables, I build two sets of regressions where I add control variables to the regressions in order to adjust the regression for the staggered market entry of Uber and consider effects in the change in number of CBP employees.⁷⁵ These control variables also ensure that the co-

⁷³Cf. Waldiger (2015); Card and Krueger (1994).

⁷⁴Cf. Autor (2003); Bapna et al. (2015); Chan and Ghose (2014); Greenwood and Watal (2017); Burtch et al. (2016)

⁷⁵Controlling for a variable is the attempt to reduce the effect of confounding variables (correlated to the dependent and the independent variable) by holding these variables constant for calculations made about the effect of the independent variable on the dependent variable.

efficients on the variables of interest do not suffer from omitted variable bias (OVB).⁷⁶ Thus, once conditioned on control variables, the regressing variables and the error term are which uncorrelated which secures unbiased coefficients of regression. This helps ensure the regression coefficient can be interpreted as the best estimate of Uber’s impact.

For this purpose, I ran two separate DID regressions with three different dependent variables, estimating the following equations:

$$\begin{aligned}
 Y_{j,c,t} = & \beta_0 + \beta_1(Post)_{j,c,t} \\
 & + \beta_2(Post * 2010CountyEmp)_{j,c,t} \\
 & + \beta_3(Post * EmpGrowth0610)_{j=1,c,t} \\
 & + \alpha_{j,c} + \gamma_{j,t} + \epsilon_{j,c,t}
 \end{aligned} \tag{5}$$

$$\begin{aligned}
 Y_{j,c,t} = & \beta_0 + \sum_{t=-3}^{t=-1} \beta_{t+4}(Pre)_{j,c,t} + \sum_{t=0}^{t=4} \beta_{t+4}(Post)_{j,c,t} \\
 & + \beta_2(Post * 2010CountyEmp)_{j,c,t} \\
 & + \beta_3(Post * EmpGrowth0610)_{j=1,c,t} \\
 & + \alpha_{j,c} + \gamma_{j,t} + \epsilon_{j,c,t}
 \end{aligned}$$

with $Y_{j,c,t} = \begin{cases} j=1: \text{share of taxi non-empl. firms to all taxi employees} \\ j=2: \text{share of taxi non-employer firms to all firms} \\ j=3: \text{share of non-employer firms to all firms} \end{cases}$ (6)

where the independent variables $(Pre)_{j,c,t}$ and $(Post)_{j,c,t}$ are time dummies with the value of “1” if the observation is before/after Uber’s entry and “0” otherwise, and the post treatment control variables $(Post * 2010CountyEmp)_{j,c,t}$ and $(Post * EmpGrowth0610)_{j,c,t}$ are controlling for the change in employment.⁷⁷

By analogy to the previous frameworks, α_c represents county fixed effects γ_t year fixed effects. The unobserved time-invariant differences between pre and post variables being correlated with the independent variables makes the fixed effects model for county and year a prudent choice. This last set of DID regression models was also performed on a more detailed industry breakdown of the dependent variables distinguishing between shares in the taxi and limousine service industry (NAICS 4853) and shares in the ground transportation service industry (NAICS 4859).

Inserting a proxy for independent work such as non-employer firm prevalence in the regression remains just a

proxy and just one variable. There is still some heterogeneity between treatment and control groups that is captured by the error term and is correlated with my treatment indicator. The question of impact and magnitude can be addressed but exact correlations can’t be estimated since the error is unobservable.

3.3.3. Impact of the rise of non-employer firms on unemployment rate

In the quest to better understand the impact of independent work on labor supply and the drivers of the gig-economy, I decided to take advantage of the constructed dataset on non-employer firms to analyze whether online labor-platforms are helping individuals out of unemployment or cannibalizing jobs from employer firms. The hypothesis is that the rate of unemployment declines with growth in the number of non-employer firms.

The frameworks I developed to shed light on this matter are based on the same methods as for examining the effects of Uber’s market entry on non-employer firm prevalence. Furthermore, I performed a set of OLS regressions to show the causality of the proliferation of non-employer firms with the unemployment rate.

The OLS regression estimating this correlation is described as follows:

$$Y_{c,t} = \beta_0 + \beta_1(NonEmpShare)_{c,t} + \beta_2(Post * EmpGrowth0610)_{c,t} \tag{7}$$

where the dependent variable $Y_{c,t}$ is the unemployment rate, and the independent variable the share of non-employer firms among all firms in the county at year t. The control variables composed of the dummy element Post and a growth part with terms for logarithmic growth in employment, in non-employer firms, and in labor force from 2006 to 2010. As in the previous frameworks they are supposed to correct endogeneity problems by removing unwanted effects correlated with the denominator of the dependent variable.

4. Results: The Role of Non-Employer Firms in the Gig-Economy

In this section, I investigate how data on non-employer firms are related to the gig-economy and how it impacts labor markets. I show that non-employer firms can be used as an adequate proxy for independent work and treat them as such to test their relevance in the case of Uber’s market entry. In the next analyses, I employ a panel differences-in-differences (DID) model approach⁷⁸ to answer the primary

⁷⁶A characteristic of control variables is that the expected value of the error term with all the variables included is the same as it would be with just the control variables. $(E[\epsilon_{i,t} | x_{1,t}, x_{2,t}, \dots] = E[\epsilon_{i,t} | x_{1,t}, \dots])$. Control variables are variables that are related to the dependent variable and their effects need to be removed from the equation in order to correct endogeneity problems and avoid biased regression coefficients. See Dougherty (2011).

⁷⁷Note that the control variable employment growth from 2006 to 2010 is only included in the regression with the share of taxi non-employer firms to all taxi employees as dependent variable (j=1).

⁷⁸Differences-in-differences is a quasi-experimental technique used to understand the effect of a sharp change in the economic environment. It is used in conjunction with natural experiment in which nature does the randomization. In this investigation the model is composed of cross-sectional difference after Uber entry and a time-series difference within the industry and state.

questions about if and to what extent the entry of Uber has impacted independent work, while controlling for differences across time, state and industry. The resulting estimates allow me to evaluate the relative impact on different metropolitan areas across time and industry. After establishing this method and central findings, I examine the growth decomposition of non-employer firms to better understand the drivers of the rise in independent work and connect the results to the prediction of my theoretical approach. Finally, I present an approach to measuring aggregate effect of independent work on unemployment and explore how gig worker characteristics correlate with employment dynamics.

4.1. The Rise of Non-Employer Firms

Non-employer firms have undergone strong growth in the last decade. The U.S. economy added almost 9 million non-employer firms between 1997 and 2014, representing an increase of 60%. By comparison the total U.S. payroll employment increased by 16 million, which is an increase of 12 %. This observation aligns with the rise in self-employment measured by *Katz and Krueger (2016b)* as well as with more current research from *Jackson et al. (2017)* who show that self-employment's increase is essentially due to sole proprietorships providing labor services.⁷⁹

Looking at trends over time, I find that the number of both non-employer firms and employer firms have increased at a similar and nearly steady rate from 1997 until 2007 and as shown in Figure 2 a major shift occurs in 2008. Non-employer firms' considerable growth continues along the trend line whereas the number of employer firms from the BDS experiences a significant drop of almost 7.5% in only 3 years. The same discrepancy can be witnessed when overlaying the number of non-employer's and employer's employees (see appendix Figure 3). However, the latter picks up again after 2010. This major shift, which is essentially related to the financial crisis in 2007, has somehow not affected non-employer firms. With this in mind, the question can be raised whether some job holders have spilled over to self-employment, which has been made easier due to online platforms, and if the recent pick-up has come from entrepreneurial activity.

A plot of employer firms' share in total employment in Figure 1 underpins the legitimacy of these questions. Employment has moved away from employer firms starting in 2001 and reaching an ultimate low in 2011. On the other hand, the share of non-employer firms among total firms has experienced an even stronger opposite effect increasing by 2 percentage points between 2005 and 2010 (see appendix Figure 4). The trend in non-employer share aggregated over all industries and states between 1999 and 2014 shows a steep ascent between 2000 and 2005, raise the share of non-employers in the total workforce from around 12 % to nearly 15 %. This increase may be caused by the appearance of the

first platforms enabling contractors and freelancers to provide services over the internet. The second ascent occurs in 2009 when online labor platforms such as Uber first entered the marketplace. This rise of 1.5 percentage points in only one year brought the share of non-employer firms to 16.5 % where it stabilized until 2014.

4.2. Tight Link between the Rise of Non-Employer Firms and Alternative Work

The considerable increase in non-employer firms on one side and the rise of alternative work arrangements described by *Katz and Krueger* on the other, suggests that both are somehow related. If this is true and if the correlation points in the same direction, it would suggest that non-employer firms are a suitable proxy for the lack of information on alternative work arrangements between 2005 and 2015. They can help measure the gig-economy and the magnitude of its implications.

In fact, my findings show that the increase in the number of non-employer firms is tightly linked to the rise of alternative work arrangements. The OLS regressions demonstrate that a one standard deviation higher share of alternative work arrangements at the state and industry level between 2005 and 2014 is associated with a 0.3 increase in the non-employer share. Nearly 48% of the increase in non-employer share is explained by the change in the share of alternative workers (see appendix Table 4). This finding is highly significant ($p \leq 0.001$) and is sufficient to suggest that non-employer firms are a good proxy for independent workers described by alternative work arrangements.

Looking at self-employed contractors, who represent a large share of the individuals working in the gig-economy and compose a subgroup of alternative workers, we recognize that the correlation is even stronger with a 0.4 standard-deviation-increase in the change of non-employer share for each standard deviation increase in the share of alternative workers. The significance remains equally high ($p \leq 0.001$). The increase in non-employer firms is explained by 51 % of the rise of self-employed contractors. This shows that the change in the share of non-employer firms and the change in the share of self-employed between 2005 and 2015 are highly correlated. According to this, the logical conclusion is that data on non-employer firms are an even better proxy for self-employment than for all alternative work arrangements. Indeed when looking at the correlations between non-employer share and the share of other component groups of alternative work arrangements such as on-call workers, temporary agency workers, and contractors, we observe that the relationships are not significant or even in the opposite direction (see appendix Table 5).

Furthermore, the regression explains that in 2015 for each standard deviation increase in alternative work arrangements share—as well as self-employed share—non-employer share rises by 0.6 standard deviations. This estimation is explained by about 40 % of the data. If however the fixed effects are incorporated in the model, over 91 % of the share

⁷⁹Cf. *Jackson et al. (2017)*.

in non-employer firms is explained by the share of alternative work or self-employed contractors. The correlation is however weaker with a standardized regression coefficient of 0.13 for alternative work arrangement share and 0.15 for self-employed share.

As a consequence of these results, the null hypothesis which assumes no increase in non-employer firms in states and sectors where alternative work arrangements' increase is the largest, can be rejected with a high probability. Thus, the findings are in favor of my initial hypotheses that non-employer firms increase more in states and industries where alternative work arrangements increase the most. And as matter of fact, the percentage of non-employer firms to all employees increase more when self-employment rises. This shows that the number of individuals having reported working as self-employed in the Contingent Work Surveys in 2005 and 2015 is strongly correlated with the number of individuals registered as non-employer firms.

Showing this correlation in the first part of my analysis was therefore essential to provide evidence of the relevance of non-employer firm data to compensate for the shortage of information on independent work, clearing the way for further investigations. As long as more detailed information on independent work is lacking, the results of my analysis suggest that non-employer firms data can be used as a proxy and help measure the size of gig-work activity and furthermore assess the implications on relevant economic issues.

4.3. Effects of Uber's Market Entry on Non-Employer Firms

In the interest of achieving the highest possible degree of statistical significance, it is not without reason that Uber was chosen to demonstrate the relevance of non-employer firms for the gig-economy. Uber made it easier for individuals to work independently and leads the list of online platforms in terms of prevalence and first market entry. Considering the launch of Uber in Metropolitan Statistical Areas (MSAs) as a quasi-natural experiment for local labor markets, we can conclude that non-employer firms are affected by this economic treatment. If this is the case, it would provide evidence that non-employer firms are relevant for measuring the gig-economy and observing implications for labor markets. The constructed dataset obtained from non-employer statistics contains information on the number of non-employer firms at a county level. This offers the opportunity to investigate at a commuting zone level, which is the significant level for labor markets and the gig-economy. The Difference-in-Differences regressions carried out to test whether non-employer firms increase more in counties where Uber comes in shows that Uber entry triggers an increase in the number of non-employer firms relative to employment in the transportation sector. The share of non-employer firms increases when becoming an independent worker is easier. In fact, the entry of Uber in a new metropolitan area is associated with a 7 % to 12 % increase in the share of non-employer firms in the transportation sector (see appendix Table 6). The overall coefficient of determination ($R^2 = 0.712$) of the underlying regression expresses that 71.2 % of the change in the

share of non-employer firms in the transportation sector is explained by the entry of Uber in the respective metropolitan area. Intriguing is the consideration of each year around the launch of Uber's services (see appendix Table 6, column 2). We can recognize that before Uber came into a local market, only little to no statistical relationship could be witnessed; all regression coefficients on year dummies are approximately zero and all are insignificant. After Uber's market entry, however, the correlation and the significance of Uber's entry on non-employer firms got stronger from year to year with an increase of 2 % in non-employer firms share in the first post-entry-year and 21 % increase and a p-value of less than 0.001 in the fourth year after market entry. One possible reason for this steady growth could be the adoption time of potential labors to use this new intermediary platform due to its subordination to network effects. A second reason could also be the entry of similar platforms such as Lyft in the post-years of Uber's market entry which increases the number of options for independent workers. These findings are obtained when computing the change in non-employer share of the transportation sector in yearly increments to the time-to-market of Uber in the respective metropolitan area.⁸⁰

Having taken out the difference to control the change in employment and equalize the observations along their common dimensions (compare column 2 and 4 in Table 6), we realize that the effect of Uber's entry is even stronger with an average of a 6 % increase (compared to 2 %) in non-employer share in the taxi sector one year after Uber's entry rising to a 24.6 % increase (compared to 21 %) four years after the launch and a significance level of $p \leq 0.001$. These results demonstrate clearly that after 2010 when Uber, one of the first intermediary gig-platform in the transportation sector, entered local markets the share of non-employer firms increased significantly over the years. This finding is graphically well illustrated in Figure 8, which shows the regression coefficients on each relative year (relative to Uber's market entry) dummy for non-employer share in the taxi industry. From this graph can be read the percentage change of non-employer share in the taxi industry from one year to another in the 3 year period before and 4 years after Uber entering the labor market. Only four years after the launch of this newcomer disrupting the taxi industry, the graph shows a nearly 20 percentage point-increase compared to the time of market entry and records a steady growth of non-employer firms in that same time period. Splitting the taxi industry into its two components taxi and limousine service (NAICS 4853) and ground transportation service (NAICS 4859) we can observe a difference in the impact of Uber (see appendix Figure 9). While the taxi and limousine service branch is affected negatively, the ground transportation service sector experiences a significant increase. This contrast in the results may be explained by a sum of stacked phenomena. The first being a partial spillover from the taxi branch to ground transportation services, i.e. that Uber has incited taxi drivers to work as

⁸⁰I have only considered the metropolitan areas in which Uber is operative and included in each area the corresponding counties at commuting level.

independent workers for individual preferences leading them to register as non-employer firm in the ground transportation service instead of the taxi and limousine service sector. At this point it must also be pointed out that false or misleading reporting of individuals can occur in both directions which can increase or counteract to this phenomenon. Considering the higher rate of change in ground transportation services (NAICS 4859) compared to taxi service sector, there must also be another source of inflow coming from other industries or labor markets that leads to a higher increase of this sector.

When jumping deeper into the matter and considering the non-employer share of the taxi sector not only among employees in the taxi industry but among all employees, the results are even more distinctive. The level and rate of increase are of course not as high as within the same industry since it is diluted, however the effect is still remarkable. Table 7 shows the results for both dependent variables, taxi non-employer firms as a share of all employees and non-employer firms as a share of all firms. With a rise of nearly fourteen times in the growth rate of taxi non-employer firms' share in all employees from 0.04 % in the year of entry to 0.6 % the fourth year after, my findings show clearly that where Uber has entered, the trend is noticeable even across broad industries. Figure 10 in the appendix illustrates the sharp increase in coefficients in the years after market entry. Considering the same coefficients for the non-employer share, displayed in column 3 and 4 of the same table and plotted in appendix Figure 11, it is clear that the rise of non-employer firm prevalence relative to all firms in the aftermath of Uber's launch is less sharp. However, it is still noticeable and goes beyond the consideration of ride-hailing platforms and encompasses other intermediaries that have popped up in other industries. Looking at the plots of the average non-employer firm ratios by year relative to Uber's entry, we recognize a similar pattern (see appendix Figure 12). More results of this analysis are illustrated in the appendix, which, on account of their secondary importance for the scope of this work, have not necessitated further interpretation. These may, however, be relevant for further research.

With the results presented above, I was able to verify the initial hypothesis that the number of non-employer firms increases more in metropolitan areas where Uber comes in, and consequentially reject the null hypothesis of no increase. Accurate measurement of non-employer firms is shown to be important for understanding the magnitude and the impact of the gig-economy. Many studies have used administrative data for this purpose. Researchers from University of Maryland and the U.S. Census Bureau have used self-employment data to analyze levels and trends of the gig-economy stating that they should expand the analysis with non-employer firms.⁸¹ The only researchers having utilized non-employer firms to try tracking the gig-economy were Hathaway and Muro (2016). Having provided evidence for the relevance of

non-employer firms in measuring the impact of online-labor platform such as Uber, one can now utilize this source of information for investigations on economic issues.

4.4. Growth Decomposition of Non-Employer Firms

So far my findings suggest that the rise of non-employer firms is an adequate proxy for compensating the shortage of information on independent work and relevant for measuring the impact of Uber's market entry as an example for online labor platforms on gig worker's activity. In the light of the conclusion drawn from these findings, it is necessary to scrutinize the decomposition of the change in non-employer share.⁸² The intention is to rule out the influence of driving forces stemming from Other state and industry characteristics. If the change in non-employer share is driven by a specific industry or state with a historically higher sensitivity or disposition to more non-employer firms it could mislead and distort the explanation of the growth in non-employer firms. The one question that needs to be answered to understand the decomposition of growth is the following: is the change in non-employer share due to the expansion of industries or states with historically more non-employer firms? To do so, I decomposed the difference in non-employer share into (1) between-state-sector growth, (2) within-state-sector growth, and (3) a covariance verifying the validity of the analysis. Furthermore, I carried out the analysis at different industry levels characterized by the 2-, 3-, and 4-digit NAICS code to gain more detailed findings. In order to witness interim development during 2000 and 2014, I split the time frame into two periods. The results are illustrated in Table 8.⁸³ The decomposition of the change in non-employer share between and within state-sectors shows that the rise of non-employer firms is not driven by differentials in sector or state growth. This can be seen in the three columns "Total Change", "Between", and "Within" displayed in the table. The "Within" column shows the negligibility of both cross-industry and inter-state spill-overs in independent worker growth, with values around zero. The covariance can be used to verify that the difference in share for the corresponding period equals the sum of the "Between", the "Within", and the "Covariance" columns thus validating the conformity with the total change. These findings helps to understand that the rise of the gig-economy is not driven by a specific industry such as the transportation sector spilling over into other industries or a specific State with favorable conditions for independent workers. On the contrary, the rise of independent workers is not influenced by cross-industry nor inter-state spill-overs.

This analysis measuring labor supply elasticities between states and industries to changes in the exposure to online platforms with the example of Uber, indicates that the rise of non-employer firms is not mechanically driven by differential industry or regional growth. In view of the conclusion drawn from these findings, we can use the constructed

⁸²Share of non-employer firms to total employment.

⁸³A more detailed table with NAICS 3- and 4-digit industry levels is accessible in appendix Table 9.

⁸¹Cf. Abraham et al. (2016).

dataset matching non-employer firms and alternative work arrangements with other administrative data to shed light on the implications arising within the labor market.

4.5. Unemployment and the Impact of Non-Employer Firms

One of the most important domestic issues economists and governments have to deal with when making decisions on labor policies is the level of unemployment. In general, the question is less about the consequences of unemployment but rather about the causes for unemployment and the economic mechanics that maintains a low unemployment rate. Having in mind that employment or work arrangements based on the traditional employee-employer relationship have declined in the last decade (see appendix Figure 14 and Figure 16), and self-employment or independent work measured in both alternative work arrangements and non-employer firms has recorded a significant increase⁸⁴, the result that the emergence of online platforms is reallocating workers in one direction is not surprising. When looking at data on unemployment, we recognize a similar trend as with employment. Unemployment rate has skyrocketed in the years after the financial crisis to a record high of nearly 10% since the beginning of the second millennium and dropped back to 6% after 2010 (see Figure 15). Certainly, this trend is highly correlated with the 2007 financial crisis, but nonetheless the decline in unemployment may also have been affected by the digitization of work. Falling back on the case of Uber and isolating the trend of unemployment rate in metropolitan areas where Uber is operating, we observe the same drop as in the whole U.S. labor market (see Figure 17). This premise raises two fundamental questions underlining the impact of online platforms on labor dynamics: by lowering barriers to entry in certain sectors and offering income opportunities for low skill services, are platforms allowing people to work when they would otherwise be unemployed? By improving the match between supply and demand are platforms increasing total labor supply and lowering unemployment, or simply shifting individuals from traditional jobs to online platform jobs?

Knowing that we can now use non-employer firms to assess socio-economic matters and labor-related impact of the gig-economy, I examined the correlation between the rise of non-employer firms and the evolution of unemployment rate. The findings are illustrated in Table 10 and show that contrary to my initial assumption the unemployment rate is positively correlated to the rise of non-employer firms. In fact, each percentage point change in non-employer share is associated with an 0.08 increase in percentage change in unemployment rate. This well-fitted estimate indicates that about 88% of the increase in unemployment rate is explained by the rise of non-employer firms. However, examining Uber's impact on unemployment rate, shown in Table 11, only a weak correlation with a low significance in year four after market entry can be detected.

The results of estimating a regression are plotted by year in Figure 18, which shows the correlation between the dependent variable unemployment rate and the predicting variable non-employer share for each year between 2006 and 2014. It clearly shows the weak correlation between these two variables preventing me from rejecting the null hypothesis that the change in the share of non-employer firms has no effect on unemployment rate. Thus, there is no evidence that the gig-economy is contributing to a decline in unemployment since the unemployment rate is increasing with the rise in non-employer share. A variety of explanations can be posited for the positive correlation of non-employer firms and unemployment rate. One arguable explanation is that unemployment raises the likelihood that workers transition to independent work as opposed to a traditional employment relationship and therefore the share of non-employer firms increases in counties and industries where unemployment is high. It changes the perspective of the guiding question, which is no longer about the correlation between non-employer share and unemployment rate but rather a causality issue. Is unemployment increasing because of the gig-economy or is the gig-economy prevailing because of the high unemployment rate? This reasoning suggests that non-employer firms are not the cause for a higher unemployment rate. It is more likely that whenever high joblessness prevails, workers with little bargaining power and few options for traditional employment turn to self-employment indicating a weak labor market. This counterintuitive explanation would be in line with a recent paper published by Katz and Krueger built on their previous work on alternative work arrangements.⁸⁵

5. Conclusion

5.1. Summary

For the past several years there has been much research done on the rise and the significance of the so called "gig-economy", work activities enabled by online platforms and characterized by temporary positions filled by independent contractors on a short-term basis. However, existing studies provide little evidence of the magnitude and the manifestation of its impact on labor markets. Public institutions such as the Bureau of Labor Statistics (BLS) have ceased tracking data on alternative work arrangements and other agencies are not well positioned to capture information. Some researchers have tried to fill the void by using tax records information on self-employment, others have worked with company data or even carried out own surveys.⁸⁶ In this work, I provide quantitative responses to the questions of how the size and the growth of the gig-economy can be measured and how labor markets respond to the exposure to online platforms using data on non-employer firms from the U.S.

⁸⁵Cf. Katz and Krueger (2016b).

⁸⁶See among others Katz and Krueger (2016a); Burtch et al. (2016); Gierten and Spiezia (2016); Hathaway and Muro (2016); Abraham et al. (2016); Chen et al. (2017); De Stefano (2016); Jackson et al. (2017).

⁸⁴Cf. Katz and Krueger (2016a); Chapter 2.4 and Chapter 4.1.

Census Bureau and on the staggered market entry of Uber in different U.S. metropolitan areas.

I begin by describing the contextual setting of the research subject and illustrating the scope of work. First, I define the online platform economy as economic activities involving online intermediaries that are marked by four characteristics: (1) they provide a digital market space that connects workers or sellers directly to customers, (2) they allow people to work on a flexible basis,⁸⁷ (3) they pay on a piece-rate basis for a single task or good at a time, and (4) they intermediate or facilitate payment for the good or service. I then distinguish between labor and capital platforms. Labor platforms, such as Uber, connect customers with contingent workers who perform discrete tasks or projects while capital platforms, such as Airbnb, connect customers with individuals who rent assets or sell goods peer-to-peer. Both are very distinct from each other. As independent work activities only occur through the intermediary of labor platforms, I narrow down my definition of the gig-economy to work activities facilitated by online labor-platforms and further distinguish between crowdwork and on-demand work. Both are different in the location where the work can be carried out. While crowdwork can be done remotely or digitally like designing a website, on-demand work can only be carried out at a local level, like a ride-hail service. Finally, I define gig workers as individuals in an alternative work arrangement earning income by providing services to a customer in a local area acquired through the intermediary of an online labor-platform.

After unveiling the difficulties in measuring the size and the change of the gig-economy workforce, I describe the construction of my datasets and the econometric frameworks used in my analyses. I then proceed with documenting the trend in the rise of non-employer firms and discover a strong growth. The U.S. economy increased by 60% adding almost 9 million non-employer firms between 1997 and 2014. By comparison, the total U.S. payroll employment increased by 16 million which represents a growth by 12%. In order to evaluate the role of non-employer firms as part of the gig-economy, I then build the observation variable “non-employer share” defined as the percentage of non-employer firms to all employees, which becomes the key element of my analyses.

In a first stage, I build on previous research by [Katz and Krueger \(2016b\)](#) who provide new survey data on alternative work arrangements to show the relevance of non-employer firms as a proxy for the rise of independent work. By means of ordinary least square estimations, I compare the rise in non-employer firms to the rise of alternative work arrangements and show that non-employer firms increase most where the increase is largest in alternative work data from 2015 Katz and Krueger compared to BLS data from 2005. Indeed, one standard deviation higher change in al-

ternative work arrangements is associated with a 0.3 to 0.4 increase in the change in non-employer share at the industry*state level. This provides evidence that the growth of non-employer firms between 2005 and 2015 is correlated with the growth in alternative work.

In a second stage, I grasp at data on the staggered entry of Uber in local markets and use differences-in-differences techniques to show the significance of non-employer firms in the emergence of online platforms. I find that non-employer firms are tightly linked to the rise of independent work. Uber triggers an increase of 20 ppt in non-employer firms relative to employment in the transportation sector 4 years after entering local labor markets. Uber’s entry is also associated with a 0.05 to 0.07 increase in non-employer share in the transportation sector. This proves that the rise of non-employer firms is tightly linked to the workforce evolution in the gig-economy which increases when becoming independent is easier.

I also explore whether the change in non-employer share is due to the expansion of industries or due states with historically more non-employer firms. For this, I decompose the change in non-employer share into three terms (1) between industry sector or state growth term, (2) within industry sector or state growth term, and (3) a covariance term. I find out that the rise of non-employer firms is not mechanically driven by differential industry or regional growth. This also means that there are no spillovers of non-employer firms from one industry to another or one state to another along the growth of independent work.

Finally, I investigate whether the gig-economy has had a positive impact on employment by improving the match between supply and demand. With the help of administrative data from the Local Area Unemployment Statistics (LAUS), I examined the correlation between the rise of non-employer firms and the evolution of unemployment rate and surprisingly found that the unemployment rate is, albeit only slightly and insignificantly, positively correlated to the rise of non-employer firms. In fact, each percentage point change in non-employer share is associated with a 0.08 percentage point increase in unemployment rate. In the transportation sector, Uber’s market entry indicates that unemployment raises the likelihood that workers transition to independent work as opposed to a traditional employment relationship and therefore the share of non-employer firms increases in counties and industries where unemployment is high. This reasoning suggests that it is more likely that whenever high joblessness prevails, workers with little bargaining power and few options for traditional employment turn to self-employment.

5.2. Inferences

This work’s findings contribute to both the literature on patterns in the gig-economy’s workforce and research issues on labor market evolution. At the same time, it offers a new perspective of the available data that can be considered to investigate trends in independent work and the implications of

⁸⁷Recent industry reports indicate that online platform economy workers vary their hours considerably. In any given week, 65 percent of Uber drivers change the number of hours by more than 25 percent. See [Hall and Krueger \(2015\)](#).

the gig-economy on socio-economic issues. My results highlight the catalyzing effects of online labor-platforms on independent work as integral part of these new work activities. The gig-economy's size does not appear overwhelming, but its growth is remarkably rapid. In recent years non-employer firms, a proxy of independent workers in the gig-economy, have started growing much more quickly than before the advent of much of the current online platform services.

While the gig-economy may create accessible, flexible, and convenient work opportunities for contractors, it may also be operating outside of various economic stabilizers such as labor market regulations, work legislation, tax policies, insurance coverage, and social benefits.⁸⁸ Since most gig-economy workers are considered independent contractors, not employees, they do not qualify for basic protections like overtime pay and minimum wages, or other employment benefits such as mandatory workplace training and social security. This challenges stakeholders and policymakers to prioritize economic stabilizers as they relate to a growing number of non-standard work arrangements. Without data on how online platforms are affecting work activities, policymakers are flying blind into the gig-economy. Understanding the magnitude and implications of the collaborative economy can help develop policy standards and support the workforce of tomorrow's labor markets. With this work, I provide quantitative responses to help understand the gig-economy and bring a new pool of workers to the forefront of the debate that suits the nature of the evolution of labor markets.

Future studies with non-employer firms data have already been announced.⁸⁹ As I was able to show that non-employer firms are a good proxy for independent workers, this thesis now allows the reflection on how future studies should be considering non-employer firms to obtain a better understanding of the occupational change in work behavior and labor markets in the gig-economy. Information captured by household surveys or in administrative data on gig workers is poor and incomplete. Knowing that non-employer statistics can fill the lack of information on independent work, researchers are now given a new source of data to obtain a better picture of the trends in gig workers activities. Thus, this work wipes out one of the major insecurities arising from the gig-economy, which is the inability of measuring its magnitude and growth. Researchers and other interested parties, also have the data availability to gain insights that go beyond the scope of this work. While my analyses is limited to a defined research question and a set of publicly available knowledge, federal institutions and other researchers have their own related research projects for which they can use the datasets created in the course of this thesis.

Non-employer firms are far from being a perfect measure because they are not entirely congruent to workers in the gig-economy. By nature, employment in the gig-economy is impossible to measure using traditional statistics, as there is no specific measure of individuals using online platforms for gig

work. However, non-employer firms are a useful proxy and until governmental institutions design more targeted measures to monitor the growth of gig employment, the Census Bureau's non-employer firms may be the best measure available.

5.3. Outlook

This thesis was carried out at the Finance Faculty of the MIT Sloan School of Management as part of a broader ongoing research project on independent work, reported income, and the effects of the online platform economy on labor markets. One objective of this research was to provide new tabulations that will inform the ability of non-employer firms data to track and detect new patterns. This analysis helps identify and assess how the dynamics in alternative work arrangements relates with working relationship, contractors' situation, and other aspects of labor markets due to the exposure to online platforms. The second objective of the research project, is to understand why individual use these new types of employment. Some possible reasons could be (1) the change in risk management preferences by workers, (2) technology improvements that allow for efficient allocation of human capital, or (3) regulatory arbitrage that allow firms to reduce labor cost.

In order to investigate these explanations the next steps would be to take advantage of the findings on non-employer firms and identify the drivers of the rise in independent work on both the supply and demand side of the labor market. A starting point would be to understand the effect that online platforms have on independent work income. In this context a first hypothesis should be that platforms allow individuals to divide and reshuffle their labor across various employers more efficiently. Individuals might be enticed to do so either to maximize their income or to mitigate labor income risk across various employers. The second explanation could be addressed by hypothesizing that technology allows for a better time allocation, leads to a cut in coordination costs, and lowers barriers to entry in certain sectors. The third explanation should be investigated by testing if the firms providing online platforms are doing so to arbitrage regulation and lower their labor costs. Another question that is worth investigating with non-employer firms data is the preferences of individuals in the gig-economy which could be explained by identifying the correlation with socio-demographic patterns. To quantify the relevance of each of these hypotheses, further longitudinal data can be used such as income reported on the 1099 MISC form and made available by the IRS or employment insurance and minimum wage data obtained from the Bureau of Labor Statistics among others. With this, one can also further examine the aggregate effect of online platforms on resource allocation, labor supply, and entrepreneurial activity.

Labor markets are being disrupted by technological advancements resulting in the polarization of income distribution and job destruction due to automation and other

⁸⁸Cf. Hargrove and Mazerolle (2016).

⁸⁹Cf. Abraham et al. (2016).

trends.⁹⁰ I believe that studying the effect of online platforms on the efficiency of labor markets using real economic experiments is crucial to understand the structural trends affecting our economies and a diligent way to nurture evidence-based decision making for the healthy socio-economic development of our workplace and society. How digital technologies are reforming our work activities will continue to be a key question for policymakers and an exciting motivation for researchers.

⁹⁰Cf. Autor (2015).

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