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FOR A FISTFUL OF DOLLARS - EFFECT OF EXCHANGE RATE SHOCKS ON  
THE LABOR SUPPLY OF ONLINE GIG ECONOMY IN DEVELOPING  
COUNTRIES

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# **For a Fistful of Dollars - Effect of Exchange Rate Shocks on the Labor Supply of Online Gig Economy in Developing Countries**

**Ahmet Taha Demiröz<sup>1</sup>**

## **ABSTRACT**

In this study, the phenomenon of the gig economy (also called the sharing economy, platform economy, or on-demand economy) and its growth over the last 3 years is analyzed through the perspective of developing countries. The focus of this study is the online gig economy in developing countries and the factors affecting people to supply their labor on the online marketplace. Studies between unemployment and online gig economy labor supply have been conducted in the past, however, these studies have concerned online labor in developed countries (mainly the US) and therefore did not account for an important factor for people in the developing world supplying their labor in the online marketplaces: getting paid with stable foreign currencies. Therefore, in this study, using the data provided by Oxford Internet Institute's Online Labour Index, the last 3 year's worker supply data is empirically analyzed with countries that went through an exchange rate shock in the last 3 years. This study aims to shed more light on the factors that affect the workforce in developing countries to supply their labor on the online gig economy, by adding the variable of exchange rates (or rather weak currencies against the dollar), which has been absent from the literature on the gig economy thus far. The results of the study are inconclusive, because of data limitations. Obtaining worker supply data specifically for the research on the effects of exchange rate shocks on the online gig economy may provide healthier results between these two factors and the phenomenon of online outsourcing in general.

**Keywords:** Gig Economy, Exchange Rates, Unemployment, Developing Countries, Emerging Markets, Freelancing

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## **Bir Avuç Dolar İçin – Döviz Kuru Şoklarının Gelişmekte Olan Ülkelerdeki Online Gig Ekonomisindeki İşçi Arzına Etkisi**

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### **ÖZET**

Bu çalışmada, gig ekonomisi fenomeni ve bu fenomenin son üç senedeki büyümesi gelişmekte olan ülkeler perspektifinden tahlil edilmektedir. Gig ekonomisini'nin tamamı kısaca açıklanmıştır, fakat bu çalışmanın odak noktası gelişmekte olan ülkelerdeki çevrimiçi gig ekonomisi olmuştur. Bu ülkelerdeki işçilerin çevrimiçi platformlara sağladıkları işgücü arzını etkileyen faktörler incelenmektedir. Daha önceki çalışmalarda çevrimiçi gig ekonomisindeki işgücü arzı ve işsizliğin etkisi araştırılmıştır, fakat bu çalışmalar gelişmiş ülkelerdeki (çoğunlukla ABD) işgücü üzerine yapılmıştır ve bu sebeple çevrimiçi işler yapan işgücünü etkileyen dövizle para kazanmak gibi önemli bir faktör göz ardı edilmiştir Buna binaen, bu çalışmada Oxford İnternet Enstitüsü'nden alınan Çevrimiçi İşgücü Endeksi verisi kullanılmıştır, bu verilerdeki son 3 yıl için işgücü arzı verileri, son 3 yılda döviz kuru şoku yaşamış ülkeler baz alınarak ampirik tahlil yapılmıştır. Böyle yaparak, gelişmekte olan ülkelerdeki işçilerin çevrimiçi platformlarda işgüçlerini arz etmelerine sebep olan etmenlere ışık tutması, ve bilhassa bugüne kadar literatürde eksik olan döviz kurunun etkisi de tahlil edilmiştir. Çalışmanın sonuçları verideki sınırlamalar nedeniyle yetersiz kalmıştır. Özellikle döviz kuru şoklarının etkisi için çevrimiçi gig ekonomisi platformlarından veri elde edilmesiyle daha sağlıklı sonuçlara ulaşılabileceği düşünülmektedir.

**Anahtar Kelimeler:** Gig Ekonomisi, Online Gig Ekonomisi, Döviz Kurları, İşsizlik, Gelişmekte Olan Ülkeler, Freelance Çalışma.

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## 1. INTRODUCTION

The gig economy has become a popular buzzword in both academic and non-academic circles during the last couple of years. Its popularity was only exacerbated with the onset of the COVID-19 pandemic due to many factors that were in favor of the gig economy. Firstly, *Working from Home* (or "WFH", as it is widely known nowadays) became the norm all around the world. As a reference, as of September 2020, 41.8% of the American workforce worked fully remotely<sup>3</sup>. This created advantageous scenarios where time usually spent commuting to and from work could be more efficiently spent in the online gig economy, or since employers did not have to physically be present in an office they could finish their work earlier and participate in many forms of the gig economy<sup>4</sup>. Secondly, the COVID-related lockdowns created a slow-down for the global economy all around the world, which resulted in job losses in both developing and developed countries. While the full economic impact of the COVID is still being discussed thoroughly and there is no consensus on a net amount, the global job losses due to lockdown measures in 2020 were reported to be as high as 114 million by the International Labor Organization, which is more than 4 times greater than the jobs lost in the global financial crisis of 2009<sup>5</sup>. This idle workforce found itself participating in the gig economy as a matter of temporary respite as they were searching for jobs in the traditional employment market. The difference between the current economic downturn and the previous large recession, the 2009 recession is evident because not all sectors are affected similarly. Not every sector was equally affected by the COVID related lockdowns and in fact, some sectors were affected positively by the lockdowns such as logistics, warehouse and postal, and food delivery workers had a huge amount of increase because of a surge in consumer demand as most consumers

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<sup>3</sup> Adam Ozimek, "Economist Report: Future Workforce," Upwork, December 2020

<sup>4</sup> Daniel Spurk and Caroline Straub, "Flexible Employment Relationships and Careers in Times of the COVID-19 Pandemic," *Journal of Vocational Behavior* 119 (2020)

<sup>5</sup> "Uncertain and Uneven Recovery Expected Following Unprecedented Labour Market Crisis," ILO, January 25, 2021

were just stuck in their home. This also created a strange situation where these jobs, which were not seen as prestigious at all, suddenly became essential during the pandemic.<sup>6</sup> Although it would not be true to claim that COVID-related lockdowns worked in favor of workers in the gig economy, this was not the case for workers who worked rideshare who saw a great decrease in customer demand. It was estimated that Uber's rides were down 94% after federal social-distancing guidelines were announced in the United States<sup>7</sup>. Nevertheless, looking at the overall picture, one can say that all of this created a perfect storm for the growth of the gig economy. Perhaps this is why a Google search of the term "the gig economy" (and its related counterparts) surged in months after February 2020 and the term is now a lot more popular compared to its popularity before 2020. Of course, all of this will become clearer as further studies are made about workforce participation in the gig economy before *and* after (as there are many studies on the size of the gig economy before 2020, however a comprehensive study comparing the sizes of these economies has not been published yet) COVID-19 pandemic started to affect our lives.

This new media and academic attraction to the topic has been leading to some misunderstanding, of course. The term gig economy was used as a catch-all term that encompassed many sectors that spanned from micro-tasking (where simple jobs such as filling out forms are divided to as many people as possible for a profit as little as \$0.01 - Amazon's Mechanical Turk (and the simple jobs in there which are called Human Intelligence Tasks or HITs) platform is a good example for this) to ridesharing with popular apps like Uber and Lyft. In fact, the gig economy has been (perhaps jokingly) called the "Uber Economy" by many news outlets in the past<sup>8</sup>. However, the gig economy means much more than driving for Uber in your free time. As this pandemic has shown many of us, there is a significant percent of the workforce (both

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<sup>6</sup> Spurk & Straub, 2020.

<sup>7</sup> Graham Rapier, "Brutal Chart Shows Just How Much Uber's Core Ride-Hailing Business Has Been Hollowed out by Coronavirus in the US," Business Insider(March 31, 2020)

<sup>8</sup> Derek Thompson, "The Uber Economy," The Atlantic (Atlantic Media Company, January 10, 2017)



in developing and developed countries) who are making their living exclusively with the income they make from gig economy platforms such as Uber, Lyft, TaskRabbit, Upwork, Freelancer.com, even if they are not covered by the benefits (such as sick leave, paid vacation, maternal leave, etc.) from a traditional employer would give them. In addition, as it will become more apparent in further pages, workers in developing and developed countries have completely different experiences in the gig economy. It is not strange to see someone in a managerial position in Brazil taking up driving for Uber in his/her free time as even managerial wages sometimes do not net sufficient disposable income<sup>9</sup>, whereas in the developed world ridesharing is usually done by people in middle-to-lower economic classes or by immigrants in the country<sup>10</sup> (although exceptions always exist of course - such as the huge number of Venezuelan population in Colombia taking up courier jobs for Rappi<sup>11</sup> - a delivery app not dissimilar to Grubhub or DoorDash). Since the gig economy is such an all-encompassing phenomenon that is understood differently depending on whom one might ask, when, and where it is asked, this study has aimed to focus on a specific aspect of the gig economy. We wanted to look at the "online" part of the gig economy, or rather the freelance side of it. Not only that, we aimed to focus on that specific aspect for specific types of countries - developing countries. This specific combination is important, as unlike the physical aspect of the gig economy, the online part of the gig economy (such as freelance work) provides the opportunity of **truly borderless work**: an employer in Canada can hire a data scraper from Bangladesh, a content writer from South Africa and a web designer from Argentina. This creates a scenario for outsourcing, where the employer in Canada will be able to hire a Bangladeshi worker with no problems whatsoever and pay the worker a lot less compared to his/her

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<sup>9</sup> Eduardo Valente, Roberto Patrus, and Rosana Córdova Guimarães, "Sharing Economy: Becoming an Uber Driver in a Developing Country," *Revista De Gestão* 26, no. 2 (July 2019): pp. 143-160

<sup>10</sup> Broughton, Andrea, Rosie Gloster, Rosa Marvell, Martha Green, Jamal Langley, and Alex Martin. "The experiences of individuals in the gig economy." HM Government (2018).

<sup>11</sup> Oliver Griffin, "Unwanted Delivery: Rappi Spawns Black Market in Worker Accounts," Reuters (Thomson Reuters, September 28, 2020)

Canadian counterpart. On the other hand, even though the Canadian employer is paying less the Bangladeshi worker will (in most cases) earn more for his/her work were s/he to offer their services to Bangladeshi employers only. The main idea behind the study will be explained more in-depth after a preliminary definition and explanation is given to the reader about the gig economy itself.

The gig economy is a relatively new phenomenon - although in concept it has been around for quite some time, its rise to prominence only began after the 2009 global financial crisis. This is why, before moving further with the main focus of our study we will it is necessary to go over key concepts such as the definition of the gig economy itself, its history, and its further classification into different branches to give a clearer idea to the readers of this study. Therefore, we will first go over the brief history of the gig economy as a whole, how the online or digital gig economy is positioned in the gig economy as a whole, and differing perspectives of the gig economy from workers' and employers' perspectives both in developing and developed countries. If the reader is already aware of such concepts and has experience of different branches of the gig economy, we advise him/her to skip to the "Literature Review" section of this study.

### **1.1. A Short History of the Gig Economy**

The gig economy, also known as the sharing economy, platform economy, on-demand economy, peer economy, the 1099 economy (referring to the name of the tax form gig workers and freelancers have to fill out in order to declare taxes in the US. In comparison, a regular wage receiving employee would fill out the 1040 form along with the W-2 form given to him/her by the employer<sup>12</sup>) or Uber economy (in this study it will only be referred to as the gig economy for sake of simplicity) is a relatively new concept in the world of work. There is no agreed-upon definition of what constitutes the gig economy, however, the Bureau of Labor Statistics in the US defines the gig economy like so: "*a gig describes a single project or task for which a worker is hired,*

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<sup>12</sup> Katharine Abraham et al., "Measuring the Gig Economy: Current Knowledge and Open Issues," 2018

*often through a digital marketplace, to work on demand.*"<sup>13</sup> The word gig has a different etymologic background altogether. It comes from the early 1900s, and it was slang used by African American jazz musicians to describe a musician's engagement in a single venue<sup>14</sup>. Just like the gig work today, the gigs of jazz musicians were not long-lasting, and they usually did not know the client beforehand. And finally, the client who hired them for the gig was not their employer in any way - they were just hired for the night. The main concept of gig work is not that strange in itself, however, this idea of temporary work arrangements has never been this mainstream until the modern era and that is what makes it significant.

Although the big platforms of today have been existing for quite some time such as Upwork, which was established in 1999, and Amazon's Mturk platform, which was established in 2005, the gig economy's popularity began to pick up steam after the 2009 global financial crisis. Coincidentally, probably the platform that is the most synonymous with the gig economy itself, Uber, was also founded in 2009. The establishment and popularity of Uber are important as it was the main factor that led to the concept of the gig economy being this successful. After all, micro-tasking and freelancing are also a part of the gig economy however it was Uber which carried the idea into the mainstream as ridesharing replaced an old and huge part of the urban life: the traditional taxicabs. This is precisely the reason which whenever a new application is brought up, it is hailed as the "Uber of X" (Uber for valet parking, washing cars, etc. Most of these new start-ups failed).

The main idea of the gig economy is not that new in and of itself, after all, throughout history, people were doing temporary work for various employers all the time. The difference stems from the platforms and the speed of employers and workers being

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<sup>13</sup> Elka Torpey and Andrew Hogan, "Working in a Gig Economy : Career Outlook," U.S. Bureau of Labor Statistics, May 2016

<sup>14</sup> Partridge, Eric; Dalzell, Tom; Victor, Terry (2007). *The concise new Partridge dictionary of slang and unconventional English*. Psychology Press. p. 288.

matched thanks to technology. There are three main actors in the gig economy business - employers, workers, and the platforms themselves. The platforms have made maximum utilization of resources possible by being able to match clients and workers at the correct time, and this was the game-changer aspect of the gig economy. An automobile that would have sat idle during the weekend can be allocated to a driver (this does not have to be the owner sometimes) for ridesharing; a mother who cannot leave her newborn child can do microwork (such as filling out questionnaires made by companies on the subject of motherhood) when the baby falls asleep, a student could deliver food on his/her bicycle whenever he/she wants without being bound to a single employer who would require him/her to work specific days and hours.

Unlike traditional forms of employment, measuring the size of the gig economy proves challenging, as only the platforms themselves have the data for the number of active users and in most cases, they have been reluctant to share that data with researchers<sup>15</sup> (it is a different matter for online gig economy platforms, which will be touched upon later in this study). Since there is no official source for how many workers there are as gig workers, indirect data was used to deduct the number of gig workers. An interesting example is a study made by the JPMorgan Chase Institute, where they looked at the percentage of payments made by gig economy platforms (up to 128 of them) to accounts of JPMorgan Chase to see the size of the gig worker population. Their findings showed that 4.5% of accounts received money from these platforms during last year, and in this 4.5% of accounts, the money received from these platforms amounted to roughly 20% of their total income<sup>16</sup>. A limitation of this was they missed money transfers made by popular payment service providers such as PayPal and Payoneer (which are widely used in these kinds of platforms).

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<sup>15</sup> Agnieszka Piasna, *Counting gigs: How Can We Measure the Scale of Online Platform Work?*, The European Trade Union Institute, September 2020.

<sup>16</sup> Diana Farrell, Fiona Greig, and Amar Hamoudi, *"The Online Platform Economy in 2018"*, JPMorgan Chase Institute, September 2018.

An independent study prepared by McKinsey in 2016 found that approximately 20-30% of the adult workforce (approximately 160 million individuals) in the US and EU-15 belonged in the "Independent Workforce", which meant that they engaged in independent work (work that has a high degree of autonomy, payment by task and a limited-time engagement between worker and client - basically gig work) for a substantial amount of income i.e., not just one time. It was also estimated that of this workforce: 30% made their primary income from independent work and 40% made supplemental income.<sup>17</sup> Another important report comes from Upwork, the biggest online freelancing platform (in terms of gross revenue), which states in its 2019 "Freelancing in America" report that 57 million Americans freelanced at least once during the year<sup>18</sup>. This would make almost 1/3 of the total workforce in the US. Of course, any report on freelancing that comes from Upwork (*the* freelancing platform) should be taken with a grain of salt, as the growth of the freelance workforce affects their revenues directly. As a final example, a Gallup study estimated that 29% of all workers in the US have an alternative work arrangement as their primary job. Apart from that section, it was also found out that 36% of all workers are engaged in some type of gig work to some extent (meaning they are using gig works to supplement their income, rather than relying solely on this type of work). Interestingly, they also found out that the Baby Boomer generation participated in alternative work arrangements at a lot higher rates than of millennial or Generation X population.<sup>19</sup>

No matter what study one looks at, one thing remains certain: The current tools at researchers' disposal are not enough to appropriately comprehend the size of the gig economy, as many factors simply do not fit in the typical workforce census perspective. Firstly, there is a huge number of workers who are doing these type of gig work just to supplement their income and they would not classify themselves as a freelancer first,

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<sup>17</sup> James Manyika et al., "Independent Work: Choice, Necessity, and the Gig Economy" (McKinsey Global Institute, October 10, 2016)

<sup>18</sup> Adam Ozimek, "Freelancing in America: 2019 Survey," Upwork, September 19, 2019

<sup>19</sup> "The Gig Economy and Alternative Work Arrangements" Gallup, August 2018.

to give an example. There have been cases where a worker could be in between jobs and doing gig work as a way of paying the bills, but that person could also classify himself as "unemployed", for example. All of these reasons add up to why it is so difficult to get a definite estimate on the size of the gig economy, and it is one of the reasons why this study is focusing primarily on the online or digital gig economy rather than the physical one. The next section will touch on the differentiation between the physical and digital gig economy to lay the groundwork for further parts of the study.

## **1.2. Classification of the Gig Economy - Digital & Physical Gig Economies**

Although the term gig economy has been used as an umbrella term to refer to all types of temporary work done through popular high-tech intermediaries such as Uber, TaskRabbit, and Upwork, this generalization and haphazard use of the word could be misleading in noticing the subtle differences between different aspects of the gig economy. While technically, the main characteristics of the gig economy is still the same in all classes of gig work (in that the work being done temporary, client-worker relationships are formed for a limited time, etc.), there are a couple of main differences that make these concepts stand out from one another. In fact, it wouldn't be too out of place to claim that it is a tale of two gig economies, not just one. Just like many things in the gig economy, there are no definite agreed-upon definitions and classifications on what these two gig economies are, however, most researchers (such as Richard Heeks, Vili Lehdonvirta, Florian Schmidt, and many more) agree upon the two-type classification of the gig economy. Schmidt<sup>20</sup> provides a detailed taxonomy of these two groups, and they are as follows:

- **Cloud Work (Web-Based Digital Labor)**
  - Freelance Marketplaces,
  - Micro tasking Crowd Work,
  - Contest-based Creative Crowd Work

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<sup>20</sup> Florian Schmidt, "Digital Labour Markets in the Platform Economy: Mapping the Political Challenges of Crowd Work and Gig Work" Friedrich-Ebert-Stiftung Research Institute, 2017.

- **Gig Work (Location-Based Digital Labor)**

- Accommodation (as gig work)
- Transportation and Delivery Services (as gig work)
- Household Services and Personal Services (as gig work)

This type of two-pronged approach to the gig economy is widely used in research, albeit with different names. For the purpose of simplicity and avoiding any unwarranted confusion, in this study these two branches are referred to as the "Physical Gig Economy" (or PGE, for short - for location-based digital labor) and the "Digital Gig Economy" (or DGE, for short) as used by Heeks in his study<sup>21</sup>. The main difference between these branches, the PGE and DGE, as pointed out by Schmidt lies in the fact that one of them is web-based and the other one is location-based. What that means is, PGE work can only be done *in situ*, unlike DGE which does not have this kind of limitation. A student who would like to utilize his/her free time by doing food delivery on a bicycle can only do that in his/her immediate surrounding. S/he cannot deliver food in another city, let alone another country, for example. Alternatively, someone cannot use his/her automobile for rideshare in another country. Since these jobs require workers' physical presence in the place where the job is performed, they are location-dependent. On the other hand, DGE jobs can be perfectly flexible. Yes, some basic conditions should be met before engaging in this type of work, such as a good enough computer or a laptop and a stable internet connection. As long as these conditions are met, the client can work wherever he/she wants. The worker may have to adjust himself to be available during the working hours of the client<sup>22</sup> (if the client is in the US and the worker is in India, for example. The worker may have to work during the night).

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<sup>21</sup> Richard Heeks, "Decent Work and the Digital Gig Economy: A Developing Country Perspective on Employment Impacts and Standards in Online Outsourcing, Crowdwork, Etc" (University of Manchester - Global Development Institute, 2017)

<sup>22</sup> Heeks, 2017

Regardless of these factors, the work would still be location-independent for both parties involved.

Another difference between these gig economies, which is implicit and not a written rule but applies to most cases, is that the gig work in PGE is more labor-intensive and requires less formal training and education. Upon first glance, it may seem like that is not the case, since doing DGE work would only require a stable internet connection and some kind of computer, which are "luxuries" even people in middle-to-lower socioeconomic classes in developing countries enjoy. As opposed to ridesharing, which requires an automobile, or delivery services, which require a motorcycle or bicycle to be fulfilled. A transportation device is not readily available (especially a car) to most people in developing countries and it may seem that PGE has higher barriers to entry. However, upon more detailed inspection it will be apparent that barriers to entry of DGE are substantially higher because it requires something that cannot be bought with money: experience and education. Workers in DGE are constantly racing each other to get the job that an employer posted and getting the job would depend on many factors:

- a. Does the worker have the necessary skills for the task at hand?
- b. What are his/her previous experiences?
- c. What is his/her educational background?
- d. How good is his/her command of English? (or any other foreign language - it will most likely be English)
- e. How is his/her profile looking as opposed to other workers?
- f. How good is his/her rating on the platform?

As one can see, these factors are not things that cannot be obtained with money, as opposed to PGE work where the requirements are a driving license and a car. In a developing country, people with cars and valid driving licenses will be a lot more easily found than workers with an excellent command of the English language. After all, if someone can drive a car they are more or less ready to pick up passengers and drop



them off at their desired destination. On the other hand, even if someone has a stable internet connection, a computer, and even a university degree, they may still be unable to engage in creative writing, which requires a lot more than those minimum requirements listed above. In fact, even if the worker fits the bill perfectly, has previous experience, and has the necessary educational credentials, it may still not be enough to be selected if he/she does not have a good rating on the current platform they are working at. The rating system can trump over any other qualification that comes before it, which is why switching platforms for gig workers is particularly difficult. An interesting idea to overcome this difficulty is creating platform-independent rating passports, however, that idea has not been materialized as of yet.<sup>23</sup> The same rating argument can also be made for PGE work as well, as almost all rideshare and delivery applications let the user rate their drivers or couriers, however, a rider will not cancel their ride (most of the time) when they see that their driver's rating is below average - most riders will not even notice that.

Related to the previous note, a PGE worker will have a lot easier time finding a job as in most types of PGE work they will not be actively searching for a client themselves - the intermediary apps will do it for them. A rideshare driver will not have to spend any effort to find a rider, other than driving in a busy part of the city where ride-requesters are not hard to find. On the other hand, one of the most difficult aspects for a DGE worker is to successfully land his/her first job with a client which will require a lot of effort from the workers' side. In most platforms, DGE works like so: a client can either find a freelancer by themselves through platforms search tools and invite them to work together. Or they could create a job posting available to all freelancers, collect job proposals from them and select which freelancer they want to work with. A new worker in a DGE platform will not be invited to any kind of jobs since they have no experience or rating to be stand out, so they would have to apply for many jobs and

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<sup>23</sup> Jeremias Prassl, *Humans as a Service: The Promise and Perils of Work in the Gig Economy* (Oxford: Oxford University Press, 2019), pp. 112-114.

hope that they would be selected out of many workers - workers who have much higher ratings than them. Therefore, although there are millions of workers registered in these kinds of DGE platforms (estimates can go as high as 70 million registered workers in total), only around 10% of these registered workers are considered active workers<sup>24</sup>. Research done in the sub-Saharan Africa region shows an even grimmer result: Even though there are 123,000 workers registered in freelancing platforms, only 6% of these workers (around 7,500 workers) earned at least 1\$ USD in the platform<sup>25</sup>. Landing that first job is an important step for DGE workers, and it seems that many of these workers are unable to pass that first step. That is why only a small number of workers do all of the jobs in these types of platforms while the majority of workers are not able to earn anything. This contrasts with the PGE, where earnings are directly correlated with time spent working and not much else. Of course, rideshare drivers can start working in strategic times, drive in more lucrative locations, drive faster, and reject or accept passengers strategically to maximize their revenue. However, those factors affect driver earnings to increase on average 7% - not a huge disparity<sup>26</sup>. On the other hand, on DGE work only 10% of workers are being paid while the rest are not earning anything, which is a lot more unequal. If DGE workers are not landing their first job, they will not be getting paid no matter how many hours they put in the platform.

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<sup>24</sup> Heeks, 2017, pp. 5-6

<sup>25</sup> Mohammad Amir Anwar and Mark Graham, "Between a Rock and a Hard Place: Freedom, Flexibility, Precarity and Vulnerability in the Gig Economy in Africa," *Competition & Change* 25, no. 2 (April 1, 2020): pp. 237-258.

<sup>26</sup> Cody Cook et al., "The Gender Earnings Gap in the Gig Economy: Evidence from over a Million Rideshare Drivers," *National Bureau of Economic Research*, June 2018

### **1.3. The Digital Gig Economy**

The differences of the Digital and Physical Gig Economy are explained above; however, DGE has further classification of its own, as stated below:

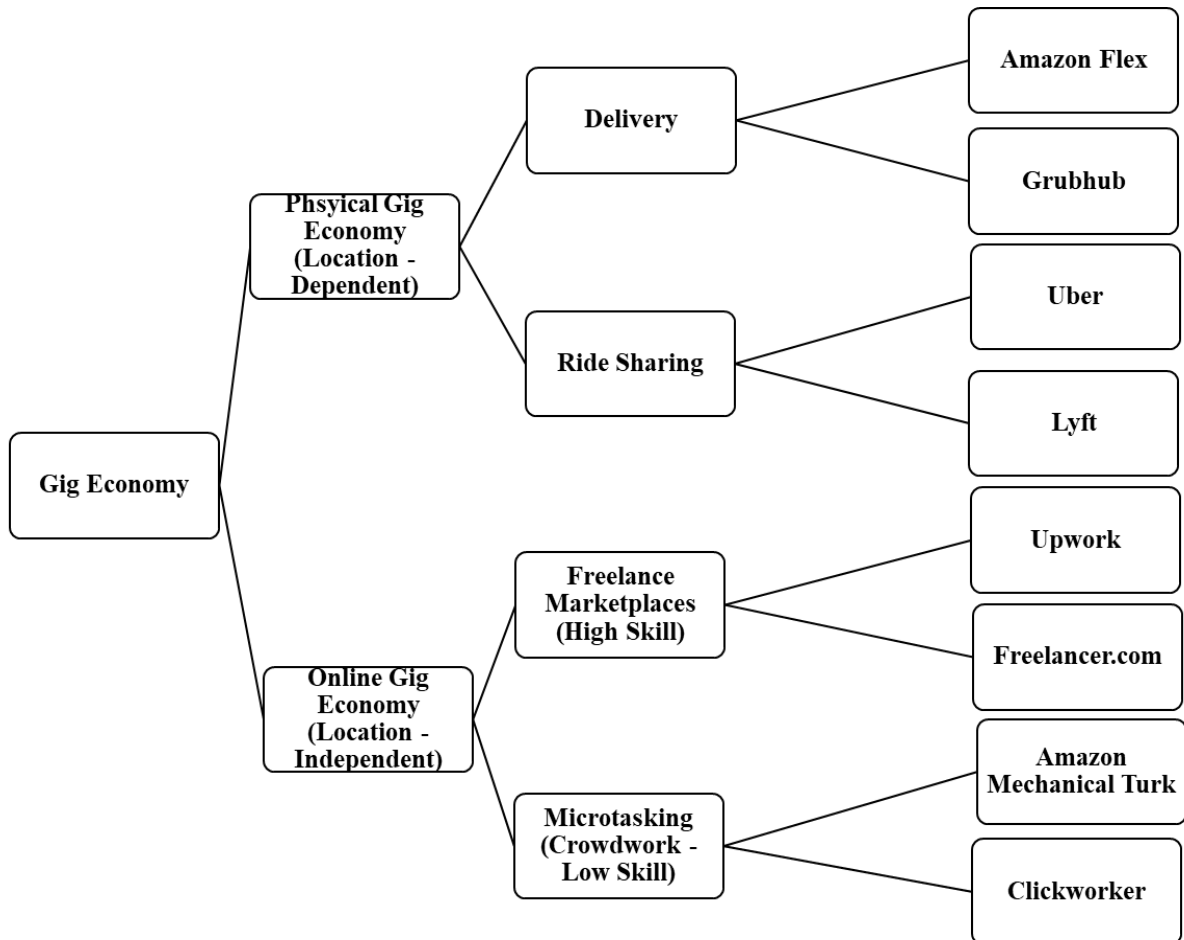
#### **1.3.1. Crowd Work**

Crowd work when tasks are not given to a certain individual, but they are divided even further to create what is called a "microwork". A common example of crowd work is platforms like Amazon Mechanical Turk, Click Worker, or Crowdfunder. The types of work done in crowd work vary a lot, such as data entry, tagging (this could be image tagging - for example, the images are tagged by actual humans in Captcha forms), completing surveys, finding contact details from big data sheets (not to be confused with data scraping) and other small types of work that can be divided to more than one worker. Since the job is divided into multiple workers, a worker usually receives a fraction of a dollar from each completed microtask. The advantage is that these micro-tasks usually take less than 10 minutes to complete, so a worker can finish micro-tasks in a single day. Although the types of jobs vary in crowd work, they all have a common characteristic: the tasks usually do not require any skills to complete. At most, they would require the worker to know a basic level of English to complete. In that sense, they are not dissimilar to many PGE jobs; however, they are not location-dependent.

#### **1.3.2. Online Freelance Work**

In this type of DGE work, a larger task is given to a specific worker who has more qualifications than the typical gig worker to do that job. The most well-known platforms for freelance work are Upwork, Freelancer.com, Fiverr, PeoplePerHour, Guru, Simply Hired, Toptal, and many others. Clients can hire freelancers to do many types of work ranging from (but not limited to) software development, web design, graphic design, data analytics, transcription, translation, creative writing, sales and marketing jobs (such as lead generation and market research), data entry or data scraping, etc. One defining aspect of this type of work is that workers are usually a lot

**Figure 1.1. Classification of the Gig Economy**



*Source: Schmidt, 2017*

more qualified than workers in other branches of the gig economy. Needless to say, that this type of gig work is very difficult to get into for many gig workers, although it is the most flexible type of work compared to other types of gig work. Workers are not only location-independent, but they (at least freelancers that have the most experience and qualifications) also have the opportunity to set their own rates, which is not possible in many other types of gig work. A delivery driver's rate will be automatically determined by the intermediary app, not by the driver himself. The only option for the driver will be to accept the job offered to him or decline it; however, in most types of apps, they do not have the flexibility to ask for a better rate. In most cases, the worker

can negotiate with the client about the deadline as well, making it the perfect case for flexibility.

#### **1.4. Developed & Developing Country Perspectives in the Digital Gig Economy**

As mentioned above, the most notable difference of DGE is that it can be completely location-independent. This creates a unique situation unlike in PGE where clients in the Global North (developed countries) can have access to workers in the Global South (developing countries) without any legal repercussion and they can do so in a single day thanks to intermediary platforms such as Upwork and Freelancer.com. Of the approximately 45 million registered workers in Western-based platforms, 36 million (or 80% of them) are from countries in the Global South, such as India, Pakistan, Bangladesh, and the Philippines<sup>27</sup>. On the other hand, the majority of clients are located in the Global North, with the United States hosting the largest number of clients for freelance work, closely followed by the UK and other Western European countries. The results should be apparent to anyone who is faced with the data: DGE is allowing clients in the Global North to effectively outsource their work to workers in the Global South, who are doing the same work for a fraction of the cost.

This can be done thanks to many factors. First and most importantly, the work done on these platforms can be done without any face-to-face contact of the client and the worker. Since the job does not require the worker to be physically present, it can be delegated digitally to workers in other countries. Secondly, since telecommunication technologies advanced in the last 20 years, even if the job requires clients and workers to talk to one another, it can be done through many applications such as apps that support VoIP communications such as WhatsApp or Telegram, or videoconference tools such as Zoom or Skype. A telemarketer in India can even cold-call potential sales leads in Canada with apps like RingCentral. And finally, all of this has become possible thanks to advances in the Fintech sector, which allows seamless transfer of funds from

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<sup>27</sup> Heeks, 2017. p.5

a client in Canada to a worker in Bangladesh within a single working day or two. With online payment systems providers such as PayPal, Payoneer, Skrill, Stripe, and others, the transaction costs have gone down significantly, making it profitable for workers in the Global South. If those funds were transferred with a traditional SWIFT transfer from a bank in Canada to a bank in Bangladesh, the transfer fees could reach up to 50-60\$ USD which would not make this type of work profitable for the worker in Bangladesh.

Now, this is not to say that all of the freelance work is done so that clients in the Global North could outsource their jobs to developing countries. Of course, there are many workers in developed countries whose primary income stems from freelance work on these platforms. After all, most types of freelance work require a lot of experience, qualifications, and skills. These factors may not be present in a typical gig worker in a developing country. This could explain why workers in the Global North are mainly doing jobs like software development, graphic, and web design which requires a lot of technical know-how. Technical know-how that may not be present in a developing country. This would also explain why less qualified jobs like data entry, virtual assistant, transcription, and so on are not done by workers in the developed countries since they have a lot of competition that is asking for a lot less money in developing countries.<sup>28</sup> As this study moves forward with the valuable Online Labor Index data, the picture will become clearer for all readers.

### **1.5. Advantages & Problems - The Question of Outsourcing**

The advantages of this North to South transfer for the clients' side should be apparent. In a traditional method of employment, a client would have to their worker (no matter how trivial their jobs may be) pay not only a salary that is in line with the standard of a developed country, but the employer should also provide social security premiums for the worker and offer government-guaranteed benefits such as minimum wage, paid

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<sup>28</sup> Otto Kässi and Vili Lehdonvirta, "Online Labour Index: Measuring the Online Gig Economy for Policy and Research," *Technological Forecasting and Social Change* 137 (July 26, 2018): pp. 241-248

leave, sick leave, maternal leave, etc. In addition, in case the employer decided to terminate his/her contract with the worker; the employer would have to provide the worker some amount of compensation as a guarantee that the employer would be financially secure until s/he can find a new job. The scope of these fringe benefits would depend on the local and national laws, and of course, in which country the employer is located. The governments (and trade unions) could also enact several laws to protect local workers' wages against immigrant workers who could easily undercut their wages. They could make it harder for immigrant workers to get work permits, which would dissuade employers from trying to employ them in the first place. The DGE changes this landscape completely. The intermediary platforms can make it seamless for employers to hire low-to-middle income workforce, have them do the job, and dismiss them in a matter of days. Moreover, the best part is, for employers that are, these actions can be made completely legal. Simple data entry and survey filling jobs can be delegated to platforms like MTurk, which would make the process even easier for the client as s/he would not have to search for a freelance worker in the first place. Not only the client will save money and time by not hiring a local worker and deal with their benefits scheme, but they will also save money as most workers in the Global South will do the same job for less money.

On the other hand, the workers in the Global South also find this arrangement beneficial (DGE would not be this popular otherwise). Even though they are working for lower rates than the usual rates offered by workers in developed countries, even these rates are still advantageous compared to earnings they would receive had they worked with a local employer. In fact, it is estimated that a worker in Global South earns one-third or two-thirds of what a worker doing the same job earns in the North. The worker in the developing country still makes a far above average salary in his/her country and earns a lot more (at least relatively) compared to a worker in a developed country. A

worker in a developed country would make around minimum wage, whereas a worker in a developing country would make around 10 times the local minimum wage<sup>29</sup>.

The advantages DGE work provides do not end with relatively higher earnings in a developing country. This kind of work creates great employment opportunities, in countries that have chronic unemployment problems. This could explain why governments in these countries welcome DGE to work with open arms by creating initiatives that are specifically addressed for promoting online gig work. A well-known example of this was the initiative launched by the Nigerian Ministry of Communications Technology named "Microwork for Job Creation - NaijaCloud" in 2013. The aim of this initiative was, reportedly " ... *to reduce unemployment and create wealth through Microwork and Elancing*"<sup>30</sup>. The word "Elancing" comes from Elance, the popular freelance platform that merged with another freelancing platform oDesk in 2013. This merger resulted in Upwork, currently the largest platform that intermediates between freelancers and clients. A government initiative that is actually promoting a platform by using its name specifically (not saying freelancing - but instead *Elancing*) shows the power these platforms have. Another popular initiative was headed by Malaysia, referred to as the "Digital Malaysia Initiative". One of the aims of this program was to create alternative income arrangements with microwork for the bottom 40% of the Malaysian population, and also promoting online freelancing for this group of the population<sup>31</sup>. However, it appears that this initiative was not successful in achieving its goals, as Malaysia is not part of the top 20 countries that supply the most labor to DGE, whereas other Asian countries such as India, Pakistan, and Bangladesh are in the top five. Why this is so is out of this study's scope, although it would make an interesting question for further studies. And finally, another initiative that did not

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<sup>29</sup> Heeks, 2017 pp. 9-10

<sup>30</sup> Mark Graham et al, "Digital Labour and Development: Impacts of Global Digital Labour Platforms and the Gig Economy on Worker Livelihoods," *European Review of Labour and Research* 23, no. 2 (March 16, 2017): pp. 135-162

<sup>31</sup> Graham et al, 2017.



yield a lot of results but resulted in a lot of media attention was the Digital Jobs Africa Initiative. The reason why it generated such attention was because of the fact the initiative was not led by an African government but rather led by the Rockefeller Foundation and the World Bank. The initiative was marketed by the Rockefeller foundation like so: "... offers significant income earning potential for those who can successfully navigate the platforms. For employees, particularly young people, online work provides a low-barrier-to-entry opportunity to earn an income, while building their skills and digital work experience."<sup>32</sup> Whether gig work can achieve these bold claims is a wholly different question, but it is apparent that a significant number of governments saw online gig work as a solution for rampant unemployment in their respective countries. Not only that, but they also saw these as an opportunity to export their workforce's labor to the Global North.

Another advantage (disadvantage for everyone except the workers, of course) of DGE for the workers in the South is that this income would be completely tax-free in most cases as most developing countries do not have the regulatory framework or tools to effectively tax this income made by online workers. The issue of taxes is strictly enforced in the developed world, popular platforms automatically create a "certificate of earnings" report on demand for freelancers so that they could declare their income. This issue is being addressed by some developing countries, albeit slowly. India was the first country to take action in this regard, Indian authorities coordinated with all of the major platforms to implement a 5% withholding tax at the source. These withheld taxes would be sent to the Indian government on a regular basis, based on a law that was passed in October 2020<sup>33</sup>.

Finally, probably the most socially impactful advantage of DGE is that it allows for the discriminated groups in society to become a part of the workforce. Women's

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<sup>32</sup> Anwar & Graham, 2020

<sup>33</sup> "Indian Tax Deducted at Source (TDS) or Withholding Tax," Upwork Customer Service & Support | Upwork Help Center, October 1, 2020

participation in the workforce is a significant problem in India, Pakistan, and Bangladesh because of societal restrictions on women. Online marketplaces do not discriminate against workers based on gender or religious beliefs, and this makes them a perfect haven for underprivileged groups in society to work and earn money.

Of course, DGE also brings some problems for both developed and developing economies. The main discussion on the topic of the gig economy has been revolving around the employment status of workers. In fact, it could be said that this was the hottest topic in academia about the gig economy, as every researcher that is involved with the gig economy one way or the other has written something about it. The same issue comes up here again. Even developed economies are updating their laws and regulations only now to keep up with this new, untraditional workforce that is growing each day. The state of California in the US just passed Proposition 22 in November 2020. The new proposition allowed the apps to classify workers as "independent contractors", but it also mandated that drivers and couriers be given 120% of the local minimum wage, health insurance stipend, and other important benefits. In the UK, the landmark "*Uber vs. Aslam*" trial has finally concluded in February 2021 and the UK Supreme Court claimed that Uber drivers (and by extension, other rideshare drivers) are not independent contractors, but they were workers for Uber and as workers, they are entitled to benefits like sick pay, minimum wage and many more. Developed economies are coming to grips with gig workers only now, so it would be safe to assume that it would take a long time for similar regulations to be enacted in developing countries as well. Until that time, gig workers in the Global South will not be part of the social security net that regular workers already enjoy and they will not have the right to a minimum wage, paid holidays, and so on.

## **2. PURPOSE OF THIS STUDY**

An important aspect of DGE and the North-South transfer is often overlooked in studies made on the gig economy. One of the most important benefits of DGE work for workers in the Global South is the fact that by doing DGE work, they are able to earn stable foreign currency as opposed to earning local currency. This is not limited to USD, in fact, Freelancer.com also accepts payments made in AUD, EUR, and GBP. This is advantageous for a couple of reasons: even if the workers are being paid one-third of what a worker in the North would be paid, that still puts the workers in a relatively better state than workers who are being paid with local currency. Foreign currency has more buying power in developing countries, which makes freelance work incredibly attractive. Not only that, but foreign currency also is a lot more stable and resilient than most local currencies of developing markets. This is especially true for countries with extremely volatile currencies, such as Argentina, Turkey, South Africa, Colombia, Russia, and many more. For workers in these countries, being paid by clients from the Global North with stable foreign currencies is a great advantage not only because of the higher purchasing power of the foreign currencies, but also the fact that they are being paid with a currency that is not losing its purchasing power so quickly. As an example, since the beginning of 2021, Argentine Peso has lost 16,25% of its value against the US Dollar. Being paid by something other than their local currency gives the workers the flexibility to convert their earnings to the local currency whenever they desire. The studies made on the effects of the gig economy rightfully state that North to South transfer gives better earnings to workers in the South, and that is true but the volatility of local currencies in these developing markets and the advantage of being paid in stable foreign currency is often understated.

The studies made on the effects of the gig economy on the workforce of the Global South are often based on surveys made with the local workforce, which provide excellent insights. However, empirical studies about the factors that drive the workforce in developing countries have so far been limited. This is, in part, because

of the absence of data available on the size of the gig workforce in developing countries. The studies for measuring the gig workforce in the global South have not been as widespread as it is for the United States, for example. However, this does not mean that there is no data for the gig workforce for these countries at all. In fact, even though they are experimental, there are data for the size of the online gig workforce in developing countries, even if it is experimental for now. The dataset used in this study will be explained in further chapters. The framework can be adapted to new and updated data when it is available in the future.

Therefore, for reasons stated above, this study will aim to see if there is empirically a connection between the labor participation of developing countries in the online gig economies and major macroeconomic variables, but most importantly exchange rate volatility, which is a huge part of economic life in these developing countries. Our aim is to empirically prove that the rising volatility of the exchange rates of local currency forces the workforce to supply their labor in online marketplaces - either as supplementary or primary income. Other macroeconomic variables' effect on the online gig economy participation is also empirically analyzed.

### **3. LITERATURE REVIEW**

Heeks (2017) offers a comprehensive overview of the effects of the online gig economy on workers in developing countries. He provides insights into the reasons why workers in developing countries join the online labor force. By focusing on developing countries only, he is able to identify the main reasons, which are different than workers in developed economies. Specifically, workers in developing economies receive higher than average wages in online marketplaces, at times 10 times the local minimum wage. This is in stark contrast to online gig work in developed economies, which pay less than minimum wage. Flexibility, which is the most attractive feature of gig work for workers in developed economies, is not as important for workers in developing economies. Even though online gig work poses serious disadvantages for workers, such as exclusion from the social safety net and lack of any government-mandated benefits such as paid leave, workers in developing nations claim that the positives outweigh the negatives. This study shows how online gig work in developing economies differ from their developed counterparts, as it provides an opportunity for clients in the Global North to outsource their more menial tasks to workers in the Global South. This outsourcing factor is unique to online gig work as it is location-independent.

Anwar and Graham (2020) give insights into the experiences of online gig workers in a developing country, particularly gig workers in sub-Saharan Africa. The study is conducted by interviewing 65 active workers in the gig economy from five countries: Nigeria, South Africa, Kenya, Ghana, and Uganda. The 4-year study is critical of the mainstream narrative (such as initiatives of the World Bank and the Rockefeller Foundation in Africa, promoting online gig work as a means to overcome unemployment), which is favorable to the online gig economy as a solution regarding economic issues in sub-Saharan Africa. The study focuses on the problems of online gig work poses for local workers. The main problem is the fact that the online gig economy created welfare for a small number of workers. Although there were 123,000 workers registered on Upwork, only 6% (approximately 7,400 workers) of these

workers earned at least \$1 on the platform. Of the workers interviewed in the study, 85% of them had an undergraduate degree or above, which further pushed the availability of gig work from the general population. Another important factor for gig workers in Africa was that almost none of them were able to get contracts on more lucrative types of gig work - such as software development or creative and multimedia. 44% of workers who were interviewed did Clerical and Data Entry types of gig work, which are the least lucrative (also requiring the least amount of skill) types of gig work available on online platforms. In addition, even though online gig work was not providing a livelihood for most of the registered workers, the minority who does earn through online gig work earned significantly higher than the average local wages. The results also show that even though worker flexibility was one of the main advantages as claimed by the advocates of online gig work in the region, that was not always the case. Only a small number of workers (who were highly educated) had the flexibility of choosing their work. Nearly all of the workers claimed that they did not have that kind of flexibility, which was especially true for migrant workers in South Africa, who had no other opportunity in the local job market due to legal and social reasons (gig work can often be the only available type of work for immigrants, another important case for this is the Venezuelan migrant delivery workers in Colombia<sup>34</sup>).

Lepanjuuri, Wishart, and Cornick (2018) of the Department for Business, Energy and Industrial Strategy in the UK provide insights into the size and workers of the gig economy in a developed country. Using the data from a nationwide survey conducted by NatCen (National Centre for Social Research), they conclude that 4.4% of the population engaged in gig work in the past 12 months. This translates into 2.8 million workers. The most popular platform among the workers is Uber, 18% of all the gig workers said that they provided their services through the app last year. As mentioned

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<sup>34</sup> Oliver Griffin, "Unwanted Delivery: Rappi Spawns Black Market in Worker Accounts," Reuters (Thomson Reuters, September 28, 2020), <https://www.reuters.com/article/us-latam-rappi-profiles-focus-reboot-idUSKCN26F2GK>.

before, in terms of size, the physical type of gig work comprised the highest share of gig work done by these gig workers. Around 42% of gig workers provided courier services. 28% offered provided their services through ridesharing apps and 21% worked in the food delivery industry. In comparison, most people did not offer their services in the digital side of the gig economy. The report states that around 9% of workers stated that their main source of income was gig work, while 32% of workers stated that earnings from gig work were supplemental to their other sources of income. An important finding of the report is that workers who performed digital gig work through platforms such as PeoplePerHour or Upwork generated the least amount of income, with 50% of workers who did gig work in these platforms stating that they made less than £250 in a whole year. Comparatively, 22% of workers who worked in the courier services claimed an income of £20,000 in a year just from the gig work they were providing. This is further evidence of the oversupply of the workforce in the online gig economy, and how the online gig economy is unable to provide income for the greater majority, but rather only for a smaller minority of freelancers and professionals. It also shows evidence for the North-to-South transfer (or rather, outsourcing) happening in the online gig economy. Since the online gig workers are not able to undercut the offers given by workers in developing countries, online gig work is only viable for professionals in developed countries, whose work can not be undercut by most workers in developing countries. On the other hand, gig workers in other countries cannot undercut rates given by physical gig workers in the UK, since those types of gig work are location-based and therefore can be a dependable source of income for many workers. This study provides an important comparison of how differently the gig economy is understood in a developed and developing country, in contrast to Heeks (2017) and Anwar & Graham (2020)'s findings.

Kässi and Lehdonvirta (2018) created the Online Labour Index to measure the size of the online gig economy. Their first inquiries into the online gig economy were interested in the demand side of the online labor (in which countries are clients located),

however, they also started crawling through the supply side of the online labor (i.e. in which countries are workers located) which they refer to as the "worker supplement". The worker supplement data is the core data this study will focus on, which will be explained in detail further in the "Data" section of this paper. For the demand side of the online gig economy, vacant job postings in 5 major online labor platforms (these platforms are: Freelancer, Upwork, Guru, MTurk, and PeoplePerHour), which include both professional freelancing platforms and microwork platforms which are offering jobs for less qualified types of work, are crawled through periodically. Every job posting was distributed into 5 main categories: Professional services (which include accounting, legal services, consulting, etc.), clerical and data entry (transcription, data entry, customer service, etc.), creative and multimedia (animation, audio, and video editing, graphic design, etc.), sales and marketing support (search engine optimization or SEO, lead generation, telemarketing, etc.), software development and technology (data science, web development, software development, etc.) and finally writing and translation (which includes translation, article writing, academic writing, etc.). The findings show that software development and technology job listings make up more than 35% of total job postings. After software development, creative and multimedia jobs make up nearly 25% of all the jobs, followed by (in this order) clerical and data entry, writing and translation, sales and marketing, and professional services. As for employer countries, half of the job postings are made from the United States. US is followed by UK, India, Australia, Canada, and other countries in Western Europe. The topic of outsourcing will be analyzed further in the latter chapters, with the worker supplement data of the OLI. The OLI data is still being updated with periodical crawls through the online platforms, and it can be accessed through Oxford Internet Institute's website<sup>35</sup>.

Huang et. al (2019) use county-level unemployment data in the United States (data sourced from Bureau of Labor Statistics, or BLS) to analyze the effect of

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<sup>35</sup> Online Labor Index can be accessed by this link: <https://ilabour.oii.ox.ac.uk/online-labour-index/>



unemployment on participation in the online gig economy. Specifically, the study aims to quantify the relationship between the unemployment rate and the supply of workers in online platforms through empirical analysis. They use a Bartik shift-share type instrument to isolate local labor demand from local labor supply by forecasting local employment growth-based growth on a national level. The results show there is a positive relationship between county-level unemployment and online gig work participation. Specifically, a 1% increase in a county's unemployment rate is associated with a 21.8% increase in the number of active workers on the platform. A 1% increase results in a 14.9% increase in the number of bids overall. Moreover, results show that a 1% increase in the entire United States correlates to approximately \$1.8 Million of earnings generated on online platforms. They also account for additional variables to reduce confounding. These additional variables are Average County Age, Ratio of Female, Education. The results show that there is a negative relationship between average age in a county and online gig economy participation. As for gender, counties with a higher ratio of females are more likely to participate in the online gig platforms, which can be a result of female workers staying at home because of childcare, or other factors. As for education, results reveal that there is a stronger relationship between counties that have workers with higher educational credentials and online gig work participation. Online labor requires skilled work, unlike physical gig work, which could explain the positive effects of higher levels of education. After running the data for the effects of state-level mass layoff events on online markets, they concluded that layoffs in IT-related industries have a positive effect on the supply of active workers on online platforms. Whereas layoffs in other sectors such as construction, food, and manufacturing do not have a meaningful effect on the supply of online workers.

Liang et. al (2018) offer an analysis of the gender wage gap in the online gig economy. Data is gathered from freelancer profiles from Freelancer.com. Log-transformed hourly wages are used as the dependent variable and *Female<sub>i</sub>* dummy variable is used as the independent variable. Country and period differences, occupation classification, and

differences in human capital (such as education) are used as control variables. Overall, they are able to find out that in online gig work, women earn 81.4% of their male peers, a figure close to the gender wage gap in full-time jobs in the United States (80%). Female gig workers tend to bid later on jobs and they are reluctant towards jobs where they have to be monitored during working (hourly contracts are monitored by software by platforms to show the client that the worker is actually working and not overcharging him/her), which affect the gender wage gap to some degree, these factors are not sufficient in explaining the gender wage gap.

Literature on the gig economy in developing economies has been limited, and available studies use survey data to measure the impact of the online gig economy in developing nations. Quantitative studies (such as studies of Huang et. al & Liang et. al.) that measure the impact of the online gig economy on other economic variables such as unemployment are focused on developed nations, the United States in particular. Access to data is difficult for the gig economy in general, this difficulty is exacerbated in developing countries. Because of this, quantitative studies on the online gig economy are limited to developed nations, with studies in developing nations relying on survey data. This study aims to overcome the barrier of accessing data by using Kässli and Lehdonvirta's (2018) Online Labor Index and its subsequent worker supplement data. Therefore, the aim is to provide a quantitative measure of the factors that affect workers supplying their data in online marketplaces. The issue of outsourcing online work to workers in developing countries by clients in developed countries, or the North-South transfer, is understated in the current literature on the gig economy. The main topics of discussion are surrounding the socio-legal issues posed by this innovation, such as the status of the workers, who are referred to as independent contractors and as such are not able to demand any rights from the platforms they work for such as minimum wage or paid vacation leave. By using OLI and its worker supplement data, the aim is to further our understanding that drives the growth of the online marketplaces in developing countries and also to fill in the gap in the current literature on the gig

economy as studies have not delved into factors affecting the North-South transfer in further

#### **4. DATA**

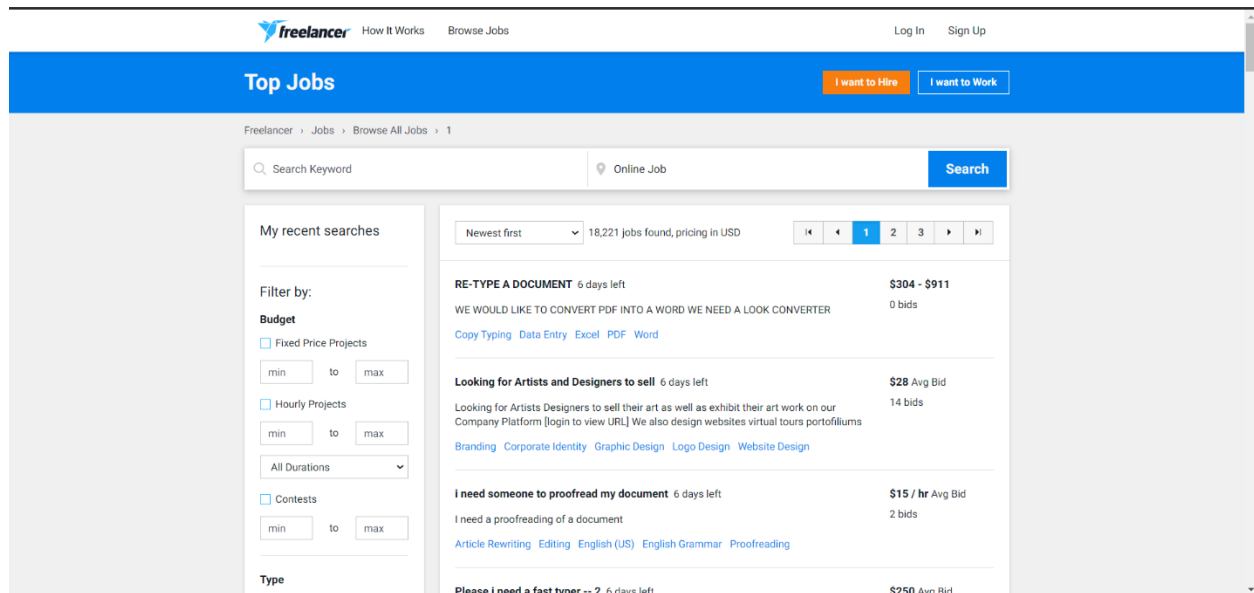
One of the most difficult factors in making research about the gig economy is access to reliable data. The most reliable data is only available in the online platforms themselves, which are reluctant to share their data with researchers. As such, researchers are left to their own devices in obtaining data about the gig economy. The methods for obtaining data usually include relying on deductions made on other supplementary data. As an example, the number of 1099-MISC forms that were reported to the IRS was used as a measuring tool to estimate the size of the gig economy. As these forms are mainly filled out by freelancers, the rising number of 1099-MISC forms would point to a rising number of gig workers<sup>36</sup>. Of course, the number of 1099-MISC would also include people who work as independent contractors and did not necessarily work through the typical gig platforms.

Focusing on the online aspect of the gig economy, or rather the DGE, presented an opportunity that was not available for other gig economy platforms like Uber or DoorDash. Although online marketplaces such as Upwork and Freelancer do not publish the number of active workers or the number of clients who are actively using the platform, the data is not kept hidden either. The information is ready to be accessed by anyone (in some cases an account on the platform might be necessary) to be viewed.

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<sup>36</sup> Katharine Abraham et al., "Measuring the Gig Economy: Current Knowledge and Open Issues," *NBER*, January 9, 2020.

**Figure 4.1. Job Postings on Freelancer.com**



*Source: Freelancer.com, May 2021.*

The example above is the "browse jobs" section of Freelancer.com, which can be accessed without registering for the website. This section shows the newly posted vacancies (or job postings) available on the website. A freelancer, who is not yet registered to the platform can use this tool to view jobs that are available for him/her.

## Figure 4.2 – Job Postings on Upwork

The screenshot shows the Upwork website interface. At the top, there is a navigation bar with the Upwork logo, links for 'Find Talent', 'Find Work', 'Why Upwork', and 'Enterprise', a search bar, and 'Log In' and 'Sign Up' buttons. Below the navigation bar, there are categories: 'Development & IT', 'Design & Creative', 'Sales & Marketing', 'Writing & Translation', 'Admin & Customer Support', and 'Finance & Accounting'. The main content area features a heading: 'Check out a sample of the 6,994 SEO Expert jobs posted on Upwork'. Below this, there is a breadcrumb trail: 'Upwork / Freelance Jobs / SEO Expert Jobs'. The main content displays four job listings in a grid:

- Looking for Reddit Expert**: New, Fixed-price, Posted 9 minutes ago. \$10 Fixed Price, Intermediate Experience Level. Description: 'We are looking for reddit expert to boost our crypto project in related and popular subreddits. We are going to hire people who have g...'. Tags: Search Engine Optimization (SEO), Reddit Marketing. Button: See More.
- Etsy Product Listing with SEO**: New, Fixed-price, Posted 16 minutes ago. \$20 Fixed Price, Intermediate Experience Level. Description: 'I have Etsy shop. There is 80 products in it. I need keyword research, seo optimized title, seo tags, products description and backlink...'. Tags: Search Engine Optimization (SEO), SEO Jobs. Button: See More.
- Long-Term Scriptwriter for YouTube Channel WANTED**: New, Fixed-price, Posted 25 minutes ago. \$17 Fixed Price, Intermediate Experience Level. Description: 'We're looking for a long-term scriptwriter to write scripts on topics related to film/movies/TV series for YouTube videos. ROLE Scrip...'. Tags: Search Engine Optimization (SEO), English. Button: See More.
- Website design**: New, Fixed-price, Posted 28 minutes ago. \$300 Fixed Price, Intermediate Experience Level. Description: 'Hello all, I'm looking for a qualified individual who can assist me in development of a website for my Electrical/Solar Contracting Or...'. Tags: Search Engine Optimization (SEO), User Flows. Button: See More.

*Source: Upwork, May 2021.*

Similarly, above is the example of job postings available for the "SEO Expert" category in Upwork. As with Freelancer.com, browsing the latest posted jobs does not require registration either as a client or as a freelancer. Clicking on the job posting will show the user more details about the job and the client, such as the home country of the client and the reviews given to him/her by a previous freelancer that worked with the client. The details will also show the amount of money spent on the platform by the client.

As opposed to major PGE platforms, most DGE platforms will not hide information regarding newly posted jobs or profiles of freelancers on their websites. As such, obtaining relatively reliable data from online gig marketplaces was proven to be easier than obtaining said data from PGE platforms such as Uber or Lyft, which do not publish this data. This is mainly because of the different business models of two types of gig

economies, a client who is looking for a web developer for their website will need to be in close contact with the worker, as it is a more specialized kind of work. On the other hand, a client that is ridesharing will not need to be in contact with the driver at all. As such, online marketplaces will need to have these kinds of information readily available for prospective clients to attract them. The Online Labor Index project was made possible because of this unique advantage of these marketplaces, which will be explained in further detail below.

#### **4.1. Online Gig Economy Data - Overview of Online Labor Index Study**

Otto Kässi and Vili Lehdonvirta<sup>37</sup> were able to make the first comprehensive index for major online marketplaces thanks to the availability of data. The Online Labor Index was made for measuring the demand for online gig work, not the supply of workers. In order to do so, Kässi and Lehdonvirta periodically crawled through five major online marketplaces. These marketplaces were chosen by their Alexa ranking (a service by Amazon, which measures a website's internet popularity. Alexa rank of 1 is the most popular site in the world<sup>38</sup>) and they were: Upwork, Guru, PeoplePerHour, Freelancer, and Mechanical Turk. Each crawl (or data scrape) counts the number of vacancies (vacancy in this sense refers to a job posting) on all of these platforms. By comparing the number of vacancies between each crawl, Kässi and Lehdonvirta were able to see the number of new vacancies available on platforms and could therefore turn this data into an index that shows the growth of the online gig economy overall. Apart from crawling for new vacancies, they also crawled for occupation classification and the employer countries (i.e. the country where the vacancy was posted from). Occupation classification and employer country data were not readily available on all platforms (as an example, both of these were observed in Upwork, but employer data was not available on Mturk). As it is already discussed in the "Literature Review" section of

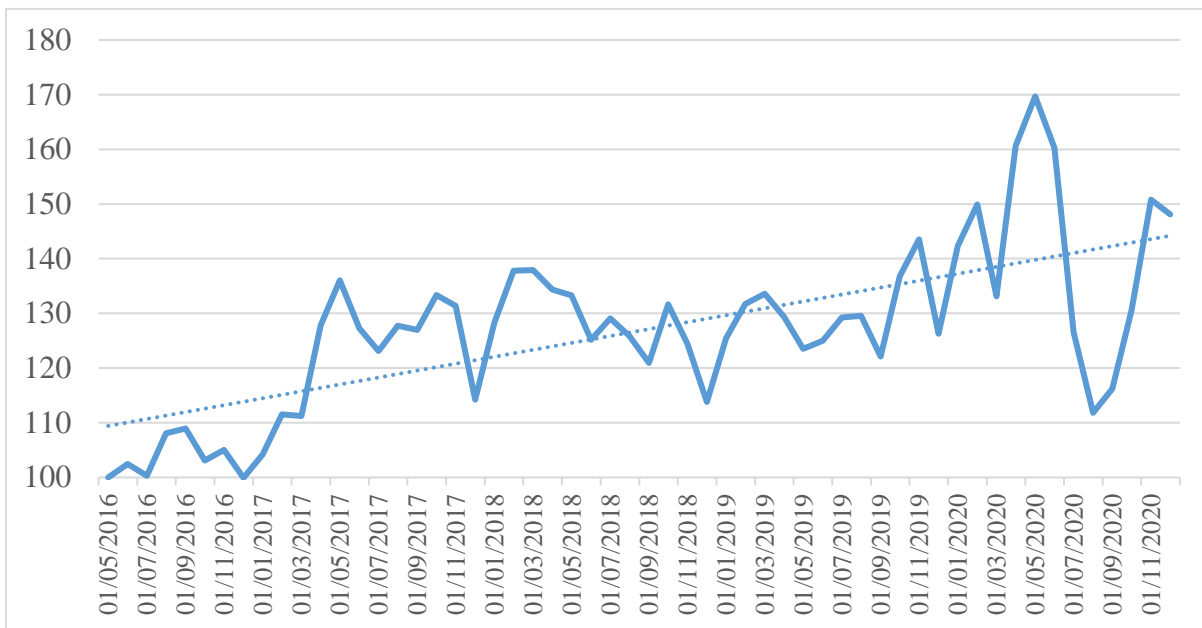
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<sup>37</sup> Otto Kässi and Vili Lehdonvirta, "Online Labour Index: Measuring the Online Gig Economy for Policy and Research," *Technological Forecasting and Social Change* 137 (July 26, 2018): pp. 241-248

<sup>38</sup> Kim Kosaka, "Alexa Rank: Definition and Resources," Alexa Blog, June 25, 2018, <https://blog.alexa.com/marketing-research/alexa-rank/>.

this study, detailed insights from the index can be obtained through Kässä and Lehdonvirta's article explaining the OLI. The data (and the graphs made with the data) is being updated every day and can be viewed in detail through the Oxford Internet Institute's webpage. The data that is used in this study is the OLI Worker Supplement data, which is concerned with the supply side of the online gig economy, not the demand side.

**Figure 4.3. Online Labor Index Demand Data - Monthly Averages**

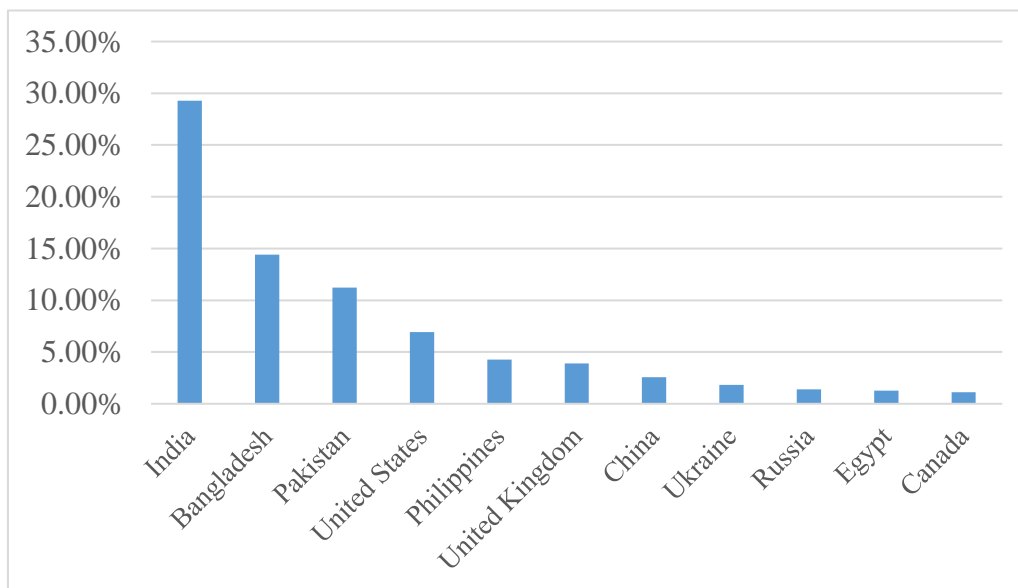


*Source: Kässä & Lehdonvirta, 2018*

The OLI's Worker Supplement was created in order to measure the growth of worker supply in the online marketplaces. Another important factor was the location of the workers. The OLI demand data clearly showed where employers were located, likewise, the location of workers around the world was an equally important data to have access to. Kässä and Lehdonvirta started collecting data in June 2017. The raw data is collected through 4 major online marketplaces: Fiverr, Freelancer, Guru, and PeoplePerHour. Like the regular OLI data, these platforms were again crawled every 24 hours. In this instance, the data collected was related to the workers themselves on

the platform, such as their home country, their occupation classification, and when they last finished a project. This sample was then weighted by the number of active workers on the platforms. As mentioned before, most of the workers who register to online marketplaces are not able to land jobs and the majority of them remain inactive without earning any amount of money from these platforms. Therefore, the number of registered workers could give misleading results in terms of the worker supply. To avoid this issue, Kässi and Lehdonvirta instead accounted for the number of "active workers" instead of registered workers. They define active workers as follows: "*anyone who has completed a project over the last 28 days*". The number of active workers is deducted from the total number of registered workers.

**Figure 4.4. Share of Workers by Country (for years 2017-2020)**



*Source: Kässi & Lehdonvirta, 2018*

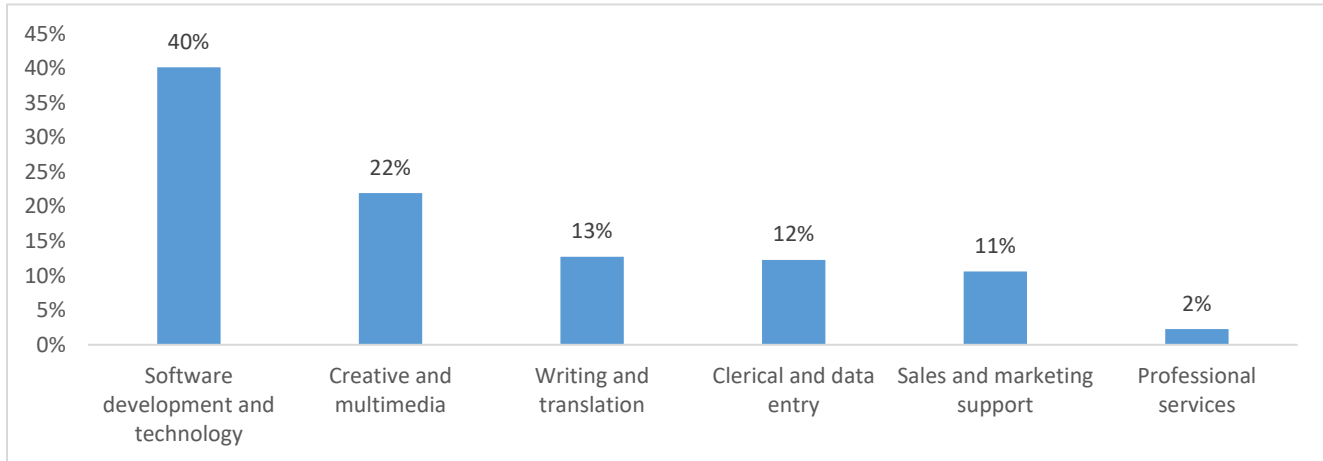


**Table 4.1: Summary Statistics for OLI Worker Supplement Data**

| <b>Variables</b>         | (1)<br><b>N</b> | (2)<br><b>Min</b> | (3)<br><b>Max</b> | (4)<br><b>Mean</b> | (5)<br><b>SD</b> | (6)<br><b>Median</b> |
|--------------------------|-----------------|-------------------|-------------------|--------------------|------------------|----------------------|
| <b>Argentina</b>         |                 |                   |                   |                    |                  |                      |
| num_worker_diff          | 41              | -47.92%           | 329.10%           | 13.49%             | 58%              | 4.43%                |
| proportional_to_all_diff | 41              | -40.69%           | 101.02%           | 4.22%              | 25%              | 0.52%                |
| <b>Turkey</b>            |                 |                   |                   |                    |                  |                      |
| num_worker_diff          | 41              | -67.01%           | 216.11%           | 15.85%             | 53%              | 10.39%               |
| proportional_to_all_diff | 41              | -21.03%           | 25.64%            | 3.42%              | 12%              | 3.42%                |
| <b>Colombia</b>          |                 |                   |                   |                    |                  |                      |
| num_worker_diff          | 41              | -4.17%            | 13.70%            | 0.72%              | 3%               | 0.34%                |
| proportional_to_all_diff | 41              | -50.02%           | 184.15%           | 11.24%             | 42%              | 2.40%                |
| <b>South Africa</b>      |                 |                   |                   |                    |                  |                      |
| num_worker_diff          | 41              | -58.31%           | 205.15%           | 10.07%             | 47%              | 2.36%                |
| proportional_to_all_diff | 41              | -46.39%           | 64.88%            | 1.10%              | 19%              | 0.20%                |
| <b>Brazil</b>            |                 |                   |                   |                    |                  |                      |
| num_worker_diff          | 41              | -53.39%           | 115.78%           | 6.74%              | 36%              | 4.49%                |
| proportional_to_all_diff | 41              | -44.19%           | 38.92%            | -0.24%             | 16%              | -1.57%               |
| <b>Russia</b>            |                 |                   |                   |                    |                  |                      |
| num_worker_diff          | 41              | -50.37%           | 836.31%           | 23.94%             | 132%             | -0.37%               |
| proportional_to_all_diff | 41              | -53.14%           | 312.52%           | 10.48%             | 56%              | -2.15%               |

*Num\_worker\_diff is the difference between monthly averages of raw number of workers (num\_workers) of OLI Worker Supplement Data.  
 Proportional\_to\_all\_diff is the monthly difference between the proportion of country-specific num\_worker data to the sum of num\_worker.  
 Data covering Jun 17 to Oct 20*

**Figure 4.5: Share of Occupation (for years 2017-2020)**



*Source: Kässi & Lehdonvirta, 2018*

The raw data of the worker supplement is obtained from the Oxford Internet Institute website. The raw data includes 5 columns: timestamp, country, occupation, num\_workers, and num\_projects. These columns indicate, in order of writing: year-month-day of the data, worker country, worker occupation, number of workers, and number of projects. Private correspondence with Kässi and Lehdonvirta indicated that the num\_projects column was not functional, therefore that column was not taken into consideration for this study. The data regarding occupational classification was also not used for analysis. Although greatly insightful, the main focus of this study was how currency volatility and other macroeconomic variables affect the supply of workers in developing countries and for this reason, the occupational classifications were not used.

#### **4.2. Country-Specific Data - What Macroeconomic Variables are Used?**

The main question of this study was to analyze the effects of exchange rate volatility on the supply of workers in online marketplaces. The Worker Supplement data provided by Kässi and Lehdonvirta included 189 countries around the world. Since analyzing all of the 189 countries around the world was not viable, countries that fulfilled certain criteria were selected for the study. These criteria were:

- i. the country should be considered as a developing country,

- ii. countries that were experiencing or experienced currency shocks in the last 3 years,
- iii. countries with a significant level of online labor participation,
- iv. countries with adequate Internet freedom (so that workers could withdraw funds from online marketplaces),
- v. countries that published macroeconomic statistics periodically.

As developing countries that experienced exchange rate volatility were the main focus of this study, the number of countries that could be analyzed was limited significantly. However, as reaching healthy macroeconomic data was integral to this study, many countries that experienced currency shocks and hyperinflation (such as Venezuela) were also excluded in this study. Overall, six countries were chosen as a base of analysis. These countries were: Argentina, Turkey, Russia, Colombia, Brazil, and South Africa. Although Pakistan was also initially on the list, difficulties in obtaining macroeconomic statistics for Pakistan resulted in it being excluded.

As for the exchange rates, the rate of US Dollar to local currencies was used. To account for potential abnormalities in daily exchange rates, monthly averages were

**Table 4.2: Summary Statistics for Exchange Rate Volatility Measures**

| <b>Variables</b>    | (1)<br><b>N</b> | (2)<br><b>Min</b> | (3)<br><b>Max</b> | (4)<br><b>Mean</b> | (5)<br><b>SD</b> | (6)<br><b>Median</b> |
|---------------------|-----------------|-------------------|-------------------|--------------------|------------------|----------------------|
| <b>Argentina</b>    |                 |                   |                   |                    |                  |                      |
| cur_diff            | 41              | -3.14%            | 28.99%            | 4.15%              | 6%               | 2.71%                |
| volat               | 41              | 0.11%             | 4.64%             | 0.89%              | 1%               | 0.61%                |
| volat_diff          | 41              | -73.98%           | 639.64%           | 33.03%             | 144%             | -12.37%              |
| <b>Turkey</b>       |                 |                   |                   |                    |                  |                      |
| cur_diff            | 41              | -69.17%           | 346.43%           | 25.28%             | 95%              | 3.48%                |
| volat               | 41              | 0.22%             | 5.20%             | 0.91%              | 1%               | 0.72%                |
| volat_diff          | 41              | -8.09%            | 23.51%            | 2.09%              | 5%               | 1.31%                |
| <b>Colombia</b>     |                 |                   |                   |                    |                  |                      |
| cur_diff            | 41              | -8.09%            | 23.51%            | 2.09%              | 5%               | 1.31%                |
| volat               | 41              | 0.55%             | 2.50%             | 1.03%              | 0%               | 0.88%                |
| volat_diff          | 41              | -69.43%           | 126.90%           | 6.74%              | 42%              | 0.32%                |
| <b>South Africa</b> |                 |                   |                   |                    |                  |                      |
| cur_diff            | 41              | -7.13%            | 11.54%            | 0.61%              | 4%               | 0.10%                |
| volat               | 41              | 0.60%             | 1.73%             | 0.95%              | 0%               | 0.93%                |
| volat_diff          | 41              | -54.34%           | 123.06%           | 4.48%              | 34%              | -1.47%               |
| <b>Brazil</b>       |                 |                   |                   |                    |                  |                      |
| cur_diff            | 41              | -8.03%            | 11.93%            | 1.45%              | 4%               | 1.59%                |
| volat               | 41              | 0.55%             | 2.50%             | 1.03%              | 0%               | 0.88%                |
| volat_diff          | 41              | -69.43%           | 126.90%           | 6.74%              | 42%              | 0.32%                |
| <b>Russia</b>       |                 |                   |                   |                    |                  |                      |
| cur_diff            | 41              | -5.06%            | 16.02%            | 0.80%              | 3%               | 0.19%                |
| volat               | 41              | 0.36%             | 2.76%             | 0.72%              | 0%               | 0.63%                |
| volat_diff          | 41              | -57.99%           | 235.90%           | 10.80%             | 56%              | -5.93%               |

*cur\_diff is the difference between monthly averages of the exchange rates of Local Currencies to the US Dollar.  
volat is the monthly Standard Deviation of the exchange rates of Local Currency to US Dollar  
volat\_diff is the month-on-month difference of volat  
Data covers Jun 2017 to Oct 2020*

used. In addition, to measure the volatility of the exchange rates, the standard deviation of bilateral exchange rates for every month was calculated. The measurement for exchange rate volatility was based on the calculations of McKenzie's studies<sup>39</sup>. Measurements for exchange rate volatility and control variables are described in further detail in the methodology section.

### **4.3. Limitations of the Data**

Although worker supply data is available daily, since obtaining macroeconomic variables in a daily format was not possible, the monthly averages of worker supply data are used for analysis. Similarly, making calculations using daily differences of the exchange rate is also not going to produce healthy results for analysis. Therefore, data is used in monthly intervals for each variable. Since data obtained from Kässi and Lehdonvirta's study only starts from June 2017 and ended in December 2020 (the data was accessed after December 2020, however for technical reasons the last date of update for the worker supply data was December 2020. This issue has now been resolved, the data is updated on a daily basis and it can be reached through the iLabour Project website. Even if this analysis was made today, the sample size would still be small), the sample size for the dataset is very limited. The sample size for monthly averages of the number of workers is 41, which reduces the power of the study. On the other hand, analyzing with daily differences in data is not possible either as the daily volatility of exchange rates was not meaningful.

Another limitation of data is the fact that Kässi and Lehdonvirta were not aiming to measure the size of the worker supply, but rather the share of workers by their countries. Since they already had the data regarding which countries were top clients of online gig work, creating similar data for the countries that were supplying the most workforce to online gig work provided valuable insights. As such, the data they obtained through crawling online platforms periodically was weighted according to the

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<sup>39</sup> Michael D. McKenzie, "The Impact of Exchange Rate Volatility on International Trade Flows," *Journal of Economic Surveys* 13, no. 1 (2002): pp. 71-106

size of the platform itself. The num\_workers column in the raw data or the number of workers was not the nominal number of active workers from these countries, but rather the share of workers. With their sampling and weighting methods, they were able to deduct the share of workers from a specific country, for a specific occupation classification. This information is obtained through private correspondence with Otto Kässi himself. In his own words:

*"Our data is collated from several platforms, and oftentimes the number of workers our data collectors capture are [sic] not proportional to the size of the platform measured in traffic. Therefore, we have weighed our observations by the platform size. The fractions of workers are caused by the weighing. Relatedly, the sampling+weighing also affects the interpretation of the results. It is incorrect to say that there were 188.2 active Uruguayan coders on any given date. Rather, you can only infer that the share of Uruguayan coders of the total workforce is  $[188.2 / (\text{sum of total coders at a given date})]$  etc."<sup>40</sup>*

Therefore, as an example, an increase in the number of workers from India does not specifically mean that more people are actively working on online platforms. It can also mean that **only the share** of workers from India has increased. While it can also show the actual number of active workers also increased in that timeframe, making assumptions on whether the increase is caused by the share of workers or the actual number of workers was not possible.

Although this limitation of the data poses some problems regarding the power of this study, meaning the increase in the worker data could not actually mean an actual increase, the data still means that there was a significant increase in the share of workers of a specific country, which can be explained with external macroeconomic variables. An increasing share of South African workers in the online marketplaces, as an example, can be related to instability caused by volatile exchange rates or rapidly rising

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<sup>40</sup> Private correspondence with Otto Kässi through e-mail.

unemployment rates. However, following advice from Kassi, num\_workers data was also transformed into the proportional number of workers data by dividing the country-specific num\_worker data to the total sum of num\_workers for that specific crawl. With a single anchor point on the data, the sampling and weighting effects on the data would be (at least in theory) reduced.

Another limitation of the worker supply data is the number of spikes in the data. These spikes are caused by the differences made to the data collector and the platforms where the data was being collected from. To overcome this issue, several days (where there was a spike in the number of workers for almost all of the selected countries - indicating a wider change in the data collection parameters) are removed from the data and the monthly averages were calculated again. Since the sample size for the worker supply data is already small, removing an entire month (or two) would not have positive impacts on the overall analysis, and therefore it was avoided.

Further minor limitations of data include different reporting standards of countries. As an example, although Pakistan (as one of the biggest suppliers of the online workforce around the world) was included in this analysis at the beginning, macroeconomic data reached through the Pakistan Bureau of Statistics website was not reliable, and ultimately Pakistan was removed from the list of countries that were analyzed. Similarly, some countries reported unemployment rates quarterly (such as South Africa and Argentina). To overcome this issue, these quarterly results are repeated over the next two months to have a monthly value for unemployment rates. Finally, not every country reported the average rates of personal loans periodically, in cases like those, the most similar variable to an average loan rate was substituted for it. Countries' own statistical agencies were the primary source for obtaining data, although in cases where it was not possible to obtain the data from the statistical agency of the country itself, external sources (such as FRED) were used.

## 5. METHODOLOGY

As OLI and its worker supplement data are crawled daily, the monthly average *num\_worker* data was calculated from June 2017 to October 2020 to reduce the noise in the data. This is also necessary as no macroeconomic indicators that are used as control variables are reported on a daily basis. Based on private correspondence with Otto Kässi, one of the creators of the OLI data, to reduce the effects of sampling and weighing on the *num\_workers* data, another set of data was created. In this new data, *num\_workers* values were divided by the total sum of all workers. Using the total sum of workers as an anchor point for every country, the goal was to minimize the effects of changing parameters of data collection which caused spikes in the *num\_workers* data, as they affected each country separately.

Monthly percentage changes between *num\_workers* and *proportional\_to\_all* were used as the dependent variables for this study. Two sets of data were run on separate regressions to test which of these data presented the most powerful results. Because of its simplicity and flexibility, a multiple linear regression model is used. The model's goal is to measure the explanatory power between the volatility of exchange rates of the local currency against the US dollar and the differences in the worker supply of online marketplaces for 6 selected countries. To reduce confounding, various macroeconomic factors were included in the regression as control variables.

Control variables included monthly unemployment rates, month-on-month inflation rates, Industrial Production Index, and the loan rates for average consumer loans. The reasoning for selecting each of these variables are as follows:

Monthly differences in unemployment rates were gathered to measure the effect of unemployment on a worker's willingness to participate in the online gig economy. As Huang et al. (2019) has shown, there is an inverse relationship between the local unemployment rate and the rate of gig economy participation. The aim was to analyze whether the same effect is present when looking at a country-wide level.



Similarly, an increase in the MoM Inflation Rates could also increase the supply of online workers. An increase in workers seeking alternative work arrangements is to be expected in a country experiencing high levels of inflation, although another advantage of online marketplaces is the fact that they offer relatively low barriers of entry (as it does not cost anything to register on a platform - even if it is difficult to land a job there) and stable earnings if the worker becomes successful. The market value of an assistant or secretary could erode locally with inflation, however, the average hourly rate for that kind of virtual assistant jobs stays relatively stable on the online marketplaces.

Differences in Industrial Production Index (IPI) is used as a substitute for analyzing the effect of economic growth on the supply of workers in online marketplaces. As GDP growth is announced yearly and quarterly for many countries, the growth in the IPI was substituted for it.

The differences in average personal loan interest rates were used to see how the availability of liquidity for consumers was affecting their behavior in deciding whether to participate in online marketplaces or not. The idea behind including this variable was seeing if workers supplied their labor in online gig works to earn supplemental income in cases where applying for loans was not possible because of high interest rates. Another important aspect of online gig work (and gig work in general) is the fact that work is being done in a shorter timeframe. Instead of working for two weeks or a month to receive a paycheck, gig workers are able to receive their earnings as soon as they finish the job for their clients. Although there are various factors that cause a delay in the transfer of money (such as intermediary platforms like PayPal, Payoneer, or Skrill), receiving earnings is a far more flexible process compared to traditional work arrangements. This extra liquidity could be beneficial for workers in developing countries, especially if access to credit is limited due to high rates.

**Table 5.1: Summary Statistics for Control Variables**

| <b>Variables</b>    | (1)<br><b>N</b> | (2)<br><b>Min</b> | (3)<br><b>Max</b> | (4)<br><b>Mean</b> | (5)<br><b>SD</b> | (6)<br><b>Median</b> |
|---------------------|-----------------|-------------------|-------------------|--------------------|------------------|----------------------|
| <b>Argentina</b>    |                 |                   |                   |                    |                  |                      |
| inf_diff            | 41              | 1.20%             | 6.50%             | 2.92%              | 1%               | 2.70%                |
| ipi_diff            | 41              | -18.81%           | 18.38%            | 0.08%              | 8%               | -0.34%               |
| loan_diff           | 41              | -9.42%            | 16.93%            | 0.80%              | 5%               | 0.42%                |
| unemp_diff          | 41              | -12.99%           | 26.69%            | 4.21%              | 12%              | 4.21%                |
| <b>Turkey</b>       |                 |                   |                   |                    |                  |                      |
| inf_diff            | 41              | -1.44%            | 6.30%             | 1.11%              | 1%               | 0.97%                |
| ipi_diff            | 41              | -30.17%           | 18.30%            | 0.62%              | 7%               | 0.69%                |
| loan_diff           | 41              | -15.85%           | 33.69%            | 0.86%              | 11%              | 0.81%                |
| unemp_diff          | 41              | -6.99%            | 9.49%             | 0.60%              | 4%               | 0.00%                |
| <b>Colombia</b>     |                 |                   |                   |                    |                  |                      |
| inf_diff            | 41              | -0.38%            | 0.71%             | 0.22%              | 0%               | 0.18%                |
| ipi_diff            | 41              | -22.87%           | 14.55%            | 0.51%              | 8%               | 1.29%                |
| loan_diff           | 41              | -9.37%            | 14.04%            | -0.83%             | 5%               | -1.31%               |
| unemp_diff          | 41              | -12.78%           | 66.20%            | 1.80%              | 11%              | -0.14%               |
| <b>South Africa</b> |                 |                   |                   |                    |                  |                      |
| inf_diff            | 41              | -0.61%            | 1.31%             | 0.32%              | 0%               | 0.29%                |
| ipi_diff            | 41              | -48.28%           | 41.13%            | 1.14%              | 13%              | 2.62%                |
| loan_diff           | 41              | -25.51%           | 19.93%            | -0.36%             | 8%               | 0.00%                |
| unemp_diff          | 41              | -22.51%           | 32.20%            | 1.31%              | 11%              | 0.50%                |
| <b>Brazil</b>       |                 |                   |                   |                    |                  |                      |
| inf_diff            | 41              | -0.38%            | 1.26%             | 0.28%              | 0%               | 0.25%                |
| ipi_diff            | 41              | -19.52%           | 12.59%            | 0.22%              | 5%               | 0.45%                |
| loan_diff           | 41              | -3.36%            | 3.11%             | -0.60%             | 1%               | -0.58%               |
| unemp_diff          | 41              | -3.45%            | 5.17%             | 0.17%              | 3%               | -1.53%               |
| <b>Russia</b>       |                 |                   |                   |                    |                  |                      |
| Inf_diff            | 41              | -0.54%            | 1.01%             | 0.28%              | 0%               | 0.29%                |
| ipi_diff            | 41              | -6.00%            | 2.51%             | 0.04%              | 1%               | 0.24%                |
| loan diff           | 41              | -4.74%            | 4.80%             | -1.00%             | 2%               | -1.25%               |
| unemp_diff          | 41              | -4.44%            | 23.40%            | 0.51%              | 4%               | 0.00%                |

*Inf\_diff: MoM differences of the CPI.*

*Ipi\_diff: MoM differences in the Industrial Production Index.*

*Loan\_diff: MoM differences of the average consumer loan rate.*

*Unemp\_diff: MoM differences of the official unemployment rate (total workforce).*

Having determined the control variables, the linear regression model(s) employed in this study to estimate the effect of volatility on worker supply is as follows:

$$\Delta num\_worker = \beta_0 + \beta_1 exchange\ rate\ volatility + \beta_2 \Delta inf + \beta_3 \Delta ipi + \beta_4 \Delta loan + \beta_5 \Delta unemp$$

$$\Delta proportional\_to\_all = \beta_0 + \beta_1 exchange\ rate\ volatility + \beta_2 \Delta inf + \beta_3 \Delta ipi + \beta_4 \Delta loan + \beta_5 \Delta unemp$$

In these models,  $\Delta num\_worker$  variable is the monthly change in the  $num\_worker$  data obtained from OLI Worker supplement,  $\Delta proportional\_to\_all$  variable is monthly differences between the ratio of a country's  $num\_worker$  data to the total sum of  $num\_workers$  in total,  $\Delta inf$  refers to the month-on-month differences in the inflation rate,  $\Delta ipi$  refers to monthly changes in the Industrial Production Index,  $\Delta loan$  refers to month-on-month differences in the average personal loan rate and finally,  $\Delta unemp$  refers to month-on-month differences between the official unemployment rate. If the country (Argentina and South Africa in this case) publishes this rate quarterly, the quarterly rate is repeated over the next two months. For determining the method to estimate the volatility of exchange rates for each country, multivariate analysis is used. McKenzie's<sup>41</sup> work on exchange rate volatility on trade flows specifies how previous methods were used under what circumstances. Overall, the three measures of volatility used in this study are as follows:

1. Absolute percentage change of the exchange rate;

$$V_t = |(e_t - e_{t-1})| / e_{t-1}$$

Where  $e$  is the spot exchange rate and  $t$  refers to time.

This is referred to as the *cur\_diff* variable in the study.

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<sup>41</sup> Michael D. McKenzie, "The Impact of Exchange Rate Volatility on International Trade Flows," *Journal of Economic Surveys* 13, no. 1 (2002): pp. 71-106

2. Standard deviation of the daily exchange rates for a month of the exchange rate against the US Dollar the mean observed during a subperiod.

$$V_t = \sigma (e_t, e_{t+1}, e_{t+2} \dots)$$

Where  $e$  is the spot exchange rate and  $t$  refers to time.

This is referred to as the *volat* variable in the study.

3. Absolute percentage change of the standard deviations of the monthly exchange rates. In other words, this is the monthly difference between *volat* variables.

$$V_t = |\sigma(e_t) - \sigma(e_{t-1})| / \sigma(e_{t-1})$$

This is referred to as the *volat\_diff* variable in the study.

For measuring *cur\_diff*, monthly averages of daily exchange rates to the US Dollar were taken into consideration, instead of using the exchange rate at the end of the month. This was done in order to smoothen the abnormalities in the exchange rate data. After monthly averages were calculated, the absolute percentage change of the monthly average rates was calculated.

Since the dependent variables in this study were percentage differences (monthly absolute differences of *num\_worker* and *proportional num\_worker*), absolute changes to *volat* variable were also taken into consideration for the analysis. Similarly, all the control variables were also monthly differences of macroeconomic variables.

Regarding the experimental nature of the data, regressions were run separately on two dependent variable datasets. Similarly, since there were 3 measurements of exchange rate volatility, each dependent variable dataset was run 3 times. The regressions were run for each country. In total, 6 models (3 with *num\_worker*, 3 with *proportional\_to\_all*) of multiple linear regression were run for each country, including all control variables.

As mentioned, registering for online marketplaces is a relatively simple process. However, it might take workers weeks or months to land their first job. As the OLI worker supplement data is only counting active workers, that is, workers who have

finished a project in the last 28 days, the effects of currency shocks or other macroeconomic shocks could present themselves later than they occur. To control for this issue 6 more sets of regressions were run for each of the countries, with dependent variables lagging one month behind every other variable.

## **6. RESULTS**

The first sets of regressions were run using the absolute percentage change of monthly average workers of each country as the dependent variable. The results of the first sets of regressions are presented in Table 6.1.

Initial runs of regressions show promising results for some countries, such as Argentina. Argentina is the country that experienced the worst currency devaluation among the countries in the timeframe of this study (between June 2017 and October 2020, the Argentine Peso lost 79% of its value against the US Dollar). Regressions (1) through (3) suggest that exchange rate volatility (all 3 measures of them) positively related to worker demand variable (dependent variable) with a significance level of 1% for Regression (1) and 10% in Regression (2) and 1% in Regression (3). On the other hand, we do not observe any significant results in Regression (4), (5), and (6), the set of regressions for Turkey, the country that is experiencing the second-worst currency devaluation in the timeframe of this study (between June 2017 and October 2020, Turkish Lira lost 53% of its value against the US Dollar). Regressions (1), (2), and (3), set of regressions for Argentina and (10), (11), and (12), set of regressions for Colombia, are in line with the initial hypothesis with this study. Regression (10) is statistically significant at 5% level, Regression (11) is significant at 5%, and Regression (12) is significant at 1% level. Overall, there is a higher level of statistical significance when using the *cur\_diff* and the *volat\_diff* variables as opposed to the *volat* variables. The results for Argentina and Colombia show a positive relationship with increasing exchange rate volatility and increasing worker supply in online marketplaces, however, regressions on other countries do not present results in favor of the alternative hypothesis.

**Table 6.1. Regressions of Raw Worker Numbers**

| Model             | Argentina       |                 |                 | Turkey          |                 |                 | Russia          |                 |                  | Colombia        |                 |                 | Brazil          |                 |                 | South Africa    |                 |                 |
|-------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|                   | 1               | 2               | 3               | 4               | 5               | 6               | 7               | 8               | 9                | 10              | 11              | 12              | 13              | 14              | 15              | 16              | 17              | 18              |
| <b>Volat</b>      | 53,44<br>(0)    |                 |                 | 4,2<br>(0,75)   |                 |                 | 18,66<br>(0,75) |                 |                  | 3,35<br>(0,02)  |                 |                 | 16,04<br>(0,32) |                 |                 | 25,03<br>(0,5)  |                 |                 |
| <b>Cur_Diff</b>   | 4,85<br>(0,01)  |                 |                 | 0,03<br>(0,74)  |                 |                 | 6,17<br>(0,36)  |                 |                  | 0,17<br>(0,06)  |                 |                 | 2,75<br>(0,12)  |                 |                 | 0,66<br>(0,74)  |                 |                 |
| <b>Volat_Diff</b> | 0,25<br>(0)     |                 |                 | -1,4<br>(0,5)   |                 |                 | 0,36<br>(0,34)  |                 |                  | 0,03<br>(0)     |                 |                 | 0,21<br>(0,16)  |                 |                 | 0,04<br>(0,85)  |                 |                 |
| <b>INF_Diff</b>   | -8,49<br>(0,38) | -8,34<br>(0,49) | -4,45<br>(0,66) | -2,36<br>(0,79) | -1,45<br>(0,87) | 0,64<br>(0,94)  | -184<br>(0,05)  | -193<br>(0,04)  | -178,5<br>(0,05) | -0,08<br>(0,97) | -0,4<br>(0,87)  | -1,22<br>(0,58) | 19,9<br>(0,33)  | 13,63<br>(0,47) | 16,03<br>(0,4)  | 40,76<br>(0,22) | 37,81<br>(0,26) | 36,1<br>(0,27)  |
| <b>IPI_Diff</b>   | 0,2<br>(0,84)   | 0,71<br>(0,56)  | 0,13<br>(0,9)   | 0,29<br>(0,83)  | 0,31<br>(0,82)  | -0,01<br>(1)    | -5,77<br>(0,75) | -6,57<br>(0,71) | -7,83<br>(0,66)  | -0,1<br>(0,16)  | -0,11<br>(0,12) | -0,07<br>(0,25) | -0,04<br>(0,98) | 0,98<br>(0,47)  | 0,35<br>(0,78)  | -0,22<br>(0,73) | -0,19<br>(0,77) | -0,23<br>(0,71) |
| <b>Loan_Diff</b>  | -2,02<br>(0,38) | -0,5<br>(0,86)  | 1,98<br>(0,39)  | -0,08<br>(0,93) | -0,14<br>(0,89) | 0,12<br>(0,9)   | 3,44<br>(0,79)  | 6,07<br>(0,65)  | 3,21<br>(0,8)    | -0,13<br>(0,22) | -0,19<br>(0,09) | -0,19<br>(0,06) | -1,65<br>(0,75) | -2,45<br>(0,63) | -2,39<br>(0,64) | 0,02<br>(0,99)  | 0,18<br>(0,91)  | 0,09<br>(0,95)  |
| <b>Unemp_Diff</b> | -0,12<br>(0,86) | -0,27<br>(0,75) | -0,2<br>(0,78)  | -6,57<br>(0,02) | -6,4<br>(0,02)  | -6,51<br>(0,02) | 3,99<br>(0,48)  | 4,98<br>(0,38)  | 3,8<br>(0,49)    | 0,03<br>(0,61)  | 0<br>(0,97)     | 0,01<br>(0,85)  | 2,16<br>(0,47)  | 1,25<br>(0,68)  | 2,42<br>(0,42)  | -0,31<br>(0,81) | -0,21<br>(0,87) | -0,27<br>(0,84) |
| <b>Adj R2</b>     | 0.42            | 0.09            | 0.35            | -0.01           | -0.01           | 0.00            | -0.03           | 0.00            | 0.00             | 0.23            | 0.18            | 0.33            | -0.11           | -0.06           | -0.08           | -0.08           | -0.10           | -0.10           |
| <b>no of obs</b>  | 41              | 41              | 41              | 41              | 41              | 41              | 41              | 41              | 41               | 41              | 41              | 41              | 41              | 41              | 41              | 41              | 41              | 41              |

*Num\_worker\_diff is the difference between monthly averages of raw number of workers (num\_workers) of OLI Worker Supplement Data.*  
*cur\_diff is the difference between monthly averages of the exchange rates of Local Currencies to the US Dollar.*  
*volat is the monthly Standard Deviation of the exchange rates of Local Currency to US Dollar*  
*volat\_diff is the month-on-month difference of volat.*  
*Inf\_diff: MoM differences of the CPI.*  
*Ipi\_diff: MoM differences in the Industrial Production Index.*  
*Loan\_diff: MoM differences of the average consumer loan rate.*  
*Unemp\_diff: MoM differences of the official unemployment rate (total workforce).*

Regressions (16), (17), and (18) on South Africa, the third country with the highest local currency devaluation in this study, do not present a statistically significant relationship between online labor supply and exchange rate volatility. Neither does it present any meaningful relationship with other macroeconomic variables. Regressions (13), (14), and (15) for Brazil also do not present statistically significant results for all of the regression models.

Interestingly, even though there are statistically significant results between exchange rate volatility and worker supply in two countries, such a relationship is absent for control variables. Considering the strong relationship between exchange rate volatility and inflation in developing countries, the relationship between inflation and the worker supply in the online marketplaces should also produce statistically significant results, however, this is not the case for Argentina and Colombia, or any other country except Russia in our dataset. Unexpectedly, the results for Regressions (7), (8), and (9) for Russia show a negative relationship between inflation and online worker supply.

Similarly, the relationship between online worker supply and unemployment rates are also is not statistically significant, except for Regressions (4), (5), and (6) for Turkey. The negative regression coefficients for regressions (4), (5), and (6) are at odds with expected results from this variable. Unlike the results shown by Huang et al.<sup>42</sup>, our regressions do not show a statistically significant relationship between online worker supply and differences in the local unemployment rates.

The next sets of regressions represented in Table 6.2., were based on proportional worker data, the number of workers per country divided by the total sum of the number of workers. This was done to reduce the effects of sampling and weighing of the `num_workers` data to give a more accurate representation of the sizes of platforms.

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<sup>42</sup> Ni Huang et al., "Unemployment and Worker Participation in the Gig Economy: Evidence from an Online Labor Platform," *SSRN Electronic Journal*, January 18, 2017

Regressions (1), (2), and (3) still show a positively correlated relationship between exchange rate volatility and the proportional number of workers for Argentina, with Regressions (1) and (3) being statistically significant at 5%, and Regression (2) being significant at 10% level. However, regressions (10) and (11) for Colombia no longer present a statistically significant relationship (with no significance in either 1%, 5%, or 10% levels) between exchange rate volatility and online worker supply. Regression (12) for Colombia, using the *volat\_diff* measure of volatility is statistically significant at a 10% significance level though. P values for regressions (4), (5), and (6) for Turkey have improved, although the negative regression coefficients suggest an inversely related relationship between volatility and online worker supply, which is at odds with the initial hypothesis of this study.

Different from the first set of regressions using raw worker data, using proportional worker data does give us statistically significant results at 1% significance levels for Regressions (1), (2), and (3) for Argentina for the *inf\_diff* variable. It is important to note that, the regression coefficients are negative, showing an inverse relationship between inflation and the worker supply in the online marketplaces.



**Table 6.2. Regression on Proportional Number of Workers**

| Model             | Argentina       |                 |                 | Turkey          |                 |                 | Russia         |                 |                 | Colombia        |                 |                 | Brazil          |                 |                 | South Africa    |                 |                 |
|-------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|                   | 1               | 2               | 3               | 4               | 5               | 6               | 7              | 8               | 9               | 10              | 11              | 12              | 13              | 14              | 15              | 16              | 17              | 18              |
| <b>Volat</b>      | 10,07<br>(0,05) |                 |                 | -3,94<br>(0,17) |                 |                 | 7,9<br>(0,76)  |                 |                 | 23,8<br>(0,29)  |                 |                 | 3,43<br>(0,61)  |                 |                 | -2,9<br>(0,85)  |                 |                 |
| <b>Cur_Diff</b>   | 1,12<br>(0,13)  |                 |                 | -0,02<br>(0,26) |                 |                 | 2,58<br>(0,39) |                 |                 | -1,39<br>(0,34) |                 |                 | 0,41<br>(0,58)  |                 |                 | -0,17<br>(0,83) |                 |                 |
| <b>Volat_Diff</b> | 0,05<br>(0,06)  |                 |                 | -0,91<br>(0,04) |                 |                 | 0,18<br>(0,28) |                 |                 | 0,32<br>(0,07)  |                 |                 | 0,04<br>(0,57)  |                 |                 | -0,04<br>(0,65) |                 |                 |
| <b>INF_Diff</b>   | -13,5<br>(0,01) | -13,7<br>(0,01) | -12,7<br>(0,01) | 0,97<br>(0,61)  | 0,16<br>(0,93)  | 1,9<br>(0,33)   | -42,5<br>(0,3) | -46,4<br>(0,25) | -40,1<br>(0,31) | -0,55<br>(0,99) | -7,26<br>(0,85) | -9,71<br>(0,79) | -6,63<br>(0,44) | -8,03<br>(0,32) | -7,6<br>(0,35)  | -12,3<br>(0,36) | -12,2<br>(0,36) | -11,9<br>(0,36) |
| <b>IPI_Diff</b>   | -0,48<br>(0,33) | -0,37<br>(0,47) | -0,5<br>(0,32)  | -0,4<br>(0,18)  | -0,41<br>(0,18) | -0,55<br>(0,07) | 3,82<br>(0,63) | 3,49<br>(0,66)  | 2,84<br>(0,72)  | 0,72<br>(0,52)  | 0,61<br>(0,58)  | 0,94<br>(0,39)  | -0,3<br>(0,59)  | -0,13<br>(0,82) | -0,22<br>(0,68) | 0,02<br>(0,95)  | 0,01<br>(0,98)  | 0,02<br>(0,93)  |
| <b>Loan_Diff</b>  | 1,39<br>(0,25)  | 1,55<br>(0,21)  | 2,14<br>(0,06)  | 0,25<br>(0,23)  | 0,28<br>(0,2)   | 0,32<br>(0,13)  | 2,94<br>(0,61) | 4,03<br>(0,49)  | 2,88<br>(0,61)  | -0,09<br>(0,96) | -0,09<br>(0,96) | -0,55<br>(0,74) | 2,63<br>(0,24)  | 2,42<br>(0,27)  | 2,44<br>(0,26)  | -0,18<br>(0,77) | -0,2<br>(0,74)  | -0,17<br>(0,78) |
| <b>Unemp_Diff</b> | -0,25<br>(0,47) | -0,29<br>(0,42) | -0,27<br>(0,44) | -0,14<br>(0,8)  | -0,3<br>(0,6)   | -0,32<br>(0,56) | 2,86<br>(0,25) | 3,28<br>(0,19)  | 2,78<br>(0,26)  | 0,25<br>(0,77)  | 0,34<br>(0,7)   | 0,11<br>(0,9)   | -1,65<br>(0,2)  | -1,77<br>(0,18) | -1,6<br>(0,21)  | 0,41<br>(0,44)  | 0,39<br>(0,46)  | 0,41<br>(0,44)  |
| <b>Adj R2</b>     | 0.20            | 0.16            | 0.19            | 0.04            | 0.02            | 0.10            | -0.11          | -0.08           | -0.07           | -0.15           | -0.16           | -0.08           | 0.05            | 0.05            | 0.05            | -0.11           | -0.11           | -0.11           |
| <b>no of obs</b>  | 41              | 41              | 41              | 41              | 41              | 41              | 41             | 41              | 41              | 41              | 41              | 41              | 41              | 41              | 41              | 41              | 41              | 41              |

*Proportional\_to\_all\_diff* is the monthly difference between the proportion of country-specific num\_worker data to the sum of num\_worker.

*cur\_diff* is the difference between monthly averages of the exchange rates of Local Currencies to the US Dollar.

*volat* is the monthly Standard Deviation of the exchange rates of Local Currency to US Dollar

*volat\_diff* is the month-on-month difference of volat.

*Inf\_diff*: MoM differences of the CPI.

*Ipi\_diff*: MoM differences in the Industrial Production Index.

*Loan\_diff*: MoM differences of the average consumer loan rate.

*Unemp\_diff*: MoM differences of the official unemployment rate (total workforce).

Using proportional values instead of the original number of workers in the OLI's Worker Supplement dataset does not increase the explanatory power of our regressions, as was expected. Since the OLI worker supplement was sampled and weighted to account for the differences in the sizes of platforms in terms of worker supply, using proportional data was suggested by the creators of the Online Labor Index. As such, using proportional worker data was expected to give more statistically significant results, yet changing the dependent variable resulted in less significant results than the raw (raw refers to original OLI worker supplement data, not that it's not sampled and weighed) worker data.

As for the measures of volatility, on almost all the regression models, the third measure, *volat\_diff* (month-on-month difference of standard deviation of exchange rates) fits the model better in comparison to other measures of *volat* and *cur\_diff*. Since the *volat* and *volat\_diff* variables are derived by calculating the standard deviation of the *cur\_diff* variable, statistically significant results do not contradict each other (for most variables – some control variables did produce different results for each measure of volatility) when different measures of volatility are concerned.

As for regressions using lagged variables in Table 6.3. and Table 6.4., which were designed to account for workers reacting to currency shocks later, the results were not statistically significant as well. As with the first models, these regressions were first run using the *num\_worker\_diff* as the dependent variable with 3 measures of exchange rate volatility, and then they were run for a second time using the *proportional\_num\_worker\_diff* as the dependent variable.

**Table 6.3. Regressions on Raw Worker Numbers - Lagged**

| Model             | Argentina       |                 |                 | Turkey          |                 |                 | Russia           |                  |                  | Colombia        |                 |                 | Brazil          |                 |                 | South Africa    |                |                |
|-------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|------------------|------------------|------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|----------------|----------------|
|                   | 1               | 2               | 3               | 4               | 5               | 6               | 7                | 8                | 9                | 10              | 11              | 12              | 13              | 14              | 15              | 16              | 17             | 18             |
| <b>Volat</b>      | 53,44<br>(0)    |                 |                 | -7,14<br>(0,59) |                 |                 | -14,22<br>(0,81) |                  |                  | 1,01<br>(0,39)  |                 |                 | 6,57<br>(0,69)  |                 |                 | -49,09<br>(0,2) |                |                |
| <b>Cur_Diff</b>   | -0,58<br>(0,75) |                 |                 | -0,09<br>(0,34) |                 |                 | -4,91<br>(0,47)  |                  |                  | -0,04<br>(0,61) |                 |                 | -0,98<br>(0,58) |                 |                 | -1,56<br>(0,45) |                |                |
| <b>Volat_Diff</b> | -0,08<br>(0,22) |                 |                 | -0,63<br>(0,77) |                 |                 | -0,41<br>(0,29)  |                  |                  | -0,01<br>(0,18) |                 |                 | -0,07<br>(0,62) |                 |                 | -0,25<br>(0,3)  |                |                |
| <b>INF_Diff</b>   | -8,49<br>(0,38) | -2,33<br>(0,85) | -2,2<br>(0,86)  | -7,1<br>(0,43)  | -8,98<br>(0,3)  | -7,13<br>(0,45) | -151,4<br>(0,1)  | -143,8<br>(0,12) | -155,6<br>(0,09) | -2,6<br>(0,21)  | -2,86<br>(0,17) | -2,6<br>(0,2)   | -5,11<br>(0,8)  | -8,44<br>(0,66) | -9,29<br>(0,63) | 0,72<br>(0,98)  | 5,79<br>(0,86) | 9,43<br>(0,78) |
| <b>IPI_Diff</b>   | 0,2<br>(0,84)   | -0,77<br>(0,54) | -0,68<br>(0,58) | 0,44<br>(0,75)  | 0,35<br>(0,8)   | 0,38<br>(0,8)   | 5,58<br>(0,76)   | 6,2<br>(0,73)    | 7,66<br>(0,67)   | -0,09<br>(0,12) | -0,1<br>(0,1)   | -0,11<br>(0,06) | -0,28<br>(0,84) | -0,45<br>(0,75) | -0,22<br>(0,86) | 0,2<br>(0,75)   | 0,13<br>(0,84) | 0,25<br>(0,69) |
| <b>Loan_Diff</b>  | -2,02<br>(0,38) | 4,08<br>(0,18)  | 3,85<br>(0,17)  | 0,92<br>(0,35)  | 1,13<br>(0,26)  | 0,93<br>(0,36)  | 3,57<br>(0,79)   | 1,45<br>(0,91)   | 3,56<br>(0,78)   | -0,05<br>(0,58) | -0,05<br>(0,56) | -0,05<br>(0,57) | 2,56<br>(0,63)  | 1,84<br>(0,72)  | 1,82<br>(0,73)  | 0,59<br>(0,7)   | 0,26<br>(0,87) | 0,52<br>(0,74) |
| <b>Unemp_Diff</b> | -0,12<br>(0,86) | -0,42<br>(0,64) | -0,41<br>(0,64) | -4,24<br>(0,12) | -4,58<br>(0,09) | -4,51<br>(0,1)  | -2,74<br>(0,63)  | -3,53<br>(0,54)  | -2,56<br>(0,64)  | 0,15<br>(0)     | 0,15<br>(0)     | 0,15<br>(0)     | 1,02<br>(0,74)  | 1,49<br>(0,63)  | 1,08<br>(0,72)  | 0,24<br>(0,86)  | 0,02<br>(0,99) | 0,16<br>(0,91) |
| <b>Adj R2</b>     | 0.42            | -0.01           | 0.04            | -0.06           | -0.04           | -0.07           | -0.03            | -0.02            | 0.00             | 0.41            | 0.40            | 0.43            | -0.14           | -0.14           | -0.14           | -0.13           | -0.17          | -0.15          |
| <b>no of obs</b>  | 41              | 41              | 41              | 41              | 41              | 41              | 41               | 41               | 41               | 41              | 41              | 41              | 41              | 41              | 41              | 41              | 41             | 41             |

*Num\_worker\_diff* is the difference between monthly averages of raw number of workers (*num\_workers*) of OLI Worker Supplement Data.

*cur\_diff* is the difference between monthly averages of the exchange rates of Local Currencies to the US Dollar.

*volat* is the monthly Standard Deviation of the exchange rates of Local Currency to US Dollar

*volat\_diff* is the month-on-month difference of *volat*.

*Inf\_diff*: MoM differences of the CPI.

*Ipi\_diff*: MoM differences in the Industrial Production Index.

*Loan\_diff*: MoM differences of the average consumer loan rate.

*Unemp\_diff*: MoM differences of the official unemployment rate (total workforce).

**Table 6.4. Regression on Proportional Number of Workers – Lagged**

| <i>Model</i>      | Argentina       |                 |                 | Turkey          |                 |                 | Russia               |                 |                 | Colombia             |                 |                 | Brazil          |                 |                 | South Africa    |                 |                 |
|-------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|----------------------|-----------------|-----------------|----------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|                   | 1               | 2               | 3               | 4               | 5               | 6               | 7                    | 8               | 9               | 10                   | 11              | 12              | 13              | 14              | 15              | 16              | 17              | 18              |
| <b>Volat</b>      | -5,48<br>(0,31) |                 |                 | -2,49<br>(0,38) |                 |                 | -<br>18,21<br>(0,48) |                 |                 | -<br>13,91<br>(0,54) |                 |                 | 9,87<br>(0,15)  |                 |                 | 14,45<br>(0,32) |                 |                 |
| <b>Cur_Diff</b>   | -0,7<br>(0,38)  |                 |                 | -0,01<br>(0,68) |                 |                 | -2,44<br>(0,42)      |                 |                 | -0,18<br>(0,9)       |                 |                 | -1,2<br>(0,11)  |                 |                 | -0,84<br>(0,29) |                 |                 |
| <b>Volat_Diff</b> | 0<br>(0,87)     |                 |                 | -0,74<br>(0,1)  |                 |                 | -0,21<br>(0,22)      |                 |                 | -0,26<br>(0,14)      |                 |                 | 0,01<br>(0,82)  |                 |                 | 0,1<br>(0,26)   |                 |                 |
| <b>INF_Diff</b>   | 9,05<br>(0,1)   | 9,32<br>(0,09)  | 8,37<br>(0,13)  | -2,68<br>(0,17) | -3,13<br>(0,11) | -1,82<br>(0,36) | -8,94<br>(0,83)      | -8,45<br>(0,83) | -14,3<br>(0,71) | 18,29<br>(0,64)      | 20,55<br>(0,6)  | 24,78<br>(0,51) | 9,17<br>(0,29)  | 4,27<br>(0,59)  | 4,93<br>(0,56)  | -10,1<br>(0,43) | -15,2<br>(0,24) | -12,6<br>(0,32) |
| <b>IPI_Diff</b>   | -0,44<br>(0,41) | -0,51<br>(0,35) | -0,44<br>(0,42) | -0,03<br>(0,92) | -0,02<br>(0,94) | -0,15<br>(0,62) | 3,71<br>(0,65)       | 4,4<br>(0,58)   | 5,15<br>(0,52)  | -0,03<br>(0,98)      | 0,03<br>(0,98)  | -0,23<br>(0,83) | -0,57<br>(0,31) | -0,75<br>(0,2)  | -0,41<br>(0,47) | 0,07<br>(0,76)  | 0,02<br>(0,95)  | 0,06<br>(0,82)  |
| <b>Loan_Diff</b>  | -1,1<br>(0,4)   | -1,14<br>(0,38) | -1,53<br>(0,22) | -0,05<br>(0,83) | -0,04<br>(0,84) | 0,02<br>(0,93)  | -3,64<br>(0,53)      | -4,26<br>(0,48) | -3,22<br>(0,57) | -0,57<br>(0,74)      | -0,41<br>(0,81) | -0,24<br>(0,88) | -0,32<br>(0,89) | -1,35<br>(0,53) | -1,09<br>(0,63) | -0,95<br>(0,12) | -0,97<br>(0,11) | -0,94<br>(0,12) |
| <b>Unemp_Diff</b> | -0,05<br>(0,9)  | -0,02<br>(0,95) | -0,05<br>(0,9)  | -0,42<br>(0,47) | -0,51<br>(0,38) | -0,53<br>(0,34) | -0,4<br>(0,87)       | -0,74<br>(0,77) | -0,26<br>(0,92) | -0,17<br>(0,84)      | -0,12<br>(0,89) | -0,07<br>(0,94) | 0,74<br>(0,56)  | 1,33<br>(0,31)  | 0,86<br>(0,51)  | 0,21<br>(0,67)  | 0,18<br>(0,72)  | 0,24<br>(0,64)  |
| <b>Adj R2</b>     | 0.06            | 0.05            | 0.03            | 0.00            | -0.01           | 0.06            | -0.12                | -0.12           | -0.09           | -0.16                | -0.17           | -0.10           | 0.04            | 0.05            | -0.02           | -0.05           | -0.05           | -0.04           |
| <b>no of obs</b>  | 41              | 41              | 41              | 41              | 41              | 41              | 41                   | 41              | 41              | 41                   | 41              | 41              | 41              | 41              | 41              | 41              | 41              | 41              |

*Proportional\_to\_all\_diff* is the monthly difference between the proportion of country-specific num\_worker data to the sum of num\_worker. *cur\_diff* is the difference between monthly averages of the exchange rates of Local Currencies to the US Dollar.

*volat* is the monthly Standard Deviation of the exchange rates of Local Currency to US Dollar

*volat\_diff* is the month-on-month difference of *volat*.

*Inf\_diff*: MoM differences of the CPI.

*Ipi\_diff*: MoM differences in the Industrial Production Index.

*Loan\_diff*: MoM differences of the average consumer loan rate.

*Unemp\_diff*: MoM differences of the official unemployment rate (total workforce).

Considering the experimental nature of the data and this study, different regression models are used to reach statistically significant results between exchange rate volatility and worker supply in online marketplaces. These different regression models include 2 sets of dependent variables, 3 measures of exchange rate volatility which are the independent variable, 4 macroeconomic indicators that are used as control variables, and lagging the dependent variable behind the independent variable for a month to check if the workers are reacting to exchange rate shocks later than they occur since it takes workers some time to land their first job.

Apart from some exceptions (Argentina as an example), the results do not show a statistically significant relationship between exchange rate volatility the supply of workers in the online gig economy. Upon further inspection, statistically significant results for regressions based on Argentina appears to be coincidental and they are caused by a single month, August 2019 to be specific. Kässi & Lehdonvirta have changed parameters of data collection in August 2019, causing a spike in the difference between the number of workers in that month (for reference, the number of workers from Argentina rose 329% and the number of workers from Russia rose 836% according to OLI Worker Supplement data). Coincidentally, in August 2019 Argentine Peso suffered its greatest losses against the US Dollar, with Argentine Peso plunging more than 30% after the election of Alberto Fernandez, running mate of the former president Christina Fernandez de Kirchner<sup>43</sup>. We believe this is coincidental because the spike in the number of workers occurred in other countries as well (Brazil's workers rose 93.8%, India's workers rose by 35%, United States' workers rose 22%, etc.). Also, since Argentina supplied a small number of workers to the online gig economy, any change in the collector parameters results in a big difference in the month-on-month number of workers. Because of the low number of observations available in the data, the regressions did not produce statistically significant results.

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<sup>43</sup> "Argentine Peso Collapses as Macri's Re-Election Chances Drop (Published 2019)," The New York Times (The New York Times, August 12, 2019)

## **7. OPPORTUNITIES FOR FURTHER RESEARCH**

The primary obstacle for this research (and all empirical studies surrounding the gig economy as a whole) is the availability of reliable data on the size of the gig economy. This problem is especially evident when looking at the body of literature on the state of the gig economy in the developing world. Conducting empirical studies on the gig economy is already a challenging task, however, these difficulties are exacerbated when developing countries are concerned, because of the lack of data. It is perhaps because of this reason that researchers focusing on how developing economies are affected by this new phenomenon such as Heeks, Graham, Lehdonvirta, Hjorth, Anwar, and many others have relied on survey data on their studies before. Therefore, there was limited access to the amount of available data for this study. Kässä & Lehdonvirta's data on the online gig economy is an exception to this situation.

The Online Labor Index is still the most comprehensive data regarding the size of the online gig economy and its top clients. Similarly, the Worker Supplement data of the Online Labor Index is also the most comprehensive data regarding the origin of the labor supply of the online gig platforms in general. Kässä & Lehdonvirta's data can show meaningful results in determining each countries' share of the online workforce in major platforms and also the share of countries' workers in specific classifications of online gig work, as the data was designed for these kinds of results in the first place. However, as previously mentioned in the limitations of the data section, the experimental nature of the worker supplement data may not show a clear relationship between exchange rate volatility (along with other macroeconomic indicators) and the worker supply in the online marketplaces. Moreover, the worker data itself is not presented as-is, but rather it is sampled and weighted in order to account for the different sizes of the platforms where the data was gathered. The Worker Supplement data was not created in order to get an accurate measurement of the size of the worker supply in these online marketplaces, but rather for seeing the origins where workers were supplied from. Kässä & Lehdonvirta were already able to see the approximate size

of the online gig economy thanks to Online Labor Index data, focusing on the demand side of the online gig economy. As such, although the worker supplement data used in this study was useful for its original intended purpose, it was not suitable for an empirical analysis of the effects of various macroeconomic variables on the supply of workforce in the online marketplaces.

This does not mean there aren't opportunities for further study regarding the effects of the local economic factors in developing countries and the workers' willingness to supply their labor in online marketplaces. A more accurate for this study could have been achieved by focusing on the number of earnings received by workers over time through these platforms, instead of calculating the number of active workers on these platforms. Focusing on earnings has numerous advantages as opposed to focusing on the supply of workers. Firstly, most online marketplaces share information about the freelancer's nationality, gender, level of education, and origin country readily available through their websites. This data is available because clients need access to this kind of information to make a final decision on choosing who are they going to work with. Although some marketplaces offer the option of hiding the level of income to workers, most workers opt out of hiding their income earned from the platform. This is because the amount of income is an important factor affecting the decisions of clients. If they see that a worker has never landed a job before, or they have earned less than a certain amount on the platform, they assume that the worker is new to the platform and ergo to the type of work. Clients can use this to their advantage by offering lower rates to the worker since clients are also aware of the importance of 5-star ratings given by previous clients for workers. They might also decide not to work with the worker altogether, instead of going with a more experienced freelancer.

Figure 7.1 – An Example Profile from Freelancer.com

The screenshot displays the profile of Anshikha K. on Freelancer.com. At the top, her name is followed by a 4.9 star rating from 540 reviews. Navigation tabs include 'About Me', 'Portfolio Items', and 'Reviews' (which is selected). A 'Hire Me' button is visible in the top right. The main content area is titled 'Reviews' and shows three reviews. The first review is from 'ashutoshkumar28' for a job worth \$200.00 USD, with a 5.0 star rating and the title 'Social media manager'. The second review is from 'Jungman A. @jungmanahn' for a job worth \$135.00 USD, with a 5.0 star rating and the title 'i need help with google ads and bing for my websit'. The third review is from 'Sam L. @sam4505089' for a job worth \$220.00 USD, with a 5.0 star rating. On the right side, there are tags for 'Internet Marketing', 'Facebook Marketing', 'Google Adwords', and 'SEO', along with navigation for 'Previous User' and 'Next User'.

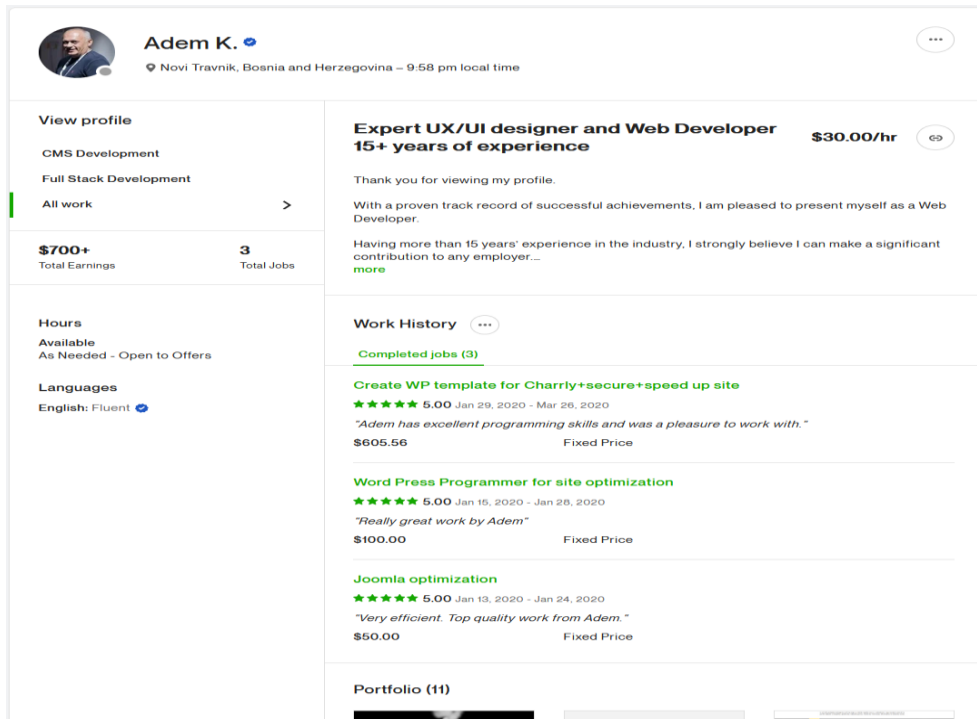
*Freelancer.com, May 2021.*

The total amount of earnings is not the only variable available on a freelancer's profile. Data regarding how many jobs have been completed, when they have been completed and the total cost of the job can only be ascertained through the profiles of workers. This information is useful to calculate the monthly earnings of freelancers and calculating averages for these earnings by country or by the occupation classification devised by Kässi & Lehdonvirta. Conducting an empirical study using monthly average earnings of Indian workers (or Indian workers in Software & Development), as an example, will provide more accurate results because the earnings data will not be sampled and weighed. Another advantage is that this data is not derived from any other data source, it is retrieved directly from the source. None of these online marketplaces openly share the number of active workers with the outside world. Whereas freelancers'



profile pages can be accessed with relative ease without creating an account on these platforms.

**Figure 7.2 – Example of a Profile on Upwork**



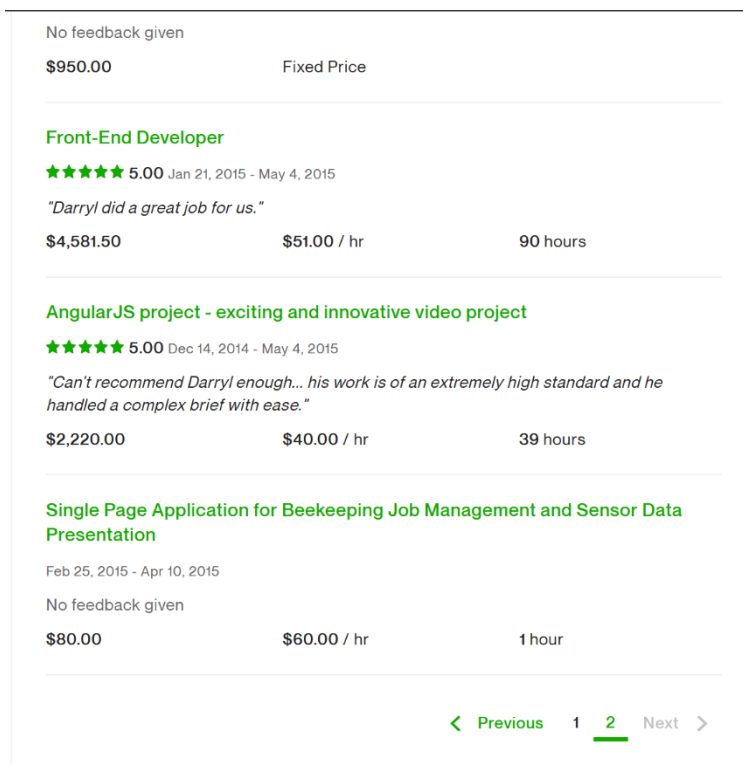
*Upwork, May 2021*

Another advantage of using data comes from the reduction of the amount of time spent in scraping the data from these online marketplaces. One limitation of using the OLI data was the fact that the data collection began in May 2016. Upwork (then known as “Elance”) was founded in 1999, and Freelancer.com was founded in 2009. PeoplePerHour was founded in 2007. One of the limitations of this study was the lack of data, the regressions were made with only 41 observations which was the main factor that led to them being unreliable. In the case of scraping the platforms for the earning data, only one scrape would be necessary. Since the worker’s profile has all the work they have completed with dates and payment amounts (unless the worker opted to hide

them, but as mentioned this is rarely done), periodic scraping is not necessary. A comprehensive scrape of one or more platforms would be enough to access data that goes back many years.

Therefore, using earnings data would also overcome one of the main limitations of this study, which is the lack of available data. It would also make the data collection process smoother. One other aspect of OLI Worker Supplement data was the fact the changing

**Figure 7.3 – Total Earnings of a Freelancer**



*Upwork, May 2021*

parameters of data collection. As data collection parameters changed (maybe new platforms were added into the mix, or a different tool was used to scrape the data. This aspect is only available for the creators of the OLI themselves), the number of workers changed drastically. At times, these changes occurred in a day. A countries' number of active workers could suddenly double between two crawls because parameters have

changed. Doing a comprehensive data scrape once on these online marketplaces could also prevent these issues from happening, as an added bonus.

Using earnings data as the basis of analysis can be prone to some issues as well. The main issue would be the fact although platforms like Upwork, Freelancer, and PeoplePerHour share the earnings data on a worker's profile page, not all platforms follow suit. This is especially true for intermediary platforms for micro work, such as Amazon Mechanical Turk. These platforms require lower-skilled work such as filling in surveys and questionnaires. Because of this reason, there is no interaction between the client and the worker. Since a survey is filled by hundreds of workers for earnings as little as \$0.01, client-worker interaction is not necessary. A client does not have to review every worker who is filling out their survey, they only need the worker to fit in some basic criteria (between ages 25-50, working full time, living in the US, etc.). Using earnings data would completely exclude the microwork aspect of the online gig economy, but rather focusing on the more professional side of it – the freelancer side. This may not pose a big problem, however. Micro-tasking is only a small aspect of the online gig economy. Micro tasking is also a way to earn supplemental income, not as a full-time job. Considering this information, the exclusion of micro-tasking platforms by using earnings data may be more beneficial in empirical analysis.

## **8. CONCLUSION**

The gig economy is a new phenomenon and because of this, neither scholars nor the general public has not grasped the full implications of this innovation. The discussion regarding the gig economy has mainly covered the social and legal aspects of the gig economy in the developed nations. It has also focused on the physical part of the gig economy, that is, location-based gig economy such as ridesharing, delivery, and so on. While these issues also deserve the spotlight, the wider implications of the online gig economy, such as the ease of outsourcing labor to the developing world which is a direct result of the online gig economy have not been given the necessary attention. Empirical studies on the effects of the gig economy have been few and far between,

empirical studies on these effects in the emerging economies have been even fewer. The lack of empirical studies on factors affecting the online gig economy stems from the lack of available data. As mentioned before, traditional assessments of employment are not effective in measuring the size of the gig economy and how it is changing over time, due to a variety of factors<sup>44</sup>.

This study aimed to investigate the main factors affecting the worker supply from developing countries, focusing primarily on the exchange rate volatility's effect. Exchange rate volatility was chosen specifically to test if volatility (or, in other words, weakening local currency) pushes workers to the online gig economy for more stable sources of income. And also did it make workers of these countries more attractive to clients in the developed world, since their labor had gotten cheaper. To test these hypotheses, experimental data from Kässä & Lehdonvirta's Online Labor Index was used as a basis for the worker supply from 6 countries (Argentina, Turkey, Colombia, Brazil, Russia, and South Africa) that had experienced currency shocks in the last 3 years. Additionally, as control variables, other macroeconomic variables were used in the analysis to test for how each macroeconomic factor affects the worker supply to online marketplaces from these 6 countries.

Taking into consideration the experimental nature of the data, many possible variations of both the dependent and the independent variables were used in order to reach a clear result. Three measures of volatility and two measures of worker supply data were used and regressions were run separately to test the hypothesis. The dependent variable was also run lagged, as the effects of exchange change shocks may not result in an increase in the number of active workers in the same month (as discussed before, a worker landing his/her first job on these online marketplaces can take some time). Alas, regardless of how the data was used, the results were inconclusive. Although models

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<sup>44</sup> Abraham et. al, 2018.

ran on some countries showed promising results (such as Argentina), the overall weak explanatory power has made those results inconclusive as well.

Some key findings can still be gathered from these results. According to the demand data of the OLI, the online gig economy has been growing since May 2016. It is also apparent that the COVID-19 pandemic has accelerated the growth of this new economy rapidly, since January 2020. The main client and worker countries have also not changed dramatically since May 2016, in fact, the share of workers from both US and the UK have declined since 2017, and India, Pakistan, and Bangladesh's share of workers have increased in the online gig economy. The share of client countries remains unchanged, developed economies (and also India) the biggest purchasers of online gig work<sup>45</sup>. This clearly shows that outsourcing through online gig work has accelerated with the COVID-19 pandemic and the factors that are affecting this phenomenon still remain unknown. Although OLI and its Worker Supplement data achieve their intended purpose, they were not suitable for an empirical analysis of macroeconomic factors affecting the growth in the online labor force in developing nations.

Since this was a pioneering study using experimental data, reaching inconclusive results should not be of surprise. An alternative for further study on this topic is to formulate a new set of data specifically for the purpose of analyzing exchange rate volatility and other macroeconomic variables' effects on worker participation from developing economies in the online gig economy. Both OLI and its worker supplement were purpose-built data – Online Labor Index was created to measure the size of the online gig economy as a whole and to identify the client, or buyer countries funding this economy. Worker supplement, on the other hand, was collected to analyze countries' share of supplying the online workforce, and the share of specific occupations in online gig work. Similarly, a new dataset needs to be constructed with

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<sup>45</sup> Otto Kässi and Vili Lehdonvirta, "The Online Labour Index," The iLabour Project (Oxford Internet Institute), accessed May 20, 2021, <https://ilabour.oii.ox.ac.uk/online-labour-index/>

the purpose of analyzing the factors that drive workers in developing economies to supply their labor in these marketplaces. For the basis of this new dataset, earnings data on freelancer's profile pages is proposed. This data is readily available in major freelance platforms, showing how much a freelancer was paid per project. The earnings data will also not be subjected to some of the limitations of the OLI, such as historic data as a freelancer's profile page will show all of their finished projects since they have joined the platform.

This study shows that the biggest roadblock regarding research of the gig economy is still the availability of reliable data. Even though the platforms are neither the clients nor the workers, they are the most important actors in this new innovative economy. As main actors, only they have the necessary data to further our understanding of the gig economy. Understandably, these platforms are reluctant to share vital data for research purposes. One thing is certain: The gig economy (both physical and digital sectors of it) is growing rapidly and it will become a larger part of "work" globally. Sooner or later, more reliable methods of measuring its size and economic impact will be discovered. Until these methods are discovered, further empirical research on the economic implications of this new way of working will be limited.

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## APPENDICES

### Appendix A: Detailed Explanation of Each Variable

#### Independent Variables

**cur\_diff:** For this variable of exchange rate volatility, daily exchange rates of local currencies to the US Dollar is obtained. Monthly averages are calculated from these daily values. Finally, month-on-month differences between these averages are calculated.

**volat:** Monthly standard deviation of the daily exchange rates of local currencies to the US Dollar.

**volat\_diff:** Month-on-month difference between the monthly standard deviation of daily exchange rates of local currencies to the US Dollar.

#### Dependent Variables

**num\_worker\_diff:** Month-on-month differences of the monthly averages of daily num\_worker numbers for each country in the Worker Supplement of the Online Labour Index by Kässä & Lehdonvirta. This can be considered as the "raw" variable, as opposed to proportional number of workers variable.

**proportional\_to\_all\_diff:** Monthly average of daily num\_workers data per each country divided by the monthly average of daily num\_worker data for all countries in total. Since num\_workers data is sampled and weighted to account for differences in platforms sizes, founders of the Online Labour Index have suggested to use this method to help alleviate the effects of sampling and weighting.

#### Control Variables

**INF\_diff:** Month-on-month differences of Consumer Price Index for each country.

**IPI\_diff:** Month-on-month differences in the Industrial Production Index. This is used as a substitute to GDP growth, since GDP growth is not reported monthly.

**Loan\_diff:** Month-on-month differences between the average consumer loan rate for each country. Data is obtained from central bank from each country.

**Unemp\_diff:** Month-on-month differences between the unemployment rate. For countries that report unemployment quarterly, the quarterly result is repeated over the next two months.