Impact of Social Networks on Supply Shaping for Gig Economy Workers using Multi-Sided Platforms

ABSTRACT

The attributes of the social networks among gig workers in technology-driven commercial enterprises of a gig economy determin­e their supply and productivity. A chief objective in such enterprises is to efficiently manage supply shaping, i.e., how to manage the supply to match the spatio-temporal variability of the market demand. The complexity of this task increases when the social interactions between various social entities occur through multi-sided platforms, wherein two or more participant groups are connected by a single technology platform. The present work examines the literature on the social networks among gig workers using multi-sided platforms and their impact on supply shaping. We also identify research gaps that can be the basis for future work.

Our review focuses on the literature at the intersection of 4 dimensions or components, namely, gig workers, multi-sided platforms, social networks, and supply shaping. The health of gig workers including mental health, social interaction patterns among gig workers, their distribution across various sectors of the economy, supply of gig workers, the impact of the recent pandemic on the gig economy, technology drivers behind multi-sided platforms, etc. are a few important aspects that are covered in this review. A wide range of gig economy workers including ride-sharing app drivers, book authors and food delivery apps, etc. from firms such as Uber, Lyft, Amazon mechanical Turk, etc. is explored in our review.

1. INTRODUCTION

This work presents a review of the impact of social networks (SN) on the supply shaping of gig workers, especially where multi-sided platforms (MSP) are used. A gig economy, as is well known, is a free-market system wherein independent, part-time workers, called gig workers, are hired for typically short-term assignments. This economy, in recent times, has become more productive, leading to cost and time reduction. It also is growing more sophisticated today because of the digital technology-based applications that drive businesses. A social network is a structure that facilitates social interactions between various social entities. Social network analysis attempts to study the features of a social network, such as its local and global patterns, factors that influence such patterns and its spatio-temporal or dynamic behavior and is essentially interdisciplinary in nature.

Human relations matter in the workplace. This has long been documented by researchers in sociology (Roy 1952, Granovetter 1973) and organizational behavior (Williams et al. 1998). More recently, this has also been corroborated by experimental evidence in economics (see Fehr et al. 2000 for a review). Social networks impact a range of individual economic outcomes, such as soliciting job offers (Granovetter 1973), obtaining promotions (Castilla 2011), and negotiating wages (Lazear 2018, Lazear and Rosen 1979). Social preferences also impact individuals’ responses to opportunities and incentives. For instance, individuals often exhibit a strong preference for fairness in the workplace and are also concerned about the impact of their actions on their colleagues (Ashraf and Bandiera 2018). In short, extant research evidence suggests that workers rarely behave as entirely rational individuals who only consider their own economic well-being. Instead, their behavior is significantly impacted by social concerns. Prior work identifies two core mechanisms to explain this “non-rational” behavior: information exchange and homophily. Information exchange refers to the tendency of connected individuals to share information regarding opportunities in their environment and the best ways to capitalize on them. Homophily refers to the tendency of similar workers to connect, help each other out and enjoy each other’s company as a form of non-pecuniary benefit. When a social network is supported by digital technology that connects two or more participant groups, it is called a multi-sided platform (MSP). A key task of social network analysis is to estimate how various factors impact supply shaping, i.e., how they influence supply cost-effectively to match the demand in the marketplace.

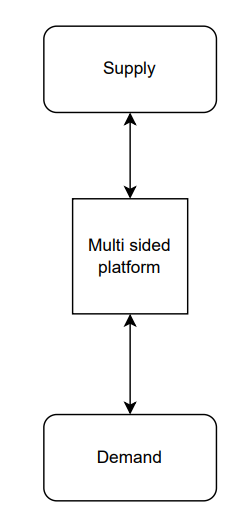


Fig 1-Multi sided platform

As an example, mobility provider companies, such as Grab, Uber, Lyft, etc., that allow customers to book transport by car with a driver have all the attributes described above. It employs drivers, who are gig workers; uses digital technology in the form of an app as well as an online booking platform, brings down the cost and time of transportation, and connects the company with the customers, drivers, and also vehicle owners so that the digital platform is multi-sided. The purpose of the business is to match the demand that exists in the market with an adequate supply in an economical manner, i.e., shaping the supply. The myriad factors affecting supply are of interest.

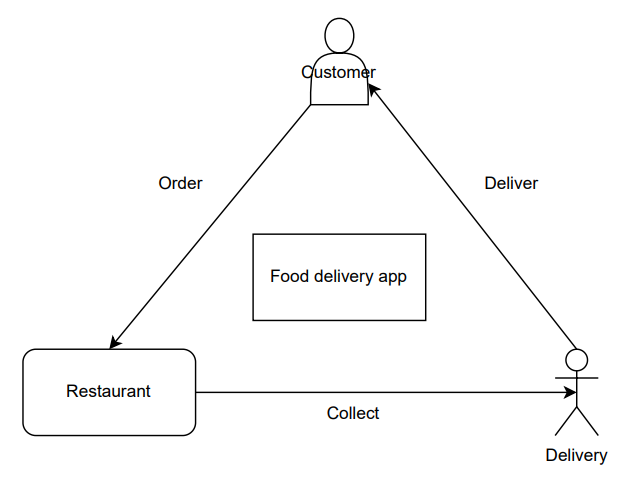


Fig 2-Food delivery multi-sided platform

2. BEHAVIOR OF GIG WORKERS

Gig work, by its very nature, is often “fleeting” and “temporary.” Shin et al. (2022) find that work in the restaurant industry is substitutable with taxi driving as a profession despite there being no immediately apparent relation between the two. A novel methodology is used to test the hypothesis whereby exogenous shocks are exploited around the entry of Uber and Lyft into the Austin, Texas market area. They report that the entry of Uber and Lyft leads to the service quality of restaurants declining, which is determined by analyzing online Yelp reviews by customers. This indicates that the entry of ride-sharing applications in the area leads restaurant workers to switch jobs to Lyft and Uber (ride-sharing apps). This provides evidence for the substitutability of certain types of work in the gig economy, even when direct connections are not clear and present.

Hong et al. (2021) report that the odds of being hired are affected by both the act of messaging the recruiter upfront as well as the tone of the messages sent. Sending messages to recruiters substantially increased the odds of being hired. (8.9%) They also find that the tone of the message in terms of politeness has a significant effect. It is also found that the effect is specifically accentuated when the prospective workers of low status, it being in terms of lacking the fit and the tenure for the job at hand. This “politeness payoff,” so to speak, is, however, found to reduce when more prospective workers adopt the same approach and do it.

Gig work on multi-sided platforms has both an employer and employee dimension to it. The risk of poor behavior, work, and treatment is an ever-clear and present danger. As the saying goes, “it takes two hands to clap.” A method or way to impose discipline to counteract and prevent bad behavior on the employer side is explored by Benson et al. (2020). They look at whether reputation can be used to impose discipline among employers. Reputation has, in other work, been shown to act as a powerful motivator. Status is, to a certain degree, commonly considered substitutable with money. Data from the Amazon Mechanical Turk (Keith et al. 2017) platform is utilized for the study. An experiment of sorts is set up to test the theoretical model that is proposed by the paper. Benson et al. (2020) found that working for employers that have a good reputation results in as much as 40% better wages, even on average. This is found to be due to the time taken to complete the tasks created by such employers being lower. On the Amazon Mechanical Turk platform, employers reserve the right to reject work done by workers and deny them payment if they are found to decide that the work is not to their liking. The likelihood of the job that has been done by the workers being rejected, which is an option on the Amazon Mechanical Turk platform, is found to be significantly lower when workers are working for employers that have better reputations. It is found that good reputations enable employers to both operate faster and scale up better. They are seen to be able to do so without suffering setbacks to the quality of the work. The whole system of reputation is found to be of greater importance for smaller firms, especially as it pertains to competing with larger and better-established forms. They conclude that reputation plays a significant role in terms of misbehavior by the employers of gig workers on online platforms.

Wu and Zhu (2022) study a somewhat unique category of gig work in the online economy. The paper examines the case of book writers using an online Chinese language platform. The platform works via a system of revenue sharing where authors who use the platform sell their works by chapter. It is determined that greater competition among novelists on the platform leads to authors producing works quicker than they would otherwise. However, the novelty of the work does not appear to be impacted or impinged in any one way or the other, suggesting that haste does make for better quality work.

Unionization and unions have, in other studies, been shown to have important implications for work outcomes such as wages and supply.

Forsyth (2021) examines how unions have been adjusting to the new normal of work. The paper focuses on the responses of unions to these changes to work in Australia and Italy. They examine the approaches utilized by unions to build worker power. Efforts at lobbying to change regulatory policy are observed in response to shifts in the workforce. Collective bargaining is attempted to be used as a way of improving outcomes for workers. Legal challenges are mounted to counter certain types of business models that appear to be exploitative to workers. Union action is sometimes synonymous with strikes, and they look at direct action by unions, such as protests. Finally, new methods of non-union organizing among workers in response to these changes are also covered. Jones (2021) takes a pessimistic view of the balance between labor and capital as it pertains to gig work. Workers are now working increasingly on online platforms under algorithmic management. They do so for significantly lower wages on average than formal employees. The book argues, among other things, that a lot of the work on these platforms involves the manual processing of data, which are tasks that are themselves being automated away at scale. It takes a political economy view on the past, present, and future of the gig economy.

Cao et al. (2022) present the results of a study on the impact that Covid-19 had on the labor supply of gig workers using an online platform. The study uses data from a large education platform with over 10000 gig workers on it. Exogenous shocks are exploited in terms of the Covid-19 lockdown stages to study their impact on supply. A significant increase is found in the labor supply of gig workers on the online platform immediately after the announcements of the first stage lockdown or national emergency (23%). This increase reduces in magnitude and scale with the declaration of the second stage. The effect in terms of increases in labor supply is found to peter out by the time of the 3rd stage. They, however, find that what drives this is not an increase in demand for workers. It is also deduced that it is not caused by an increase in the number of new workers on the platform as one might be inclined to suppose. Rather they report that this phenomenon was driven by unemployment and “non-pharmaceutical interventions.” The risk of getting Covid-19 is also not found to be the cause. They conclude that the change in gig workers’ supply was created by the changes in temporary working conditions due to these policies. These results suggest that designing lockdown and containment strategies while keeping work restrictions in mind is of the utmost importance.

Conflicting evidence is found on that all-important question of the effect of gig work on entrepreneurship. Barrios et al. (2022) resent the finding that the expansion of the gig economy leads to an increase in entrepreneurship. It is observed that the entry of Uber and Lyft leads to an increase in entrepreneurship. Results suggest that the introduction of gig opportunities leads to a 5% increase in new business registrations okay. A similar increase is observed in lending to new businesses. Burtch et al (2018), however, find that Gig work reduces entrepreneurship. The silver lining is that the effect works mainly in terms of reducing unsuccessful entrepreneurship ventures. The authors posit that this happens by giving underemployed and unemployed people the option to go into gig work instead of engaging in desperate business ventures with low probabilities of success.

After the financial crisis in 2008, the social protection systems in Europe have seen major cuts and reductions in scope as well as scale. Gig work is often simply not covered under laws on labor standards. Kenner et al (2019), in “Precarious Work,” examines the big question of whether gig work should be included under labor law in Europe. The literature on legal aspects of gig work is few and far between, and this can be a direction for future research.

3. SOCIAL NETWORK ANALYSIS METHODOLOGY AND APPLICATIONS

In social network analysis, which depends on access to the data of interaction between the various participant groups, learning occurs by statistical methods, graph algorithms, unsupervised learning, and various other machine learning methods plus algorithms. The interaction of gig workers with each other is likely significantly less than that between formal employees working in the organized sector. Therefore, the connections between nodes in the social networks of gig workers are likely to be sparse, and hence the occurrence of outliers is more likely. Outliers can often skew datasets and make it difficult for models to learn from the data. This particularly affects parametric models. Non-parametric methods like tree-based models are not as affected by outliers. In certain instances, outliers can also be all-important, the proverbial black swans (Taleb 2007). Kaur and Singh (2016) survey the various outlier detection methods used for the social network analysis task. Outlier detection is an angle by which one can approach the supply of gig workers using multi-sided platforms. Not only is outlier detection important to ensure that the models do not pick up noise, but if the nature of the data is such that it exhibits heavy tails (a la Pareto distribution type case) it becomes of great import to predict and explain or interpret the outliers themselves. The problem needs to be attacked from this angle as well to ensure that models, results, and insights are robust to outliers and any potentially heavy-tailed nature of the distributions of outcomes.

Freeman (2004) develops the workhorse baseline Degree Centrality method (Freeman 1979) and traces the trajectory of the social network analysis field in its infancy during the early phase between the 1930s and 1970s. Academic networks are another application area, which is presented by Thelwall and Kousha (2014) using the networking site Academia.edu. Among the most famous early applications of social networks is the Erdos number (Goffman 1969), which is a metric almost in jest of how many “nodes” or “connections” or “collaborators” removed a researcher is from Paul Erdos, a prolific Hungarian mathematician with an h-index of 127.

A collection of social network analysis datasets can be found in [Stanford Large Network Dataset Collection](https://snap.stanford.edu/data/) (Leskovec and Sosič 2016). It contains various types of social networks, including social networks, citation networks, communication networks, web graphs, temporal networks, etc. Among very many other things, the project repository provides the following data.

Social network data or the “ego network” for Meta or Facebook as it was then known, as well as Twitter, is from Laskovec and Mcauley (2012). Two and a half years of subreddit hyperlink network data are taken from the data given in Kumar et al (2018)

In terms of the graph properties, the subreddit hyperlink network graph is attributed, signed, temporal and directed. Rozemberczki et al (2019) introduced data on networks among GitHub developers. It also contains tagged labels for binary classification for classifying what type of developer each node is and, as such, is a classic prediction problem using social networks.

A widely used library for social network and network analysis, in general, is [NetworkX — NetworkX documentation](https://networkx.org/). A comprehensive list of social network parameters and the methods to implement them in python can be found in the project documentation. It offers a wide range of functionalities that aid and enable social network analysis.

Malin and Carley (2007) perform social network analysis on the editorial board network of journals in medical informatics and bioinformatics journals. They find that members of the editorial board occupy central positions in the network. Merrill and Hripcsak (2008) use faculty expertise and research method self-declarations to perform social network analysis in a biomedical informatics department.

Woods et al. (2019) explore the social network dimension of innovation in the industry. They report the results that greater network activity is positively associated with innovation.

Lee et al. (2016) studied network and friendship formation in a spatial social network. They use multiple similarity metrics, including ones relating to geography, biology, and mobility, finding them to be relevant to social network formation. They also use an instrumental variables approach to demonstrate the robustness of their approach. **Pendersen** (2022) creates a model which finds that securities markets demonstrate phenomena such as bubbles, the disproportionate impact of high centrality nodes, momentum, etc. Hong and Xu (2019) use stock holdings data to infer underlying social networks. Engelberg et al. (2012) find that firms and banks are connected via personal links such as having worked together or being from the same university. Interest rates substantially fall in such cases. However, they also find that the firm's performance improves following such deals implying that they reflect either better information or monitoring of the deals.

Wilcox and Stephen (2013) carry out some social network analysis experiments on self-control and social network usage. They find that social network usage acts as an esteem booster among users who focus on strong and close ties. They further find that this leads to lesser self-control after browsing. Evidence is presented of an association between social network usage with higher body mass index and credit card debt for those users focused on strong ties to their network.

Balasundaram et al. (2011) developed an algorithm that is found effective in optimally solving high dimensional sparse graph problems. Fang et al. (2013) predict adoption probabilities in a social network using naïve Bayesian learning using two large-scale social networks for validation.

Social networks are represented as graph structures, and graph algorithms are often the most efficient way of analyzing social networks due to being typically optimized in terms of things like complexity. Farasat et al. (2015) use probabilistic graphical models for social network analysis. The standard graph or social network metrics such as degree centrality and betweenness centrality are often insufficient as metrics for the kinds of real-life problems social network analysis seeks to solve. Various types of social network analysis problems require specific types of metrics (as well as algorithms) that are suited for the task at hand. Nikolaev (2015) introduces and uses entropy centrality as a metric for social network analysis. Time series problems often exhibit features that are unique to the temporal system. For instance, the workhorse linear regression model cannot be properly directly used as it is for time series problems. For time series problems, suitable modifications are required, such as ARMA, ARIMA, ARIMAX (Peter and Silva 2012), etc., to make them suited for temporal systems. Elmezain (2021) proposed a centrality metric suitable for time series problems.

Collaborative filtering is widely used in recommendation engines. It is used on e-commerce sites, search engines, music apps, movie and video recommendation systems, etc. It is one of the methods to come up with and recommend tasks on online platforms. Pham et al. (2011) perform collaborative filtering using a social network analysis approach. A lower mean average error is found in the use cases it is demonstrated when compared to baseline models. Freeman (2017) and Sandra et al. (2021) cover the methodology of social network analysis in terms of the algorithms.

Climate change and global warming are major topics of research and study at this juncture. Gig workers are often connected online over a large distance. They interact across continents (space) and time zones. (Time) Climate change is likely to shape these interactions directly and indirectly. Fountalis et al. (2014) perform space-time network analysis for analyzing underlying grid-level pertaining to climate. They create grid-level climate data that are internally homogenous, form networks out of it, and compute and compare some metrics for the climate network.

Finding structure and patterns in data without human inclinations, presuppositions, blind spots, and bias is one of the most promising aspects of and dimensions of artificial intelligence. Unsupervised learning methods have been used in a wide variety of domains and to solve varied types of problems, sometimes in conjunction with supervised learning methods such as regression and classification. Unsupervised learning methods, which are typically used on raw data, can be applied to various ways of representing social networks, such as graphs, distance matrices, etc. Rasmussen (1999) developed the workhorse Gaussian mixture model (GMM). An et al. (2015) use GMM for predicting interest in social networks. Ankerst et al. (1999) developed the workhorse optics algorithm. Deng et al. (2015) create a faster version of optics suited for big data. Agrawal et al. (2016) create and validate a Spatio-temporal implementation of optics. Zhang et al. (2016) introduce BIRCH (balanced iterative reducing and clustering using hierarchies). Venkatesan and Prabhavathy (2019) perform outlier detection in a social network using unsupervised learning.

Knowledge graphs can be regarded as a special case of network analysis. The development of a lot of state-of-the-art graph algorithms was based on knowledge graph-related problems and are often used for modeling social networks. They have been created and utilized successfully in a variety of domains. Knowledge graphs have been used to model drug interactions such as antihistamines, vitamins, minerals, antibiotics, etc. Karim et al. (2019) and Lin et al. (2020) use knowledge graphs to represent drug-drug interactions. In this paper, data on known pair-wise drug-drug interactions are aggregated into a knowledge graph. Karim et al. (2019) use 12000 drug features from 3 different sources, and the ensemble of the top 3 classifiers achieves an F1 score of 0.92. Lin et al. (2020) propose knowledge graph neural networks to solve the problem of drug interactions and find them to outperform the state-of-the-art baseline on standard tasks. Several commercial software exists for testing interactions using knowledge graphs. Scientific publications represent a major opportunity and challenge in terms of extracting insight from the whole length and breadth of the literature. Xu et al. (2020) extract insight from the PubMed database. Among the most important applications is integrating and utilizing medical knowledge. Rotmensch et al. (2017) glean information from medical records to construct a knowledge graph. Data from de-identified medical records are used along with 3 models, namely, logistic regression, naive Bayes, and a Bayesian network with noisy OR gates. They obtain a precision of 0.85 in the clinical evaluation.

The actions of gig workers can be regarded and modeled as being similar to that of agents in multi-agent systems. Madhawa and Murata (2019) use multi-armed bandits to search and explore partially observed networks more optimally in real time. The behavior of multi-agent systems can be modeled using social network analysis too. Shahrampour et al. (2017) deal with utilizing multi-armed bandits for multi-agent networks.

A variant of the UCB1 algorithm (Drugan and Nowe 2013 as well as Durand et al 2014) is used for the same. Ma and Zhang (2014) perform social network analysis using a multi-agent system in a school system setting. They used data from 15 school districts in Texas for the experimental validation. Galadima and Gan (2007) analyze information transmission in power markets by combining several measures that are based on social network analysis. Xiao and Yu (2011) employ multi-agent simulations to study rumor-mongering in a virtual social network. Kamdar et al. (2018) review the many dimensions of multi-agent systems.

4. SOCIAL NETWORKS AMONG GIG WORKERS

Börsch-Supan and Schuth (2014) study the relationship between early retirement, mental health, and social networks among older people. An implicit assumption that is typically made is that work is mostly negative for the mental health of workers. It is found that early retirement is not entirely a bed of roses as it is often made out to be. It is found that early retirement leads to a significant decrease in the size of the social networks of older individuals. This is found to lead to cognitive decline. Perhaps somewhat counter-intuitively, the interactions that workers have with both their own social circle and those they meet and speak to in the course of doing their work are found to be important for their mental health. This has implications, especially for older gig workers who might be looking to hang up their boots.

Kerr and Mandorff (2015) examine the curious case of massive overrepresentation of certain ethnic groups in certain sectors of the United States economy. This is especially observed for minority groups. The sheer scale (as much as 1 or 2 orders of magnitudes in some cases) of the relative overrepresentation is totally out of the range that would be expected, whether by chance or that predicted any purely econometric model that does not explicitly account for this phenomenon. For instance, Gujarati people in the United States are found to be over 100 times over-represented in terms of ownership of motels. Korean Americans are found to be over 30 fold over-represented in terms of self-employment in the dry cleaning area. A couple of principal characteristics are found by the study to drive this phenomenon. The first is that smaller groups are more likely to exhibit coordinated entrepreneurship, where members of the group tend to concentrate and specialize. Their entrepreneurial activity is focused on specific sectors and lines of work. The second principal finding is that more isolated ethnic groups demonstrate a greater likelihood of entrepreneurship along community lines.

Bernhardt et al. (2022) utilize data from de-identified tax records to look at among other things, the distribution of gig workers by sector. The study uses tax record data from the state of California. Large distributional effects were found in terms of the prevalence of gig work when stratified by the sectors of the economy. It is found that close to 1/6th of all workers in California have some kind of self-employment source of income. They determine that younger workers are heavily overrepresented among online platform work economy workers (OPE) or gig workers. Gig workers were found to be significantly more numerically in the urban areas of Los Angeles, San Francisco, and San Diego relative to the rest of the state. This suggests significant differences between urban and rural areas in terms of the prevalence of gig work. The paper also found that those in the first quartile in terms of individual earnings were as much as 6 times overrepresented relative to those in the 4th quartile among gig workers. Interestingly those who filed the tax returns as the head of the household were more likely to be gig workers than those who were single. It is not immediately apparent why that would be the case. Storage and warehousing, as well as transit and ground passenger transport, were found to have the highest proportion of gig workers by a distance. With anywhere between 1/3 to a half of all workers in this sample being gig workers. The information sector is a distant second with 7.1%. Gig workers. A number of sectors of the economy such as utilities, oil, and gas, public administration, etc. had zero gig workers. An honorable mention is professional scientific and technical services, a sector whose share might increase in the future.

There has been considerable work on social network analysis of social media platforms which are rich sources of data. Among the most popular social media networks on whom work has been done are Lewis et al. (2008) and Akhtar et al. (2013) on Facebook, Sharma et al. (2012) and Myers et al. (2014) on Twitter, Manikonda et al. (2014) on Instagram and so on. Lewis et al. (2008) introduce Facebook data as a social network and find differing behavior when stratified by gender and ethnicity. Akhtar et al. (2013) find a low association between high-degree nodes in the Facebook social network data. A toxic online environment is a major and growing concern vis-a-vis the internet. Sharma et al. (2012) utilize the list feature on Twitter and finds that they can find out the attributes of the vast majority of Twitter’s most influential users.

Zhong et al. (2016) looked into detecting cyberbullying on Instagram based on images. An F1 score of 0.95 was obtained on the top-performing specification out of the ones tested. “Bowling Alone” (Putnam 2015) popularized the idea of social capital, which is inexorably linked to social networks.

Reagans and Zuckerman (2001) take a look at opposing views or theories on the diversity and productivity debate and present evidence for both views. Fang et al. (2015) carried out a meta-analysis and examined 3 research problems on the impact of personality. They find that controlling for the big-5 traits predicts in-degree centrality. It is determined that the in-degree centrality was related to job performance as well as career success. Personality was found to predict job performance above and beyond network position, and it was seen that network position somewhat mediated the effects of some personality parameters on work outcome. Personality-related factors that can explain the performance of gig workers merit further work.

Wu (2013) determines that 'information-rich' networks have a positive effect on work outcomes. Xu et al. (2014) use data from a time period spanning a third of a century to analyze social capital using 5 different aspects of social capital. Boulet and Lebraty (2018) observe that classic network centrality metrics such as degree and betweenness centrality are heavily correlated and hence are capturing similar information. They propose and validate new approaches based on data from tweets on the Uber *vs.* Taxi conflict in June 2015.

Predicting whether gig workers stay or exit is important for platforms to account for their churn rate and strategize accordingly. Chen and Sharma (2013) examine persistence on social networking sites. A model is proposed which identifies factors or values which determine the call made by users to stay and continue using the platform. It is validated using data from a survey that was carried out. Culotta and Cutler (2016) use Twitter to compare brand perceptions. They look at the brand's social connections to find out their perceptions. A strong relationship between the proposed methods, rating estimates, and survey data is found.

The ability to modify the tendencies and behavior of gig workers via strategies on the platform side is of utmost importance. Burt et al. (2022) look at the persistence or stickiness of behavior which is expressed in the adage “old habits die hard” in the context of social networks. The paper sees whether CEOs stick to their guns, specifically if they stick to their network. They found CEOs in networks that were less open were less likely to cooperate beyond their network. It is also found that successful CEOs were even more likely to do so. They conclude that successful history within a network reduces the odds of working outside the network. The proclivity of gig workers to stick to certain types of behavior, as well as the continuity in their social networks, is of interest. “Landlords with no lands” (Trabucchi and Buganza 2021) performs a systematic review of the work of the literature on two-sided platforms. Credit card industry players such as Visa and MasterCard are classic cases of two-sided platforms. Other platforms studied include ones like Uber, Airbnb, etc.

desMesnards et al. (2022) observe the impact that bots in social networks have on sentiment. Deep learning is used to train a model to find the views of users on the basis of their posts. They find that bots interact more with humans than bots and have an impact on certain networks but not so on other networks where they have no major impact on opinions. Reagans (2011) performs an analysis of the impact of social similarity on network connections. It is found that teachers of similar ages tend to form close friendships. It is also observed that teachers with closer Spatio-temporal distances, such as those with classes on the same floor and who took breaks at the same timings communicated more often and formed stronger connections. A reasonable hypothesis would be the assumption that gig workers who tend to spend their time off together are friends. This is a Spatio-temporal similarity method of estimating social networks among gig workers.

Mollica et al. (2003) find that racial or ethnic commonalities have a significant and persistent impact on friendship formation and circles of friends. They use surveys that are administered at different time periods to MBA students at 2 time periods, one at the beginning of the program and a later one. They find this tendency and pattern of forming friendships to persist over time. The various variables or factors that are of importance for social network formation among gig workers require further exploration.

Credit scores, bond ratings, etc. are some of the classic artificial intelligence applications. Wei et al. (2016) use social network data for credit scoring. In terms of research down the line, it may be possible to use credit score data to check for any effects that it might have on the supply.

Johannessen (2014) looks at the social network aspect of political sites with an emphasis on the Norwegian labor party. Certain party sites such ones like the 5-star movement (more direct democracy and members approving legislation) and conservative home (extensive polling of the opinions of members on various candidates) have interesting properties which can be a basis of future work.

Brands et al. (2015) observe that the perception of CEO charisma is a function of the match or mismatch between the leader and the nature of the social network. They observe that in networks centralized around a small number of people, women are seen as less charismatic than men. The reverse or converse is also found to be true, namely that in more cohesive networks, women are seen as more charismatic. Benton presents results showing that post the mid-2000s, the cohesion among and unity in corporate boards declined in response to shareholder activism in a way that had not happened prior. Venkatesan et al. (2021) perform a wide range of analyses of the tweets around the Egyptian revolution. Various aspects of real-time feedback systems in organizations are explored by Pertryk et al. (2022). They examine how ratings given pertain to factors such as hierarchy, positional and structural embeddedness, and anonymity. Velichety and Ram (2020) examine the matter of social media recommendations for communities. They use data from the lists created by Twitter users to create a community recommendation system.

Chetty and Hendren (2014) find those results to be replicable at a micro-neighborhood level. Ellison et al. (2007) dive into the social capital element of Facebook usage using survey data of undergraduate students using the platform and find an association with the metrics of social capital. Mental health is of great importance, especially in today’s world. Yoon et al. (2019) investigate the link between social media usage and depression with Facebook data. They find that time spent on social media, as well as social comparisons made by users of the platform, is correlated with depression. As it becomes more and more important further work on social circles and mental health will probably be forthcoming.

5. HEALTH OF GIG WORKERS

The mental health of workers in the gig economy who do not have stable, formal long-term employment is a major matter of concern and requires study. Gig economy workers typically lack formal health insurance plans, which include employer contributions. Depending on the medical insurance and healthcare system, Government employees are usually covered by either insurance or have free or partly free healthcare, while formal private sector workers often have insurance plans to which employers contribute. The degree of employer contributions to insurance plans is often determined by the tax benefits aspect to it as well. Discussing the nature of the various types of medical insurance plans across the world is beyond the scope of this review. It suffices to say that the lack of health insurance can often mean gig economy workers are a single mishap or accident away from disaster. Some who have lost employment elsewhere and have become gig workers as a result also sometimes lose their health insurance plans due to being fired. Certain types of gig workers might also be more exposed to certain types of calamities, such as natural disasters. The supply during such events, such as during a cyclone, might be markedly different from the vanilla normalcy scenarios. Most importantly, health and safety standards often either do not apply to gig workers or are not enforced properly for them. The physically taxing element to work might go both ways for gig workers. Certain types might be more physically intensive, whereas certain other aspects, such as more flexible timings, might be less physically intensive. Health outcomes are affected by peer and friend groups over a wide range of parameters. One heavily peer and friendship circle-influenced factor is that of habits formed. Habits formed during adolescence are known to have a disproportionate impact on life outcomes. Volkow et al. (1996) find that sensitivity to dopamine falls with age. This makes habits formed when young (high dopamine sensitivity) critical to health outcomes later. Valente et al. (2014) and Schaefer et al. (2014) look at the relationship between adolescent social networks and obesity, finding an association. Zhang et al. (2018) review the literature on social network analysis as applied to obesity. Seo and Huang (2012) look at the relationship between and impact of peer groups on teenage smoking. Jeon and Goodson (2015) review studies pertaining to friendship circles and their effects on general risky behavior in terms of health.

Devices like Fitbit have become popular in recent years, and this trend is expected to continue and grow from strength to strength. During the pandemic, oximeters became ubiquitous in their usage and utilization. As a result, substantial data on pulse oximeter data now exists. Taken together, these devices, as well as applications, track a variety of healthcare-related parameters. Depending on the device and app these include both directly measured variables and indirect estimations of various variables. The medical significance of each of these variables/metrics/parameters is often well known, and they have been used and utilized in predictive analytics as well. Ceteris paribus, a heart rate of 72 per minute is typically considered optimum. There exists evidence that sports persons might, on average, have significantly lower pulse rates. Studies on the perfusion index support the view that a very broadly higher “PI” is desirable (Hasanin et al 2017).

Oxygen saturation is the principal variable that oximeters track. The >= 95 or hit the panic button cutoff became something of pop culture, especially during the height of the pandemic. De-identified Medical records are another data source that can be combined and would make for important work. Privacy is an important feature, and the principal source would probably be from devices plus applications which users acquiesced to utilize when buying them or from apps they download. Combining data from health apps with those from might help in identifying proxy behavior that allows us to estimate the state of mental health of the drivers.

The Covid-19 pandemic has brought renewed, and intensified focus on epidemiology, and social network analysis is no exception. Some of the pre-Covid-19 works are Gardy et al. (2011) on Tuberculosis, Bragazzi et al. (2017) on the Zika virus, and Lichoti et al. (2016) on swine flu, among others.

From a race against time for mitigation point of view, Maia et al. (2019) give insight into the networks among researchers who worked on the Zika outbreak. The Covid-19 pandemic, by its very nature, is a function of the social and contact networks among people. These effects vary based on time and place due to differences in the nature of the social networks as well as the general conditions in a region. For example, due to the long distances that workers have to commute, Cars in the United States are often the go-to method of transport. This is likely to be different from the state of affairs in, say, China, Europe, or the Indian subcontinent.

Kinship networks are often the closest of social networks. Coile (2004) finds that spouses pick up the slack when a husband or wife faces sudden health issues or health shocks and cannot work or reduce the labor supply as a result.

Yum (2020) performs a spatial network analysis of Covid in the United States. Saraswathi et al. (2020) perform it for the province of Karnataka in India. Yie et al. (2021) create a dashboard to find patterns in the spread of Covid-19. The question of visualizing social networks in epidemiology is tackled by Christakis and Fowler (2009). Nagarajan et al. (2020) analyze Covid contact tracing data from Karnataka.

The apps that have become widespread for contact tracing app could be rich sources of information on social networks and an avenue for many types of future work, including natural experiments. An example of this is the Trace Together app for Singapore. Where good data does not exist on the spot, Covid sentiment can be used as a proxy for Covid spread or at least “dread.”

Microfinance networks are explored by Banerjee et al. (2021). Gupta and Hossain (2011) attempt to detect insider trading from social networks in real time. Ek-Khatib et al. (2017) find that CEO network centrality is strongly associated with abnormal positive returns on buying stocks in a few different types of scenarios. Ahern (2017), in a study on insider trading, observes massive returns (35%) among those indulging in it over as short a time period as 3 weeks. Further work on public trading forums pertaining to how networks influence trading decisions would be an interesting line of research. Marketing is a prime example of leveraging social networks to drive outcomes. Pentina et al. (2012) cover small and medium enterprise adoption of social network marketing. Kilduff and Tsai (2003) cover the aspects of social networks in institutions and organizations in detail. The influencer phenomenon has exploded with the advent of platforms like Instagram, TikTok, etc. Werayawarangura et al. (2016) work on identifying influencers.

6. SUPPLY SHAPING OF GIG WORKERS

Working hours are often either unpredictable or, in rather happier instances, flexible to varying degrees when it comes to gig work. This introduces certain factors to take into consideration when estimating supply. In early work, Kahn and Lang (1988) Attempted to get more accurate estimates of the labor supply by accounting for the fact that most workers cannot choose their working hours and that there are discontinuities in the amount of time worked. They do so using. Hourly estimates and determine that using the actual number of hours worked results in the labor supply estimates being upward biased to a small degree. Taxi demand forecasting is performed by Davis et al (2018). Karamshetty et al (2020) tackle the question of empirically forecasting food demand and find that it becomes harder as food delivery platform dependance rises.

The key task in quantifying the supply shaping of gig workers depends on decision-making strategies employed in the network analysis. Liu et al. (2019) use a social network model to look at group decision-making. Dong et al. (2018) review the literature on decision-making in social networks.

A Bank of Canada survey report (Kostyshyna and Luu 2019) finds that gig work was not entirely captured in the standard metrics used to capture work and employment patterns. People from the poorest provinces of Canada and the provinces with the highest historical unemployment rates were found to have the highest rates of gig work. Gig workers are also overrepresented among part-time workers and the youth. They find that a significant explainer of the choice to do gig work is poor economic conditions. It is also observed that gig work peaks in areas with the most labor market slack. The report concludes by positing that gig work is one of the causes of reducing wage pressures on firms.

On the subject of climate change and any impacts on the supply of gig workers that it may have, Cook and Heyes (2022) perform an interesting experiment to test the impact that pollution has on labor supply via an experiment. Doing so physically in person would involve putting workers in a risky environment, and to circumvent that, a novel approach is utilized. An interesting approach using psychological inducement of the thought of pollution is used where workers are shown polluted and unpolluted pictures of the job/s assigned. The former is the treatment, and the latter is the control group, respectively. It is found that workers in the treatment group are less likely to work despite being offered significantly higher wages. Payment for this work is by piece rate. Among those who accepted the offer in the treatment group (pollution), the workers were less efficient and finished between 5-10% less work depending on the task that had been assigned. No difference is observed in terms of the quality of the work done between the polluted (treatment) and unpolluted (control) groups.

An existing, as well as emerging dimension to gig work, is the automation of various types of gig work. Many types of gig work are increasingly becoming automatable. For instance, art has long been something that is done by commission. A lot of it has moved online to producing art and selling it on platforms online. It’s often done with artists who receive orders for art online doing it based on orders received. An example of the automation aspect is that of artificial intelligence-created art. This is likely to become a major paradigm in the near future. Generative adversarial networks have been around for some time. (Creswell et al 2018) Their potential in terms of image generation was well-known in the literature. Mid-journey has revolutionized art production in a very short period of time. (Oppenlaender 2022)

On this subject of platform monitoring strategy, Norlander et al. (2021) analyze the effect that monitoring by platforms has on driver motivation. Using survey methodology, they find that UberX drivers perceive greater control over themselves relative to unaffiliated and independent taxi drivers. They, however, find that there are no adverse effects of this on their motivation. It is also seen that this has no impact on the enjoyment of work and needs satisfaction relative to independent taxi drivers. The study has a small sample size and it will be of interest to see larger studies on this that are analyzed from various relevant dimensions to the problem.

It allows users to use simple text commands to generate art of high caliber at high speeds and low costs. Given the quality of the artwork produced, there is the possibility that this might make artists obsolete altogether. This might throw a spanner into the whole of the existing system. Platforms like mid-journey and DALL-E have enabled complete automation of art creation at a massive scale with very simple-to-use interfaces. All this can be done in a minute fraction of the amount of time that it takes to do so in real life and at almost no cost. This raises the question as to whether such things will continue to happen in other domains as well. For instance, now that art has so become, will the composition of music become automated? There has already been substantial automation in various aspects of the music industry. Technical work on the creation of music using artificial intelligence already exists. (Frid et al. 2020)

Breza et al. (2021) study rationing in the Indian labor market. Hiring shocks are induced, and their impacts are observed to glean insights. During lean months it is found that wages and total employment do not change. Positive employment spillovers are also found for other workers. Over 25% of the labor supply is found to be rationed. Importantly, they determine that at least 24% of self-employment among casual workers is due to being unable to find jobs.

Papanikolaou and Schmidt (2022) find that sectors of the economy that did not have the work-from-home option saw a significantly greater decline in terms of employment. These firms also had substantially worse revenue growth. More uneven stock market performance as well as a greater likelihood of default was observed in them too. In terms of individuals lower paid workers, especially mothers with young children were the most affected by these disruptions. Some of these patterns possibly apply to gig workers as well.

Driving taxis and vehicles is among the largest gig work professions today. For a long time, the transport sector was among the best-paid working-class jobs in the United States in terms of wages. This obvious thing that might hugely disrupt gig work in this domain is driverless cars. There is a possibility of it being automated away. That too the domain which is often the majority fraction of gig work. New opportunities might also open up as tends to happen. For instance, drivers might remotely control vehicles over stretches of snow where AI control is known to be harder to perform due to being unable to read lines on the road. Gig work by its very nature is likely to become more automated, at least to some degree. Something that cuts against this trend might be that those kinds of work that are hard to automate might tend to become more and more overrepresented in the gig economy. This has significant implications in terms of the supply of gig workers and requires further study.

7. FUTURE RESEARCH DIRECTION AND GAPS IN THE LITERATURE

Carranza et al. (2022) analyze whether informal redistributive mechanisms within social networks have an impact on supply. Social and kinship networks often have internal and informal systems where wealth and incomes are re-distributed. A novel approach is used where workers are given the opportunity to opt for either public or private savings accounts. This is performed for piece rate factory workers working full time in Côte d’Ivoire. Piece rate workers are paid by their output, and hence, measuring the performance can be done with greater precision than in cases where performance is more nebulous and difficult to quantify. It is found that the take-up is much higher for private accounts than public accounts, the difference being greater than 4-fold (60% vs. 14%, respectively). Substantially greater effort is exerted by workers who are given private accounts. They exhibit close to 10% higher attendance and near 15% greater earnings and output. The study estimates that there is as much as an 18% social tax on income.

We recommend a number of directions and pathways for future research. From the data point of view, we are most obviously concerned with estimating as well as explaining the labor supply curve (Prasch 2000, Random and Sims 2010). It will be interesting and important to see the fit that various labor economics models (Borjas and Van Ours 2010) in the literature have with data on gig workers using multi-sided platforms. This could be the basis of future work on this subject. Insights gained from such analyses are likely to illuminate new pathways as well. Social capital (Arrow 2000) dimensions to gig work are possibly worth exploring, especially identifying if it matters to supply outcomes, and if these effects are heterogeneous across sub-sectors or categories of gig work. The literature on the legal aspects of gig work on multi-sided platforms is sparse and can be a direction for future work.

Automation is very possibly just around the corner for many types of gig economy jobs. Perhaps the most concerning factor is that these appear to be heavily concentrated in those very areas where gig work is currently the most over-represented, most notably that of vehicle drivers for ride-sharing and food delivery apps. Further study is required on the likely impacts that automation will have on gig worker supply. As seen from our literature review, types of gig work have been found to be substitutable to a degree even without immediately obvious similarities between the lines of work. Increased automation might firstly increase opportunities elsewhere as productivity rises, and there might be a migratory effect into other categories of gig work as well as the formal sector. Studying these potentially upcoming changes ex-ante is important for all stakeholders to prepare for what is coming. Care and consideration need to be taken in terms of the robustness of the estimates for supply curves and other empirical relationships. A well-known example of divergent and sometimes diametrically opposite conclusions arrived at by different studies is that of varying Phillips curve (Hooper et al. 2020) estimates in different specifications, and the debate over its existence (Reinbold and Wen 2020) and relevance (Hazell et al. 2022).

Customer churn prediction is an important priority for businesses, especially online ones. Vafeiadis et al. (2015) compare a number of supervised machine-learning approaches for the customer churn prediction task. Multi-sided platforms have dropouts (users leaving the platform) of multiple types of stakeholders to factor into account. The gig worker turnover also needs to be factored in, say in the case of a food delivery app, some customers might stop using the app for reasons it's important to predict beforehand. Some restaurants and riders might leave the platform too. It is important that research is directed into the prediction as well as the explanation of the retention and loss of different types of multi-sided platform users.

Integrating data from other sources relevant to gig work in multi-sided platforms and utilizing it in supply-related tasks can uncover fresh insights. For example, credit scores which are now ubiquitous might enable us to better predict and explain the supply of individual gig workers in a multi-sided platform. Dastile and Potsane (2020) present a review of the machine learning and statistical methods and models utilized for credit scoring in the literature.

Behavioral economics could illuminate the behavioral patterns of gig workers which has likely implications for both gig worker and platform outcomes. One of the most widely known concepts in the behavioral economics literature is that of “nudges” (Thaler and Sunstein 2009). To illustrate some of the insights that might be gleaned from behavioral economics, a pivotal finding in the literature is that of the power of default options. Simply flipping the choice from, say, an opt-in to opt-out or vice-versa can lead to major shifts in outcomes. This has been found to drive outcomes greatly in savings schemes. Beshears et al. (2009) cover some of the evidence on default options as it pertains to retirement savings and finds that default options have a major impact. Studies on the feasibility of harnessing the power of nudges and behavioral economics strategies on gig work multi-sided platforms would be a welcome addition to the literature.

An important question would be testing for whether there are any monopsony effects seen in the gig economy, specifically with respect to multi-sided platforms. It might be worth looking and checking for the presence of such effects if any and estimating its magnitude on remuneration and supply outcomes for gig workers. A number of general econometric models in the literature can also be tested on gig worker supply data in future research. Such an approach is likely to uncover further new findings and avenues for research.

Arguably among the most important things are to estimate and explain the labor supply curve using diverse metrics of supply to bring in a measure of robustness to our estimates. Different metrics need to be utilized to estimate and measure supply to that end. For instance, in the food delivery app case, these parameters might come out to be the number of hours worked, the take-home pay at the end of the day, the number of rides carried out, income earned in different time periods which might exhibit patterns of their own, etc. We are also interested in important phenomena that are oft exhibited such as discontinuities, tipping points, etc. in the curves. Decision trees represent an interpretable algorithm that can account for threshold effects and can pick up such signals. Testing for the role that Information asymmetry plays in shaping supply choices might be an interesting hypothesis to test out in future work. Taxi drivers are sometimes given prompts on the expected demand in the form of information such as heatmaps by the applications that they use. Some platforms on the other hand do not do so. This could be a natural experiment to test for the impact that the presence or absence of such information has on the supply of drivers.

Explainable AI (Molnar 2020) has the potential to shed more light on the nature of the supply of gig workers that are using multi-sided platforms and might be invaluable in unveiling new insights. They have the potential to give significantly better model fits and out-of-sample generalization than traditional econometric methods as well as potentially new highly non-linear model explanations. Game theory can illuminate the ideal approaches that all stakeholders in multi-sided platforms should use to maximize the payoffs in terms of the parameters of interest.

SHAP (Shapley additive explanations) uses a game theoretic approach (Lundberg and Lee 2017) to explain black box machine learning models using simpler interpretable models such as linear models or vanilla decision trees. The social network analysis literature on its own merit is vast and has a number of paradigms, theories, models, methods, and algorithms. Testing them on data pertaining to gig workers could be the basis for future work.

The platform design is important for optimal functions and outcomes in gig work facing multi-sided platforms. It is essential to optimize platforms for things like latency which might have relationships with relevant outcomes such as click-through rates, site traffic, customer churn, turnover rates, etc. A number of such high-traffic platforms exist and considerable work has been done on the recommendation engines (Schrage 2020) that are used in them.

More large databases and especially databases with real-time data need to be studied and released to the public domain for more researchers to take a crack at answering the pertinent questions at hand. Benchmark tasks on such datasets would encourage attempts to find solutions better than the state-of-the-art so that proposed solutions keep improving.

With real-time data, time series operations (Brockwell and Davis 2009) and paradigms like windowing, seasonality, etc. might be useful and show different results when it comes to time series gig worker data in the mold of, say, real-time vehicle location timestamp data. Real-time strategy can be implemented and deployed using multi-armed bandits. Kuleshov and Precup (2014) address the subject of bandit algorithms in some detail. We hope that our review can serve as a beacon to illuminate directions for future research.

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