COVID-Driven Technology Adoption and Worker Inequality in the US

1 Motivation and Study Objectives

A recent report by McKinsey (2020) finds that U.S. companies have accelerated their digitization of customer and supply-chain interactions as well as their internal operations by up to 6 years relative to their average rate of technology adoption from 2017 to 2019. Additionally, a survey by Riom & Valero (2020) of 375 UK businesses finds that more than 60% of firms report adopting new technologies or management practices during the pandemic. Importantly, it is not just videoconferencing-type of software that is likely responsible for these findings. Another survey by IEEE of 350 business executives in the US, UK, China, India, and Brazil finds that over half of the respondents accelerated adoption of cloud computing, 5G, AI and machine learning, while at least a third reported accelerated adoption of the Internet of Things, augmented and virtual reality, and virtual conferencing (Anderton, 2020).

One potential implication of this COVID-accelerated technology adoption might be an increase in the demand for more advanced skills (Lewis, 2006).[1] One recent piece of evidence that technology adoption raises the demand for skills comes from Jiang et al. (2021), who examine how US firms reacted to fintech shocks over the past 10 years. They find that firms most exposed to fintech shocks reacted by reducing the number of, and upskilling, their job postings. In particular, the authors find that such firms started requiring "combo" skills, more years of education, and more years of experience. Another recent piece of evidence for the link between technology adoption and upskilling is the study by Hershbein & Khan (2018). The authors find that recessions have a permanent upskilling effect, and they suggest that this upskilling effect is driven by technology adoption, which accelerates during recessions including because the opportunity cost of adopting new technologies goes down in times of downturns. This permanent upskilling effect might, in turn, reveal the process of the economy restructuring toward more higher-skilled workers, which is simply accelerated by recessions (Hershbein & Khan, 2018). However, although the authors propose technology adoption as the mechanism for the upskilling effect of recessions, they do not have data on firm-level technology adoption decisions or spending to test for this mechanism directly.[2] The **first objective of this project**, therefore, is to provide more *direct* evidence that technology adoption has a permanent upskilling effect, using granular firm-level data on technology adoption decisions and spending linked to the data on firm-level labor demand, with the identification strategy that addresses the endogeneity of firm technology adoption decisions and spending.

The **second objective of this study** is to examine in great detail the heterogeneity in the impacts of technology adoption on firm labor demand by type of technology. Understanding this heterogeneity might be crucial to understanding the potential impacts of *new* technologies on the inequality among workers of different skill levels. To show why this is so, we need to situate this study in the literature on the commonly used task-based model of technological change, which we do below.

[1] However, this relationship is not straightforward, as reverse causality has also been suggested in the literature, in particular, it has been suggested that the rising skills of US workers are incentivizing businesses to adopt new technologies. This view is summarized by Lewis (2006); more recent studies include Beaudry et al. (2014) and Beaudry et al. (2016).

[2] They used data on total firm-level capital spending.

The type of technological change often studied in the more recent literature is automation,[3] which is often studied with the task-based model of technological change (developed by Acemoglu & Autor, 2011; Autor, 2013; Acemoglu & Restrepo, 2019). One main prediction of that model is job polarization between higher-skilled and lower-skilled workers. This is because in the task-based model, automation is theorized to push out middle-skilled workers by taking away from them some of the tasks they did previously and assigning those tasks to higher-skilled workers, who can now be more productive in those new for them tasks because of the new technologies (Autor, 2013). As a result, middle-skilled workers lose some of their comparative advantage and their wages go down, while the wages of higher-skilled workers go up as they become more productive. However, other forces at play might reduce this negative effect of automation on middle-skilled workers in the task-based model. For example, technology adoption might raise firm productivity and consequently its labor demand, so middle-skilled workers do not necessarily have to lose from automation (Acemoglu & Restrepo, 2019). Whether the middle-skilled workers are negatively affected by automation ultimately depends on the relative strengths of this and other counterveiling forces, the most powerful of which might be the creation of *new* labor-intensive tasks (Autor, 2013; Acemoglu & Restrepo, 2019).

Note that the implication of polarization between lower- and higher-skilled workers from the task-based model[4] would follow from a researcher's decision to study the automation type of technological change (we will return to this in the next paragraph) and the assumption that the automation in question automates the tasks done previously by middle-skilled workers. But automation does not have to mean automating the tasks of middle-skilled workers only. The economist Jason Furman asks, "Should we be re-assured if automation in the future looks like automation in the past?", questioning the expectation that the spread of AI, which might automate cognitive tasks typically done by higher-skilled workers, is really going to have the same polarization effect that other automation in the past seems to have had (Furman, 2019). To add to this concern, a study by Almeida et al. (2017), situated in Chile, finds that adoption of complex software by firms reallocates employment from higher-skilled to lower-skilled workers. Webb (2020) finds that it is workers in high-skilled occupations who are most exposed to AI, especially those with college degrees, including Master's degrees. The total effect of technology adoption on workers, therefore, might depend on the types of technologies adopted (whose tasks do those technologies really automate?).[5]

Returning to the task-based model again, it is often used to study technological change of the automation type. But other possible types of technological change include labor-augmenting technological advances, deepening of automation, and the creation of new tasks (Acemoglu & Restrepo, 2019). These types of technological change might happen simultaneously with automation and they might reduce the negative effects of automation on workers (Acemoglu

[3]Other types of technological change are labor-augmenting technological advances, deepening of automation (this is technology adoption on the intensive margin, whereas automation is technology adoption on the extensive margin), and the creation of new tasks (Acemoglu & Restrepo, 2019).

[4]This relationship has indeed been confirmed by empirical studies; see, for example, Song et al. (2019) and Dunne et al. (2004).

[5]Note that this potential heterogeneity in the impacts of technology adoption on workers does *not* contradict the task-based model of automation-type technological change, but rather shifts the focus away from middle-skilled workers to consider the possibility that some types of automation might affect workers of other skill levels, and as a result, the "new" automation might not necessarily lead to the polarization between higher-skilled and lower-skilled workers like the "old" automation did in the past.

& Restrepo, 2019). Or they might aggravate the existing inequalities.[6] Among other types of technological change, new task creation is deemed in the literature as potentially the most powerful force against the negative effects of automation on workers (Acemoglu & Restrepo, 2019). Therefore, the **third objective of this study** is to attempt to identify and quantify empirically the amount of new task creation that resulted from technology adoption accelerated by COVID, using natural language processing methods to identify and map new skill requirements in firms' job postings to potentially new tasks. We approach this research task following the view of Acemoglu & Resrepo (2019) that new task creation does not have to be limited to the same firms that adopted new technologies, or even to the same sectors, and intend to look for evidence of new task creation processes in the post-COVID economy broadly. That said, we start with the premise that it is firms that adopted AI that are especially likely to engage in new task creation (Acemoglu & Restrepo, 2019).[7]

2 Project Contribution

The first contribution of this project will be to directly establish (or reject) the upskilling effect of a technology adoption shock in the broader economy, for a wide range of technologies (from digitization of information to cloud computing to various types of AI[8]) and industries, using a plausibly exogenous source of variation in firm-level technology adoption decisions (an economic shock associated with the COVID pandemic) to limit the selection bias associated with more productive firms self-selecting into sooner and more technology adoption. The second contribution of this project will be examining in detail potential heterogeneity of the impacts of firm technology adoption on workers across all skill levels, depending on technology type. The third contribution of this project will be being the first, to the best of our knowledge, to attempt to quantify new task creation empirically, using microeconomic data and natural language processing techniques. Understanding new task creation is important for understanding whether studies that focus exclusively on automation might overstate the negative effects of technological change on workers. Our fourth contribution will be methodological. To the best of our knowledge, there are no published studies linking the rich Lightcast (formerly known as Burning Glass Technologies) dataset with the restricted firm-level Census Bureau datasets that we intend to use or the Aberdeen Computer Intelligence Technology Database. Importantly, **we intend to make the crosswalk between firms in the Lightcast data and County Business Patterns Business Register (CBPBR) available to all**

[6] In the context of COVID-driven technology adoption in particular, it does appear, at least on the surface, that this technology adoption might favor higher-skilled workers. In particular, Davis et al. (2021) developed an equilibrium model to study the effects of the work-from-home technology adoption (which is likely a labor-augmenting technological change only available to higher-skilled workers), in which only high-skilled workers can work from home. They found a relatively large increase in the productivity of high-skilled workers leading to a permanent shift in incomes and income inequality between high-skilled and low-skilled workers. However, it is important to keep in mind (1) that it is not only work-from-home technologies that were adopted during COVID; and (2) that several types of technological change might be occurring simultaneously, such as, for example, automation and new task creation.

[7] Indeed, Wilson et al. (2017) provide some evidence of this by identifying three new types of labor-intensive jobs that appeared as a result of AI adoption: "trainers", "sustainers", and "explainers" (all involve working with AI systems).

[8] These are the types of technologies identified in the Annual Business Survey first technology module, one of our primary sources of data on firm-level technology adoption. AI technologies identified in the ABS include automated guided vehicles, machine learning, machine vision, natural language processing, and voice recognition software (Zolas et al., 2020).

other researchers who sign a data use agreement with Lightcast and who have a project that has been approved by the Census Bureau. This crosswalk will allow other researchers to link many restricted Census Bureau firm-level datasets with the Lightcast data.

3 An Outline of Methods

In this section, we outline only one of our models (the model to be used with two-period panel Annual Business Survey module data) due to space constraints.

We intend to use an **Instrumental Variable** research design, with the instrument for firm-level investment in technology being firm's exposure to COVID, defined at the geography and (in an alternative model specification) industry level. The main identifying assumption is that COVID, an exogenous shock, has differenitally affected firms' economic outlook, depending on their degree of exposure to that shock, and consequently, firms' decisions to invest in technology adoption.

For our first stage regression, we will use the TWFE estimator with variation in treatment intensity formalized by Callaway, Goodman-Bacon, & Sant'Anna (2021). One, geography-based, treatment (alternative definitions of treatment will be used as well) will be the number of weeks a stay at home order was in effect during March 2, 2020 to August 1, 2021 in the state / county where a firm is located. That is, for all firms in our sample, the timing of treatment will be the same (second period in a two-period model), but the intensity of treatment will vary. Variations of the following model will be estimated:

$$Y_{ijtck} = \alpha + \delta_i + \theta \cdot Post_t + \beta \cdot Treat_{ckt/kt} + \mu \cdot Post_t \cdot Treat_{ckt/kt} + \gamma \cdot X_{ijtck} + \lambda \cdot M_{tck} + \tau_j + \epsilon_{ijtck}$$

where Y_{itck} is the amount invested in new technology by firm i located in county c in industry j in state k in year t; δ_i is firm fixed effects; $Post_t$ is a dummy variable equal to 1 in the post-treatment period; $Treat_{ckt/kt}$ is a continuous treatment variable defined at the county or state level constructed as in Callaway, Goodman-Bacon, & Sant'Anna (2021); X_{ijtck} is a vector of firm-level time-varying controls; M_{tck} is a vector of time-varying county-level controls such as demographics and economic indicators following Hershbein & Khan (2018); τ_j is industry-fixed effects; and ϵ_{ijtck} is the error term. Then, for the second stage, we will estimate:

$$Z_{ijctk} = \alpha + \delta_i + \rho \cdot \hat{Y}_{ijtck} + \gamma \cdot X_{ijtck} + \lambda \cdot M_{tck} + \tau_j + \epsilon_{ijtck}$$

where Z_{ijctk} is the average number of skills required (or years of education / experience required) across all job postings by firm i located in county c in industry j in state k in year t, standardized by the average length of that firm's job postings in that year in order to avoid picking up the effect of job postings just becoming more wordy over time. $\widehat{Y_{ijtck}}$ is an estimate of Y_{ijtck} from the first stage.

To understand changes in skill / education / experience requirements within and across firms and occupations, we will follow the approach taken by Hershbein & Khan (2018) and disaggregate the data to estimate the model using occupation-county, sector-county, firm-county, and firm-occupation-county cells.

For the second study objective, we will estimate similar models focusing on different types of technologies. For the third study objective, we will use natural language processing methods to identify new tasks in firm job postings.

4 Data

This project relies on three data sources for data on technology adoption, i.e., three analyses will be conducted in parallel.

Our first source of data on firm-level technology adoption will be **The first and second Technology Modules of the Annual Business Survey (ABS)**. The ABS 2018 is a firm-level survey with a nationally representative sample of more than 850,000 firms (Zolas et al., 2020). This first technology module has questions on firms' spending on the digitization of information, cloud computing services, and advanced technologies such as "robotics, cognitive technologies, radio frequency identification, touchscreens/kiosks for customer interface, automated storage and retrieval systems, and automated guided vehicles" (Zolas et al., 2020). The second technology module asks firms about the impact of their technology adoption on their workforce (Zolas et al., 2020). The first module was first conducted in 2018 and repeated in 2021; the second module was conducted in 2019 and is scheduled to be repeated in 2022 (Zolas et al., 2020).

Our second source of data on firm-level technology adoption will be **the Annual Capital Expenditures Survey (ACES)**. ACES is a cross-sectional firm-level survey.[9] It includes relevant questions such as (1) "Report [investment in] computer software, IT equipment, computers, website development... "; (2) "Report capital expenditures for computer software developed or obtained for internal use during the year. Important: Exclude capital expenditures for computer hardware."; and (3) "Report capital expenditures for new and used robotic equipment in 2019."

Our third data source will be the **Aberdeen Computer Intelligence Technology Database**. This is a proprietary database on firm-level technology adoption, which provides a much more detailed data on the kinds of technologies that were adopted than the Census Bureau data. It is this comprehensive disaggregated by the type of technology information that makes it a valuable data source for this study.

The data on firm labor demand will come from the **Lightcast** dataset. This dataset contains information on online job postings, including credentials, skill requirements, salary, job hours, job title, and detailed geography identifiers of employers. This dataset covers nearly the universe of online job postings in the US and firms are identifiable in this data. We intend to link the Lightcast data with the restricted Census Bureau data through the **County Business Patterns Business Register (CBPBR)**.[10]

Firm-level exposure to COVID based on geography will be defined in several alternative ways, with the primary geography-based definition of exposure to COVID based on the variation over time and across geographies in the issuance of county-level stay-at-home orders. This data will come from the **Centers for Disease Control and Prevention**.[11]

Data on county-level controls will come from the **American Community Survey**.

Anna Malinovskaya, the PI for this study, *already has the Special Sworn Status* necessary for access to restricted Census Bureau data.

[9]Since it is a cross-sectional survey, data will be pooled and aggregated to the county level.

[10]We have confirmed with our local RDC administrator that such a linkage is feasible.

[11]Since one of our definitions of firm exposure to COVID will be based on geography, a complication arises from the fact that ABS and ACES are not establishment-level surveys, making it difficult to determine location where new technologies were adopted for multi-establishment firms (Zolas et al., 2020). One approach for dealing with this issue is focusing on smaller, single-unit firms. In fact, we might not even need to limit the ABS sample much, as close to 70% of the ABS firms surveyed in 2018 had fewer than 10 employees and only 3% had at least 250 employees (Zolas et al., 2020). For ACES, we estimate that this approach will still leave us with thousands of firms in our ACES sample. Another approach might be to link firm-level ABS and ACES data with establishment-level surveys, such as the Annual Survey of Manufactures or Economic Censuses, to determine the adoption of specific technologies by location (Zolas et al., 2020).

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Doing Bond Together: Agents, Support Networks, and the Multiple Costs of Affording Bail

Context and Project Summary

While the crisis of mass incarceration has taken center stage in today's national debates, less understood is the cash bail system which extracts millions of dollars from already financially insecure individuals and their social networks following arrest. Bail in the United States refers to the practice of releasing defendants from custody before their hearing, on payment of bail, which is money to the court which may be refunded if all court appearances are made. Because defendants disproportionately come from low-income backgrounds and often cannot afford the full court-set bond amount for pre-trial release, they instead seek out commercial bail bond agreements where they pay a portion of the total bail amount, typically 10%, as a nonrefundable fee to a bail bondsman (a private citizen working for a for-profit bonding company). As few low income defendants have the resources to enter bail bond agreements on their own, many rely heavily on cosigners—usually a family member, romantic partner, or close friend (Page et al. 2019). Likely to be under similar financial constraints, proponents of bail reform have argued that the cash bail system disproportionately drains resources from low-income communities (Neal 2012; Page and Scott-Hayward 2022). This claim is supported by statistics revealing that upwards of two million defendants are released annually through the usage of U.S. commercial bail agents (Page et al. 2019).

In this study, *Doing Bond Together*, I will systematically unpack the process of meeting bail and examine how networks of social support are activated, transformed, and sustained or broken in the face of justice induced, yet private sector mediated financial extraction and surveillance. Additionally, because bail-meeting processes produce interactions and relations with not just network members, but also bail agents, I will analyze how agent logics, decisions, and practices work to ease and/or complicate bond meeting experiences. Consequently, to develop a dynamic and nuanced discussion that acknowledges bond (and its consequences) as a process shaped by multiple actors with differing resources, social statues, and priorities, I employ a relational framework to analyze qualitative data. This approach is particularly useful for examining experiences not as isolated outcomes, but as dynamic processes responding to and shaped by other actors or entities within a shared social sphere.

Research Questions

The research questions guiding this project are:

(1) What is the bail meeting process(es) and who are the actors?

(2) What role(s) do agents serve and how might their work shape such process(es)?

(3) How are networks of social support activated and transformed during this process? Related, does doing bond induce strain, solidarity, or both?

(4) What are the financial, social, and emotional implications for defendants and their families/support networks?

(5) Last, how and why is inequality exacerbated along the lines of gender, class, and race through the workings of networks during the bail meeting process?

Method of Data Collection

This project utilizes an ethnographic method of data collection in three bail bond agencies owned and operated by members of different race/ethnic groups (i.e., Black, Hispanic, White) and at different scales of operation (i.e., mom and pop vs. multi-agency corporation). Observations within agencies, a physical space in which exchanges occur between all parties, will provide insight into how interactions—a critical part of bail meeting processes—are shaped by monetary loans, obligations, and expectations. Moreover, they offer a window into daily business operation and decision making, both of which structure the experiences and consequences of meeting bail. In-depth interviews will also be conducted with 60-90 defendants and co-signers to understand what occurs outside the agency walls, or how bond shapes day-to-day subsistence, familial/network relations, and emotional health and well-being. Recruitment is occurring via Craigslist, social media, justice-related organization, and participant referrals.

I relocated to Harris County in June 2021 to begin my 12+ month long period of data collection. There are compelling reasons for why Texas, and Harris County specifically, is ideal for this study. First, Texas has one of the largest incarcerated populations and some of the most draconian bail. Second, Harris County has recently taken the national stage in bail reform in addition to being a trend-setter among liberal counties within the state. Third, Harris County houses Houston, the most racially/ethnically diverse large metropolitan area in the nation. The availability of a population of racially and socioeconomically diverse individuals might allow for detection of obstacles or privileges during bail navigation that are stratified by such demographic characteristic. Fourth, Harris County yields approximately 80 bail bond companies that differ in scale of business conduction, predominant demographic served, and race/ethnic background of agency owners. Successfully tapping into this diversity will yield a comprehensive view of bail agents' on-the-ground business conduction and decision making.

Study Contributions and Alignment with RSF's Priority Areas

This project will address several gaps in the literature offering four novel contributions: 1) developing a theoretical framework for integrating the financialization of the criminal justice system with social support networks many defendant rely upon; 2) characterizing how the temporal nature of bail processes puts strain upon and intersects with the relational dynamics of support networks; 3) determining how agent evaluation, along with imposed bond conditions, influence the experience of meeting bail; 4) and articulating the ways in which race, gender, and class pattern how networks meet bail *and* how bail shapes networks.

Using data collected so far, I have written a draft manuscript that examines agents' perceptions of risk, their attempts to mitigate it through assessment of co-signers, and the potential consequences stemming from co-signer inclusion in bond agreements (Contribution 3 listed above). Briefly summarized, 3 main risks structure bail-agents' practice: 1) risk of non-payment for services, usually 10% of the court-established bail amount, 2) risk of recidivism, or the defendant getting into further trouble while on bond, and 3) risk of the defendant failing to appear in court, an act that sidesteps sentencing and prolongs agents' assumed liability. Co-signers, then, are evaluated on the presence (or absence) of perceived social markers that agents believe mitigate this mix of financial- and justice-based risks. To this end, the ideal co-signer is one who is 1) employed, 2) willing to surveil and/or provide a prosocial influence, and 3) has a relationship to the defendant that can be leveraged to induce responsibility. Ethnographic fieldwork reveals that all three qualities are sought out, with agents privileging some forms of employment over others, relying on performances to ascertain willingness, and using inferences or assumptions about social-tie strength to predict leveraging capacity. When all three factors are not perceived, agents use creative strategies to compensate and, in some cases, make exceptions.

In-depth interviews with borrowers (defendants) and co-signers reveal potential consequences arising from co-signer inclusion. Specifically, the transfer of risk onto co-signers can manifest into at least 3 consequences for support networks. First, the potential creation of quasi-defendants in which those not facing criminal charges become subjected to surveillance and, like Comfort's (2009) quasi-inmates, internalize and conform to institutional logics. Second, *horizontal surveillance* in which agent displacement of work and financial responsibility encourages co-signers to become surveillants of defendants. Last, *horizontal abuse* in which the co-signer designation creates a power differential that, similarly to Del Real's (2019) toxic ties, can lead to abuse and/or exploitation. Overall, while the competing objectives and social markers utilized for risk mitigation may be specific to the idiosyncrasies of respective lending domains, the wide-spread surveillance and exploitation that can arise from co-signed loans may be universal consequences that offset the benefits derived from such financial arrangements.

I am also in the early stages of conceptualizing a paper project that explores how organizational policies/ practices shape tie mobilization, or who people turn to for support. Social capital and poverty research has suggested a declining significance of kin-and-friend networks among the urban poor for making ends meet (Lubbers et al. 2020). Instead, these communities are increasingly characterized by isolation and mistrust, and thought to get by on their own or through the formation of fleeting, brittle ties (Desmond 2012; Smith, 2010). This project could offer an alternative perspective in which observed reductions in support is not the outcome of decreased willingness or capacity to offer support, but the product of organizations manipulating, and often times constraining, who can provide support for whom.

These facets of my dissertation are in direct alignment with the RSF's special initiative on *Decision Making and Human Behavior in Context*. Specifically, the first project falls under the *Motivations and Incentives* section as it explores how risk, derived from justice and for-profit logics, shape agent decision making; and subsequently, how those decisions manifest into real consequences on the health, relations, and daily existence of defendants and their support networks. The second project fits into the *Networks and Contexts* category as it tentatively explores how institutional practices (i.e., co-signer requirement) structure support among defendants' kin-and-friend networks.

Timeline, Career Goals, and Broader Impact

I plan to complete data collection during the Summer of 2022 and utilize the following academic year to analyze data and write the dissertation, completing one chapter every six weeks. The dissertation will tentatively be defended in Spring 2024. Operating at the nexus of pre-trial justice, financialization, public-private partnerships, and support networks, my dissertation makes several contributions to the field of sociology, criminology, and policy studies. Importantly, it does so utilizing data that centers the perspectives and experiences of actors who have largely been left out of the literature and more importantly, are rarely examined in relation to one another (bail agents, defendants, social support members). As states across the nation are in a decisionary moment regarding the future of cash bail, and pre-trial operations more broadly, my work might help identify possible paths forward informed by those closest to the process.

Budget and Existing Support

RSF funds would cover *transcription costs* of between 60-90 interviews at a rate of $0.90 per minute of audio; and reimbursement of *past transportation costs* and funding *for future travel costs* throughout Harris County. As an NSF-GFRP fellow my tuition and living expenses are covered. Thus far, research expenses (predominantly preliminary fieldwork) have been covered through small internal university grants administered through the UT Ethnography Lab and Rapoport Center for Human Rights and Justice. I am in the process of applying for several fellowships in addition to the Russell Sage Foundation Grant (i.e., Horowitz Foundation Social Policy Grant, Ruth D. Peterson Fellowship) however, these other fellowships are just as competitive and there is no guarantee that I will receive funding from them.

In addition to much-needed funds to carry out this research, this fellowship will signal to my future potential employers and to other scholars that I am a capable scholar and researcher, successful at positioning myself and my research as worthy of funding. As I move further along in my academic career, I will continue to need funding for my research so that I can continue to conduct ambitious and impactful research such as the project I am proposing.

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