Blood Money: The Financial Implications of Plasma Sales for Individuals and Non-Bank Lenders

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Abstract

In the United States, households donate plasma for compensation at a higher rate than they use payday, auto-title, rent-to-own, or pawn loans. Our paper is the first to explore the household financial implications of plasma donation. Plasma donors tend to be younger and less educated with lower incomes and credit scores; they are also more reliant on non-bank credit. We use dramatic growth in plasma centers between 2014 and 2021 to study the causal effect of the ability to donate plasma on non-bank credit. We find that access to a plasma donation center reduces demand (inquiries) for payday and installment loans by 6.5% and 8.1%, respectively, with larger effects (13.1% and 15.7%, respectively) on younger borrowers. Moreover, foot traffic increases by 7-10% at essential and non-essential goods establishments when a new plasma center opens nearby. Our findings suggest that plasma donation helps households smooth consumption without appealing to high-cost debt.

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1 Introduction

Plasma is a component of blood that helps manage blood pressure, blood clotting, the immune system, and transports nutrients. Plasma derived medications treat millions of people with $26 billion global annual value and form nearly 2%, the 8th largest category, of U.S. exports (Economist, 2018; Hotchko, 2021; USTradeNumbers, 2022). Plasma centers in the United States collect around two-thirds of global plasma supply. Between 2012 and 2021, the number of plasma centers in the United States increased from 400 to over 1000 and plasma collected in the U.S. more than doubled.

To collect this level of plasma, pharmaceutical corporations pay donors in the United States between $30 and $70 per donation. An individual can donate up to two times per week (104 donations annually). In 2019, between 2 and 3% of households in the United States donated plasma. This is higher than the share that use payday loans (1.5-2.4%), auto-title (0.9%), rent-to-own (1.2%), and pawn loans (1.5%).[1] During the pandemic, households donate plasma and use payday loans at much higher rates (10.2% and 11.4%, respectively); this supports a consumption insurance role for plasma donation and non-bank credit. Despite the prevalence and rapid growth of plasma donation in the United States, we are aware of no studies on the financial implications of this form of discretionary income. Our paper provides the first description of the financial characteristics of plasma donors and the effect of being able to donate plasma on their finances – in particular, on their use of debt.

The effect of being able to sell one's biological resources on household debt is unclear. On the one hand, households may use the income from donating plasma to smooth consumption and substitute away from debt (Koustas, 2018; Agarwal & Qian, 2014; Fos *et al.*, 2019). On the other hand, access to discretionary income can prompt the household to take on debt to, for example, purchase durable goods (Buchak, 2019) or invest in human capital (Moser, 2020), or because the debt will be easier to repay later (Cookson *et al.*, 2020). Similarly, if plasma income relaxes credit constraints and borrowers suffer from present-bias or forecasting problems, they may borrow

[1] Non-bank credit prevalence is measured in 2019 by the Federal Reserve's Survey of Consumer Finances and the FDIC's Survey of Household Use of Banking and Financial Services.

more (Laibson, 1997; Skiba & Tobacman, 2008; Heidhues & Kőszegi, 2010). Finally, if frequently selling plasma affects an individual's health or labor output, the additional income from plasma may be offset.

In this paper, we describe who donates plasma, their financial situation, and their motivation. We then measure how access to a plasma center affects a household's use of non-bank debt. Due to high borrowing costs, non-bank debt has garnered substantial policy interest in recent years. We will show that non-bank debt is a relevant form of credit for plasma donors because the individuals who use these activities are similar. Finally, we measure the effect of access to a plasma center on foot traffic at local establishments as a proxy for consumption.

We describe the characteristics and motivations of donors with two proprietary national surveys. Both surveys ask a national sample of respondents about their recent plasma donation activity and also capture information about their finances during the 2018-2021 period. Prior to the pandemic, we find that 3.3% of respondents donate plasma in the prior 6 months – a rate that is higher than payday (2.6%) and auto-title loan (2.1%) use in our sample. Donors tend to be younger, are less likely to hold a bachelor's degree, and have lower incomes. Plasma donors are also more vulnerable, with lower savings, worse credit scores, and greater reliance on non-bank credit. The primary reasons for donating plasma are to pay for essential goods, emergencies, and debt (collectively 70%), followed by discretionary spending (19%). Plasma donors overlap more closely with non-bank borrowers than gig workers. In fact, plasma donors are much more likely than non-donors to report being unable to afford the cost of entering gig work (e.g., you must have a car to drive for Uber) and not having the required skillset (e.g., crafting items to sell on Etsy). Whereas financial and skill barriers limit access to gig work, plasma donation is limited only by basic health and is, therefore, more universally accessible.

To study the use of non-bank credit, we manually assemble a time-series of the opening dates for all U.S. plasma centers. Plasma centers must draw donors from local residents to be certified by their trade association. We use plasma center openings as a shock to local residents' access to this form of discretionary income. We apply a difference in difference strategy, comparing individuals in recently treated geographies with those who will be treated in the future or were essentially always treated. Our identifying assumption is that two areas which receive plasma centers at different points in time would trend identically absent treatment. We verify that, prior to opening, treatment and control areas trend similarly in terms of socio-economic covariates, non-bank credit outcomes, and establishment foot-traffic.

We study non-bank credit inquiries and transactions between 2014 and 2019 for a random sample of borrowers present in Experian's Clarity Services data. We find that when a plasma center opens, the probability that an individual inquires about a payday or installment loan decreases significantly by 0.22pp (6.5%) and 0.38pp (8.1%) after four years. Access to a plasma center decreases demand for non-bank credit exclusively among young individuals – who are more likely to donate plasma according to our survey data. The probability of inquiring about a payday or installment loan decreases by 0.51p.p. (13.1%) and 0.82p.p. (15.7%) after four years for individuals younger than 35. We find that access to a plasma center significantly decreases the extensive margin probability of taking out a payday loan by 18% among young borrowers. These effects are large and are on par with the estimated effect of a 1$ minimum wage increase on low-wage workers in Dettling & Hsu (2021). A back-of-the-envelope estimate suggests U.S. households save between $180 and $230 million in payday and installment borrowing costs annually because of access to plasma centers.

After a plasma center opens, we do not find that nearby households repay loans faster. Treatment does not increase the time between inquiries or reduce the total number of inquiries in a quarter, nor do we see a larger effect on households with a history of recent credit applications. In other words, there is no intensive margin effect on the probability of additional inquiries to support a debt trap/repayment channel. Instead, our results suggest that access to a plasma center has a large impact on the use of non-bank credit at the extensive margin by infrequent borrowers, which is consistent with precautionary savings.

Households can use the income from plasma donation to expand their budget and consumption. We use cell phone tracking data from Safegraph, which aggregates monthly foot-traffic data for 6 million storefronts in the United States between 2018 and 2021. We find that within 2 years after a plasma center opens, visits and distinct visitors to local establishments increase by 7-10%. Plasma donors report being primarily motivated by essential (70%) rather than non-essential spending (19%). However, we find that visits increase similarly for both essential (e.g., grocery stores) and non-essential (e.g., restaurants) establishments. The large effect on non-essential establishment foot-traffic suggests discretionary income may support discretionary spending. Without plasma income, a household's discretionary spending would erode savings and lead to non-bank borrowing. We cannot determine whether intentional savings or matching of discretionary income to consumption achieves the non-bank debt reduction we measure in this paper. The effects of access to plasma income on local foot traffic imply large benefits to local businesses and municipalities from facilitating access to flexible employment opportunities that provide even modest compensation. Finally, the increase in foot traffic affirms that, while short-term credit may allow households to briefly smooth consumption, it cannot completely substitute for discretionary income.

It is important to emphasize that the results in this paper do not speak to consumer welfare because neither we nor the consumer understands the true cost of donating plasma. There have long been concerns that compensating plasma donors could exploit vulnerable populations (Titmuss *et al.*, 1970). Few medical studies measure the consequences of regularly donating plasma and they focus on a narrow set of short-term outcomes (Schulzki *et al.*, 2006; Laub *et al.*, 2010; Winters, 2006). Anecdotal evidence suggests the short-term consequences may include blackouts, fatigue, and susceptibility to infection. Negative health outcomes from donation may carry direct financial costs from diagnosis and treatment. Indirectly, physical weakness may lower hours worked or productivity at a primary job, thus affecting overtime, bonuses, and commissions. Moreover, health effects, should they exist, may take a long-time to build, materializing as a financial cost only after our four-year study window closes. We cannot rule out the possibility that overtime such costs offset the immediate financial benefits we estimate in this paper.

2 Conceptual framework and related literature

If borrowers use discretionary income to pay down debt they should start with the highest cost debt. Payday and installment loans, which often carry interest rates and fees with an APR above 100%, can burden the borrower with interest expenses they cannot bear. Access to payday lenders has been shown to increase hardship and reliance on social programs (Melzer, 2011, 2018) and using payday loans increases delinquency and foreclosure (Skiba & Tobacman, 2019; Gathergood *et al.*, 2019). Of course, these costs are only realized if the household borrows repeatedly throughout the year. Discretionary income from sources like plasma may allow a household to repay their loans faster, decreasing total financing costs. However, as the cost of credit decreases, households may be more willing to decrease precautionary savings to consume now, relying on loans to manage a shock. Therefore, even though discretionary income increases the ability to save, the need for precautionary savings decreases with cheaper financing.

Adding further ambiguity, even the existence of a precautionary savings response is not a given. In 2017, many American households (40%) did not have enough precautionary savings to handle even a $400 shock (Federal Reserve Board, 2018) and many papers find no evidence that households maintain precautionary savings (Deaton, 1991; Guiso *et al.*, 1992; Dynan, 1993). Households may also consume rather than pay down debt because they do not understand the high cost of non-bank credit. While households are not over-optimistic about their ability to repay high-cost loans (Allcott *et al.*, 2021), they do not appreciate the true cost of non-bank credit and are, therefore, easily influenced by disclosures and behavioral nudges (Bertrand & Morse, 2011; Wang & Burke, 2021; Agarwal *et al.*, 2009). In sum, households will only reduce borrowing if the utility from saving outweighs the tangible benefit of marginal consumption and the perceived cost of non-bank debt. Therefore, the net effect of additional discretionary income on debt in general and non-bank debt, in particular, is unclear.

Several aspects of donating plasma make the credit effect of this form of discretionary income particularly hard to predict. FDA regulations prevent individuals from donating more than twice per week. Plasma donors cannot earn enough money from selling plasma in one week to, for example, cover a typical rent payment. The typical payday and installment loans are $400 and $800, respectively. Saving enough plasma income to cover even small shocks requires weeks of foresight and commitment. We expect that it is harder to commit to donating repeatedly than it is to work for 6 to 8 hours in a single day (Jones, 2012; Andersen *et al.*, 2020). This discreteness may amplify the desire for immediate consumption (Olafsson & Pagel, 2018) or facilitate mental accounting (Thaler, 1999). Hence, both the direction and the magnitude of the relationship between plasma and non-bank debt is an empirical question.

This paper contributes to two bodies of literature. First, we extend the literature on the sale of human biological resources. The existing economics literature on plasma donation is extremely small and unrelated in research question. Kominers *et al.* (2020) study how market design can expand access to convalescent plasma therapy to treat COVID-19. Other studies weigh the ethics of compensating plasma donors against the public policy objective of maintaining an adequate supply of plasma for life-sustaining therapies (Lacetera, 2016; Grabowski & Manning, 2016, 2018; Lacetera & Macis, 2018). A more developed economics literature exists on organ donation; however, it is comprised entirely of studies that either analyze efficient market design of organ exhanges (Ergin *et al.*, 2017) or test various monetary (e.g., tax incentives or reimburable travel expenses) and non-monetary incentives (e.g., persuasive messaging or 'opt-out' defaults) to donate organs.[2] Additional avenues of research on the topic may be obstructed by the fact that few countries (currently, only Iran) permit the sale of organs (Becker & Elias, 2007) and the markets for egg and sperm donation, though compensated, are small and highly selected. To our knowledge, plasma donation is the largest market for human tissue that compensates donors monetarily. Our paper is the first to study the financial well being of plasma donors and why they donate.

Second, we measure the effect of access to discretionary income from donating plasma. Koustas (2018) and Fos *et al.* (2019) show that households use discretionary income to complement their primary income and smooth consumption across time. A growing literature shows that access to

[2] For studies on the incentives to register as an organ donor or to donate organs, see Howard (2007); Kessler & Roth (2012, 2014b,a); Lacetera *et al.* (2014); Eyting *et al.* (2016); Bilgel & Galle (2015); Li (2016); Schnier *et al.* (2018); Bedendo & Siming (2019).

discretionary income encourages households to take bank credit (Buchak, 2019), start businesses (Barrios *et al.*, 2020), and invest in human capital (Moser, 2020). The literature on substitutes for payday loans focuses on bank overdrafts and other forms of debt (Melzer & Morgan, 2015; Morgan *et al.*, 2012; Di Maggio *et al.*, 2020) rather than on income sources. A notable exception is Dettling & Hsu (2021), who find that, after a minimum wage increase, low-income households report less payday loan usage and delinquency in surveys. In comparison, we find that simply having a plasma center in ones neighborhood (i.e., a source of quick cash) decreases the demand for payday and installment loans among younger adults at a rate that is on-par with the effect of a $1 minimum wage hike estimated in Dettling & Hsu (2021). Moreover, this effect seems to come primarily from precautionary savings by occasional non-bank borrowers rather than repeat non-bank borrowers repaying loans faster.

3 Plasma Donation Background

This section describes the donation process before moving into a discussion of the medical research on the health effects of donating. Next, we discuss the compensation offered to donors. Finally, we highlight key features of the plasma industry and the global regulatory landscape that governs it.

3.1 Plasma donation process

Plasma is a component of blood, alongside red and white blood cells and platelets. Plasma contains the electrolytes, vitamines, anitbodies, and clotting factors that complete many tasks in the body. Pharmaceutical companies create medicine from components of plasma including coagulation factors (to treat trauma and hemophilia patients), immunoglobins (to treat individuals with immune systems that are compromised, either genetically or by outside factors like viruses, bacteria, and chemotherapy), and albumin (a protein used to treat burn and surgery patients) through a process called fractionation.[3] Demand for immunoglobins, which boost the immune system, drive demand for plasma (Berman & Robert, 2019). Grabowski & Manning (2018) summarize the diseases that are treated with plasma therapies.

An individual can donate plasma in two ways. First, nonprofit centers (e.g., Red Cross, Blood Banks, Hospitals, and government centers) collect whole blood, which they can later process to separate and harvest red blood cells, platelets, and plasma (this is called "recovered plasma"). Second, an apheresis machine can draw blood into its centrifuge which separates the blood components by density and collects the plasma before returning all other components of the blood to the donor's body (this is called "source plasma"). Because the blood is processed and returned to the donor it takes longer to donate plasma than to donate whole blood. The typical visit to a plasma center lasts 90 minutes (versus a 1 hour for whole blood). If an individual donates whole blood frequently they may become iron deficient so the maximum frequency for whole blood donation is once every 8 weeks. However, a donor can give plasma twice weekly because apheresis returns all components of the blood except plasma to the donor's body so there is no risk of iron deficiency (Schreiber *et al.*, 2018). Commercial centers collect plasma exclusively via apheresis to increase the frequency and volume of donations. This paper focuses on plasma centers that collect source plasma via apheresis and compensate donors.

During the first visit, prospective donors receive a physical, answer questions about their medical history, and are tested for viruses including HIV and Hepatitis. Doctors check for signs of drug use, which place the donor at higher risk of having a sexually transmitted disease that may contaminate the plasma. Plasma centers also test blood for valuable characteristics like an Rh Negative blood type or being vaccinated for hepatitis or tetanus. Plasma centers periodically test donor blood to verify it contains sufficient medical proteins to produce medicine. At each visit donors weigh in to determine the volume they are allowed to donate. An individual with the minimum weight of 110 pounds can donate up to 690 mL (1.55lbs of plasma) while those weighing

[3]Hemophilia is a hereditary condition where blood lacks a clotting factor that affects as many as 1 in 10,000 individuals and requires 1,200 plasma donations to treat a single patient for one year. Similarly, it can take 130 plasma donations per year to treat a patient with a genetically weak immune system annually.

at least 175 pounds can donate 880 mL (1.99 lbs of plasma). Both groups can donate twice per week.

3.2 Health effects from donating plasma

Medical evidence on the health impact of regular plasma donation is limited. Existing research focuses on physiological reactions observed at the plasma center and measurable characteristics of donor blood. This research finds that plasma donors experience hematoma (bruising) and vasovagal (faintness or fainting) reactions during or immediately following donation at lower rates than whole blood donors (McLeod *et al.*, 1998; Winters, 2006; Schreiber *et al.*, 2021). However, because some anticoagulant is returned to the donor with red blood cells during apheresis there is a 0.4% risk of citrate toxicity, which is generally mild but can involve hospitalization (Winters, 2006). There is mixed evidence that donating plasma frequently reduces protein concentration in plasma, which could make donors vulnerable to infection (Rodell & Lee, 1999; Schulzki *et al.*, 2006; Laub *et al.*, 2010).[4] Some individuals drop out of plasma donor studies for low protein levels (16% in Schulzki *et al.*, 2006) and medical reasons unrelated to plasma (7-12% in Rodell & Lee, 1999; and 10.4% in Schulzki *et al.*, 2006). Donors who drop below the FDA's limit on total protein and IgG concentration are deferred until their levels normalize. Still, the primary reason for donors leaving plasmapheresis studies is socioeconomic changes (e.g. time constraints, schedule conflicts, insufficient compensation, no longer need money; see Rodell & Lee, 1999; Schulzki *et al.*, 2006).

There is surprisingly little research on the quality of life of donors between donation or the incidence of sicknesses not directly transmissible through plasmapheresis. Indeed, Weinstein (2018) points out the dearth of controlled trials on the health consequences of donating plasma. Chen (2014) finds negative associations between donating plasma and self-reported health in sur-

[4] Laub *et al.* (2010) show lower protein concentrations in pools of plasma from U.S. fractionation plants than European plants and suggest that frequent plasma donation in the United States depletes protein levels of donors. However, the PPTA retort that the lower protein levels in pools cannot be linked to donation volume or frequency or to poor donor health because pools may have different characteristics and be processed in different ways across countries (Kimber *et al.* (2011)).

veys of Chinese farmers. However, he does not control for potentially confounding factors like income, which are associated with both donation and fatigue. Interviews with frequent plasma donors published in the The Atlantic and ProPublica offer anecdotal evidence of symptoms like blacking-outs and extreme fatigue (Edin & Shaefer, 2015; Shaefer & Ochoa, 2018; Dodt & Strozyk, 2019). On the other hand, plasmapheresis has been proposed as a viable treatment for hypertension and high cholesterol (Rosa-Bray *et al.*; Rosa-Bray *et al.*), implying possible health benefits for some donors.

3.3 Plasma compensation

Plasma centers compensate donors by adding money to prepaid cards, often based on the volume of plasma they donate. Before shortages attributed to the pandemic, the typical payment was between $30 and $70 per donation or roughly up to $400 per month. Plasma centers do not report donor compensation to the IRS because individual payments are below the reporting thresholds for cash or electronic payments ($600 and $20,000 respectively). However, the income is still taxable, such that donors who earn more than $400 are supposed to report the compensation as self-employment income, file a 1040-SE, and pay the associated Social Security and Medicare taxes (though we suspect that few households complete these actions).[5,6]

Plasma centers do not report donation income to credit rating agencies which maintain employment or payroll services. Donating plasma may directly increase the supply of credit near lenders who accept prepaid cards as collateral. Plasma centers use common marketing methods to attract donors including advertising and referral payments. Some centers also employ behavioral strategies to retain customers like rewards or loyalty programs, referral bonusses, raffles based on donations, and convex compensation that grows with the number of donations within a month (see Appendix Figure A.1). The industry's focus on encouraging repeat donation stems

[5]There is legal precedent where a woman with a rare blood type received material compensation in 1967-1969 for her plasma but did not report the income. She was sued by the IRS in 1979 and found guilty of tax evasion (see case here).

[6]When someone donates an asset they incur a material financial loss and the IRS allows a tax deduction offset. However, since plasma donors receive a financial reward, plasma donation is considered a sale that yields taxable income.

from regulation.

It may seem odd that pharmaceutical corporations seek the ability to compensate donors. The cost of source plasma contributes 40-60% of the total cost for plasma derived products compared to 10-15% for the broader pharmaceutical sector (Ballem *et al.* (2018); Grabowski & Manning (2018)). But creating medicine from recovered plasma (from nonprofit centers) is often more expensive. Nonprofit organizations sell recovered plasma at a market rate to hospitals and clinics, for the transfusion needs of patients, to cover their operating expenses (i.e. pay staff, buy equipment, manage inventory, marketing etc.) (see Slonim *et al.*, 2014). The Australian government directly manages all domestic blood and plasma collections and imports 44% of their immunoglobulin (Ig); but it costs Australia roughly three times more per unit of domestic Ig than a unit of imported Ig (Slonim, 2018). Weinstein (2018) points out several regulatory barriers that limit the ability for recovered plasma to satisfy plasma demand for derived therapies –most notably that nonprofits generally collect plasma less frequently, in smaller quantity, at greater marketing cost, are subject to more shipping restrictions, and have longer mandatory hold requirements than plasma centers. This motivates pharmaceutical companies that operate fractionation plants to integrate vertically and run their own plasma centers.

3.4 Global regulation of the plasma industry

Plasma centers in the United States are regulated by the Food and Drug Administration (FDA), international regulators, and the Plasma Protein Therapeutics Association (PPTA) industry group. There is a legacy of caution in how plasma centers are regulated that originates with the HIV/AIDS epidemic of the 1980s. Immediately after being collected, plasma is frozen on-site and sent to storage warehouses for a minimum 60 day hold.[7] Government regulations require that plasma from a donor who tests positive for Hepatitis (B or C) or HIV be destroyed. Repeat donation is very important for plasma centers. Manufacturers cannot process any donation until a second donation within 6 months passes all tests. Burnouf, 2018 explains each stage of how plasma is collected,

[7] Plasma can be frozen and stored for one to seven years, unlike whole blood which keeps for 35 days to 9 weeks refrigerated (Hess, 2010, and American Red Cross).

treated to remove contaminants, and processed into medicine.

The PPTA offers the International Quality Plasma Program (IQPP) as a voluntary certification program for pharmaceutical corporations that collect plasma. As part of the certification, corporations must verify that donors live near the plasma center where they seek to donate at least annually.[8] Pharmaceutical corporations report all donation activity to a Cross Donation Check System (CDCS). Plasma center staff check the CDCS before an individual donates to enforce the FDA's limit of 2 donations in 7 consecutive days. Plasma centers also report to a National Donor Deferral Registry (established in 1993), which records individuals who are temporarily or permanently banned from donating plasma.[9] Collectively, efforts by the plasma industry appear to effectively limit the transmission of infectious diseases through plasma derived medicines as there have been no confirmed transmissions in the past two decades (Ballem *et al.*, 2018).

Contrary to current U.S. policy, the World Health Organization's recommends that all blood products should be collected from domestic, voluntary, *uncompensated* donors (World Health Organization; World Health Organization).[10] In an influential early book, Titmuss *et al.* (1970) argues against compensating donors. However, support has recently emerged for compensating donors (Farrugia *et al.*, 2010; Jaworski, 2020). Like the U.S., Germany, Austria, Hungary, and Checkoslovakia allow their plasma centers to compensate donors and currently maintain around 161 plasma centers (Kluszczynski *et al.*, 2020; www.donatingplasma.org provide a global registry of plasma centers). Currently, only these four European countries and the United States collect sufficient plasma to satisfy their domestic demand and, collectively, they provide 90% of global plasma (Ballem *et al.*, 2018). Countries which do not compensate plasma donors depend on plasma

[8] Plasma centers require proof of residence like a driver's license, recent utility bill, or rental agreement. Students at a local college or university and military members stationed at a local base are exempt from the requirement to prove residence.

[9] An individual may be temporarily banned from donating plasma due to a medication they are on, signs of non-IV drug use, or problems during the medical screening. An individual will be permanently banned for intentionally violating the limits on plasma donation frequency, possessing a virus that may contaminate their plasma, or for IV drug usage.

[10] For summaries of historical regulatory perspectives see Flanagan (2017); Weinstein (2018). The two arguments to prefer volunteer over compensated donations appear to be safety (Slonim *et al.*, 2014) and the concern that compensation would crowd out altruistic donation (Lacetera *et al.*, 2012; Lacetera & Macis, 2013). Countries sometimes skirt the WHO resolution and incent donation through gift cards or paid time off.

recovered from volunteer whole blood donations and on imported plasma to satisfy demand.

We estimate that in 2019 between 2.54 and 3.7 million adults in the U.S. (0.04-0.06% of the world population) provide 64% of the plasma world's plasma.[11] This figure masks the true degree of concentration since 1 million U.S. individuals (the top 28% of U.S. donors) donate more than 20 times annually for an annual income of $630-$5,200 (at $30-$50 per collection) and provide roughly 50% of the world's plasma. The fact that 50% of global plasma supply is sourced from about 1 million donors in the United States constitutes a risk for national health departments. In 2020 plasma donations in the U.S. fell by 19% because of COVID.[12] To mitigate the supply chain risk, countries are exploring how to reach self-sufficiency.[13]

3.5 Exponential growth of the plasma industry in the U.S.

The high cost of recovered plasma from volunteers and a limited ability to compensate donors globally drive demand for source plasma from compensated donors in the United States. Consequently, the U.S. plasma sector has experienced material growth and consolidation over the past two decades. Figure 1 shows that between 2009 and in 2021 the number of plasma collection establishments has more than tripled, from roughly 300 to 1000 locations. Plasma centers have also expanded the number of beds and purchased more efficient apheresis machines. Therefore, plasma collections in the U.S. increased by roughly 250 percent between 2009 and 2019. The plasma sector is currently concentrated (see Table 1). As of 2021, four pharmaceutical corporations operated 85.5% of plasma centers in the U.S. and the next four operate a further 9.6% of

[11] The Market Research Bureau estimates 64% of all plasma collected globally (recovered and source) was collected in the United States (Roberts, 2017). A 2006 report for the Australian government found that the United States supplied 70% of all plasma globally (Flood (2006)). More recently, a Canadian report states that the United States collects 74% of global source plasma (Ballem *et al.* (2018)).

[12] Such national shocks are not unprecedented. In 1998 the U.K. and several other countries banned the use of medication derived from British plasma over fears that Creutzfeldt-Jakob (a.k.a., mad cow) Disease could spread through the donations. Until the ban was removed in February 2021, Britain imported all plasma derived medicine. In China, lax health standards led to transmission of Hepatitis among donors and temporary shutdown of all plasma collection (McLaughlin, 2018). The HIV/AIDS outbreak in the 1980s was partially transmitted through U.S. plasma centers, though no shutdown was enforced.

[13] In Canada, a bill passed in November 2020 authorizes plasma centers to compensate donors in Alberta for up to 2 donations in 7 days. Egypt signed a joint venture with Grifols in spring 2021 to open 26 plasma centers that compensate donors and permit one plasma donation per individual every 14 days (Javeed, 2021; Grifols, 2021; AhramOnline, 2021).

plasma centers. These companies are all owned by global pharmaceutical corporations.

Plasma centers in the U.S. are growing rapidly to satisfy global demand. The U.S. certainly has the highest use per capita of plasma derived therapies in the world. However, plasma derived therapies have not been affordable for much of the developing world. Weinstein (2018) states that at least 70% of demand from hemophiliac and primary immune defficient patients is unmet, hundreds of thousands of newborns die or have brain damage because a plasma derived medication is unavailable, and doctors in some countries do not attempt to diagnose these conditions because treatment would not be available. As global demand continues to grow, the reliance on compensated plasma from the United States will likely continue to drive rapid expansion of U.S. plasma centers in a search for new donors.

4 Data and Empirical Methodology

This section provides a framework to understand the empirical work in the rest of the paper. We first describe the data. Since we use several datasets, we defer quantitative descriptions of each sample to the pertinent analysis section. This section concludes with our difference-in-difference (DiD) regression approach.

4.1 Data

One goal of this study is to describe the prevalence, characteristics, motivations of plasma donors. For this, we use two economic surveys administered by Social Policy Institute (SPI) at Washington University in St. Louis. To our knowledge, these are the only national surveys that ask respondents about their plasma donation activity.[14] In addition, these two surveys capture a comprehensive picture of respondents' financial assets and liabilities, employment and income, shocks and hardships, and household demographics.

[14]There are certainly surveys of plasma, platelet, and whole blood donors that focus on the discomfort of donating (e.g. McLeod *et al.*, 1998; Newman, 1997), the social perception of donating and compensation (Van Dyke *et al.*, 2020; Lacetera & Macis, 2018), and the motives of donors (Charbonneau *et al.*, 2015; Thorpe *et al.*, 2020). But none of these studies contain information about the donor's financial situation or capture the same information for respondents who do not donate plasma.

The first survey focuses on low-income households that file taxes online through The Free File Alliance (FFA). The FFA is an IRS program in which companies offer limited versions of their software for free to individuals with low adjusted gross income (AGI) or who qualify for an Earned Income Tax Credit (EITC). SPI partnered with an FFA member company to offer this survey (henceforth, the "IRSFFA survey") to a random sample of tax filers. The survey is collected as individuals file their taxes and invitations to complete a follow up survey are sent out via email six months later. Participants receive a small-value Amazon gift card for completing the survey. Each year, roughly 16,000 and 2,500 respondents complete the first and second IRSFFA survey waves, respectively. We use the initial and follow up survey responses from the 2017 and 2018 tax years (the only years to ask about plasma donation).[15]

The second source is the Socioeconomic Impacts of COVID (SEIC) survey. At the onset of the COVID-19 pandemic the SPI designed a nationally representative survey to understand how people react to and are affected by the pandemic. The survey asks many of the same questions as the IRSFFA survey, including questions about plasma donation, that allow us to study a broader sample during the pandemic. SPI administered the SEIC survey in 5 quarterly waves between May 2020 and May 2021 of roughly 5000 respondents. Each respondent who completes the survey is invited to complete future waves of the survey. Over the 5 waves there are 12,977 unique respondents and 24,921 survey submissions. Because of the limited overlap in survey respondents across waves, we will use IRSFFA and SEIC data as repeated cross-sections to understand who donates plasma, their motivation, their financial condition, and their outlook.

The survey data from IRSFFA and SEIC provide the best available cross-sectional descriptions of plasma donors and non-donors. However, the short timeframe of the SIEC and IRSFFA, sample size limitations, and sampling differences between the surveys limit our ability to estimate the causal impact of donating plasma in survey data. Instead, we draw on large administrative data

[15] A detailed evaluation of the potential for sample selection bias in this dataset is provided in the Appendix of Gallagher *et al.* (2019). While Gallagher *et al.* (2019) find the IRSFFA sample to be more often white, young, and better educated than the population of low-income households, within the broader pool of FFA tax filers, those who take the survey are similar to those who do not along observable dimensions and their observable qualities do not vary by compensation amount (e.g. $5 versus $15).

sources to understand the effect of the ability to donate plasma on non-bank debt and storefront foot-traffic.

We use a sample from Experian's proprietary alternative finance credit bureau, Clarity Services, to study non-bank credit. Clarity is the largest alternative credit bureau overseen by the Fair Credit Reporting Act. Its purpose is to offer lenders information about the non-traditional credit history of prospective borrowers, many of whom are not tracked by traditional credit bureaus. Clarity gathers credit inquiries and transactions reported by non-bank lenders – including payday, installment, rent-to-own, and auto-title lenders. Our sample from Clarity contains inquiry and transaction information for a nationwide random sample of 2.5 million and 0.5 million individuals, respectively. Records for some products are only available for part of the sample, experience abrupt changes in prevalence, or are used infrequently. Therefore, we study only installment and payday loans which, respectively, constitute 56% and 25% of the credit inquiries and 15% and 50% of the transactions present in our Clarity sample.[16]

In the United States, it is more common to take out a payday loan in person than online (i.e., 54% only use in-person loans versus 31% are only entirely online borrowers according to our IRSFFA data, with similar estimates in PEW Charitable Trust, 2012). However, internet loans form 95% and 93% of installment and payday loans inquiries, respectively, and 87% and 69% of installment and payday transactions. Payday and installment loans often bear effective interest rates above 100% that violate some states' usury laws. Internet lenders act as credit brokers and partner with banks to offer loans. Internet lenders argue that only the laws of the state where the lender is incorporated govern the loan (a strategy called "rent-a-bank" or "rent-a-charter").[17]

[16]It is odd that the frequency of inquiries for installment and payday loans is the opposite of their prevalence for transactions. The reversal is not because payday loans may be extended repeatedly as distinct transactions; Clarity records consecutive payday loans as a single transaction account. We expect that while some credit inquiries will not be approved, each transaction has a corresponding inquiry. In practice, the correlation between having an inquiry and opening an account for a specific product type in a given month is nearly zero (<1%). Therefore, we believe that some partner companies report inquiries to Clarity while a smaller group of partners report transactions.

[17]The rent-a-bank strategy to bypass state usury laws has existed in some form for over 20 years and is still very active. It has received both scrutiny and support over time from regulators depending on what type of chartered bank the high-cost finance corporation partners with (Eaglesham *et al.*, 2020; CRL, 2019, 2021). State AG offices challenge the tactic in the judicial system (Office of the New York State Attorney General, 2021). Non-bank lenders have also partnered with Native American tribes to bypass state laws (NCLC, 2019; Goldberg, 2021).

Therefore, Clarity's focus on internet lenders reflects an important segment of non-bank credit and allows us to study states that ban payday and installment loans.

Table 8 presents descriptive statistics for our Clarity data, both in terms of a balanced panel (Panel 1) and the stacked cohort data we use for analysis (Panel 2), as will be explained in Section 4.2. In our sample the mean age is 38 years old. The average monthly take home income is $2,900 (or $34,800 annually), though the income distribution includes many households with higher incomes (weighty upper tail). On average, the sample probability of submitting a payday or installment loan inquiry in a given quarter is 3.4% and 4.7% respectively. The probability of submitting multiple inquiries within a quarter conditional on submitting any inquiries is high at 65% (2.2/3.4) and 54% (2.8/5.2) for payday and installment loans respectively. Clarity collects income information when an individual applies for credit, but not all vendors provide income information. Also, for most individuals, we have more complete information for inquiries than actual credit transactions.

Finally, we use cellphone tracking data from Safegraph to measure foot traffic at over 6 million establishments in the United States between January 2018 and July 2021. Safegraph collects data from cell phone application developers that have users who authorize tracking. Safegraph processes the tracking information to record visits, defined as a stay of at least 15 minutes within a space they register as an establishment. Safegraph distributes visit information aggregated at the establishment by month level. We are not able to track individual cell phones to identify plasma donors, their donation habits, and which other stores they visit. We use this data for two purposes. First, for each establishment Safegraph provides the number of visitors from each origin Census block group (CBG); this allows us to verify how far individuals travel to donate plasma. Second, as a proxy for demand and consumption of essential and discretionary goods, we measure changes in foot traffic at different types of local establishments when a plasma center opens nearby.

Our causal identification strategy relies on variation in an individual's ability to donate plasma. Recall from Section 3.4 that, to be certified by their trade association, corporations must verify that donors live near the plasma center where they seek to donate. Therefore, we build a panel dataset of where all plasma centers in the United States are located and when each plasma center opens. This allows us to use plasma center openings as shocks to the ability of nearby residents to donate plasma. We use data from the FDA, Infogroup, Google, and the Wayback Interet Archive to identify plasma center locations and define a window in which each plasma center opens, setting the opening date equal to the midpoint of this window. For full details on this process, see Appendix B. With an average opening window precision of 5.25 months, we are able to assign an opening time to 589 of the 616 plasma centers that we believe opened in the 2014–2021 period. Appendix Figure B.1 plots timing accuracy around plasma center openings.

4.2 Empirical Strategy

4.2.1 Design

We estimate the effect of the ability to donate plasma on an individual's demand for high-interest credit and on local establishment foot traffic. The identification challenge is that plasma centers are not randomly placed within metropolitan areas. We show in Appendix C that pharmaceutical corporations open plasma centers in poor and densely populated neighborhoods with more non-bank lenders (i.e. location is not random). So, if we compare households near a plasma center to households further from the plasma center (for example 0-5 km versus 5-10 km) we will compare households that live in neighborhoods that differ on observable and, possibly, unobservable dimensions. Instead, we could compare a neighborhood near a plasma center after the center opens to itself prior to the opening. But corporations may choose to place a plasma center in a neighborhood when the neighborhood is growing or decaying. A simple pre- versus post-opening comparison will not be able to separate treatment from trend. Therefore, we use a difference-in-difference approach, comparing the change in a neighborhood which experiences a plasma center opening against the change in a neighborhood where no plasma center opens. The identifying assumption is that, if the plasma center had not opened, the treated and control observations would trend in a similar manner – i.e., the parallel trends assumption.

There are two ways to study events that are staggered in time using a difference-in-difference regression. In the traditional approach, recently labeled two-way fixed effects (TWFE), all events are studied together in a static or dynamic regression like example equations 1 and 2, respectively. These equations are appealing for their simplicity and they have been widely used in very influential work (e.g. Jayaratne & Strahan, 1996; Bertrand & Mullainathan, 2003). However, Goodman-Bacon (2021) shows that the treatment effect β is the weighted average of comparisons not just between treated and not-yet-treated observations, but also of treated against never treated, always treated, and *recently treated* observations. It is this "forbidden comparison" of treated to *recently treated* which causes problems in practice.[18] Moreover, β will be biased if the effect of treatment is not constant across cohorts and even the sign of β may be incorrect. Sant'Anna & Zhao (2020) and Sun & Abraham (2020) show that the forbidden comparison problem can cause the econometrician to observe significant pre-trends when there are none and will attenuate the post-treatment effect. They show that, under some assumptions, we can adjust for the forbidden comparison problem by dropping an additional pre-period.[19]

$$y_{i,t} = \beta \times 1(i,t) + \alpha_i + \delta_t + \epsilon_{i,t} \tag{1}$$

$$y_{i,t} = \sum_{\tau} \beta_\tau \times 1(i,t,\tau) + \alpha_i + \delta_t + \epsilon_{i,t} \tag{2}$$

Sun & Abraham (2020); Sant'Anna & Zhao (2020) and others offer tools to manage the main problem with TWFE: that it compares treated and recently treated observations. If we could simply omit the recently treated observations from our control group then the critique in Goodman-Bacon (2021) no longer applies. This is essentially what the "stacked difference-in-difference"

[18] Goodman-Bacon (2021) notes that β is a weighted average of estimates based on all four types of comparisons groups. If there are many control observations that are never treated, then relatively little weight may be assigned to the forbidden comparison and the bias may be small. But, if treatment is significantly staggered and a material fraction of observations are treated by the end of the sample, then, at the end of the sample, the estimator is entirely driven by the forbidden comparison.

[19] See Gardner (2021); De Chaisemartin & d'Haultfoeuille (2020); Wooldridge (2021) for additional discussion of TWFE with staggered treatment.

approach, proposed by Gormley & Matsa (2011) and supported by Baker *et al.* (2021), achieves. Under this approach, each treatment event (i.e. cohort) is handled as a simple, and isolated, difference-in-difference study. The treatment estimator β is the average of cohort specific treatment effects. We compare treated and control observations within cohorts simply by making the time and individual fixed effects cohort specific (following equation 3). We can ensure that recently treated observations are not used as controls by excluding observations that have been recently treated. An additional difference between TWFE and the stacked regression approach is that, when we estimate equation 3, we use data only for a window around the treatment event (the window need not be balanced). TWFE typically uses all observations in the regression even observations far after treatment occurs.

$$y_{c,i,t} = \sum_{\tau} \beta_\tau \times 1(c,i,t,\tau) + \alpha_{c,i} + \delta_{c,t} + \epsilon_{c,i,t} \tag{3}$$

We implement our identification strategy in regression equation 4. We treat each opening plasma center as a treatment event with its own cohort-specific dataset. We stack all the cohorts, c, into a single dataset and estimate the average effect of treatment. The treatment coefficients β_τ capture the difference between treated and control observations at event time τ relative to a baseline period. We choose the period before the plasma center opens ($\tau = -1$) as our baseline since it is the last observation that is entirely untreated. For each cohort we use only data for a window, T, spanning up to 4 years before and after treatment, as feasible.

$$y_{c,i,g,t} = \sum_{\tau \in T \setminus -1} \beta_\tau 1_{c,g}(\tau,t) + \alpha_{c,i} + \delta_{c,\tau,d(g,c)} + \gamma_{s(g),t} + \epsilon_{c,i,g,t} \tag{4}$$

The independent variable $y_{c,i,g,t}$ contains information about each individual or establishment i residing in geography g at time t in cohort c. The dynamic effect of treatment is measured through cohort- and geography-specific dummies, $1_{c,g}(\tau,t)$, which take the value of one if geography g is treated (i.e. near the opening plasma center) and t is τ periods after opening c; otherwise, it is zero. We allow for correlation in the error term by clustering standard errors at the cohort level (Cameron *et al.*, 2011; Cameron & Miller, 2015).

We include fixed effects for each individual by cohort, $\alpha_{c,i}$, to adjust for individual traits that do not vary across time within cohort.[20] We also consider including event time by cohort fixed effects, $\delta^*_{c,\tau}$. However regressions in Appendix D show modest pre-trends between treated and control observations in population growth and poverty. Closer inspection reveals plasma centers open in dense urban areas early in our sample and open in suburbs as well as smaller towns later in the sample. Therefore, we include cohort by event time by population density decile fixed effects, $\delta_{c,\tau,d(g,c)}$ to ensure that, within-cohorts, we compare treated and control observations in areas with similar urban densities. We measure the population density decile, $d(g, c)$, for geography g at event time $\tau = -1$ for cohort c. Similarly, we include individual i in our study of cohort c based on where they live at event time $\tau = -1$. Since population density is fixed for each geography and geography is fixed for each individual within cohorts, we do not need to interact $d(g, c)$ with the cohort-individual fixed effects $\alpha_{c,i}$.

Finally, we include state by time fixed effects, $\gamma_{s(g),t}$, to adjust for local shocks that may affect subsets of each cohort. Specifically, we want to control for two kinds of regulatory changes that may affect our outcomes and limit the ability to compare treated and control groups. First, several states have passed laws during our sample that limit or ban payday and installment loans (Melzer, 2011). If non-bank loans complement (substitute for) plasma donation, these state restrictions may decrease (increase) plasma donation. Second, several states have actively raised their minimum wages over the past decade (Gopalan *et al.*, 2021). We expect a higher minimum wage to reduce the need to donate plasma and to affect credit utilization (Dettling & Hsu, 2021). Naturally, the state by time fixed effects will control for other state level legislation that we have not considered.

[20] Researchers often use a simple individual fixed effect, α_i, in a stacked difference-in-difference design. This is acceptable only if individuals are only observed in a single cohort (e.g., as is the case in Skrastins, 2021 and Sovich, 2018). If individual i appears in multiple cohorts, say as a control for multiple cohorts $c \in C_i$, where treatment occurs at date $t_c \in T_{C_i}$ (and $T_{C_i} > 1$), then α_i is the average of individual i's outcome $y_{i,t}$ across the cohort-specific omitted periods. Therefore, with α_i we interpret β_τ as the effect of treatment on the treated at event time τ relative to a weighted average of omitted periods rather than the cohort specific omitted period achieved with $\alpha_{i,c}$.

4.2.2 Implementation

Implementating the stacked DiD method described above requires care on two fronts. First, we must select control observations for each cohort. TWFE will compare the geographies around every opening to every other opening (that is, openings in downtown Los Angeles against openings in rural Texas) which we don't find appealing. We prefer the stacked difference-in-difference approach because it allow us to explicitly identify and use units which we believe are reasonable controls. Prior studies choose control observations based on proximity (e.g. adjacent counties as in Sovich, 2018 and Melzer, 2011), propensity score matching (Abadie & Imbens, 2016), or by building synthetic controls (Ben-Michael *et al.*, 2019). We follow several studies (Guryan, 2004; Fadlon & Nielsen, 2015; Deshpande & Li, 2019; Stein & Yannelis, 2020) which propose that two geographic areas are similar if they experience the same treatment. Therefore, we use areas with future and existing plasma centers as controls.[21] Because plasma centers open in progressively less urban areas over the past two decades we restrict comparison within population density decile through our time fixed effects $\delta_{c,\tau,d(g,c)}$. Therfore, we are assuming that parallel trends hold for treated and control geographies with similar urban density. We support this assumption by verifying parallel pre-trends in geographies with similar urban density.

Second, we must decide how to delineate households in terms of their access to a plasma center. Many prior papers study treatments that occur at a state or city level (e.g., state minimum wages or uber's expansion to new cities). In contrast, plasma centers mostly affect the areas in their immediate vicinity. Therefore, we define treatment intensity as the distance from each geographic centroid to the nearest plasma center. An individual or establishment will be strongly treated if they are close to the opening plasma center and were not close to a plasma center before. More specifically, we consider geography g treated if it's centroid is within 5 kilometers of an

[21] The standard objection to using treated observations as controls is that we do not know the dynamics of treatment. If treatment causes a difference in the long-term trend of treated observations they no longer trend in a similar manner to untreated regions (so parallel trends is violated and we will not observe parallel pre-trends empirically). However, if treatment causes a shift from one equilibrium to another (i.e., a swift vertical shift) then, so long as we do not include the adjustment period, these treated observations can act as controls for future cohorts (Goodman-Bacon (2021) calls these "always treated" controls). We require existing plasma centers to be open for at least 4 years before the areas around them can be used as controls.

opening plasma center c, which is at least 5 kilometers closer to g than any prior plasma center.[22] Both of these restrictions address the strength of treatment due to opening.[23] For each plasma center opening we select control zip codes that are within 5 kilometers of a plasma center opening that was (or will be) at least 5 kilometers closer than any existing plasma center upon opening. Then, for each treatment opening c we select 10 counterfactual plasma center openings from the region closest to c to serve as controls. For consistency, we also design cohorts to study Safegraph data based on their zip code (even though we know their precise coordinates).

Since several plasma centers often open in the same city over time, we are careful to study only geographies that are not exposed to multiple openings in a brief period of time. When we study plasma center c opening at t_c, to prevent confounding distinct treatments, we require that each zip code (treated or control) must not be within 10 kilometers of a plasma center which opens and becomes the closest plasma center in the four years prior to t_c. Moreover, if a plasma center opens at time t^* after t_c which is closer to zip code g than the closest plasma center at t_c we stop using g for analysis after t^*. In each cohort c, we include observations from four years prior to t_c through up to four years after t_c.

We use the IRSFFA survey to support the 5 km distance we use. In Table 2 we regress donating plasma on the distance from the respondent's zip code centroid to the nearest plasma center. Across specifications we see that proximity to a plasma center significantly increases the probability of donating plasma. In column 4, there is a significant marginal increase in the probability of donating plasma for households within 5 kilometers of a plasma center. Moreover, in column 5, after accounting for the presence of a plasma center, the number of plasma centers within 10 kilometers has no significant effect on donation (the same result holds for 5 kilometers). So

[22] Suburban zip codes sometimes span large regions even though most residents live in a small area close to the urban center. Therefore, we calculate zip code centroids using the population-weighted average of the latitudes and longitudes of each Census block with a centroid within the zip code. This has a large effect on the estimated centroids of suburbs and rural towns and allows for a much more accurate depiction of how close the typical resident is to a plasma center.

[23] For example, if a plasma center opens within 5 kilometers of a geographic centroid that already contains a closer plasma center then there is no change in access. Similarly, if the nearest plasma center to a geography is 25 kilometers away and a new plasma center opens 10 kilometers away, then access increases but only marginally and, therefore, we do not consider residents in that geography to be treated by the new opening.

donation is primarily determined by the distance to the closest plasma center (i.e. access) not the prevalence of plasma centers.[24] Based on these results we believe that a 10 kilometer buffer to avoid confounding openings is conservative and that a 5 kilometer radius to focus on high treatment intensity geographies is reasonable.

4.2.3 Examples

We illustrate the effect of our restriction on timing in Figure 2. Suppose four plasma centers a through d open sequentially. Each plasma center is at least 10 kilometers from any other plasma center since 2005 (to avoid confounding openings) and they are all close to each other geographically so they face similar economies. When b opens, a has not been open for at least 4 years while c and d have not yet opened. Therefore, we use only zip codes near c and d as controls for b. However, the zip codes around plasma center c can only serve as controls for a little over two years until they are affected by c's opening. For opening c, both a and d are able to serve as controls, but the regions around b cannot serve as a control because of b's recent opening. Zip codes near plasma centers a, b, and c can all serve as controls for d. Note that later openings will rely more heavily on past treatments for counterfactuals.

Figure 3 presents examples of the treated and control geographic regions we use for analysis. The red shaded region is near an opening plasma center while yellow and purple regions are controls. We use neighborhoods with large changes in access within the red boundary for analysis. In panel 1 we have a nearly ideal scenario where plasma centers open up far enough apart to allow a clean comparison for the full disc around both target and controls. Note that we do not use the southwestern half of the eastern most control group because it is too close to a plasma center which will open within two years of the target. Several plasma centers open to the southeast of our target but we do not use them as controls because the earliest opens within

[24]For each establishment, Safegraph tells us how many monthly visitors live in each census block group (cbg). Appendix Figure A.1 plots the fraction of a cbg's residents that visit the plasma center on the y-axis as a function of the distance between center and census block group. Conditional on observing any visitors from the census block group, the probability of donating plasma decreases rapidly from 6% of donors coming from within 1 km to 4.6% of residents at 5 km, and 4% of residents at 7.5 km.

24 months of our target. In panel two, for the plasma center which opens in Denver Colorado the southeastern future opening has no viable high intensity region for us to study. We apply geographic restrictions at the CBG level to use the areas around plasma centers where we believe there is no confounding treatment instead of rejecting treated or control discs which are not perfect. Looking for a perfect disc of clean controls might introduce bias by forcing comparisons between regions that have fewer plasma centers (such as the suburbs or rural towns). To study strong and clean treatment events we limit our sample to 323 cohorts opening between April 2014 and Sept. 2019. For the narrower window of Safegraph data we study 130 cohorts that open between 2018Q2 and 2021Q1 with strong treatment.

5 Who Donates Plasma?

In this section, we describe the characteristics of plasma donors and their motivation for donating using the IRSFFA and SEIC surveys – the only two large-scale household financial surveys that ask about plasma donation (to our knowledge). To help characterize the relative importance of plasma donation as a source of quick cash for low-income households, throughout this section we compare the sale of plasma to the use of payday loans as well as to other forms of discretionary ("gig") income. We will show that plasma donors and payday loan borrowers are very similar groups with substantial overlap.

In Table 3 we provide summary statistics for demographic and borrowing variables from the IRSFFA and SEIC surveys. In the first three columns, we describe households that complete the IRSFFA initial surveys in 2018 and 2019 (recall that this is a sample of low-income online tax filers). In the IRSFFA sample 3.3% of households donated plasma at least once in the past 6 months – more than took out a payday, auto-title, or rent-to-own loans and fewer than used a pawn loan. So donating plasma is marginally more common than taking out a payday loan both in our sample and in the broader population. Other forms of gig work appear to be more common than plasma donation (7.4% versus 3.3% of respondents). However the IRSFFA asks whether the respondent worked a gig job in the past 12 months but asks about non-bank credit and plasma donation over the prior 6 months. So plasma donation may actually be only slightly less common than the cornucopia of gig work.[25]

Descriptive statistics from the SEIC sample, implemented during the early days of the COVID-19 crisis, are provided in the remaining columns. In the SEIC sample, the mean respondent is aged 46, married, more educated, and has a much higher income than in the IRSFFA sample. Moreover, more households are employed full time and fewer are employed part time than IRSFFA respondents. We split out the first wave (distributed in May 2020 during the initial lock-downs) of the SEIC from the later waves (August 2020 - May 2021). Plasma donation and non-bank credit were lower in wave 1 but remained fairly constant across subsequent waves. Plasma donation and payday borrowing surged to 11.4% and 12.6%, respectively, during the pandemic which reveals the insurance these tools provide.[26]

Next, we run simple OLS regressions to explore who donates plasma and why. Table 4 studies the demographics of plasma donors. Because the base rate of donation and the factors that affect donation (i.e., the pandemic) vary across surveys, we study the IRSFFA and SEIC separately in columns 1-3 and 4-6 respectively. For the IRSFFA sample (taken before the pandemic), we see in column 1 that age, education, and income have the strongest association with donating plasma. Individuals younger than 35, who do not hold a bachelors degree, or are in the lower two income terciles are roughly 30% more likely to donate plasma. In contrast, payday borrowers are more likely to be employed full time, have multiple children and are less likely to be white. Like plasma donors, gig workers also tend to have lower incomes, but gig workers are better educated and more likely to be married and work part time.

Table 4 (in conjunction with the descriptive statistics in Table 3) suggests that plasma donation along with gig work and non-bank credit were used to obtain liquidity during COVID. Individuals who are married or have children as well as those in the lowest income tercile are much more

[25]See Appendix Table A.1 for decomposition of gig work.

[26]The questions about donating plasma and non-bank credit use in the SEIC ask about use over the prior 3 months since that is the time between SEIC surveys. So the difference between the rate of donation in the IRSFFA and SEIC is actually 3.3% over the recent 6 months versus 11.4% over the recent 3 months. This highlights that COVID was a very material shock.

likely to donate plasma, take a payday loan, and work a gig job. Students also appear to have also turned to alternative sources of income and credit. Since analysis of the SEIC appears to primarily reflect differential vulnerability to the pandemic, for the remainder of this section we study the characteristics of plasma donors during normal times using the IRSFFA.

First, we find 8.5% of plasma donors took a payday loan and 10.5% of payday borrowers donate plasma, so there is substantial overlap in these populations. In table 5, we find that plasma donors, payday borrowers, and gig workers have low liquid assets, higher debt, and poor credit scores.[27] In Appendix Tables A.2 and A.3 we study the respondent's ability to meet shocks and their recent credit habits. In Appendix Table A.2, all groups express doubt that they would be able to meet a hypothetical $2,000 shock (the omitted category is that they could handle the shock). To handle a hypothetical $400 shock, plasma donors and payday borrowers are less likely to use cash or bank credit and more likely to appeal to non-bank credit or to simply not meet the shock. In contrast, gig workers are more likely to leverage formal bank credit (credit card or personal loan). In Appendix Table A.3, payday borrowers and plasma donors have shorter planning horizons than gig workers. Plasma donors and payday borrowers are less likely to pay the full balance on their credit card and are much more likely to miss payments. Payday borrowers are more likely to make late payments while gig workers, in contrast, tend to make the minimum payment. The results above nearly universally show that payday borrowers are the most vulnerable, followed by plasma donors, while gig workers are comparatively affluent.

Table 6 summarizes why households donate plasma as a function of donation frequency. The most common reason for donating plasma is to support day-to-day expenses (58%) with other essential expenses such as paying for emergencies (6%), pay off debt (5.5%), and limited access to credit (1.4%) collectively accounting for 70% of donations. The second most common reason is to pay for non-essential goods (19%).[28] There is a touch of variation in how frequently households

[27]Note that the gig regression is not immediately comparable to the payday or plasma regressions because the dependent variable is working a gig job in the past 12 months not 6 months. For example, a household with low liquid assets is 66% (2.2/3.3) more likely to donate plasma, 115% more likely to use a payday loan, and 20% more likely to work a gig job.

[28]These results are consistent with small sample interview surveys. Anderson *et al.* (1999) survey 411 college students of whom 44 donate plasma. They find that donors tend to use the income for discretionary purchases

donate based on their motivation. Households that seek to pay for unplanned emergencies make fewer donations than households that pay off debt. While 19% of plasma donors use the income for non-essential expenses, 47% of gig workers report that the the income is “just nice to have” (30% state gig income is “essential for basic needs” and 23% report that it is “important to the budget but not essential”). Therefore, gig work is less motivated by necessity than plasma donation.

Both plasma donation and gig jobs allow the worker to control their schedule. However, plasma borrowers can only donate twice per week so their income potential is limited. In the IRSFFA, the mean (median) gig worker puts in 9.5 (resp. 5) hours per week and earns $300 (resp. $100) per month; 75% of gig workers earn under $300 per month. An income of $300 per month is achievable by donating plasma with some foresight. However, the mean (median) plasma donor donates 2 times (less than once) per month for an income below $100 per month. Gig workers also earn lower hourly wages (75th percentile is $11.5 per hour) than plasma donors (compensation exceeds $20 per hour). In 2019, all respondents to the IRSFFA survey who do not work a gig job are asked why they did not pursue the opportunity. In Table 7, the top reasons given for not engaging in gig work are lack of time, cost of entering, and insufficient skill. However, plasma donors are twice as likely as non-donors to report that gig work is too costly for them to access. So gig workers, on average, earn a lower hourly wage than plasma donors and earn a monthly income that is achievable through plasma donation; however, gig workers are more prevalent than plasma donors. Although one interpretation is that individuals prefer gig work to selling plasma, gig work often requires the individual to possess an asset (e.g., a car for Uber or Doordash) or skill (e.g. Etsy), which creates a barrier to entry. These features may explain why individuals donate plasma to fund essential spending while gig work is more closely tied to discretionary spending.

This section shows that plasma donation is fairly common and is used by financially vulnerable households to spend on essential expenses. In contrast, gig work has asset and skill barriers

(particularly alcohol and tobacco) and do not come from wealthier families. Olsen *et al.* (2019) survey 64 donors at a plasma center in Cleveland Ohio and find that donors use the income for food, gas, rent, and general spending money.

to entry and supports more discretionary spending. It follows that access to a plasma center is a relevant source of income for the same types of people who are likely to use non-bank credit. We explore this interaction next.

6 The Effect of Marginal Income Control

This section presents the main empirical results exploring the causal effect of the ability to sell plasma on demand for non-bank credit. Then, we study foot-traffic at stores near plasma centers to understand how households consume.

6.1 The effect of plasma access on demand for non-bank loans

From the IRSFFA and SEIC surveys we know that plasma donors tend to have low incomes and credit scores. They are also more likely to use non-bank credit and less likely to have available bank credit (see Tables A.2 and A.3). It follows that non-bank credit may act as an important source of liquidity to help these households smooth consumption. Plasma sales may either replace the need for non-bank loans ex ante or facilitate their use through faster repayment ex post. In this section, we examine how the ability to sell plasma affects demand for high cost credit.

In Table 9, we study the effect of gaining access to a plasma center on non-bank credit inquiries. Consistent with equation 4, we use cohort by quarterly event time by population density decile fixed effects. However, to simplify the tables, we present annual event time treatment effects. In columns 1 and 2, we measure the effect of access to a plasma center on whether the individual has submitted at least one inquiry within the quarter. We find that individuals are 0.22p.p. and 0.38p.p. less likely to submit a payday and installment loan inquiry respectively during a quarter (though the effect on payday loans is only marginally significant). These effects represent a material 6.5% and 8.1% decline in the probability of applying for payday and installment loans, respectively. We interpret the decrease in payday and installment loan inquiries as a decrease in the demand for credit.[29]

[29] Households may switch from multiple small loans to a single larger loan with a longer maturity. If this were the

Since we cannot directly observe precautionary savings, we focus on isolating a repayment channel. Conditional on submitting at least one inquiry, the probability of submitting multiple payday or installment inquiries within a quarter does not change economically or significantly in columns 3 and 4. Payday loans normally have a 2 week maturity (in our sample 54% have a maturity below 15 days and 96% are below 31 days). Failing to detect a decrease in multiple inquiries within a quarter suggests that access to a plasma center does not affect whether a payday loan is rolled over (i.e., the speed of repayment). This assumes rolling over a payday loan would trigger an additional inquiry in the same quarter. In contrast, 9.4% of installment loans transactions in our sample have maturities less than 90 days, 46% have maturities under 180 days, and 87% have maturities under 360 days. As an installment loan is being paid down the borrower may decide to refinance the debt into a new loan – potentially triggering a new inquiry.[30] Hence, the decrease we observe in the probability of submitting at least one installment loan inquiry could imply either fewer installment loan openings or fewer refinances.

To drill down further, in Table 10 and Figure 4 we explore when an individual submits their next inquiry. We estimate at time τ how the propensity to submit another inquiry has changed since $\tau = -1$ for treated and control observations.[31] In Figure 4 panels A and B, we do not find any effect of a plasma center opening on the time until the next inquiry (conditional on there being a subsequent inquiry). In Figure 4 panels C and D, we generally find no evidence of a

case we would expect households to also switch from payday loans to installment loans which often have maturities exceeding 6 months. We find a larger decrease in installment loans so households are not switching credit form. Alternately, it is possible that households increase the probability that their credit application is approved by offering the plasma donor prepaid card as collateral. If this were the case then we would observe fewer inquiries submitted in a short period of time. However, in unreported regressions, we find no evidence that the probability of submitting a second inquiry decreases in the 6 days after a first payday or installment loan inquiry. Therefore, we maintain that the decrease in credit inquiries among households that live near an opening plasma center corresponds to a decrease in demand for credit.

[30] Rolling over installment loans is an important strategy for installment lenders because, in several states, installment lenders charge origination fees that are financed as part of the loan principal. Each time the installment loan is rolled over, these fees are charged again and raise the effective cost of the loan. For more information about which states have laws that foster this strategy and how it plays out see National Consumer Law Center (2018); Pew Charitable Trust (2016); Kiel (2013).

[31] For payday and installment loans we consider separate sets of horizons relevant to rolling over the loan. For payday loans we use the 1 to 30 days, 31 to 60 days, 60-90 days (we also tested for differences in the probability of submitting an inquiry in the proximate month). For installment loans we consider 1 to 180 days, 181 to 360 days, and 361 to 730 days.

reaction in terms of the distribution of repeat borrowing. There is a small decrease of 2.1p.p. (4%) in the probability of a submitting a second installment loan inquiry at the 181 to 360 day horizon after a plasma center opens. However, this effect is only present at the intensive margin directly after the plasma center opens and is much smaller than the 8% decrease we observe at the extensive margin. Therefore, our evidence is not consistent with a repayment channel driving the decrease in payday or installment loan inquiries. In Table 11, we find no evidence that demand for non-bank credit decreases significantly more for households who have applied for credit before the plasma center opens.[32] The absent reaction among individuals with many inquiries at the intensive margin suggests that plasma centers decrease the probability of inquiries at the extensive margin among infrequent borrowers.

We cannot identify individuals in our Clarity sample who donate plasma. However, we know from Section 5 that plasma donors tend to be younger. Clarity collects age for most credit applicants. Therefore, we test whether access to a plasma center has stronger effects on the demand for non-bank loans among individuals younger than 35 in Table 12 and Figure 5. In Figure 5, young individuals decrease both payday and installment loan inquiries more than the average respondent, as would be expected if effects are related to donating plasma. The difference between young and older individuals is statistically and economically significant in Table 12, with a peak net decrease in the probability of submitting a payday or installment loan inquiry 4 years after a plasma center opens of 0.51p.p. (0.6p.p. - 0.09p.p.) and 0.82p.p. (0.9p.p. - 0.08p.p.), respectively. These effects correspond to a, respective, 13.1% and 15.7% decrease in the probability of submitting a payday or installment loan inquiry compared to the y-means for individuals younger than 35 (of 3.9% and 5.2%). This is roughly double the effect of access to a plasma center on the full sample (estimated in table 9). In effect, the entire credit demand response to a plasma center opening is attributable to young individuals. Moreover, we now observe an immediately significant

[32] We cannot test whether there is an incremental reaction in the probability of submitting multiple inquiries within a quarter conditional on there being at least one inquiry for households with prior inquiries. This is because before the plasma center opens the only individuals for whom we can possibly observe multiple inquiries have at least one inquiry and are by definition in the high treatment intensity group. So before the plasma center opens we do not have groups with high and low sensitivity to treatment.

decrease in the probability of submitting an inquiry.

One may ask whether these changes in demand for non-bank loans translate into changes in actual transactions. We test this by aggregating transactions into a panel dataset with the amount each household borrows through payday and installment loans over time. Unfortunately, Clarity only records transaction information for roughly 20% of individuals present in the inquiry dataset. Moreover, while 56% of our inquiries are for installment loans they compose only 15% of the transactions dataset. In fact, the transactions data primarily contains payday loans (50%). Hence, any analysis of transactions, particularly installment loans, will have dramatically reduced statistical power. Therefore, we focus our tests in Table 13 and Figure 6 on payday loans to young individuals. In column 1 of Table 13, we see that young borrowers are significantly less likely to have a payday loan transaction after the plasma center opens than their older treated peers. At its peak 3 years after the plasma center opens, young households borrow with 1.32p.p. lower probability than older households. The net reaction by young borrowers varies between a 0.29p.p. decrease in the quarterly probability of having a payday loan the year the plasma center opens and a 0.79p.p. decrease 4 years later. This response is comparable to the effect we measure using inquiries but has weaker statistical significance due to the smaller sample. The quarterly probability of taking out a payday loan in the transaction sample is 4.3% for young households (4.8% for all households). So, the treatment effect represents an 18% decrease in the extensive margin use of payday loans among young people after a plasma center opens. Conditional on holding a payday loan, plasma center openings do not affect the log balance (column 2). There are some sporadically significant coefficients for young individuals in column 2. However, we do not observe the balance of each loan across time.[33] Therefore, coefficients in column 2 are estimated based on a small subset of individuals who have debt in multiple quarters making them less precise.[34] In Figure 6 panel A we plot the baseline decrease in the quarterly probability

[33]It is important to understand how Clarity records payday and installment loans to interpret our results. Clarity does not provide the initial loan amount or the interest rate. Moreover it does not provide sufficient information to reconstruct the principal outstanding on the loan over time or the amount and timing of payments. Instead, we see the highest balance the loan achieves over its life, the original loan maturity and payment frequency, when the loan begins and ends, and how the account closes.

[34]In untabulated analyses, we find no evidence that households pay off loans faster, or roll over loans less after a

of having a payday loan transaction. In panels B and C we find no evidence that the actual to expected maturity decreases or that borrowers repay loans on time after a plasma center opens which further supports a precautionary savings channel.

The treatment effect of access to a plasma center is large. For comparison, Dettling & Hsu (2021) estimate that a \$1 increase in the minimum wage will decrease the probability of taking out a payday loan in the prior year by 0.49p.p. (16%) among minimum wage households. Similarly, we estimate that access to a plasma center decreases the quarterly probability of taking out a payday by 18% for young people in the Clarity sample. The fact that our estimates are similar is remarkable given that they speak to the effect of merely having access to income from selling plasma rather than a realized income shock.

Because high-interest loans can lead to debt traps, having fewer one-off borrowers open a payday or installment loan can produce substantial aggregate savings from reduced financing costs. We can estimate this aggregate savings through simple, back-of-the-envelop calculations. Currently, 22% of the U.S. population lives within 5 kilometers of a plasma center. However, poorer households that use non-bank credit are more likely to live near a plasma center. In our randomly drawn sample from the Clarity database, 28% of individuals who have used or inquired about a payday loan live within 5 kilometers of a plasma center in 2020. In the United States, installment and payday loan storefronts collect roughly \$10 billion in interest and fees annually (PEW, 2018). Therefore, we estimate that households save between \$182 million and \$230 million in credit fees annually because of access to a plasma center ($28\% \times X\% \times \$10$ billion where $X \in (6.5\%, 8.2\%)$ depends on the mix of payday and installment loans).[35]

To briefly summarize these results, we find that access to a plasma center significantly decreases inquiries for payday and installment loans. This result could be driven by faster loan

plasma center opens, or that the loan is charged off less when we analyse data at the transaction level. We exclude these regressions because the identification of the treatment coefficients relies on a small number of individuals with multiple transactions of the same type in different periods and as such the estimates are less precise.

[35]The estimate that consumers pay \$10 billion in fees and interest on non-bank credit annually from PEW (2018) is based on data from 2014. Reliance on non-bank credit varies considerably across time. For instance, in the Federal Reserve's Survey of Consumer Finance the fraction of households that have used a payday loan in the prior year varies from 1.7% in 2007 to 3.74% in 2013 before falling to 2.41% in 2019. We expect the interest savings will vary across time with demand for non-bank credit.

repayment or by precautionary savings. However, conditional on having one inquiry, there is no marginal effect on the total number of inquiries an individual submits within a quarter and the rate of subsequent credit inquiries over multiple horizons is unchanged. Moreover, the time to repay payday loans is unchanged. The decrease in non-bank credit demand and utilization from plasma center openings is exclusive to young households, which matches the higher donation rate among young households.

6.2 Consumption smoothing: foot-traffic at local establishments

In this section, we explore how individuals spend the income from plasma donation. From the IRSFFA survey we know that 58% of households donate plasma to support spending on essential goods and a further 19% use the funds for non-essential purchases while only 5% intend to use the income to pay off debt. Therefore, we expect the income from plasma donation to increase spending and physical visits to stores. To explore this hypothesis, we test whether the arrival of a plasma center boosts the foot-traffic of various local businesses.

In the cell phone tracking data from Safegraph, we do not observe who donates plasma or which other local establishments donors subsequently visit. So, we are not able to estimate the effect of plasma donation on foot traffic. Moreover, we do not observe the income from plasma donation or the amount individuals spend during their visits to local establishments. Therefore, we cannot, for example, estimate the marginal propensity to consume from each dollar of plasma donation income. Still, for many categories of establishments we believe foot traffic is a good proxy for consumption since the good or service has fairly uniform pricing and a visit almost always corresponds to a sale (e.g., restaurants, movie theater, gas station, oil change). However, for other establishments (e.g., grocery, clothing, electronics) a household may shop at more locations but not change the total expenditure. So, we caution that the effect of access to plasma centers on foot traffic is an imperfect measure of demand and consumption. We study two outcomes: the number of visits and the number of distinct visitors per establishment per month –

both normalized by the average number of store visits and visitors in 2018-2019.[36]

For simplicity, we group establishments by their industry NAICS codes into three categories. We consider groceries, personal care (barber or stylist), gas stations, auto repair, and medical facilities to be essential goods or services that we have limited ability to delay. In Table 14, columns 1 and 5 measure the effect of a plasma center opening on nearby essential goods establishments. We find that the number of visits and visitors increase materially over time after a plasma center opens, peaking at a 7% increase in establishment foot traffic 2 years after opening. If plasma donors predominately just expand the set of stores they visit, then we should see an increase in distinct visitors and little change in visits. However, access to a plasma center expands the number of stores that households visit and new visitors use the establishments at the same rate as existing visitors.

In columns 2 and 6 of Table 14, we study establishments that provide non-essential goods and services like restaurants, entertainment (bowling, theaters, zoo, museum), luxury goods, and alcohol vendors. These establishments also react strongly to plasma center openings with a peak effect after 2 years of 10% higher establishment foot traffic. The retail group includes establishments that are difficult to classify as essential or non-essential such as clothing, furniture, and electronics retailers. The average effect for retail establishments in columns 3 and 7 is nearly identical to non-essential establishments.

In columns 4 and 8 we use foot traffic at schools and day-care establishments as our best attempt at a natural control group. If plasma centers open in neighborhoods as they begin growing (e.g. burgeoning suburbs) this should affect local school attendance. We do not find that foot traffic at schools changes substantially after a plasma center opens nearby which supports the validity of our regression specification. We graph the reactions of several establishment types in Figure 7 and further decompose non-essential establishments in Table15.

[36]The number of devices that Safegraph surveys each month varies as cell phone applications start and stop providing geographic tracking information and as users install and delete the applications. Therefore, we weight visits and visitors proportional to Safegraph's coverage within a state in each month. Moreover, stores each have their own baseline set of customers and level of foot traffic. Therefore, we study the proportional change in foot traffic by normalizing by the average number of visits and visitors in 2018-2019.

The effects we measure in table 14 are quite large. Less than 5% of households within 5 kilometers of a plasma center donate plasma (Panel A of Appendix Figure 3). Yet many of the effects we measure approach a 10% increases in the number of visitors. This disproportionate increase in visitors may arise mechanically if individuals visit a plasma center from further than 5 kilometers away and make purchases while they are in the area, i.e. the set of customers expands. However, roughly 40% of plasma center visitors live within 5 kilometers (Panel B of Appendix Figure 3) so it would require a large fraction of these distant donors to reconcile the increase in foot traffic. Alternatively, non-donors may see the presence of a plasma center in their neighborhood and increase their non-essential consumption now, knowing that they can sell plasma should their extra consumption lead to a financial shortfall later. This kind of response would be broadly consistent with how consumers have been shown to alter their consumption in response to perceived changes in income (Pagel, 2017; Olafsson & Pagel, 2020), financial "slack" (Zauberman, 2005), and housing wealth (Mian *et al.*, 2013; Aladangady, 2017). In line with this interpretation, in Table 15 we see that the increase in foot traffic at non-essential establishments is not driven by a narrow group of establishments. Visits and visitors to restaurants and luxury stores increase by 9% over two years. The luxury category includes goods retailers that are in no way physically essential for survival such as jewelers and flower shops but also stores that support sports, pets, instruments, cosmetics, and hobbies. Visits to bars and entertainment establishments (theaters, bowling alleys, museums, zoos) increase by roughly 14%. There may also be behavioral explanations for why plasma income seems to directly support non-essential spending, such as mental accounting (Shefrin & Thaler, 2004) or the "liquid hand-to-mouth" effect documented in Olafsson & Pagel (2018). Indeed, the material increase in foot traffic at non-essential establishments suggests that households match discretionary income to discretionary spending; if this spending would have otherwise eroded precautionary savings then the decrease in non-bank credit may be a byproduct of this consumption behavior.

Our study of Safegraph data highlights that plasma center income expands foot traffic at local establishments that provide both essential and non-essential goods and services. The results suggest a wide boost in consumption, extending into non-essential and luxury goods. There may even be a consumption response among households who do not sell plasma. One potential policy implication is that access to even small-dollar, quick sources of income may generate substantial local economic multipliers. Indeed, our results suggest that access to plasma income increases restaurant sales by up to $8 billion in the United States.[37] To estimate these multipliers accurately we need actual spending amounts. We leave this task to future research.

7 Conclusion

The U.S. plasma sector has grown at an annual rate of 11% over the past decade in an attempt to satisfy global demand and 22% of the United States population currently lives within 5 kilometers of a plasma center. Plasma donors tend to young, low income, have low financial assets, and little access to bank credit. When a plasma center opens, inquiries for payday and installment loans decrease by 6.5% and 8.1% respectively; this is entirely driven by a decrease in inquiries of 13.1% and 15.7% among households younger than 35. The decrease in quarterly payday loan demand (13%) and usage (18%) that we measure among young households is similar to the 16% decrease in annual credit utilization among minimum wage workers after a $1 increase in the minimum wage documented in Dettling & Hsu (2021). We find no evidence that the ability to donate plasma affects debt repayment which suggests that households use the discretionary income to support precautionary savings. Moreover, visits and visitors to essential and non-essential establishments

[37]Restaurant visits increase by 6-9% in column 1 of Table 15. Assuming restaurant prevalence reflects population density, roughly 22% of restaurants are within 5 km of a plasma center. Moreover, according to the National Restaurant Association, in 2019 total sales for commercial restaurants reached $613 billion. So up to $8 billion in restaurant sales ($613 \times 0.06 \times 0.22$) may be attributable to the ability to donate plasma. The spending on restraunts alone is considerably larger than the $2-3.5 billion that households received in compensation for plasma donation before the pandemic (53 million donations in 2019 at $40-60 per donation). Three points may help explain the difference between the large estimated impact on establishment sales like restaurants and the modest income from plasma donation. First, plasma income may allow households to manage their money more efficiently and free up savings for near term consumption. Second, nearly half of the data we use for Safegraph analysis is from the pandemic; shortages caused plasma compensation to triple during the pandemic which may 1) inflate the spending response compared to normal times and 2) makes a comparison against 2019 donor compensation inappropriate. Third, we are assuming that plasma donors have similar purchase habits as the average establishment visitor; in reality plasma donors are likely to be budget constrained and to make smaller purchases. For these reasons, the sales effect we estimate based on safegraph establishment reactions to a plasma center opening should be viewed as an upper bound.

increase by 7-10% when a new plasma center opens nearby. The significant increase in foot traffic at non-essential establishments suggests that households may match discretionary income to discretionary spending that would otherwise erode savings yielding the decrease in non-bank credit demand as a byproduct. In aggregate, access to quick sources of even small-dollar income from plasma centers significantly boost local economic activity save over $180 million annually in financing costs.

Our paper is a first step towards understanding the short-term financial impact on households of being able to sell their biological material, which is a subject of substantial ethical and policy debate. We study the largest market that allows compensation for biological material. We find that households use the income to avoid expensive debt and for consumption. Importantly, we do not observe the health costs associated with donating plasma and the medical research on this topic is surprisingly limited. Without measures of the costs of potentially adverse outcomes, we cannot comment on whether the ability to donate plasma improves household welfare.

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Table 1: Plasma Center Corporations

Corporation	Parent	Country	Ticker	PCs (2015)	PCs (2021)
CSL Plasma	CSL Ltd.	Australia	CSL (ASX)	109	284
Grifols	Grifols S.A.	Spain	GRF (BMAD)	216	276
Biolife Plasma	Takeda Pharmaceutical	Japan	TAK (NYSE)	71	151
Octapharma	Octapharma AG	Switzerland	Family Owned	51	144
BPL Plasma	Creat Group	China	Private	19	31
KED Plasma	Kedrion Biopharma	Italy	Private	7	31
Immunotek Bio Centers	N/A	USA	Family Owned	0	22
GCAM Inc.	Green Cross Group	South Korea	006280 (KRX)	6	12
ADMA BioCenters	ADMA Biologics	USA	ADMA (NASDAQ)	0	4
Other				22	36

Table 2: Plasma Donation and Proximity

	(1) Plasma	(2) Plasma	(3) Plasma	(4) Plasma	(5) Plasma	(6) Plasma
PC within 5.0km	0.015^{***}			0.010^{**}		
	(0.004)			(0.005)		
PC within 10.0km		0.016^{***}		0.006^{*}	0.012^{**}	
		(0.003)		(0.004)	(0.005)	
PC within 25.0km			0.020^{***}	0.015^{***}		0.035^{***}
			(0.004)	(0.004)		(0.005)
Num PCs within 10.0km					0.003	
					(0.002)	
PC Distance (up to 25km)						-0.001^{***}
						(0.000)
Zip and Resp. Cont.	Yes	Yes	Yes	Yes	Yes	Yes
Year Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey	IRSFFA	IRSFFA	IRSFFA	IRSFFA	IRSFFA	IRSFFA
Cluster by	CBSA	CBSA	CBSA	CBSA	CBSA	CBSA
KP F-stat	13.69	24.23	30.99	17.42	13.02	27.37
N	27862	27862	27862	27862	27862	27862

The outcome is whether the household has donated plasma in the past 6 months. The independent variables are whether there is a plasma center within X kilometers of the zip code, the number of plasma centers, and the distance to the closest plasma center up to 25 kilometers (beyond which it is zero). Our zip code controls include the fraction of households that commute by car (proxy for mobility and urban sprawl), population density deciles, and whether the zip code is part of a CBSA. We do not include CBSA fixed effects as they would unduly limit the sample we can study. We further control for the fraction of households 1) below 100% of the Federal Poverty Line, 2) with an income below $50,000, 3) who receive government monetary aid, and 4) who receive food stamps or SNAP. Demographic controls include the fraction of households that are white, hold at least a bachelors degree, or are employed full time for the prior year. Finally, we also control for the number of payday stores within 5 kilometers. Our respondent controls include the variables from Table 4 (i.e. gender, race, age gt 35, married, children, etc.) except that we use income deciles instead of income terciles within year.

Table 3: Summary Statistics

	IRSFFA 2018-19			SEIC 5/20			SEIC 8/20 - 5/21		
	Observations	Mean	StdDev	Observations	Mean	StdDev	Observations	Mean	StdDev
White	33562	0.829	0.377	5038	0.758	0.428	19881	0.733	0.442
Black	33562	0.070	0.256	5038	0.135	0.342	19881	0.147	0.354
Age	39427	35.197	16.299	5038	46.619	16.942	19878	46.948	16.918
Male	34359	0.467	0.499	5038	0.492	0.500	19881	0.492	0.500
Married	39455	0.110	0.313	5038	0.508	0.500	19883	0.525	0.499
Children	39325	0.330	0.779	5038	0.439	0.850	19883	0.490	0.894
Single Parent	39454	0.153	0.360	5038	0.078	0.268	19883	0.084	0.277
Employed FT	39455	0.413	0.492	5038	0.484	0.500	19883	0.495	0.500
Employed PT	39455	0.317	0.465	5038	0.104	0.305	19883	0.109	0.311
Student	39455	0.267	0.442	5038	0.213	0.410	19883	0.341	0.474
Bachelor Degree	34575	0.468	0.499	5031	0.574	0.495	19836	0.555	0.497
Income	26867	15717.488	10359.293	5022	86195.558	70118.895	19848	77851.447	69538.772
Plasma	34753	0.033	0.178	5038	0.059	0.235	19883	0.114	0.318
Payday Loan	33759	0.026	0.160	5025	0.070	0.255	19780	0.126	0.332
Pawn Loan	33706	0.054	0.225	5019	0.073	0.260	19738	0.127	0.333
Auto Title Loan	33744	0.021	0.142	5026	0.087	0.282	19774	0.121	0.326
Rent-to-Own Loan	33699	0.016	0.126	0	.	.	0	.	.
Gig	37234	0.074	0.262	0	.	.	19835	0.121	0.326
Observations	39455			5038			19883		

This table provides summary statistics for the IRSFFA and SEIC surveys. The age, children, and income variables are numeric while all other variables are binary. The plasma, payday, pawn, auto-title, and rent-to-own variables ask whether the household has used the service in the past 6 months for the IRSFFA and in the past 3 months for the SEIC. The IRSFFA and SEIC both ask whether the household has worked a gig job in the past 12 months however the SEIC did not ask about gig work in the first wave.

Table 4: Demographic Traits of Donors

	(1) Plasma	(2) Payday Loan	(3) Gig	(4) Plasma	(5) Payday Loan	(6) Gig
Male	0.003	-0.008***	-0.011***	0.024***	0.030***	0.016***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
White	0.004	-0.021***	0.002	0.007	0.001	0.008
	(0.003)	(0.003)	(0.005)	(0.006)	(0.007)	(0.007)
Age gt35	-0.012***	0.022***	-0.023***	-0.050***	-0.048***	-0.069***
	(0.003)	(0.003)	(0.004)	(0.006)	(0.006)	(0.007)
Married	0.002	-0.003	0.016**	0.023***	0.024***	0.033***
	(0.005)	(0.004)	(0.008)	(0.005)	(0.004)	(0.005)
Children Any	0.013	0.005	0.006	0.095***	0.113***	0.099***
	(0.009)	(0.010)	(0.012)	(0.008)	(0.010)	(0.013)
Children gt1	-0.000	0.018**	0.008	0.015	0.017*	0.005
	(0.006)	(0.008)	(0.009)	(0.010)	(0.010)	(0.010)
Single Parent	-0.001	0.014	0.007	-0.033***	-0.050***	-0.033**
	(0.009)	(0.009)	(0.013)	(0.011)	(0.014)	(0.014)
Employed FT	0.004	0.015***	0.008	0.019***	0.020***	0.032***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
Employed PT	0.002	-0.001	0.028***	0.004	0.017**	0.038***
	(0.003)	(0.003)	(0.004)	(0.008)	(0.008)	(0.007)
Student FT	0.001	-0.002	-0.020***	0.247***	0.258***	0.252***
	(0.004)	(0.002)	(0.005)	(0.009)	(0.009)	(0.010)
Student PT	-0.002	-0.002	0.005	0.165***	0.197***	0.195***
	(0.004)	(0.004)	(0.007)	(0.013)	(0.013)	(0.016)
Bachelor Degree	-0.012***	-0.017***	0.023***	-0.000	-0.005	0.008
	(0.003)	(0.002)	(0.004)	(0.005)	(0.005)	(0.005)
Income Low	0.014***	-0.004	0.032***	0.075***	0.081***	0.083***
	(0.004)	(0.003)	(0.006)	(0.007)	(0.007)	(0.010)
Income Mid	0.013***	0.000	0.013***	0.001	0.011**	0.009
	(0.003)	(0.002)	(0.004)	(0.004)	(0.005)	(0.007)
Zip Cont.	Yes	Yes	Yes	Yes	Yes	Yes
Year-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	IRSFFA	IRSFFA	IRSFFA	SEIC	SEIC	SEIC
Cluster by	CBSA	CBSA	CBSA	CBSA	CBSA	CBSA
N	27862	27620	27994	24368	24281	19395

The outcomes are whether someone in the household has donated plasma or taken out a payday loan in the past 6 months, and whether someone in the household has worked a gig job in the past year. Our zip code controls include the fraction of households that commute by car (proxy for mobility and urban sprawl), population density deciles, and whether the zip code is part of a CBSA. We do not include CBSA fixed effects as they would unduly limit the sample we can study. We further control for the fraction of households 1) below 100% of the Federal Poverty Line, 2) with an income below $50,000, 3) who receive government monetary aid, and 4) who receive food stamps or SNAP. Demographic controls include the fraction of households that are white, hold at least a bachelors degree, or are employed full time for the prior year. Finally, we also control for the number of payday stores within 5 kilometers.

Table 5: Financial Assets and Liabilities of Donors

	(1) Plasma	(2) Payday Loan	(3) Gig
Own Home	-0.011***	-0.012***	-0.016***
	(0.003)	(0.003)	(0.005)
Own Car	0.002	-0.001	0.011***
	(0.003)	(0.003)	(0.004)
Fin Asset ST Low	0.022***	0.029***	0.015***
	(0.003)	(0.003)	(0.005)
Fin Asset ST Mid	0.006**	-0.000	0.006
	(0.003)	(0.002)	(0.005)
Fin Liab ST Low	-0.011***	-0.031***	-0.030***
	(0.004)	(0.004)	(0.006)
Fin Liab ST Mid	-0.000	-0.008**	-0.010*
	(0.003)	(0.004)	(0.006)
Fin Liab LT gt0	0.011***	0.014***	0.017***
	(0.003)	(0.002)	(0.004)
Score Poor	0.012***	0.030***	0.001
	(0.003)	(0.002)	(0.006)
Score Mid	-0.001	-0.001	0.004
	(0.003)	(0.002)	(0.006)
Zip and Resp. Cont.	Yes	Yes	Yes
Year-Wave FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Sample	IRSFFA	IRSFFA	IRSFFA
Cluster by	CBSA	CBSA	CBSA
N	23394	23300	23415

The outcomes are whether someone in the household has donated plasma or taken out a payday loan in the past 6 months, and whether someone in the household has worked a gig job in the past year. Our zip code controls include the fraction of households that commute by car (proxy for mobility and urban sprawl), population density deciles, and whether the zip code is part of a CBSA. We do not include CBSA fixed effects as they would unduly limit the sample we can study. We further control for the fraction of households 1) below 100% of the Federal Poverty Line, 2) with an income below $50,000, 3) who receive government monetary aid, and 4) who receive food stamps or SNAP. Demographic controls include the fraction of households that are white, hold at least a bachelors degree, or are employed full time for the prior year. Finally, we also control for the number of payday stores within 5 kilometers. Our respondent controls include the variables from Table 4 (i.e. gender, race, age gt 35, married, children, etc.) except that we use income deciles within year instead of income terciles.

Table 6: Why Donate

	Donations in past 6 months			
	0-5	6-10	>10	Total
1. To pay for an unplanned emergency expense	8.88	3.11	2.11	6.08
2. To cover day-to-day expenses	54.67	59.63	63.44	57.94
3. To pay off debt	4.05	9.94	6.04	5.47
4. To pay for non-essential expenses	19.47	18.63	18.43	19.05
5. Couldn't get a loan elsewhere	1.87	0.62	0.91	1.41
6. Other	8.57	4.97	8.16	7.94
7. I don't know	2.49	3.11	0.91	2.12
Total	100.00	100.00	100.00	100.00
	(642)	(161)	(331)	(1134)

This table provides the reason that plasma donors provide as their primary motivation for donating as a function of how often they have donated plasma over the prior six months. Data for this table is from the IRSFFA.

Table 7: Why not work a gig job?

	Mean(Plasma Donors=0)	Mean(Plasma Donors=1)	Diff.	Std. Error	Obs.
No time	0.450	0.410	-0.040	0.026	11145
Too costly	0.096	0.209	0.113^{***}	0.016	11145
Insufficient skill	0.151	0.180	0.029	0.019	11145
Don't need money	0.126	0.070	-0.056^{***}	0.017	11145
Other	0.177	0.131	-0.046^{**}	0.020	11145

Table 8: Summary Statistics: Clarity Data

Panel A: Full Clarity Sample:

Variables	N	Mean	Std. Dev.	min	25%	50%	75%	90%	95%	99%	max
Age	71457932	39.161	14.051	11	28	37	49	59	65	74	87
Income	49945196	2255.389	1746.615	0	1800	2600	3800	5157	6250	8750	10000
Payday	72578772	0.111	0.921	0	0	0	0	0	0	3	410
Payday gt0	72578772	0.034	0.181	0	0	0	0	0	0	1	1
Payday gt1	72578772	0.022	0.146	0	0	0	0	0	0	1	1
Installment	72578772	0.255	2.101	0	0	0	0	0	1	7	557
Installment gt0	72578772	0.052	0.222	0	0	0	0	0	1	1	1
Installment gt1	72578772	0.03	0.171	0	0	0	0	0	0	1	1
Trans Payday gt0	15048488	0.045	0.207	0	0	0	0	0	0	1	1
Trans Payday Bal	676192	305.339	350.821	0	77	201	411	704	982	1500	26086

Panel B: Analysis Clarity Sample:

Variables	N	Mean	Std. Dev.	min	25%	50%	75%	90%	95%	99%	max
Age	32276102	37.867	13.797	12	27	36	47	58	63	73	86
Income	21447577	2895.544	1638.371	0	1800	2500	3624	5000	6000	8500	10000
Payday	33043814	0.118	0.982	0	0	0	0	0	0	4	114
Payday gt0	33043814	0.034	0.182	0	0	0	0	0	0	1	1
Payday gt1	33043814	0.022	0.147	0	0	0	0	0	0	1	1
Installment	33043814	0.233	1.987	0	0	0	0	0	0	6	252
Installment gt0	33043814	0.047	0.213	0	0	0	0	0	0	1	1
Installment gt1	33043814	0.028	0.164	0	0	0	0	0	0	1	1
Trans Payday gt0	6660406	0.048	0.213	0	0	0	0	0	0	1	1
Trans Payday Bal	317286	304.408	345.475	0	78	202	408	700	973	1483	10329

Table 9: Non-Bank Credit Inquiries

Model:	Payday gt0 (1)	Installment gt0 (2)	Payday gt1 (3)	Installment gt1 (4)
Treated × Event Time Y = -4	0.0006	0.0003	0.0316*	0.0043
	(0.0009)	(0.0011)	(0.0173)	(0.0174)
Treated × Event Time Y = -3	0.0001	0.0005	0.0127	0.0012
	(0.0007)	(0.0008)	(0.0126)	(0.0104)
Treated × Event Time Y = -2	0.0007	0.0006	0.0112	0.0124
	(0.0005)	(0.0005)	(0.0102)	(0.0087)
Treated × Event Time Y = 0	0.0003	-0.0004	0.0051	0.0045
	(0.0005)	(0.0006)	(0.0088)	(0.0074)
Treated × Event Time Y = 1	-0.0012	-0.0016**	-0.0036	0.0023
	(0.0008)	(0.0008)	(0.0101)	(0.0075)
Treated × Event Time Y = 2	-0.0017*	-0.0032***	0.0098	-0.0020
	(0.0009)	(0.0012)	(0.0098)	(0.0085)
Treated × Event Time Y = 3	-0.0022*	-0.0038**	0.0140	-0.0066
	(0.0011)	(0.0017)	(0.0141)	(0.0107)
PC Cohort-Indiv FE	Yes	Yes	Yes	Yes
PC Cohort-Event Time YQ-Pop Dens Dec FE	Yes	Yes	Yes	Yes
State-Date FE	Yes	Yes	Yes	Yes
Observations	32,930,842	32,930,842	1,127,048	1,568,452
R^2	0.2186	0.2014	0.5542	0.6003
Within R^2	0.0000	0.0000	0.0000	0.0000

Clustered (PC Cohort) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: Non-Bank Credit: Time Between Inquiries

Panel A: Payday Loan Inquiries

Model:	Time to Next Inq (1)	Inquiry in 1-30D (2)	Inquiry in 31-60D (3)	Inquiry in 61-90D (4)
Treated × Event Time Y = -4	1.8470	-0.0215	-0.0144	-0.0215
	(9.7794)	(0.0174)	(0.0173)	(0.0172)
Treated × Event Time Y = -3	0.3456	-0.0078	-0.0137	0.0031
	(6.0964)	(0.0099)	(0.0137)	(0.0113)
Treated × Event Time Y = -2	-1.0762	-0.0087	-0.0154	-0.0171*
	(5.0297)	(0.0085)	(0.0113)	(0.0102)
Treated × Event Time Y = 0	1.3560	0.0064	0.0104	0.0018
	(3.8776)	(0.0072)	(0.0090)	(0.0081)
Treated × Event Time Y = 1	0.6279	-0.0063	0.0017	-0.0193**
	(5.0693)	(0.0088)	(0.0093)	(0.0098)
Treated × Event Time Y = 2	0.9688	-0.0134	0.0107	-0.0140
	(5.5294)	(0.0098)	(0.0117)	(0.0107)
Treated × Event Time Y = 3	3.4879	0.0006	0.0204	0.0022
	(7.1339)	(0.0138)	(0.0133)	(0.0134)
PC Cohort-Indiv FE	Yes	Yes	Yes	Yes
PC Cohort-Event Time YQ-Pop Dens Dec FE	Yes	Yes	Yes	Yes
State-Date FE	Yes	Yes	Yes	Yes
Observations	1,502,343	1,814,896	1,814,896	1,814,896
R^2	0.5341	0.3686	0.4085	0.4063
Within R^2	0.0000	0.0000	0.0000	0.0000

Clustered (PC Cohort) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: Installment Loan Inquiries

Model:	Time to Next Inq (1)	Inquiry in 1-180D (2)	Inquiry in 181-360D (3)	Inquiry in 360-730D (4)
Treated × Event Time Y = -4	-3.8469	-0.0016	-0.0021	-0.0171
	(10.0115)	(0.0113)	(0.0229)	(0.0196)
Treated × Event Time Y = -3	-5.9566	-0.0098	0.0062	-0.0100
	(6.8695)	(0.0088)	(0.0138)	(0.0147)
Treated × Event Time Y = -2	-1.4413	0.0016	-0.0101	0.0099
	(4.2219)	(0.0057)	(0.0141)	(0.0097)
Treated × Event Time Y = 0	-1.8117	-0.0028	-0.0212**	-0.0096
	(2.7806)	(0.0048)	(0.0096)	(0.0091)
Treated × Event Time Y = 1	-4.5891	-0.0050	-0.0204*	-0.0028
	(3.8658)	(0.0055)	(0.0120)	(0.0101)
Treated × Event Time Y = 2	-5.0903	-0.0057	-0.0095	0.0106
	(5.2899)	(0.0068)	(0.0119)	(0.0143)
Treated × Event Time Y = 3	-3.7027	0.0059	0.0048	-0.0025
	(6.0914)	(0.0094)	(0.0143)	(0.0177)
PC Cohort-Indiv FE	Yes	Yes	Yes	Yes
PC Cohort-Event Time YQ-Pop Dens Dec FE	Yes	Yes	Yes	Yes
State-Date FE	Yes	Yes	Yes	Yes
Observations	2,237,079	2,629,049	2,629,049	2,178,110
R^2	0.6053	0.5465	0.6215	0.7506
Within R^2	0.0000	0.0000	0.0000	0.0000

Clustered (PC Cohort) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 11: Non-Bank Credit Inquiries

Model:	Payday gt0 (1)	Installment gt0 (2)
Treated × Event Time Y = -4	-0.0001	0.0006
	(0.0005)	(0.0011)
Treated × Event Time Y = -3	0.0002	0.0006
	(0.0004)	(0.0007)
Treated × Event Time Y = -2	0.0002	0.0005
	(0.0002)	(0.0004)
Treated × Event Time Y = 0	-0.0010*	-0.0008
	(0.0005)	(0.0006)
Treated × Event Time Y = 1	-0.0020***	-0.0016*
	(0.0008)	(0.0008)
Treated × Event Time Y = 2	-0.0023**	-0.0027**
	(0.0011)	(0.0012)
Treated × Event Time Y = 3	-0.0021	-0.0029*
	(0.0015)	(0.0015)
Treated × Inq Before Open gt0 × Event Time Y = -4	0.0003	-0.0023
	(0.0022)	(0.0025)
Treated × Inq Before Open gt0 × Event Time Y = -3	-0.0017	-0.0008
	(0.0023)	(0.0021)
Treated × Inq Before Open gt0 × Event Time Y = -2	0.0012	0.0001
	(0.0018)	(0.0019)
Treated × Inq Before Open gt0 × Event Time Y = 0	0.0033*	-0.0004
	(0.0019)	(0.0018)
Treated × Inq Before Open gt0 × Event Time Y = 1	0.0011	-0.0015
	(0.0025)	(0.0022)
Treated × Inq Before Open gt0 × Event Time Y = 2	0.0002	-0.0016
	(0.0027)	(0.0028)
Treated × Inq Before Open gt0 × Event Time Y = 3	-0.0042	-0.0034
	(0.0044)	(0.0044)
Inq Before Open-PC Cohort-Indiv FE	Yes	Yes
Inq Before Open-PC Cohort-Event Time YQ-Pop Dens Dec FE	Yes	Yes
Inq Before Open-State-Date FE	Yes	Yes
Observations	32,930,842	32,930,842
R^2	0.2257	0.2106
Within R^2	0.0000	0.0000

Clustered (PC Cohort) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 12: Non-Bank Credit Inquiries by Age

Model:	Payday gt0 (1)	Installment gt0 (2)	Payday gt1 (3)	Installment gt1 (4)
Treated × Event Time Y = -4	0.0009	-0.0001	0.0389*	-0.0030
	(0.0012)	(0.0014)	(0.0204)	(0.0223)
Treated × Event Time Y = -3	0.0005	0.0001	0.0204	0.0102
	(0.0011)	(0.0011)	(0.0151)	(0.0138)
Treated × Event Time Y = -2	0.0008	0.0010	0.0227*	0.0159
	(0.0008)	(0.0008)	(0.0122)	(0.0103)
Treated × Event Time Y = 0	0.0010	0.0007	0.0180*	0.0090
	(0.0008)	(0.0010)	(0.0104)	(0.0094)
Treated × Event Time Y = 1	0.0003	0.0007	0.0059	0.0021
	(0.0010)	(0.0011)	(0.0122)	(0.0096)
Treated × Event Time Y = 2	0.0001	-0.0022	0.0163	0.0003
	(0.0013)	(0.0017)	(0.0119)	(0.0105)
Treated × Event Time Y = 3	0.0009	0.0008	0.0283*	-0.0070
	(0.0017)	(0.0020)	(0.0168)	(0.0155)
Treated × Age lte35 × Event Time Y = -4	-0.0004	0.0013	-0.0143	0.0331
	(0.0015)	(0.0015)	(0.0311)	(0.0274)
Treated × Age lte35 × Event Time Y = -3	-0.0010	0.0008	-0.0392*	-0.0329
	(0.0012)	(0.0012)	(0.0237)	(0.0243)
Treated × Age lte35 × Event Time Y = -2	-0.0002	-0.0008	-0.0343	-0.0043
	(0.0010)	(0.0011)	(0.0211)	(0.0165)
Treated × Age lte35 × Event Time Y = 0	-0.0016	-0.0023*	-0.0337**	-0.0151
	(0.0010)	(0.0013)	(0.0168)	(0.0144)
Treated × Age lte35 × Event Time Y = 1	-0.0031**	-0.0047***	-0.0297	-0.0006
	(0.0014)	(0.0013)	(0.0186)	(0.0150)
Treated × Age lte35 × Event Time Y = 2	-0.0035**	-0.0025	-0.0237	-0.0052
	(0.0016)	(0.0018)	(0.0189)	(0.0173)
Treated × Age lte35 × Event Time Y = 3	-0.0060***	-0.0090***	-0.0406	0.0031
	(0.0022)	(0.0023)	(0.0278)	(0.0236)
Age 2Q-PC Cohort-Indiv FE	Yes	Yes	Yes	Yes
Age 2Q-PC Cohort-Event Time YQ-Pop Dens Dec FE	Yes	Yes	Yes	Yes
Age 2Q-State-Date FE	Yes	Yes	Yes	Yes
Observations	32,164,347	32,164,347	1,124,183	1,552,144
R^2	0.2201	0.2041	0.5814	0.6159
Within R^2	0.0000	0.0000	0.0000	0.0000

Clustered (PC Cohort) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 13: Non-Bank Credit Transactions by Age

Model:	Payday gt0 (1)	Payday Bal Log (2)
Treated × Event Time Y = -4	0.0040	-0.0050
	(0.0035)	(0.0846)
Treated × Event Time Y = -3	0.0056**	-0.0045
	(0.0028)	(0.0673)
Treated × Event Time Y = -2	0.0033	-0.0250
	(0.0024)	(0.0527)
Treated × Event Time Y = 0	0.0028	-0.0096
	(0.0027)	(0.0406)
Treated × Event Time Y = 1	0.0030	-0.0376
	(0.0036)	(0.0596)
Treated × Event Time Y = 2	0.0054	0.0839
	(0.0040)	(0.0849)
Treated × Event Time Y = 3	0.0021	0.0589
	(0.0050)	(0.1069)
Treated × Age lte35 × Event Time Y = -4	-0.0038	-0.4892**
	(0.0055)	(0.1976)
Treated × Age lte35 × Event Time Y = -3	-0.0039	-0.0994
	(0.0045)	(0.1156)
Treated × Age lte35 × Event Time Y = -2	-0.0009	-0.0658
	(0.0032)	(0.0904)
Treated × Age lte35 × Event Time Y = 0	-0.0059*	-0.0227
	(0.0033)	(0.0736)
Treated × Age lte35 × Event Time Y = 1	-0.0078**	-0.0278
	(0.0037)	(0.1175)
Treated × Age lte35 × Event Time Y = 2	-0.0132***	-0.1474
	(0.0043)	(0.1632)
Treated × Age lte35 × Event Time Y = 3	-0.0100	-0.3039*
	(0.0066)	(0.1675)
Age 2Q-PC Cohort-Indiv FE	Yes	Yes
Age 2Q-PC Cohort-Event Time YQ-Pop Dens Dec FE	Yes	Yes
Age 2Q-State-Date FE	Yes	Yes
Observations	6,293,007	312,051
R^2	0.2857	0.7205
Within R^2	0.0000	0.0001

Clustered (PC Cohort) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 14: Essential vs. Discretionary

	Visits				Visitors			
Est. Type	Essential	Non-Essential	Retail	School	Essential	Non-Essential	Retail	School
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × Event Time Q = -7	0.0228	0.0310	0.0468	-0.0156	0.0207	0.0267	0.0538	-0.0012
	(0.0265)	(0.0327)	(0.0338)	(0.0177)	(0.0239)	(0.0328)	(0.0337)	(0.0162)
Treated × Event Time Q = -6	0.0100	0.0071	0.0281	-0.0241	0.0093	0.0079	0.0346	-0.0065
	(0.0239)	(0.0307)	(0.0266)	(0.0253)	(0.0231)	(0.0313)	(0.0244)	(0.0219)
Treated × Event Time Q = -5	0.0061	0.0057	0.0174	-0.0387**	0.0086	0.0074	0.0263	-0.0190
	(0.0225)	(0.0290)	(0.0210)	(0.0163)	(0.0221)	(0.0292)	(0.0200)	(0.0159)
Treated × Event Time Q = -4	0.0072	0.0028	0.0090	-0.0446**	0.0034	0.0039	0.0136	-0.0251
	(0.0136)	(0.0184)	(0.0144)	(0.0193)	(0.0144)	(0.0182)	(0.0135)	(0.0171)
Treated × Event Time Q = -3	0.0108	0.0095	-0.0005	-0.0169	0.0066	0.0069	0.0045	-0.0023
	(0.0105)	(0.0110)	(0.0121)	(0.0125)	(0.0102)	(0.0100)	(0.0117)	(0.0101)
Treated × Event Time Q = -2	0.0047	-0.0003	0.0017	-0.0075	0.0020	-0.0019	0.0035	0.0029
	(0.0081)	(0.0097)	(0.0083)	(0.0117)	(0.0078)	(0.0098)	(0.0086)	(0.0101)
Treated × Event Time Q = 0	0.0077	0.0078	0.0086	0.0071	0.0090	0.0047	0.0041	0.0128*
	(0.0063)	(0.0064)	(0.0074)	(0.0083)	(0.0061)	(0.0064)	(0.0068)	(0.0066)
Treated × Event Time Q = 1	0.0096	0.0084	0.0217***	-0.0121	0.0120*	0.0124	0.0216***	0.0033
	(0.0068)	(0.0088)	(0.0081)	(0.0140)	(0.0065)	(0.0084)	(0.0077)	(0.0101)
Treated × Event Time Q = 2	0.0212*	0.0150	0.0189	-0.0092	0.0218*	0.0171	0.0183	0.0090
	(0.0117)	(0.0140)	(0.0128)	(0.0162)	(0.0111)	(0.0140)	(0.0122)	(0.0130)
Treated × Event Time Q = 3	0.0284*	0.0297*	0.0338**	-0.0039	0.0277*	0.0347**	0.0319**	0.0077
	(0.0151)	(0.0162)	(0.0154)	(0.0206)	(0.0145)	(0.0175)	(0.0145)	(0.0147)
Treated × Event Time Q = 4	0.0466***	0.0480**	0.0557***	0.0064	0.0483***	0.0535**	0.0511***	0.0202
	(0.0173)	(0.0217)	(0.0165)	(0.0228)	(0.0164)	(0.0212)	(0.0156)	(0.0178)
Treated × Event Time Q = 5	0.0450***	0.0518***	0.0428**	0.0011	0.0511***	0.0576***	0.0427***	0.0135
	(0.0166)	(0.0199)	(0.0185)	(0.0279)	(0.0149)	(0.0193)	(0.0163)	(0.0195)
Treated × Event Time Q = 6	0.0470**	0.0565**	0.0660***	0.0085	0.0493***	0.0651***	0.0602***	0.0231
	(0.0198)	(0.0234)	(0.0205)	(0.0274)	(0.0184)	(0.0238)	(0.0188)	(0.0210)
Treated × Event Time Q = 7	0.0670***	0.0946***	0.0963***	0.0164	0.0725***	0.1028***	0.0885***	0.0257
	(0.0233)	(0.0274)	(0.0249)	(0.0309)	(0.0206)	(0.0285)	(0.0248)	(0.0258)
PC Cohort-Est FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PC Cohort-Event Time M-Pop Dens Dec FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,096,320	12,709,443	5,999,115	1,561,204	11,096,320	12,709,443	5,999,115	1,561,204
R^2	0.2417	0.3146	0.2980	0.3919	0.2533	0.3518	0.3273	0.4015
Within R^2	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

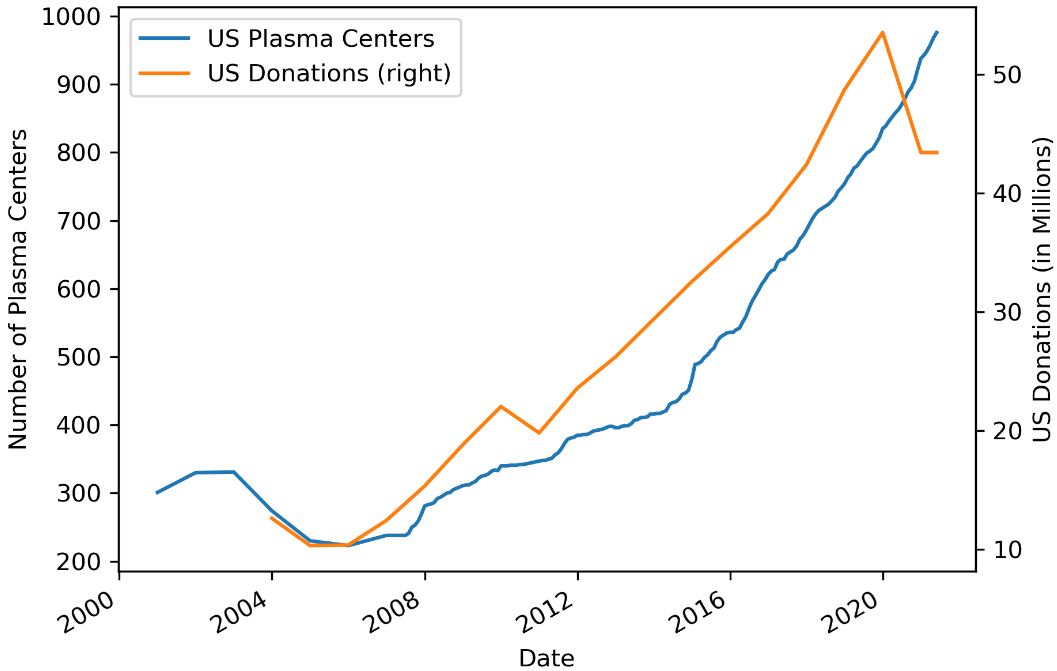
Clustered (PC Cohort) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 15: Discretionary Establishments

	Visits				Visitors			
Est. Type	Restaurant	Entertainment	Liquor	Luxury	Restaurant	Entertainment	Liquor	Luxury
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × Event Time Q = -7	0.0118	0.0254	0.0499	0.0485	0.0111	0.0197	0.0481	0.0454
	(0.0331)	(0.0358)	(0.0329)	(0.0337)	(0.0328)	(0.0339)	(0.0389)	(0.0320)
Treated × Event Time Q = -6	-0.0006	-0.0122	0.0101	0.0080	-0.0014	-0.0082	0.0120	0.0148
	(0.0339)	(0.0318)	(0.0326)	(0.0241)	(0.0347)	(0.0287)	(0.0353)	(0.0235)
Treated × Event Time Q = -5	-0.0082	0.0036	0.0068	0.0194	-0.0074	0.0046	0.0150	0.0235
	(0.0310)	(0.0268)	(0.0322)	(0.0247)	(0.0316)	(0.0265)	(0.0332)	(0.0225)
Treated × Event Time Q = -4	-0.0100	-0.0117	0.0015	0.0092	-0.0073	-0.0013	0.0038	0.0123
	(0.0199)	(0.0218)	(0.0237)	(0.0153)	(0.0195)	(0.0207)	(0.0231)	(0.0144)
Treated × Event Time Q = -3	0.0042	0.0005	-0.0014	0.0144	0.0049	-0.0005	0.0030	0.0114
	(0.0122)	(0.0236)	(0.0143)	(0.0128)	(0.0116)	(0.0217)	(0.0135)	(0.0125)
Treated × Event Time Q = -2	0.0030	-0.0108	-0.0144	0.0001	-0.0003	-0.0137	-0.0129	0.0014
	(0.0099)	(0.0196)	(0.0135)	(0.0104)	(0.0103)	(0.0162)	(0.0128)	(0.0111)
Treated × Event Time Q = 0	0.0098	0.0089	0.0178*	0.0080	0.0049	0.0133	0.0197**	0.0020
	(0.0077)	(0.0187)	(0.0094)	(0.0096)	(0.0073)	(0.0172)	(0.0099)	(0.0078)
Treated × Event Time Q = 1	0.0101	0.0215	0.0124	0.0056	0.0098	0.0276	0.0204	0.0138
	(0.0116)	(0.0210)	(0.0148)	(0.0107)	(0.0105)	(0.0198)	(0.0139)	(0.0100)
Treated × Event Time Q = 2	0.0093	0.0555**	0.0111	0.0108	0.0126	0.0411*	0.0106	0.0113
	(0.0150)	(0.0277)	(0.0180)	(0.0146)	(0.0148)	(0.0248)	(0.0196)	(0.0129)
Treated × Event Time Q = 3	0.0279	0.0662**	0.0452**	0.0249	0.0374**	0.0430	0.0464*	0.0229
	(0.0172)	(0.0296)	(0.0215)	(0.0181)	(0.0185)	(0.0274)	(0.0236)	(0.0166)
Treated × Event Time Q = 4	0.0488**	0.1138***	0.0559**	0.0325	0.0584***	0.0890**	0.0624**	0.0353*
	(0.0222)	(0.0393)	(0.0282)	(0.0234)	(0.0225)	(0.0373)	(0.0285)	(0.0199)
Treated × Event Time Q = 5	0.0596**	0.1104***	0.0512*	0.0477**	0.0653***	0.0934***	0.0639**	0.0422**
	(0.0234)	(0.0372)	(0.0305)	(0.0203)	(0.0228)	(0.0359)	(0.0298)	(0.0172)
Treated × Event Time Q = 6	0.0542*	0.1120***	0.0802**	0.0556**	0.0626**	0.0859**	0.0945**	0.0483**
	(0.0285)	(0.0379)	(0.0406)	(0.0217)	(0.0286)	(0.0374)	(0.0399)	(0.0195)
Treated × Event Time Q = 7	0.0874**	0.1452***	0.1315***	0.0837***	0.0972***	0.1513***	0.1356***	0.0754***
	(0.0346)	(0.0361)	(0.0409)	(0.0309)	(0.0358)	(0.0350)	(0.0410)	(0.0280)
PC Cohort-Est FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PC Cohort-Event Time M-Pop Dens Dec FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,002,368	888,848	1,593,812	3,450,994	5,002,368	888,848	1,593,812	3,450,994
R^2	0.3882	0.3428	0.3827	0.2666	0.4309	0.3706	0.4265	0.2914
Within R^2	0.0001	0.0002	0.0002	0.0000	0.0002	0.0002	0.0002	0.0001

Clustered (PC Cohort) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 1: Plasma Centers in the United States



The figure shows the number of plasma centers and the number of donations over time according to the authors' tabulations of data from the FDA, PPTA, and from InfoGroup's ReferenceUSA data.

Figure 2: Selection of Control Events

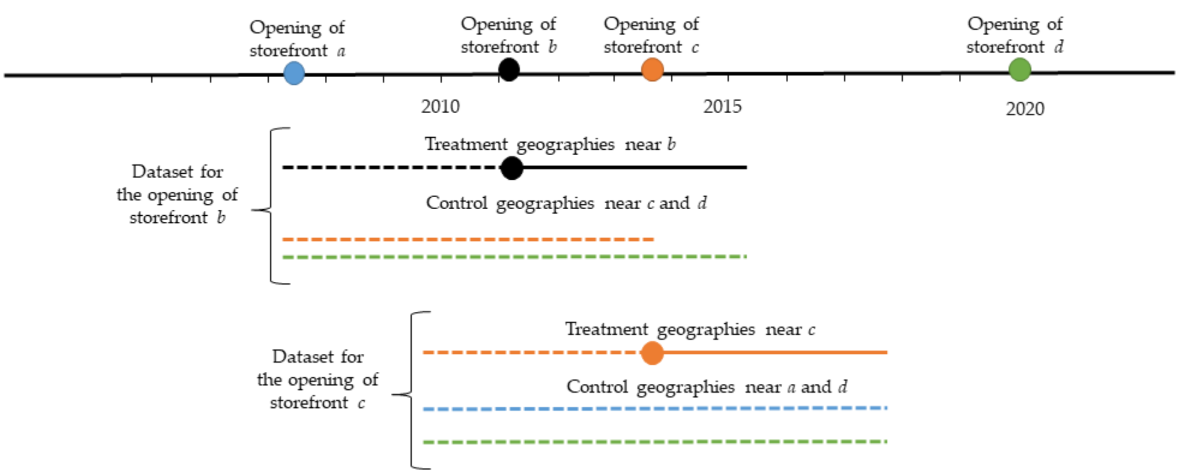
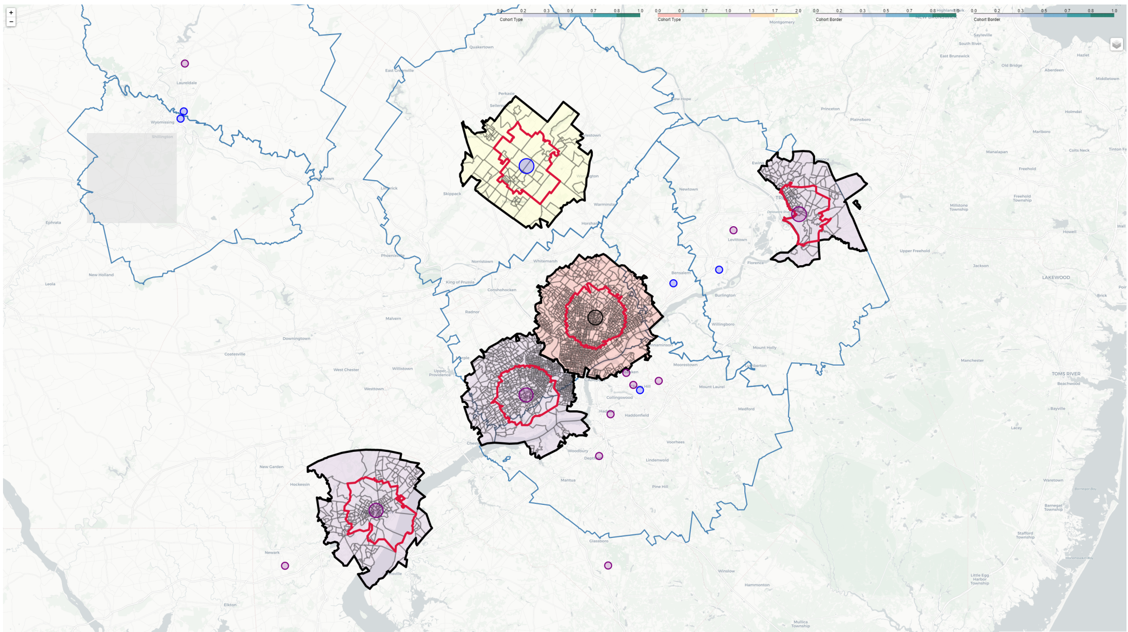
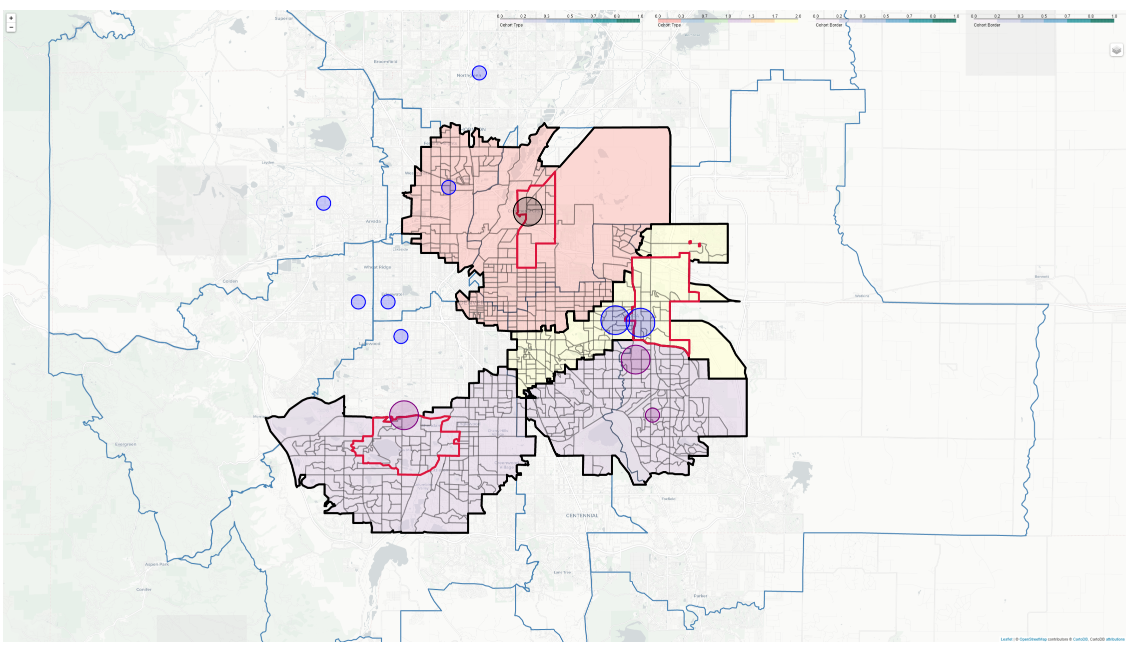


Figure 3: Map of treatment and control events

Panel 1: Philadelphia, PA (2015)



Panel 2: Denver, CO (2018)



Each panel depicts the Census Block Groups (CBGs) we study during eight plasma center openings. The black circles indicate a target opening plasma center which treats the surrounding region shaded in red. Control regions shaded in yellow link to counterfactual plasma centers which opened in the future denoted by large blue circles. Control regions shaded in purple link to counterfactual plasma centers which opened in the past denoted by large purple circles. Small purple and blue circles represent plasma centers which open before and after the target plasma center respectively. The shaded regions around each plasma center have a maximum radius of 10 kilometers which provides a sense of scale. Finally, we use the areas bordered in red for our difference-in-difference regressions.

Figure 4: Non-Bank Credit: Time Between Inquiries

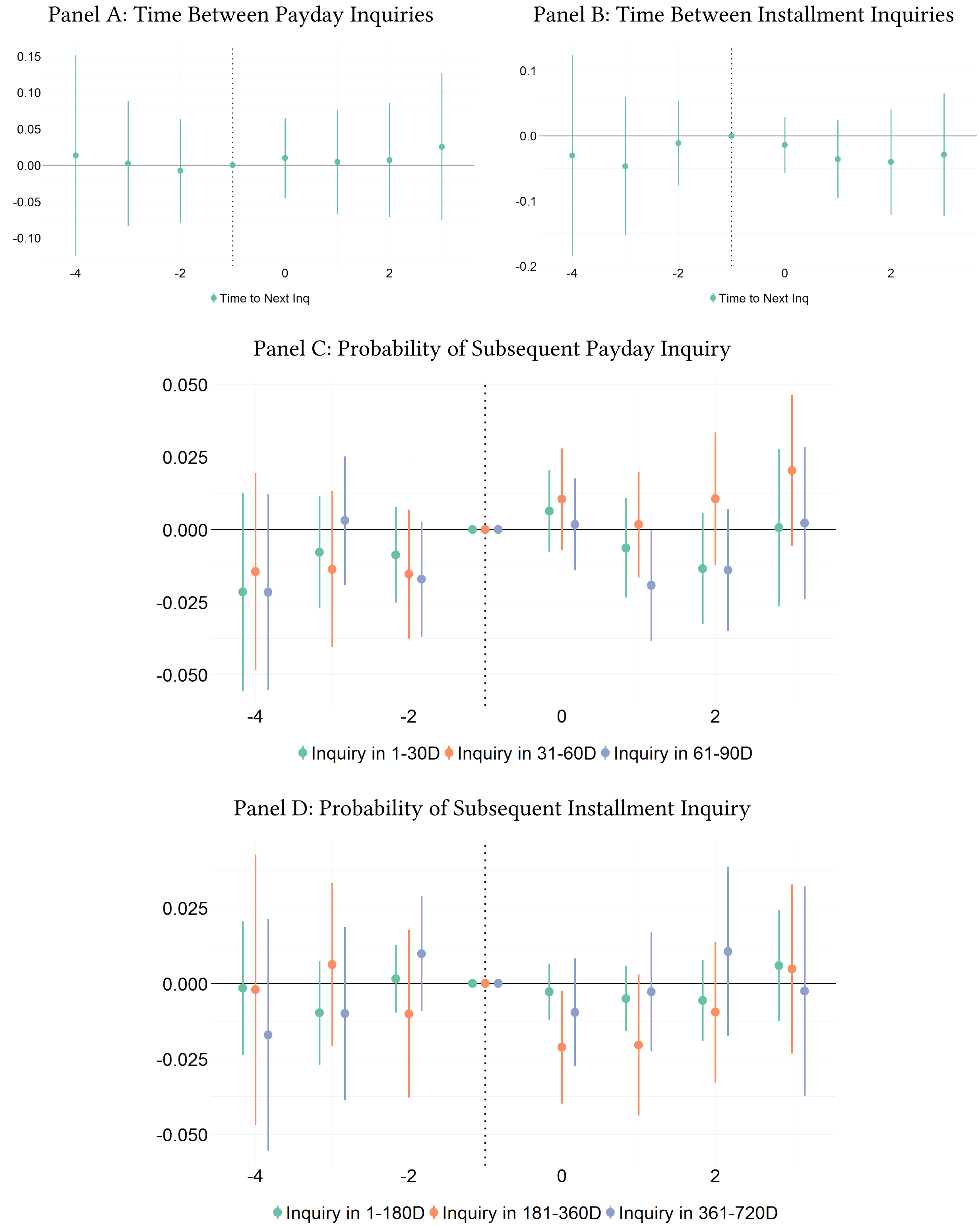
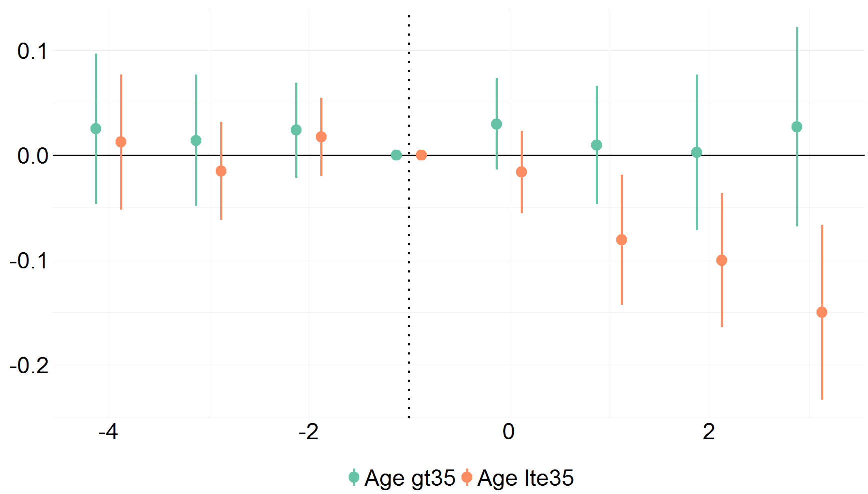


Figure 5: Non-Bank Credit Inquiries Age

Panel A: Payday Loans



Panel B: Installment Loans

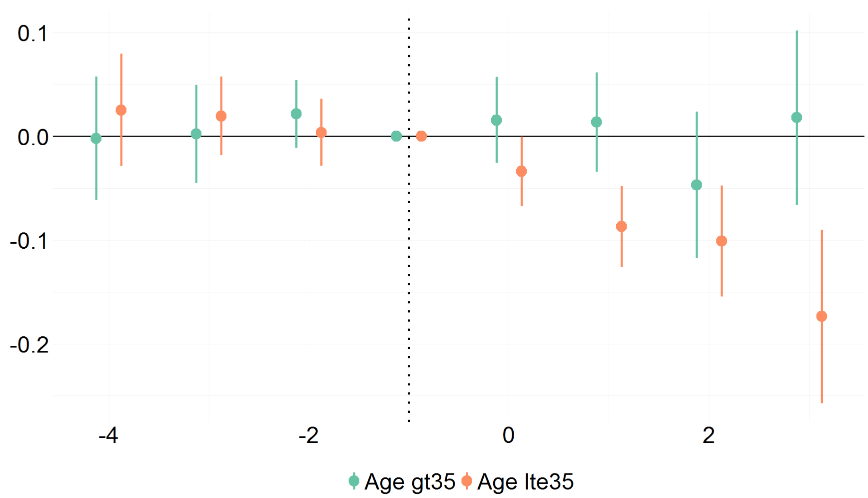
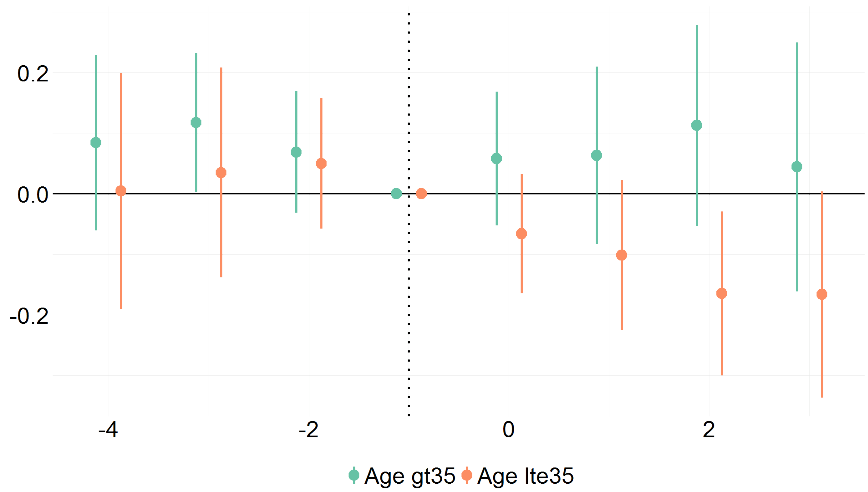
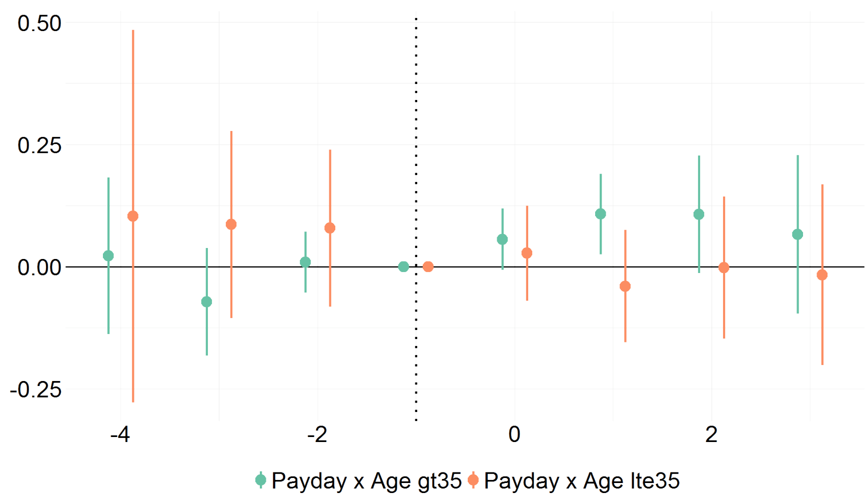


Figure 6: Payday Transactions and Repayment by Age

Panel A: Payday gt0



Panel B: Actual to Expected Duration



Panel C: Late Payment

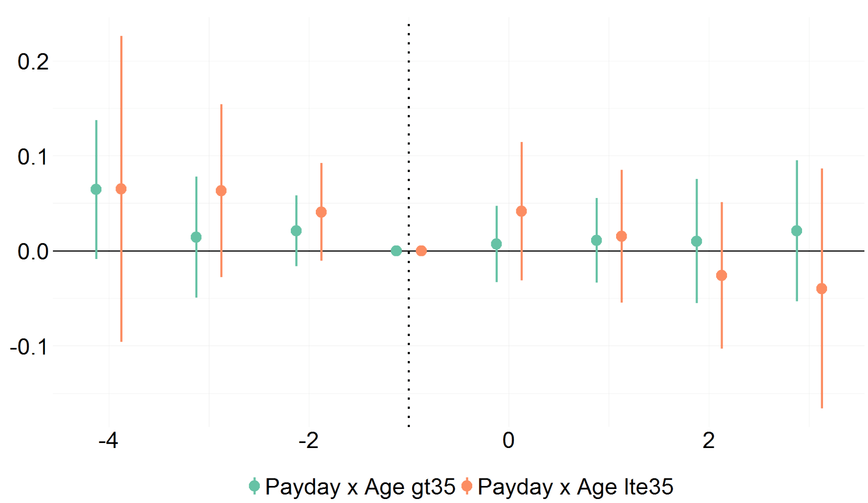
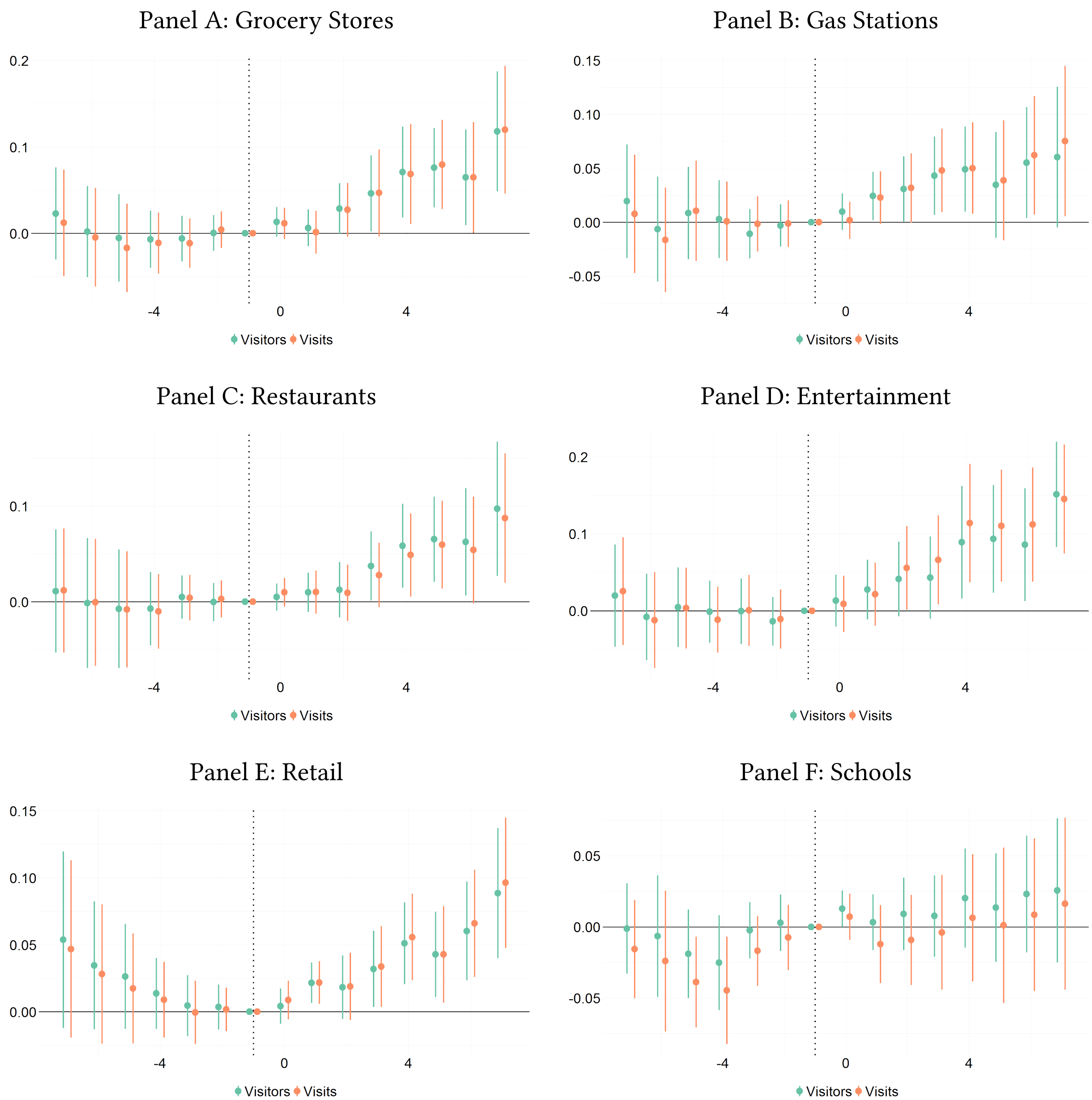


Figure 7: Establishment Foot Traffic



Appendix

A Additional Tables and Figures

Table A.1: Type of Gig Worker by Plasma Donation

	Mean(Plasma Donors=0)	Mean(Plasma Donors=1)	Diff.	Std. Error	Obs.
Making and selling products	0.3378	0.3254	-0.0124	0.0432	2539
Perform tasks online (eg. surveys)	0.2516	0.1984	-0.0531	0.0395	2539
Ride-sharing / transportation	0.1637	0.1429	-0.0208	0.0337	2539
Shopping / Delivery / Warehouse	0.1662	0.2381	0.0719**	0.0343	2539
Pet Care	0.0825	0.0635	-0.0190	0.0250	2539
Child Care	0.0220	0.0317	0.0098	0.0135	2539
Household Tasks	0.0215	0.0556	0.0340**	0.0138	2539
Home share	0.0274	0.0317	0.0044	0.0150	2539
Other	0.1272	0.1270	-0.0002	0.0305	2539

Table A.2: Emergency Resources of Donors

	(1) Plasma	(2) Payday Loan	(3) Gig
Emergency 2K? –No	0.027***	0.031***	0.022***
	(0.004)	(0.004)	(0.006)
Emergency 2K? –Prob Not	0.018***	0.014***	0.022***
	(0.004)	(0.003)	(0.005)
Emergency 2K? –Maybe	0.006**	0.008***	0.012***
	(0.003)	(0.002)	(0.004)
Expense 400 : $Cash$	-0.004	-0.015***	-0.006
	(0.003)	(0.002)	(0.004)
Expense 400 : $CCPaynext$	-0.002	-0.016***	0.002
	(0.003)	(0.002)	(0.005)
Expense 400 : $CCPaytime$	-0.004	-0.013***	0.010**
	(0.003)	(0.003)	(0.005)
Expense 400 : $BankLoan$	-0.009	0.004	0.031**
	(0.009)	(0.012)	(0.014)
Expense 400 : $Non - BankCredit$	0.039***	0.339***	0.008
	(0.012)	(0.021)	(0.011)
Expense 400 : $Family$	-0.003	-0.008***	-0.008*
	(0.004)	(0.003)	(0.005)
Expense 400 : $SellSomething$	0.025***	-0.000	0.043***
	(0.006)	(0.005)	(0.007)
Expense 400 : $Other$	0.024*	0.011	0.020
	(0.013)	(0.011)	(0.015)
Expense 400 : $CannotMeet$	0.012*	0.017**	-0.002
	(0.006)	(0.007)	(0.007)
Zip and Resp. Cont.	Yes	Yes	Yes
Year-Wave FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Sample	IRSFFA	IRSFFA	IRSFFA
Cluster by	CBSA	CBSA	CBSA
N	27743	27518	27746

The outcomes are whether someone in the household has donated plasma or taken out a payday loan in the past 6 months, and whether someone in the household has worked a gig job in the past year. Our zip code controls include the fraction of households that commute by car (proxy for mobility and urban sprawl), population density deciles, and whether the zip code is part of a CBSA. We do not include CBSA fixed effects as they would unduly limit the sample we can study. We further control for the fraction of households 1) below 100% of the Federal Poverty Line, 2) with an income below $50,000, 3) who receive government monetary aid, and 4) who receive food stamps or SNAP. Demographic controls include the fraction of households that are white, hold at least a bachelors degree, or are employed full time for the prior year. Finally, we also control for the number of payday stores within 5 kilometers. Our respondent controls include the variables from Table 4 (i.e. gender, race, age gt 35, married, children, etc.) except that we use income deciles within year instead of income terciles.

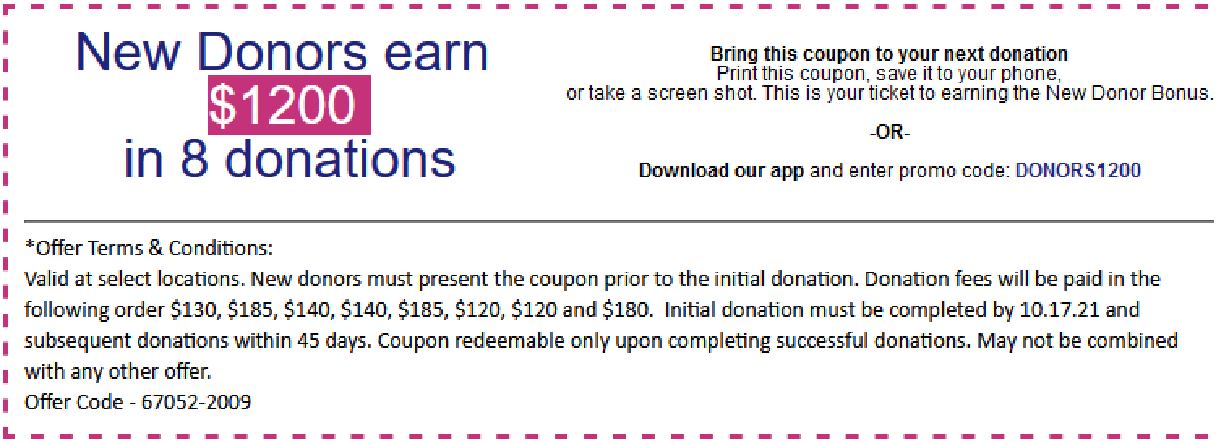
Table A.3: Financial Education and Credit Habits of Donors

	(1) Plasma	(2) Payday Loan	(3) Gig
Fin Education	0.001	0.002*	0.007***
	(0.001)	(0.001)	(0.002)
Money Management	0.000	-0.007***	0.002
	(0.002)	(0.002)	(0.003)
Planning Horizon: Next few days	0.018**	0.036***	0.014
	(0.007)	(0.008)	(0.010)
Planning Horizon: Next few weeks	0.013***	0.005	0.019***
	(0.005)	(0.004)	(0.006)
Planning Horizon: Next few months	0.009**	0.005	0.005
	(0.004)	(0.003)	(0.005)
CC Paid Full	-0.009**	-0.011**	0.000
	(0.005)	(0.004)	(0.007)
CC Carried Balance	-0.009*	-0.009*	0.002
	(0.005)	(0.005)	(0.005)
CC Paid Minimum	0.008	0.009**	0.019***
	(0.005)	(0.004)	(0.006)
CC Late Payments	0.004	0.018***	0.014*
	(0.006)	(0.006)	(0.008)
CC Missed Payments	0.033***	0.058***	0.007
	(0.009)	(0.009)	(0.011)
Zip and Resp. Cont.	Yes	Yes	Yes
Year-Wave FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Sample	IRSFFA	IRSFFA	IRSFFA
Cluster by	CBSA	CBSA	CBSA
N	13276	13209	13276

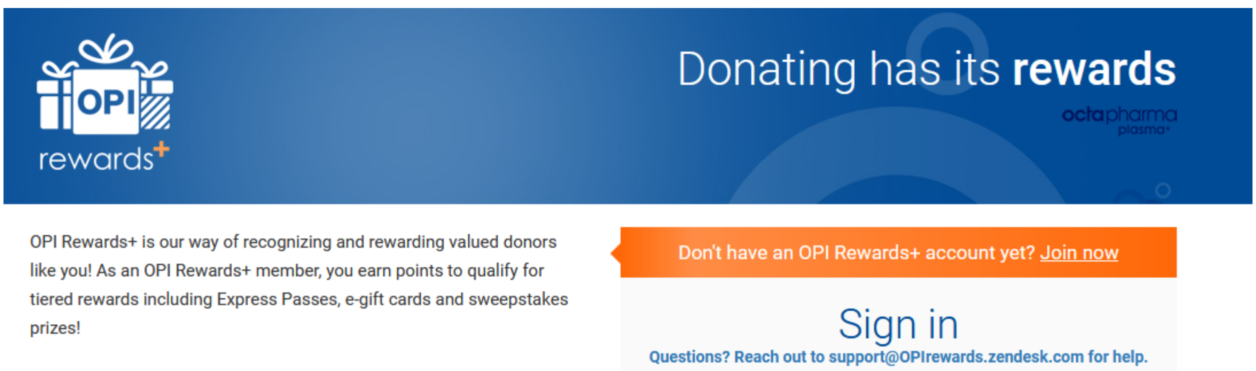
The outcomes are whether someone in the household has donated plasma or taken out a payday loan in the past 6 months, and whether someone in the household has worked a gig job in the past year. Our zip code controls include the fraction of households that commute by car (proxy for mobility and urban sprawl), population density deciles, and whether the zip code is part of a CBSA. We do not include CBSA fixed effects as they would unduly limit the sample we can study. We further control for the fraction of households 1) below 100% of the Federal Poverty Line, 2) with an income below $50,000, 3) who receive government monetary aid, and 4) who receive food stamps or SNAP. Demographic controls include the fraction of households that are white, hold at least a bachelors degree, or are employed full time for the prior year. Finally, we also control for the number of payday stores within 5 kilometers. Our respondent controls include the variables from Table 4 (i.e. gender, race, age gt 35, married, children, etc.) except that we use income deciles within year instead of income terciles.

Figure A.1: Plasma Center Marketing Materials

Panel 1: Biolife Coupon



Panel 2: Octapharma Rewards Program

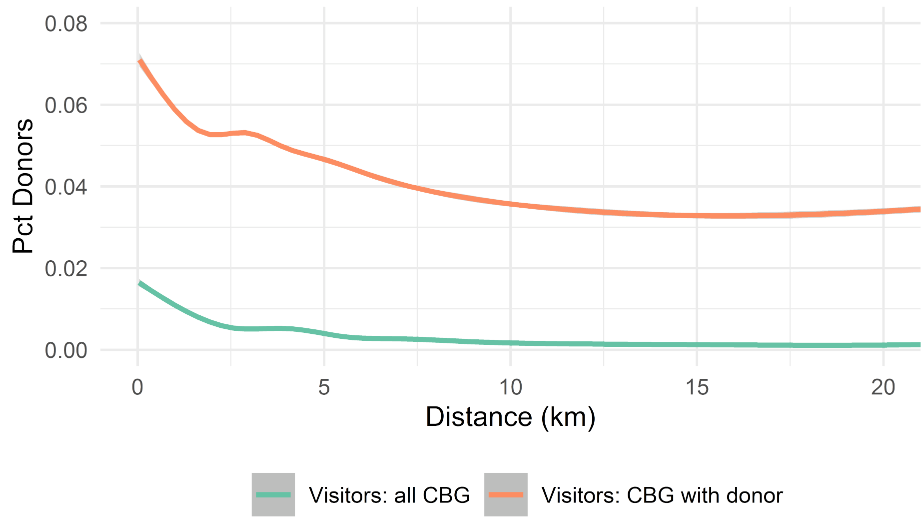


Panel 3: CSL Plasma Coupon

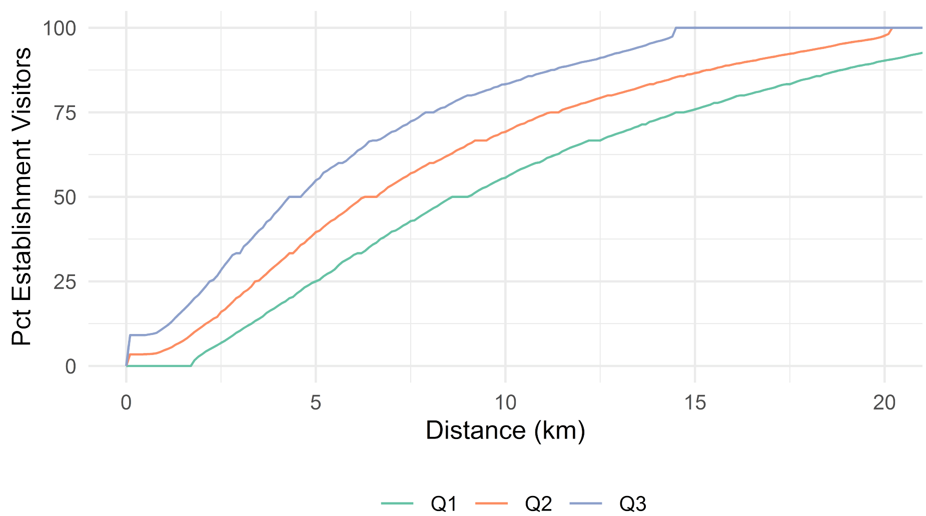
Panel 4: Grifols Donor Referral Bonus

Figure A.2: Plasma Storefronts Visitors: Distance to Residence

Panel 1: Fraction of residents who visit a plasma center:



Panel 2: Fraction of unique visitor living within X kilometers:



Source: Authors' tabulations of SafeGraph cell phone tracking data. In Panel 1, the horizontal axis is the distance in kilometers between a census block group (CBG) and the closest plasma center, the vertical axis is the fraction of cbg residents who donate plasma (either unconditionally or conditional on Safegraph indicating that at least two cell phones visit the plasma center). Safegraph truncates their data to preserve annonymity, if there were 0-1 visitors from a cbg to a plasma center in a month they code this as zero and they code 2-4 visitors as 4 (which we recode as 2 which is more likely). In Panel 2, the vertical axis is the fraction of the plasma center's donors who live within x kilometers of a plasma center in a given month. Specifically, we pool together all establishment months that have at least 10 unique visitors. For each radius we calculate the 25th, 50th, and 75th percentile of the fraction of visitors who live within X kilometers of the establishment (quantiles are calculated across establishments and dates). So in Panel 2, for the median plasma center - date we have 37% of donors live within 5 kilometers and nearly 70% of donors live within 10 kilometers.

B Plasma Center Openings

In this section we describe how we assemble a unique dataset which identifies the opening dates for each plasma center in the United States. We begin with a FOIA request to the FDA for historical records of their Blood Establishment Registration database (BER).[38] BER contains the most recent annual registration forms for all establishments authorized to handle blood, which includes plasma centers, hospitals, blood banks, and all of the processing and distribution facilities. The registration form includes the address, parent company, contact information, and a detailed list of the activities the establishment conducts (e.g., plasma collection versus whole blood collection). Corporations must register each establishment with the FDA annually (between October and December) or within two weeks of opening. Unfortunately, the BER database only contains the most recent registration information for each establishment and the FDA maintains only paper records of historical registration forms. Moreover, the FDA was unable to deliver electronic copies of the forms due to the large number of locations we requested. Therefore, we received snapshots of BER from January 2015 and February 2016 and scrape the BER website weekly from September of 2019 to present to accurately track new plasma center openings. We can, therefore, accurately identify openings in years when the BER snapshots are available (2015-2016 and from 2019 onward).

To more precisely pinpoint when a plasma center opens we use two additional sources. First, we manually inspect historical photos in Google Streetview and Google Earth of each plasma center address in BER that was last registered more recently than 2007. Google Streetview allows users to view panoramic pictures from the vantage point of vans that google sends out on survey drives. Google surveys most business areas every 6 months to 2 years with the frequency increasing over time. We mark the latest date on which a driveby does not reveal the plasma center and the earliest date on which a driveby does reveal a plasma center. We also look at the establishment's description in Google, which often contains promotional photos. If the photos

[38]The BER is freely available to the public at https://www.fda.gov/vaccines-blood-biologics/biologics-establishment-registration/find-blood-establishment.

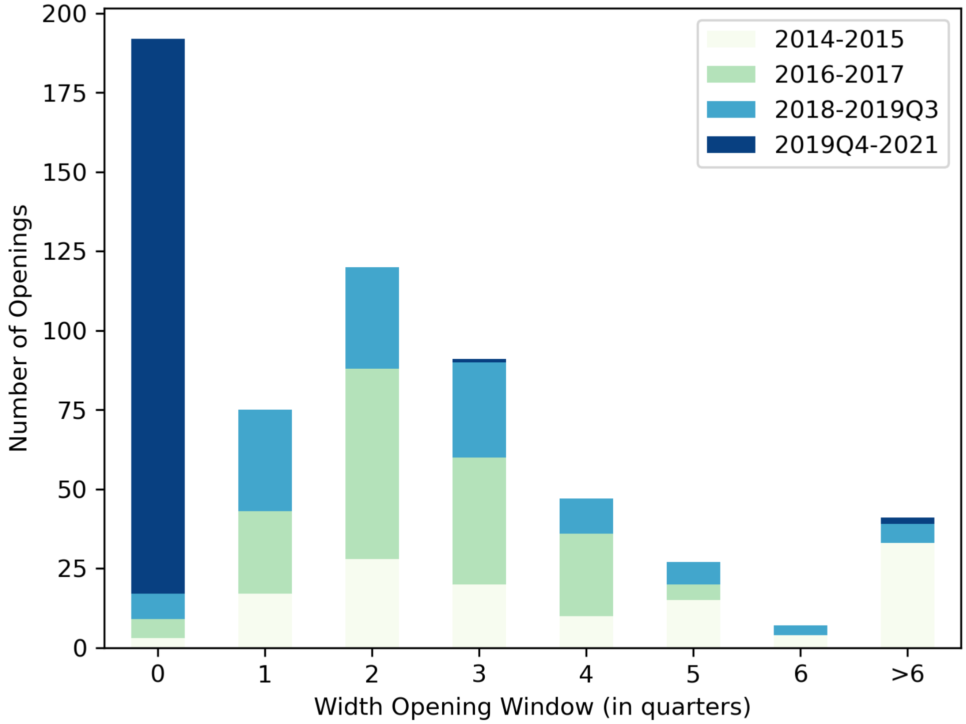
are specific to the establishment (e.g. ribbon cutting event) and are time stamped we use these as proof the location was operating on that date. We examine plasma center addresses in Google Earth which contains very detailed satellite photos at up to monthly frequency. We are able to identify when plasma centers that occupy their own distinct building complete construction and have cars in the parking lot to indicate operations. Second, pharmaceutical corporations often publish a list of currently open plasma centers on their websites. We manually review archives of pharmaceutical corporation websites to extract historical plasma center directories using the Internet Archive Project's Wayback Machine.[39]

Finally, we purchase historical establishment records from Infogroup for plasma collectors (SIC 809953) and blood banks (SIC 809916). Infogroup collects data about businesses and consumers to support marketing efforts. We received information for 1,000-1,600 establishments as of June for each year between 1997 and 2019.

To establish an opening window for each establishment, we use the BER registrations, Wayback Machine archives alongside Google's Streetview and Earth products as administrative and photographic evidence of when a plasma center is and is not present. When we compare photos from Google against Infogroup we find establishments are frequently active several years before Infogroup creates a location record. Therefore, we only use Infogroup as evidence that an establishment is active by year end but we do not rely on Infogroup to identify that a plasma center opened within the year of the first Infogroup record. In the end, we identify the opening date for 589 of 616 plasma centers that we believe open since Jan. 2014 to within an accuracy of 18 months, though the average window has width of 5.25 months. We provide the distribution of opening window widths in Figure B.1.

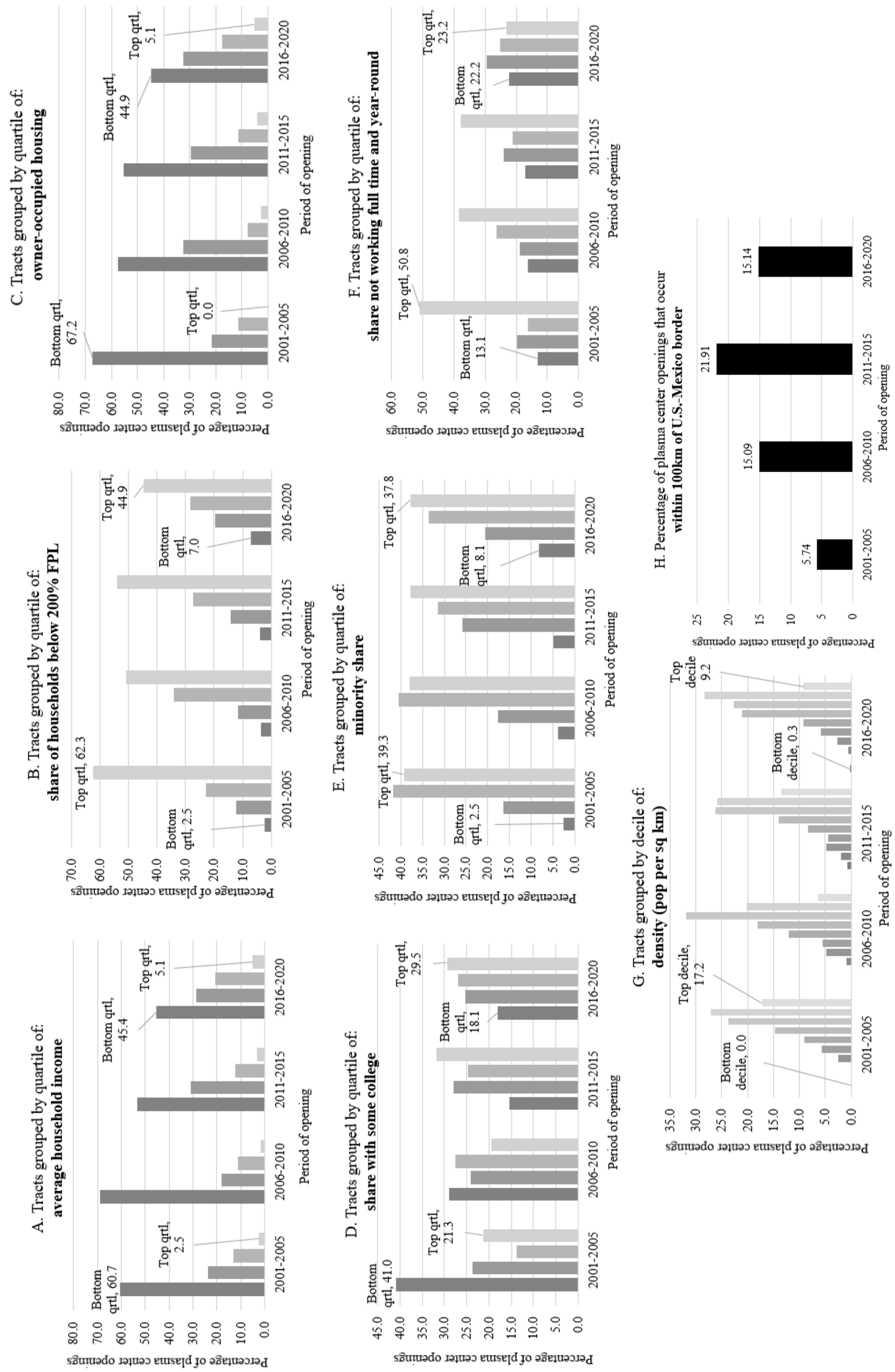
[39] Currently, most companies offer directories as a utility that allows the user to look up the closest plasma center to a given zip code. Because the lookup tool runs queries on a database file that has not been archived, these pages are not helpful. However, before 2015 several websites published simple lists of all locations nationally which we collect at up to a quarterly frequency (depending on archive availability).

Figure B.1: Accuracy of Plasma Center Opening Identification



C Plasma Center Locations

Figure C.1: Opening location by tract characteristics over time



Graphs depict the percentage of all plasma center openings within a time window that are located in Census tracts with certain characteristics. We study the Census tract of opening (instead of the block or block-group) because that is the finest geography available for some American Community Survey (ACS) variables. Tracts are grouped into quantiles of socio-economic variables by year. For example, Panel A shows that 60.7% of plasma opening that occurred in the 2001–2005 period were located in Census tracts in the lowest quartile of average income during that same period. Over time, as more plasma openings begin to occur in middle income tracts, that figure drops to 45.4% of all plasma openings during the 2016–2020 period. Data comes the U.S. Census, ACS, and the authors' tabulations of plasma center locations.

Table C.1: Correlates of plasma center opening locations

Panel A. Dependent variable = $\mathbb{1}(PlasmOpen_{j,t}) \times 100$; 2001–2014	(1)	(2)	(3)	(4)
$\#NonBankLender_{j,t-1}$	0.047***	0.045***	0.042***	0.044***
	(7.427)	(6.726)	(6.294)	(6.453)
$\#BankCreditUnion_{j,t-1}$		0.004**		0.002
		(1.978)		(0.860)
$\#AllEstablish_{j,t-1}$			0.001***	
			(3.056)	
$\#Resto_{j,t-1}$				-0.000
				(-0.019)
$\#Grocery_{j,t-1}$				-0.001
				(-1.243)
$\#BarsLiquor_{j,t-1}$				0.007***
				(2.849)
$\#GasStation_{j,t-1}$				-0.002
				(-0.876)
$\#Plasma_{j,t-1}$	0.375***	0.375***	0.375***	0.388***
	(12.373)	(12.365)	(12.360)	(12.396)
$< 100\% \, FPL_{j,t}$ (%)	-0.198**	-0.194**	-0.193**	-0.210***
	(-2.459)	(-2.416)	(-2.393)	(-2.609)
$< 200\% \, FPL_{j,t}$ (%)	0.205***	0.213***	0.212***	0.195***
	(3.156)	(3.312)	(3.281)	(3.016)
$OwnerOccupied_{j,t}$ (%)	-0.090***	-0.076***	-0.072***	-0.068***
	(-3.956)	(-3.553)	(-3.240)	(-3.004)
$Minority_{j,t}$ (%)	-0.018	-0.015	-0.013	-0.011
	(-0.919)	(-0.753)	(-0.673)	(-0.519)
$Bachelor's\ Degree_{j,t}$ (%)	-0.025	-0.032	-0.031	-0.060**
	(-0.890)	(-1.093)	(-1.099)	(-2.039)
$Not\ working\ fulltime_{j,t}$ (%)	0.143***	0.136***	0.144***	0.159***
	(3.363)	(3.216)	(3.375)	(3.560)
$Log(Pop\ per\ sqkm)_{j,t}$	0.010***	0.010***	0.010***	0.009***
	(7.024)	(7.010)	(7.115)	(6.075)
N	972462	972462	972462	907626
Y-mean	0.062	0.062	0.062	0.062

Panel B. Dependent variable = $\mathbb{1}(PlasmOpen_{j}) \times 100$; 2018–2020	(1)	(2)	(3)	(4)
$\#NonBankLender_{j,18-20}$	0.387***	0.378***	0.378***	0.375***
	(3.562)	(3.469)	(3.354)	(3.402)
$\#BankCreditUnion_{j,18-20}$		0.012		0.011
		(0.690)		(0.497)
$\#AllEstablish_{j,18-20}$			0.000	
			(0.557)	
$\#Resto_{j,18-20}$				0.002
				(0.438)
$\#Grocery_{j,18-20}$				0.033
				(1.537)
$\#BarsLiquor_{j,18-20}$				-0.029**
				(-2.118)
$\#GasStation_{j,18-20}$				-0.016
				(-1.126)
$\#Plasma_{j,17}$	0.692***	0.691***	0.692***	0.692***
	(4.271)	(4.271)	(4.270)	(4.276)
$< 100\% \, FPL_{j,18}$ (%)	-0.240	-0.234	-0.236	-0.218
	(-0.392)	(-0.383)	(-0.385)	(-0.358)
$< 200\% \, FPL_{j,18}$ (%)	-0.096	-0.081	-0.087	-0.120
	(-0.221)	(-0.186)	(-0.200)	(-0.275)
$OwnerOccupied_{j,18}$ (%)	-0.012	0.006	0.004	-0.030
	(-0.074)	(0.033)	(0.025)	(-0.176)
$Minority_{j,18}$ (%)	0.296*	0.302*	0.301*	0.286
	(1.696)	(1.724)	(1.718)	(1.623)
$Bachelor's\ Degree_{j,18}$ (%)	-0.504***	-0.511***	-0.508***	-0.481**
	(-2.752)	(-2.780)	(-2.766)	(-2.538)
$Not\ working\ fulltime_{j,18}$ (%)	-0.039	-0.052	-0.041	-0.056
	(-0.133)	(-0.177)	(-0.141)	(-0.191)
$Log(Pop\ per\ sqkm)_{j,18}$	0.069***	0.068***	0.069***	0.068***
	(5.442)	(5.378)	(5.440)	(5.310)
N	64826	64826	64826	64826
Y-mean	0.282	0.282	0.282	0.282

This table presents estimates from regressions relating a plasma opening to the number of establishments of different types located in that tract, including non-bank lenders (payday and pawn), banks and credit unions, restaurants, grocery stores, bars and liquor stores, and gas stations. In Panel A, the specification uses tract-year level panel data spanning 2001–2014 – i.e., the period of our access to National Establishment Time-Series (NETS) data. The dependent variable is a binary indicator (multiplied by 100) of a plasma opening in tract j in year t, $\mathbb{1}(PlasmOpen_{j,t}) \times 100$. Key explanatory variables are counts of establishments as of the prior year, t-1, aggregated using the NETS data. These regressions include county-year fixed effects. In Panel B, the specification uses a tract-level cross-section from collapsing the 2018–2020 period (2018 is the first year of SafeGraph data). The dependent variable is a binary indicator (multiplied by 100) of a plasma opening in tract *j* at any point in the 2018–2020 period. Key explanatory variables are counts of establishments as of the same 2018–2020 period, collected from SafeGraph. We collapse the data in this way because of the short panel available in SafeGraph and, unlike with NETS, we cannot see establishment openings/closings by year using SafeGraph. These regressions include county fixed effects. All specifications control for the number of plasma centers already present in the tract. Tract socio-economic controls include contemporaneous measures of the the share of residents earning under 100% of the Federal poverty line (FPL) and under 200% FPL, the owner-occupied housing share, the minority share, the share with a bachelor's degree, the share not working or not working full-time, and the log of population per square kilometer (density). Parentheses contain t-statistics: *p = 0.1; **p = 0.05; ***p = 0.01 (statistically significant), generated using robust (Huber-White) standard errors.

D Demographic Analysis

In this appendix we verify that the treated and control geographies do not have different demographic trends using data from the American Community Survey (ACS). We consider population growth and the poverty rate at 100% and 200% of the federal poverty line. All regressions use the exact same set of treated and control zip codes for each plasma center opening cohort that we use to study the Clarity and Safegraph data. However, since we use ACS demographic information there is a single observation for each zip code and year (we use ZCTA as a close approximation to actual zip codes).[40] We find some modest evidence of pre-trends in population growth and poverty in columns 1-3 of Table D.1. We believe this occurs because pharmaceutical corporations first target densely populated urban areas which are able to support plasma centers if even a small fraction of the population donates. However, as cities have become saturated, plamsa centers have expanded to suburbs and rural towns. This is supported by Appendix C. We choose counterfactual openings which are geographically closest to the treated group assuming that close regions are comparable. However, some counterfactuals will be recent rural openings in communities that have different growth rates. Therefore, we adjust the empirical strategy by interacting the cohort by time fixed effect with the population density decile of the geography in equation D.2. This allows for different trends for downtown, suburb, rural towns and everything in between. We find that adjusting for the differing trends in urban and rural areas, the treated and control geographies are comparable along most dimensions in columns 4-6 of Table D.1.

We also consider the race, gender and education, income, employment, poverty, and participation in government assistance programs to mitigate concerns of material income trends. We look for differences in the receipt of public assistance and SNAP, as well as the fraction that are insured. Finally, we look at differences in homeownership rates and commuting patterns. In unreported regressions, across all these variables, there are only two characteristics with significant

[40] We use demographic information from the annual ACS 5 year estimates which use a five year window to estimate information about the geography of interest. Using demographic information based on a 5 year window is not ideal. However, if there is a constant growth rate within each cohort the moving average will not affect our estimates. If there is a change in the growth rates between the treated and control observations we will still accurately identify the time of the change but the magnitude of the difference will be attenuated.

differences between treated and controls. The treated are becoming less well educated than the control geographies, but the effect is quite small with an aggregate difference over 8 years of 1.4p.p. difference and we do not expect this to drive our results. There is also a decrease in the fraction of residents insured after a plasma center opens but it does not begin before the plasma center opens and is very small (0.7p.p.).

$$y_{c,g,t} = \sum_{\tau \neq -1} \beta_\tau 1_{c,g,t} + \alpha_{c,g} + \alpha_{c,t} + \epsilon_{c,g,t} \tag{D.1}$$

$$y_{c,g,t} = \sum_{\tau \neq -1} \beta_\tau 1_{c,g,t} + \alpha_{c,g} + \alpha_{c,d(g,c),t} + \epsilon_{c,g,t} \tag{D.2}$$

Table D.1: Population and Poverty

Model:	Log Population (1)	Poor <100FPL (2)	Poor <200FPL (3)	Log Population (4)	Poor <100FPL (5)	Poor <200FPL (6)
Treated × Event Time Y = -4	0.0072**	-0.0075	-0.0075	0.0057	-0.0028	-0.0007
	(0.0034)	(0.0058)	(0.0060)	(0.0037)	(0.0052)	(0.0056)
Treated × Event Time Y = -3	0.0057*	-0.0074*	-0.0076*	0.0049	-0.0037	-0.0025
	(0.0029)	(0.0042)	(0.0043)	(0.0039)	(0.0028)	(0.0035)
Treated × Event Time Y = -2	0.0013	-0.0028	-0.0035*	0.0037*	-0.0008	-0.0004
	(0.0021)	(0.0017)	(0.0018)	(0.0020)	(0.0019)	(0.0021)
Treated × Event Time Y = 0	-0.0006	0.0013	0.0018	-0.0010	0.0020	0.0031*
	(0.0014)	(0.0011)	(0.0013)	(0.0018)	(0.0013)	(0.0016)
Treated × Event Time Y = 1	0.0006	0.0035**	0.0036	-0.0010	0.0035	0.0039
	(0.0025)	(0.0018)	(0.0022)	(0.0028)	(0.0024)	(0.0029)
Treated × Event Time Y = 2	0.0010	0.0037	0.0030	-0.0034	0.0035	0.0023
	(0.0041)	(0.0024)	(0.0029)	(0.0038)	(0.0034)	(0.0042)
Treated × Event Time Y = 3	0.0026	0.0035	0.0018	-0.0044	0.0023	0.0008
	(0.0062)	(0.0032)	(0.0039)	(0.0054)	(0.0052)	(0.0060)
PC Cohort-Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes
PC Cohort-Event Time Y FE	Yes	Yes	Yes			
State-Date FE	Yes	Yes	Yes	Yes	Yes	Yes
PC Cohort-Event Time Y-Pop Dens Dec FE				Yes	Yes	Yes
Observations	34,724	34,138	34,138	34,683	34,099	34,099
R^2	0.9989	0.9218	0.9602	0.9993	0.9491	0.9734
Within R^2	0.0003	0.0007	0.0006	0.0004	0.0003	0.0002

Clustered (PC Cohort) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*