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We study whether drug-related activities are helping drive fintech use, especially along the U.S. borders. We hypothesize fintech's shift from soft information to hard information to gauge a borrower's risk may allow illicit actors to participate in the lending marketplace to finance their illicit enterprises. We find counties with significant drug-related activities request more P2P loans in both amount and count after controlling for social and economic factors. The same pattern reemerges in counties where community banks have a higher market share. These results are robust to alternative measures of drug-related activities.

This study is a working paper and subject to change. All errors are those of the authors.

"Really, whose gonna look at Marshall a fuckin' mortgage advisor driving around in his sensible car (Cliff, 24, small-business owner | cocaine retailer and midlevel runner)." (Salinas 2018, 232)

I. Introduction

The disruption to the consumer lending landscape by financial technology firms (hereafter fintech) has allowed for more participation in the consumer credit market, but has it simultaneously allowed for illicit actors to more openly and frequently partake in this market? We argue that individuals who partake in illicit activities also participate in the financial sector.[3] Due to the nature of these individuals' business, traditional financial intermediaries' strict regulatory environment and, at times, the strong reliance on relationship banking, such as community banks and especially along the U.S. borders and low populated communities, it is in these actors' best interest to be an arm's length participant. We hypothesize that fintech's shift from soft information to hard information to gauge a borrower's risk and make credit decisions has allowed illicit actors to more openly and frequently participate in the peer-to-peer borrowing marketplace (hereafter P2P) to possibly finance their illicit enterprises or supplement their income.

We study whether drug-related activities are helping drive P2P demand in the United States. This question is important to address given that billions of dollars are lost to drug abuse. For

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[3] We define illicit activities as the production, manufacturing, importation, or distribution of illegal drugs.

example, in 2002, the Office of National Drug Control Policy estimated a $180.9 billion-dollar economic cost because of drug abuse (Harwood and Bouchery 2004). Furthermore, the illegal drug trade has the tendency to increase corruption (Jancsics 2021). We pay close attention to the two land borders given that U.S. border communities are inherently different. First, border communities, particularly along the U.S.-Mexico border, tend to be financially underserved and rely heavily on relationship banking (Brannon, English, and Kriner 1987). Furthermore, these communities face high drug and criminal activity. For example, more than half of all drugs seized by U.S. Customs and Border Protection were at either of the two U.S. land borders (U.S. CBP 2021). Additionally, the U.S. federal government has designated most counties within the U.S. southern border as high intensity drug trafficking areas (hereafter HIDTA). Thereby, it is important to identify potential long-term repercussions these communities might face given that such behaviors might negatively affect their economic development (i.e., labor productivity and financial and trade sectors) and simultaneously increase the cost of health care or mortality rates in these areas.

Although scholars have given great importance to contemporary forms of financing, for example, crowdfunding (Da Cruz 2018; Ghazali and Yasuoka 2018), peer-to-peer lending (Ghazali and Yasuoka 2018), and marketplace lending (Tang 2019; Vallee and Zeng 2019; Wang 2018), we close the literature gap by analyzing contemporary forms of financing using a U.S. border lens as well as incorporating a local measure of drug activity seldom used in the finance literature (Agca, Slutzky, and Zeume 2021; Gao et al. 2020). Furthermore, we extend the literature in several areas. First, we contribute to the growing field of *forensic economics* which focuses on the economic repercussions of undisclosed illegal behavior (Zitzewitz 2012). Second, we contribute to the literature stream related to fintech use and its potential use to finance illicit activities (Foley, Karlsen, and Putniņš 2019; García, Li, and Mahmud 2021; Goldstein, Jiang, and Karolyi 2019; Phillips and McDermid 2021). Lastly, we add to the existing literature of soft and hard credit information to make lending decisions (Ding, Huang, and Meng 2019; Liberti and Petersen 2019).

We conduct a county-level analysis during the sample period of 2013 to 2019 using data from the first peer-to-peer platform founded in the United States, Prosper Marketplace, and multiple measures of local drug-related activities to test the relationship between drug-related activities and P2P demand. A test of means shows that there is a significant difference in P2P demand between the two groups of counties (high intensity versus non-high intensity drug trafficking areas). Using either an ordinary least squares or a quasi-maximum likelihood Poisson model, our results indicate that HIDTA counties request more P2P loans in both amount and count after controlling for social and economic factors. The same pattern reemerges in counties where community banks have a higher market share. These results are robust to alternative measures of drug-related activities. When we analyze the P2P demand of border counties, we do not find that border counties behave any different from interior U.S. counties when the HIDTA designation is used as a proxy for drug-related activities. On the other hand, P2P demand increases in the southern border if overdose rate is used as a proxy for illegal drug-related activities.

II. Literature Review and Hypotheses Development

Information is crucial in a relationship and is particularly crucial in a financial relationship (Liberti and Petersen 2019; Lin, Prabhala, and Viswanathan 2013; Wang, Zhao, and Shen 2021). The theory of financial intermediation states the existence of a financial institution in a lending relationship is based on two key components: 1) reduction of transaction costs and 2) reduction of asymmetric information to avoid moral hazard and adverse selection (Allen and Santomero 1997; Morse 2015).

Financial intermediaries reduce asymmetric information through the gathering and processing of two main types of information. The first type is soft information which Liberti and Petersen (2019, 2) defines as "difficult to completely summarize in a numeric score, requires a knowledge of its context to fully understand, and becomes less useful when separated from the environment in which it was collected." The second type is hard information. This type of information is defined as being "quantitative, easy to store, and can be transmitted in impersonal ways" (Liberti and Petersen, 11). In this study, we look at how contemporary intermediaries (i.e., P2P platforms) are using information to make credit decisions and whether illicit actors are taking advantage of the type of information being used by these platforms.

Traditional financial intermediaries and information

Traditional financial intermediaries (i.e., banks) are an integral part of our economy, facilitating economic transactions (Contreras and Vazquez 2016) with the purpose of effectively allocating resources (Allen and Santomero 1997). In other words, banks help transfer unused household income (i.e., deposits) to individuals with an economic need/opportunity (i.e., loans) through two main functions: one, a reduction in transaction costs; and two, a reduction of information asymmetry by brokering the relationship between the borrower and lender (Havrylchyk and Verdier 2018).

First, traditional financial intermediaries are in a unique position to reduce transaction costs because they work with many borrowers and lenders. Thereby, banks can allocate these costs amongst the group. Second, these institutions have "access to a lot of private hard and soft data on credit history and current accounts of their borrowers" (Havrylchyk and Verdier 2018, 5), allowing them to make more informed credit decisions. Interestingly, an institution's size matters in determining why type of data (e.g., soft, hard) is used. For example, Berger et al. (2005) argue that a large bank's competitive advantage lies in credit decisions that rely on hard information because such information can be easily transferred within the hierarchy. On the other hand, the competitive advantage of small banks lies in credit decisions based on soft information which can be easily transmitted between individuals with credit-granting authority. The authors find that large banks "do not alleviate [small business or consumer] credit constraints as effectively" (238). For example, they find that small businesses located in areas with no small banks face credit obstacles.

Unfortunately, the global financial crisis had a significant and negative impact on liquidity opportunities due to either many banks ceasing to exist or the implementation and compliance of new regulatory capital requirements like Basel III (Fidrmuc and Lind 2020; Kirby and Worner 2014; Roulet 2018). Such circumstances and restrictions resulted in banks focusing on financing large loans (King and Tarbet 2011; Phung, Van Vu, and Tran 2022) while reducing the amount of credit extended to small and medium businesses as well as individuals interested in personal consumer loans (Angelkort and Stuwe 2011; Kirby and Worner 2014).

Peer-to-peer lending platforms and information

Some argue that the cost via traditional financial intermediation has not decreased (Havrylchyk and Verdier 2018; Naceur and Kandil 2009), and the traditional financial intermediary model has left many unbanked or underbanked (Griffin, Kruger, and Mahajan 2021). Fintechs have taken the opportunity to fulfill this unmet demand.[4] A fintech is a firm who has shed the traditional intermediary model (Chou 2019; Havrylchyk and Verdier 2018) by using "technology to augment, streamline, digitize or disrupt traditional financial services" (Walden 2020) such as in the consumer loan, mortgage loan, and working capital management arenas.

One fintech of interest, which we focus on in this study, is P2P lending platforms. Borrowers use these platforms to directly request unsecured personal or small business loans from an investor without the need to transact with a bank (Bertrand and Weill 2021; Wang, Zhao, and Shen 2021).[5] In other words, in these types of transactions, a fintech plays a secondary role in the transaction and only facilitates the connection between the borrower and lender via its technology and support services. This new form of borrowing contrasts traditional channels where the bank is the gatekeeper, or ultimate decision maker, of whether the loan is granted or not.

P2P lending platforms like Prosper Marketplace and LendingClub, among others, have gained worthy attention in the consumer and small business lending market (Kirby and Worner 2014) with Goldstein, Jian, and Karolyi (2019, 1658) stating "market-based lending gained popularity as an alternative to traditional financial institutions" by increasing transparency in the intermediation process (Havrylchyk and Verdier 2018; Wang, Zhao, and Shen 2021). This statement is supported by the rapid growth in fintech lending to consumers and small businesses (Wang 2018). For example, there was a 26%, or $53 billion, increase in global fintech investments from 2010 to 2018 (Accenture 2020) with "loans issued by [peer-to-peer] platforms represent[ing] one-third of unsecured consumers loans volume in the United States in 2016" (Vallee and Zeng 2019, 1940). Chou (2019) states that 10% of all consumer loans in the United States and United Kingdom will be originated by these platforms in the next three years. Balyuk, Berger, and Hackney (2020) find that in 2018, one peer-to-peer lending platform alone originated $176.3 million in small business loans – over a 1000% increase from 2006 to 2018.

Many argue that fintech may be a more efficient intermediator than traditional financial institutions because of their ability to reduce intermediation costs (Bertrand and Weill 2021; Havrylchyk and Verdier 2018), thereby having the potential of substituting the traditional bank (Bachman et al. 2011; Boot et al. 2020; Tang 2019). Due to technological advances in data processing and data science, fintech platforms have shifted from soft information to hard information to make faster and more precise credit decisions. This approach has given an opportunity to many who have been previously overlooked by the traditional financial channels to obtain liquidity (Atkins, Cook, and Seamans 2022; Berger et al. 2005; Kirby and Worner 2014).

Furthermore, because fintechs are considered non-financial companies from the non-financial sector (Wu 2017), they can operate remotely (Nakashima 2018) and avoid certain regulations and oversight (Magnuson 2018; Wu 2017) such as Basel III. For example, P2P platforms are regulated at the federal level by the Securities and Exchange Commission, and the state level (Magee 2011; Warren 2016). Thereby, fintechs do not have to adhere to the complex banking regulatory environment which traditional financial intermediaries must adhere to.

[4] Maskara, Kuvvet, and Chen (2021) find that a decrease in bank branches in rural communities results in an increase in P2P participation.

[5] P2P platforms follow multiple business models (e.g., client segregated account model, notary model, and guaranteed return model, among others). The model used by the leading P2P platforms in the United States is the notary model where the platform connects the lender and the borrower, but a bank originates the loan. To remove any risk from the originating institution, "the platform then issues a note…to the lender for the value of their contribution to the loan" (Kirby and Worner 2014, 18).

Illicit activities and the financial behavior of the illicit actor

Who is the typical illicit actor? What are their characteristics? Ethnographic studies in the field of criminology have worked hard to classify such individuals and have put forth two views. The traditional and more dominant view is that these actors act in a way that goes against overall society and society's values (Salinas 2018), or how Taylor (2008, 371) frames it, "a threat to the fabric of mainstream society." Such actors are thought of by many as belonging to an ethnic minority group (i.e., black, Hispanic, and other non-white races) living and operating in deprived and poor urban communities (Salinas 2018).

A new and growing view, coined by Mohamed and Fritsvold (2010) as the "silent majority", argues that the traditional depiction of illicit actors in the drug trade business is by far different. Such actors are in fact part of and live in everyday mainstream society (Askew and Salinas 2019; Salinas 2018). For example, individuals who take part in upstream drug-related activities are said to come from a middle-class background, have a college-level education, and have minimal criminal records (Adler and Adler 1983; Desroches 2007; Mohamed and Fritsvold 2010; Salinas 2018). Furthermore, such individuals consider themselves entrepreneurs who are responsible with their money, use credit wisely, liquidate their debt, and keep legitimate businesses for security purposes (Adler and Adler 1983; Desroches 2007).

Given that a marketplace is composed of many buyers and sellers, it is only logical to assume that not all participants are 100% law-abiding individuals. Traditional intermediaries have relied on formal (e.g., Know Your Customer, Anti-Money Laundering) and informal (e.g., relationship banking) regulations and policies to avoid business relationships with individuals of dubious backgrounds. For example, Aldama-Navarrete (2021, 2) finds that Anti-Money Laundering (AML) regulations in Mexico successfully drove away "illicit cash flows from the [country's] financial system, at least on the margin." Simultaneously, Agca, Slutzky, and Zeume (2021, 27) have found that such regulations have "imposed disproportionate costs on small banks" which has caused many small banks to close their doors and allowed larger banks to move in. In the same token, many banks, especially smaller community banks, rely on interpersonal information or opinions made through a personal and/or professional relationship to make credit lending decisions (Balyuk, Berger, and Hackney 2020; Hein, Kock, and Macdonald 2005). Figures 1 through 3 illustrate these findings. Figures 1 and 2 illustrate that both community banks and small banks are closing their doors in counties which experience significant problems related to drug activity in the last decade. On the other hand, operations of large banks, as depicted in Figure 3, have been quite steady in these areas.

P2P lending platforms are not exempt from risks associated with money laundering related to drug trade. In fact, Kirby and Worner (2014, 26) state that such risk increases in P2P and crowdfunding platforms due to the "anonymity that the internet offers" and the loose regulatory environments these platforms must adhere to. Griffin, Kruger, and Mahajan (2021, 2) find that fintech borrowers are "more than 3.5 times as likely to have a felony record." For example, the authors find that only 1.36% of traditional borrowers compared to 4.55% to 4.92% of fintech borrowers have criminal records. Figure 4 illustrates the P2P demand facilitated by the founding P2P platform, Prosper Marketplace, for the years 2013 through 2019. This figure clearly shows that the demand for liquidity is driven by individuals living in counties who experience significant drug-related activities.

Figure 1. Number of community banks per 1,000,000 inhabitants by county designation.

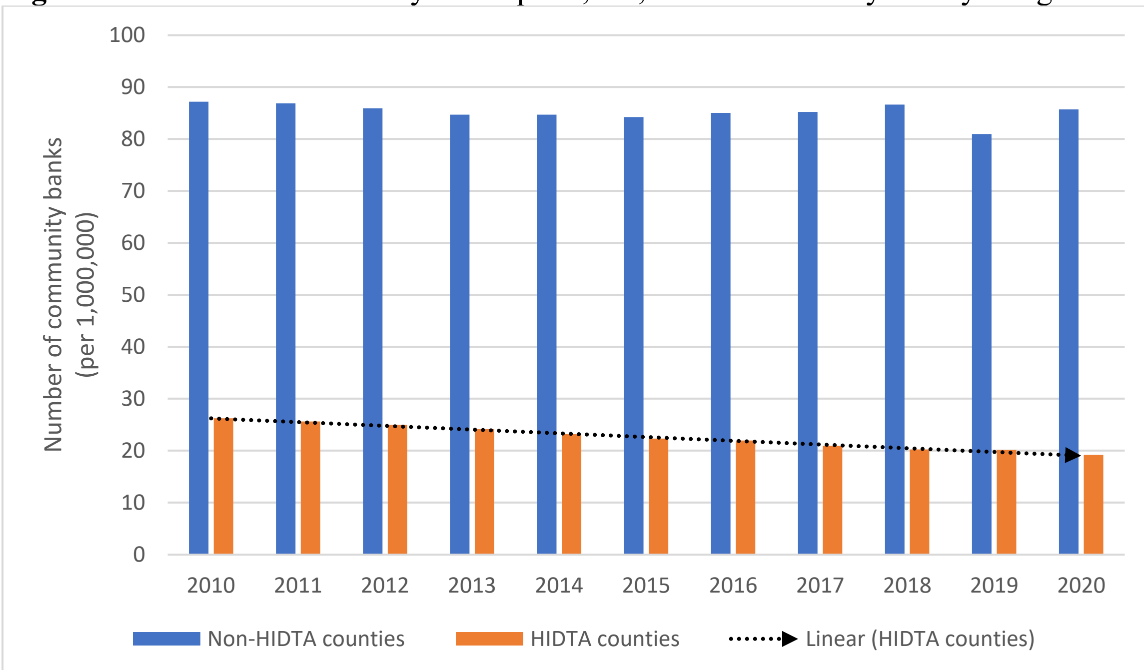


Figure 2. Number of small banks per 1,000,000 inhabitants by county designation.

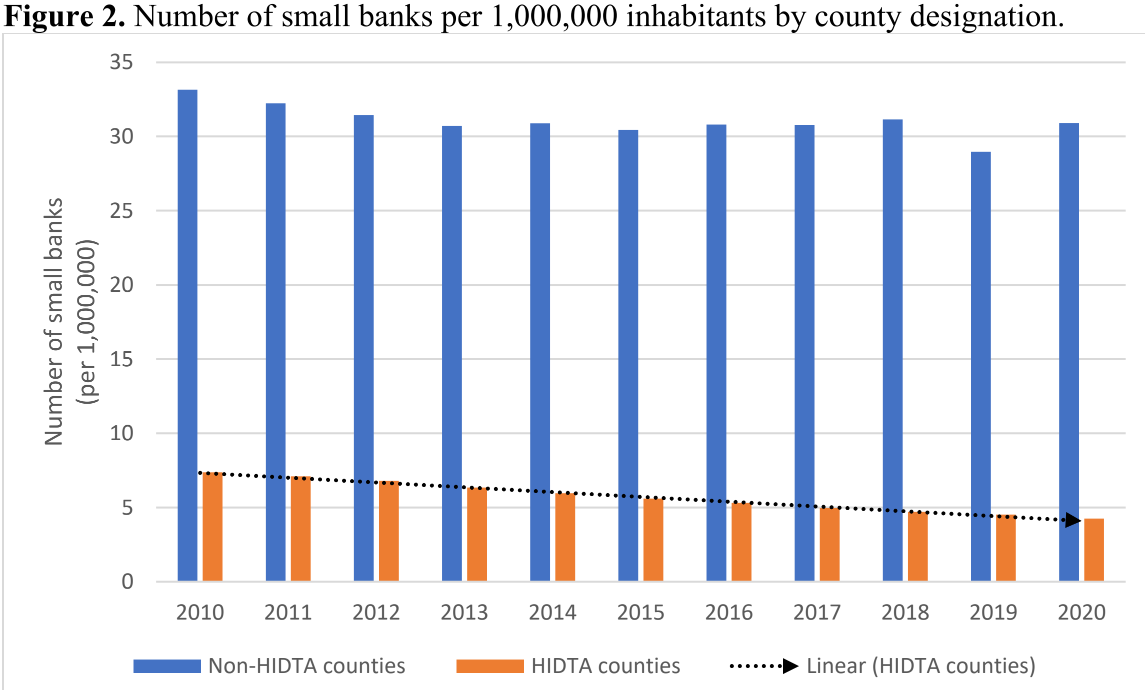


Figure 3. Number of large banks per 1,000,000 inhabitants by county designation.

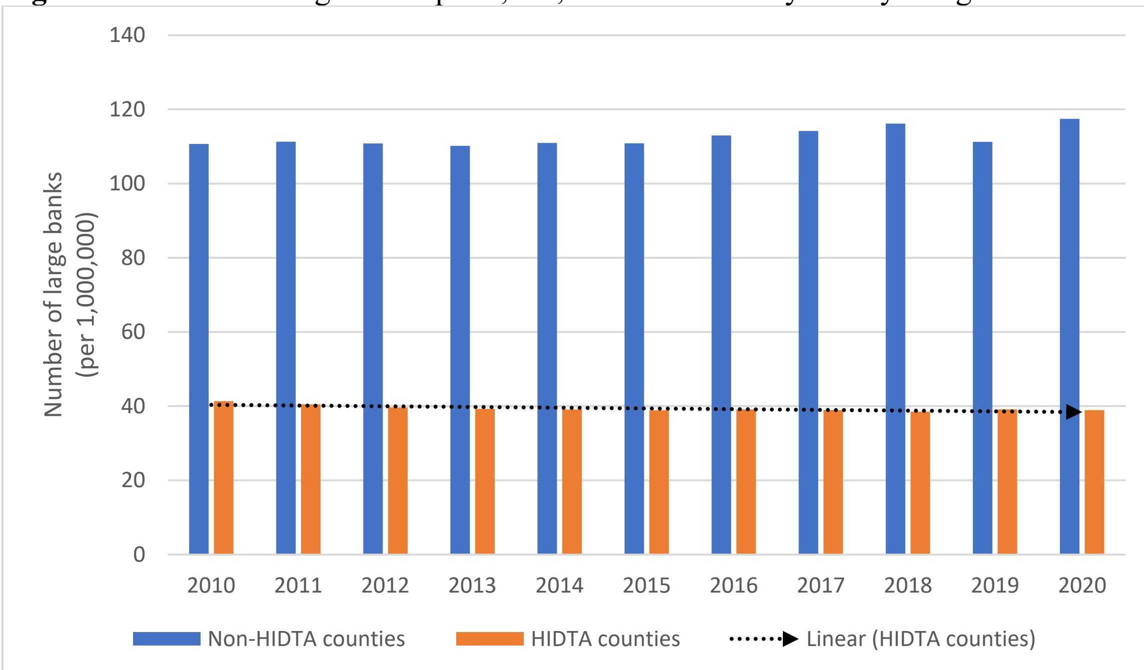
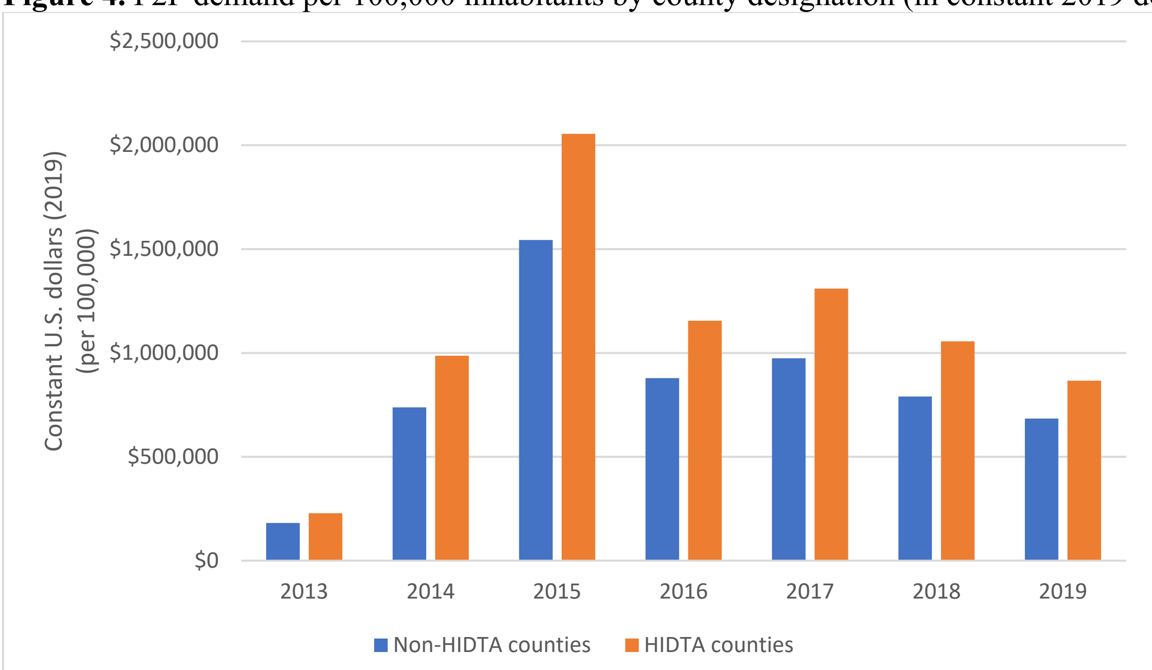


Figure 4. P2P demand per 100,000 inhabitants by county designation (in constant 2019 dollars).



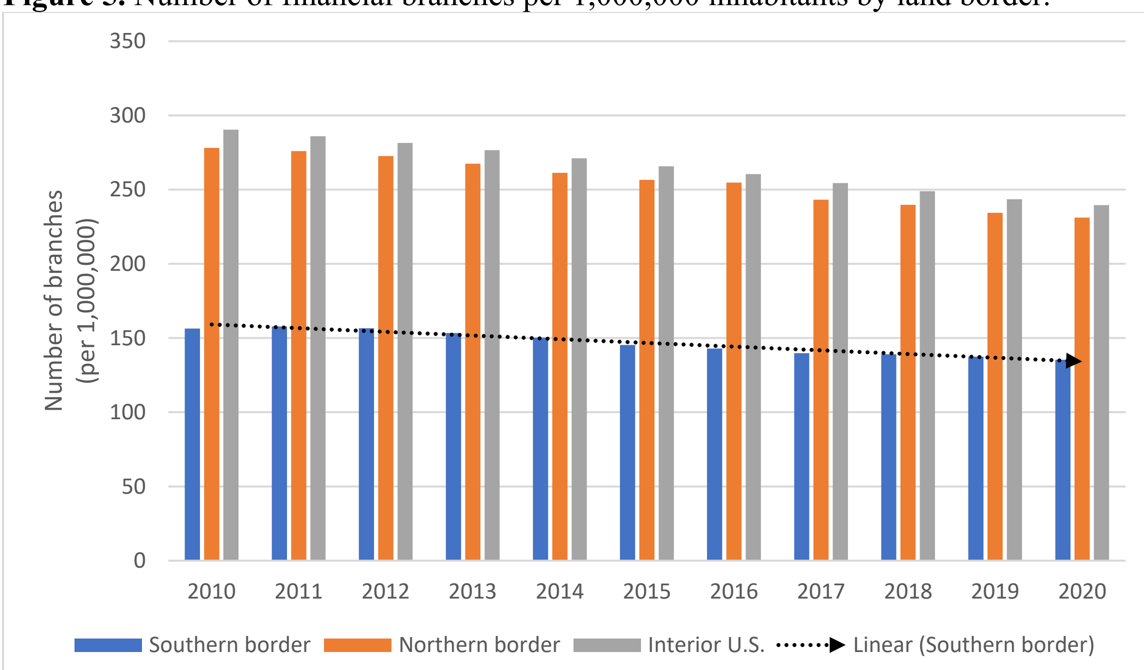
We summarize the above and hypothesize that:

H1: HIDTA counties are associated with higher P2P demand.

U.S. border economies

Border communities are special in that the region does not 100% resemble its home nation and, simultaneously, it does not resemble 100% its foreign neighbor; thereby, as Fullerton (2003) puts it, unilateral policy will not be effective. First, the demographics, especially along the southern border, are inherently different from those of the interior United States (Brannon, English, and Kriner 1987). For example, individuals living along the U.S.-Mexico border tend to be predominantly of Hispanic ethnicity with large language barriers. For example, Blanco et al. (2019) find that language is a predominant contributing factor why this ethnic group does not participate in the traditional financial sector. Second, the available resources presented to the regions such as financial services, health care, education, and high wage opportunities are quite heterogenous, not only within the country but within the two borders.[6] Figure 5 shows the difference in the number of branches serving counties situated along the two land borders and interior United States.

Figure 5. Number of financial branches per 1,000,000 inhabitants by land border.



Finally, and very importantly, more than half of all drugs coming into the United States are seized at the U.S. land borders (U.S. CBP 2021), while border counties are designated as high intensity drug trafficking areas and have experienced a moderate increase in drug arrests (Contreras 2019a) which have caused a reduction in financial activity by small traditional financial

[6] Contreras (2019b) argues that there is a positive association between initial resources given to children and the quality of opportunities presented to them later in life.

intermediaries along the U.S.-Mexico border (Agca, Slutzky, and Zeume 2021; Aldama-Navarrete 2021). Therefore, it is of no surprise that the traditional financial sector is distinct in these communities as well.

During the late 80s and early 90s, the U.S. border financial sector, especially in the southern border, was considered a growing sector (Brannon, English, and Kriner 1987), and this is no different today (Contreras, 2018). For example, Contreras and Vazquez (2016) state that deposits in national and small banks increased in the South Texas region while regional, local, and small banks also experienced an increase in the number of branches operating in the region. On the other hand, research has found that credit availability may be hindered in areas with low economic development (Wang, Zhao, and Shen 2021) and high drug trade activity (Agca, Slutzky, and Zeume 2021). For example, Brannon, English, and Kriner (1987, 17) found that although the southern border financial sector was growing in the late 80s and early 90s, many banks "channel[ed] a large proportion of their resources out of the border region for lack of profitable investment opportunities." From a contemporary perspective, Contreras and Vazquez (2016) find that credit opportunities have improved since the global financial crisis but make no mention of whether the improvement has been restored to pre-global financial crisis levels.

P2P intermediation is said to have given individuals the opportunity to overcome, or at least diminish, discriminatory practices by traditional financial intermediaries (Bartlett et al. 2022; Bertrand and Weill 2021). Thereby, we summarize the above and hypothesize that:

H2: Border counties experience equal or more P2P demand.
H3: a) Southern border counties will experience higher P2P demand while b) northern border counties will experience no difference in P2P demand.

III. Data and Sample Construction

We conduct a county-level analysis during the period of 2013 to 2019 using data from Prosper Marketplace, the first peer-to-peer platform founded in the United States in 2005 and one of the two largest U.S. lending platforms generating $12 billion in loans by the end of 2018 (Bollaert, Lopez-de-Silanes, and Schwienbacher 2021; Maskara, Kuvvet, and Chen 2021). We exclude all observations where the state is missing or the customer, themselves, withdraws their application. We argue that all listings' statuses, apart from withdrawals, are a good measure of actual P2P loan demand. These filters reduce the number of individual-level observations from 1,542,421 to 1,532,990.

We follow a two-stage aggregation approach to aggregate P2P loan demand from the individual to the county level. In the first stage we aggregate the individual-level P2P data at the year, state, and city-level.[7] We use a city-county-state listing from the U.S. Postal Service which provides primary city (frequently used city names)-county-state information and assign respective counties to the first stage aggregated P2P dataset using a *fuzzy match* approach. Such an approach, commonly used in the innovation literature (see Lerner et al. (2021)), uses optimal string alignment distance, also known as *restricted Demerau-Levenshtein distance*, to find the best city-state and city-county-state match between the two datasets.[8] This approach results in a total of 33,678 city-county-state observations. We keep all observations with a distance equal to 0 and 1 and hand-

[7] We aggregate as how the city appears in the dataset and disregard any typos, colloquial use, etc. at this stage.
[8] Refer to the Appendix for a description on *fuzzy match*.

select observations with a distance equal to 2.[9] In the second stage, we aggregate the data at the county level and address those cities which are part of multiple counties. We assign the city's P2P demand to its respective counties using a population-weighted approach.[10] This aggregation approach results in a total of 18,211 county-level observations during our sample period.

Drug-related data is sourced through multiple federal data sources. Data sourced from the Office of National Drug Control Policy (ONDCP), the National HIDTA Assistance Center, and several regional High Intensity Drug Trafficking Areas offices allows us to identify federally designated high intensity drug trafficking areas during our sample period.[11] We search the ONDCP and National HIDTA Assistance Center's websites to identify which counties and in which years such counties received the HIDTA designation or whether the designation was removed. We review the annual HIDTA national maps illustrating the change in designations (see Figure 6 for an example). To ensure that there are no misclassification errors, we make direct and FOIA requests to the thirty-three regional HIDTA offices. During our sample period, a total of 718 U.S. counties were classified as HIDTA, of which slightly over 19% of our sample had such designation.

We use the Center for Disease Control and Prevention (CDC) National Center for Health Statistics and the Federal Bureau of Investigation (FBI) National Incident-Based Reporting System (NIBRS) as additional sources to measure drug activity. The CDC National Center for Health Statistics provides county-level drug overdose deaths per 100,000 habitants during the sample period. Like the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) Program data, NIBRS provides information about crimes reported to the police. Unlike the UCR database, which only reports limited types of crime, NIBRS not only provides reports with a wider range of crimes but captures more offenses because it is not limited to reporting only the most serious crimes.[12] We extract agency level data by finding all local and state agencies that report to the FBI's NIBRS database. The agency's originating agency identifier (ORI) supplies two key pieces of information. First, the county in which the agency operates; and second, the agency's count of drug/narcotic offenses differentiated by the violation type (i.e., drug equipment violations, drug violations). We county-aggregate the violations by year, state, and county using a population-weighted approach given that an agency's jurisdiction may cover multiple counties and we cannot properly identify in which county the offense happened.

All yearly control data is sourced from the U.S. Census Bureau, U.S. Bureau of Economic Analysis, U.S. Bureau of Labor Statistics, and Federal Deposit Insurance Corporation (FDIC). Table 1 highlights our final sample descriptive statistics.

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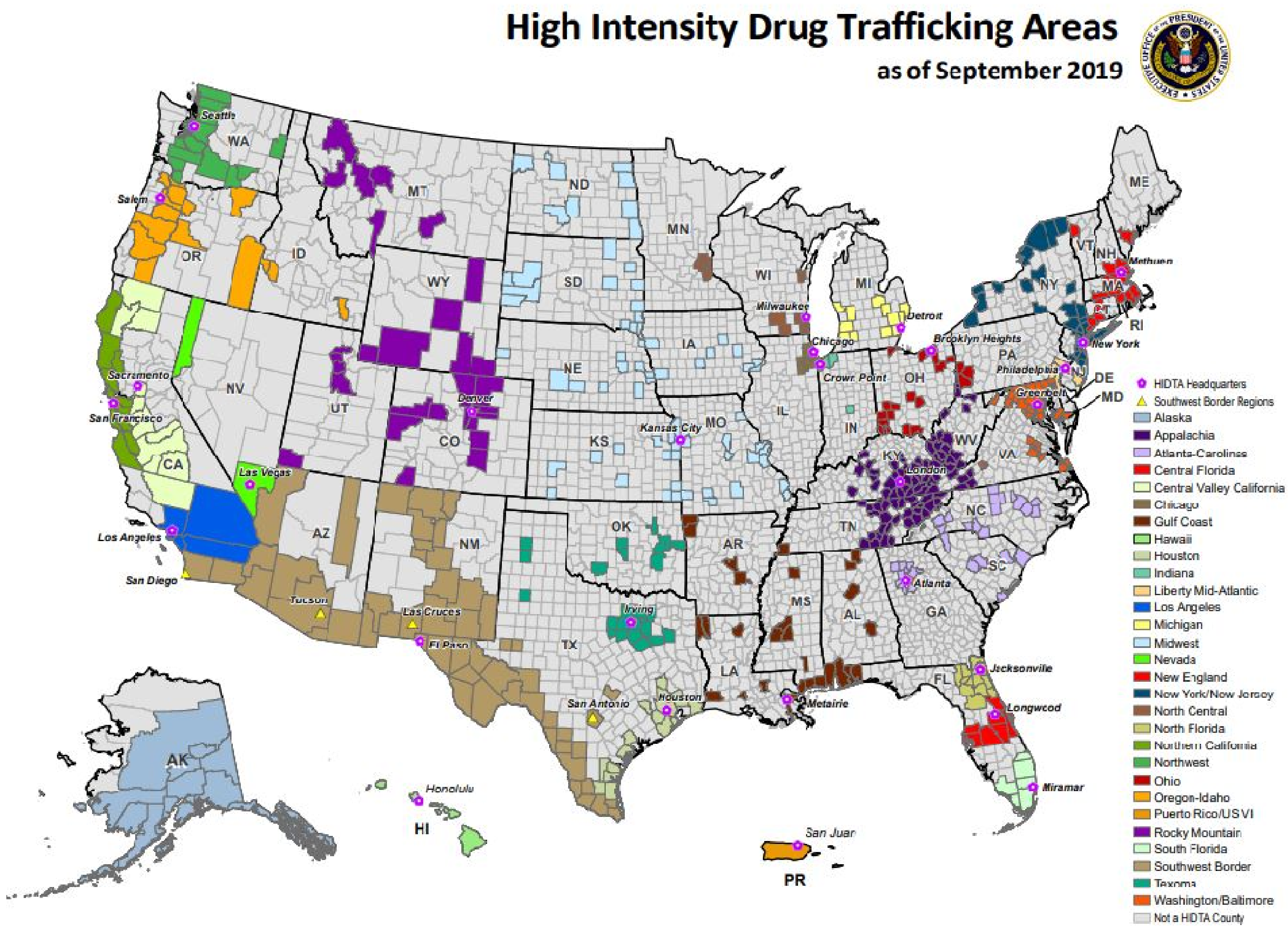
[9] We hand-checked all observations with a distance equal to two and omitted all observations with a distance greater than two.

[10] One example is Dallas, TX. Although the majority of the city is part of Dallas County, some parts of the city are also in Collin County, Kaufman County, Denton County, and Rockwall County whose population varies.

[11] HIDTA is a federally funded program established by the Office of National Drug Control Policy under the Anti-Drug Abuse Act of 1988. Agca, Slutzky, and Zeume (2021) state that HIDTA counties are more prone to money laundering.

[12] The *Hierarchy Rule* means "in incidents with multiple crimes, only the most serious is recorded" (Kaplan 2021).

Figure 6. High intensity drug trafficking area map.



Source: Office of National Drug Control Policy, High Intensity Drug Trafficking Areas Program (HIDTA), May 2021.

Table 1. Descriptive statistics.

	N	Min	P25	Median	Mean	P75	Max
P2P demand: Amount (scaled)	18211	0.0207	3.4121	6.2556	7.2213	9.6031	150.9434
P2P demand: Count (scaled)	18211	0.0000	0.0003	0.0005	0.0006	0.0007	0.0102
P2P demand: Average (scaled)	18211	0.0011	0.1518	0.3782	0.8356	0.8534	43.4243
Overdoses	18155	2.6759	10.0593	14.3623	16.5994	20.5014	113.9403
Violations (scaled)	8347	0.0000	0.0026	0.0053	0.0065	0.0092	0.0502
Non-HIDTA	14700						
HIDTA	3511						
Interior county	17439						
Border county	772						
Non-southern county	17953						
Southern county	258						
Non-northern county	17697						
Northern county	514						
Non-interior county	772						
Interior county	17439						
Poverty	18211	0.0260	0.1190	0.1560	0.1651	0.2000	0.5670
GDP per capita	18204	11651.0000	441226.2500	1113588.0000	6533317.2904	3229254.0000	752017612.0000
Unemployment	18211	0.0150	0.0420	0.0550	0.0597	0.0730	0.2770
Household income	18211	22045.0000	40064.0000	46496.0000	48483.0761	54180.0000	125933.0000
Establishments	18211	10.0000	324.0000	719.0000	3220.5708	1948.0000	495918.0000
Population	18211	427	13653.5000	30224.0000	116443.3182	78971.5000	10105708
Elderly	18211	0.0330	0.1400	0.1650	0.1684	0.1910	0.5560
Foreign	18211	0.0000	227.0000	790.0000	15435.7924	3379.0000	3485724.0000
Language	18211	0.0000	0.0030	0.0090	0.0194	0.0220	0.4120
Education	18211	0.2270	0.6100	0.7010	0.6992	0.7920	1.2930
Minority (Black/African American)	18205	0.0000	0.0068	0.0238	0.0926	0.1079	0.8587
Minority (American Indian/Alaskan Native)	18205	0.0000	0.0023	0.0036	0.0180	0.0074	0.8555
Minority (Asian)	18205	0.0000	0.0040	0.0064	0.0143	0.0129	0.4234
Minority (Native Hawaiian/Other Pacific Islander)	18205	0.0000	0.0002	0.0003	0.0009	0.0007	0.1206
Minority (Hispanic)	18205	0.0038	0.0212	0.0408	0.0933	0.0958	0.9613

Table 1. Descriptive statistics. (continued)							
	N	**Min**	**P25**	**Median**	**Mean**	**P75**	**Max**
Branches	18115	1	5.0000	11.0000	29.8056	23.0000	1669
Exchange (CAN/USA)	18211	1.0300	1.1043	1.2957	1.2421	1.3243	1.3269
Exchange (MEX/USA)	18211	12.7584	13.3022	18.6674	16.9485	19.2179	19.2469

IV. Methodology

Our overarching hypothesis is that fintech's shift from soft information to hard information to gauge a borrower's risk may allow illicit actors to more openly and frequently participate in the lending marketplace to finance their illicit enterprises. Equation 1 serves as our main empirical model where we use either an ordinary least squares (OLS) or quasi-maximum likelihood Poisson regression to assess our hypothesis.

$$(1) \qquad y_{i,s,t} = \alpha + \beta_1 HIDTA_{i,s,t} + Controls + Fixed\ Effects + \varepsilon_{i,t}$$

Variable $y_{i,s,t}$ represents our three dependent variables of interest which we use as a proxy for P2P loan demand. $y_{i,s,t}$ is an aggregation of $Amount_{i,s,t}$, the natural log of total P2P amount requested by county i of state s in year t; $Count_{i,s,t}$, the number of P2P requests of county i of state s in year t; and finally, $Average_{i,s,t}$, the natural log of total listing amount requested divided by the number of requests by county i of state s in year t. We use the dummy variable and main variable of interest, $HIDTA_{i,s,t}$, as a proxy for drug-related activities where we code as one if county i of state s is a federally designated high intensity drug trafficking area in year t and zero otherwise.[13] We control for several factors that might influence crime. For example, $Poverty_{i,s,y-1}$, defined as the percentage of households below the poverty level in county i of state s in year $y-1$; $GDP\ per\ capita_{i,s,y-1}$, defined as the natural log of "an estimate of value added for each industry as the sum of the incomes earned by labor and capital and the costs incurred in the production of goods and services" (BEA 2019) of county i of state s in year $y-1$; $Unemployment_{i,s,y-1}$, defined as "the unemployed percent of the civilian labor force" (BLS 2006) of county i of state s in year $y-1$; $Household\ income_{i,s,y-1}$, defined as the natural log of the median household income of county i of state s in year $y-1$; $Establishments_{i,s,t-1}$, defined as the natural log of the annual average establishment count of county i of state s in year $y-1$; $Population_{i,s,t-1}$, defined as the natural log of total estimated population size of county i of state s in year $y-1$; $Elderly_{i,s,t-1}$, defined as percentage of population age 65 or more; $Foreign_{i,s,t-1}$, defined as the natural log of the estimate of foreign born individuals in county i of state s in year $y-1$; and $Language_{i,s,t-1}$, defined as percentage of households where "no member 14 years old and over (1) speaks only English at home or (2) speaks a language other than English at home and speaks English 'Very well'" (U.S. Census Bureau 2022). We also control for high school education, $Education_{i,s,t-1}$, defined as the percentage of population aged 18 or higher with a high

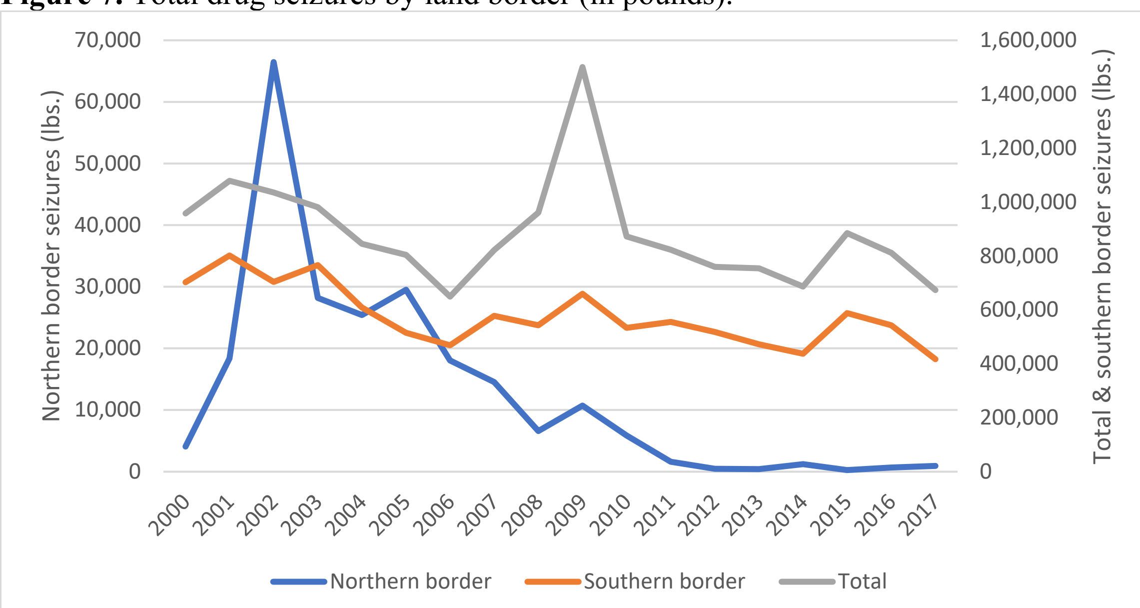
[13] The real value of drugs in the United States is substantially underestimated in any database given that a vast number of drugs go unreported or undetected. For this reason, we opt to use the federal designation of HIDTA as a proxy for drug-related crime.

school degree or equivalent of county i of state s in year $y-1$, and minority population, $Minority_{i,s,t-1}$, defined as the percentage of county i of state s non-white, non-Hispanic population in year $y-1$.[14] Finally, we control for the number of brick-and-mortar bank branches, $Branches_{i,s,t-1}$, defined as the natural log of the number of financial *branches* located in county i of state s in year $y-1$. We include both time and state fixed effects and cluster our standard errors at the county level.

U.S. land borders

It is important to compare the behavior of U.S. border counties and non-border counties in the context of P2P borrowing because a large majority of border counties, especially along the U.S.-Mexico border, are designated by the U.S. federal government as experiencing significant illegal drug production, manufacturing, importation, or distribution activities (refer to Figure 7). For example, most drugs enter the country through the U.S. land borders. In 2021, more than 56% of all drugs seized by U.S. Customs and Border Protection were at U.S. land borders (U.S. CBP 2021).

Figure 7. Total drug seizures by land border (in pounds).



To see if illicit actors in border communities are taking the opportunity to more openly and frequently participate in the consumer lending market by taking advantage of this shift in soft to hard information, we use Equation 2.2.

$$(2.2) \quad y_{i,s,t} = \alpha + \beta_1 HIDTA_{i,s,t} + \beta_2 Border_{i,s,t} + Controls + Fixed\ Effects + \varepsilon_{i,s,t}$$

The variable $Border_{i,s,t}$ is a dummy variable which denotes whether county i of state s is situated along one of the U.S. land borders. We code the variable as one if county i is situated in

[14] We disaggregate minority population based on race and Hispanic ethnicity.

one of the seventeen states that make up the U.S. border and is located either within 62.5 miles or less from the international southern boundary or is next to the international northern boundary and zero otherwise.[15] Fullerton (2003) states that border counties' business transactions are affected by the exchange rate due to their proximity to either of the two international borders. For this reason, we also control for exchange rate, $Exchange_t$, defined as either the Mexican peso/U.S. dollar or Canadian dollar/U.S. dollar exchange rate of year t. The definitions of all dependent and other control variables remain the same as previously discussed. We use either an ordinary least squares (OLS) or quasi-maximum likelihood Poisson regression to evaluate this hypothesis and include state fixed effects and cluster our standard errors at the county level.

$$(3) \qquad y_{i,s,t} = \alpha + \beta_1 HIDTA_{i,s,t} + \beta_2 South_{i,s,t} + \beta_5 North_{i,s,t} + Controls + Fixed\ Effects + \varepsilon_{i,s,t}$$

Due to the two U.S. land borders being distinct from a social, demographic, and economic perspective as well as the economic development of neighboring countries possibly influencing the behavior of U.S. counties, it is imperative the two borders are analyzed separately. Equation 3 is an extension of our previous model and serves to compare the P2P loan demand of border counties by their respective border. In this model, we disaggregate the border dummy variable, $Border_{i,s,t}$, into $South_{i,s,t}$ and $North_{i,s,t}$ where the former equals to one if county i of state s is situated within 62.5 miles or less from the international southern boundary and zero otherwise. The latter equals to one if county i of state s is situated immediately next to the international northern boundary and zero otherwise. The dependent and control variables remain the same, and we once again include state fixed effects and cluster our standard errors at the county level.

V. Results

Table 2 tests the difference in P2P demand between HIDTA-designated counties and those counties without such designation. The results indicate that P2P demand, in all aspects, is significantly different among both groups which supports the notion that there is a distinct difference in P2P demand.

Table 2. Test of means.

	HIDTA designated county	**Non-HIDTA designated county**	**Difference**	**t-Statistic**
Amount of P2P demand (ln)	13.8238	11.7217	2.1021	61.082***
Count of P2P demand	299.6354	28.9594	270.6760	23.7490***
Average P2P demand (ln)	9.4556	9.3793	0.0763	17.382***

[15] The La Paz Agreement of 1986 sets the southern border classification.

Is the increase in fintech use a result of the transition from soft to hard information allowing illicit actors to more openly and frequently participate in the credit market?

Identifying illicit actors is difficult to nearly impossible given that no individual in this line of business will openly and willingly disclose their illicit occupation. For this reason, we assume that most of these illicit actors reside in counties that are federally designated as a high intensity drug trafficking area. Table 3 shows that counties with significant illegal drug production, manufacturing, importation, or distribution, or HIDTA designated counties, tend to request 8.60% more P2P loans, in amount, while making 4.17% more number of P2P requests when compared to counties without such designation after controlling for a county's social and economic factors.

One of the biggest distinctions between community and small banks compared with large banks is that the former tends to rely heavily on relationships, or soft information, to make their credit decisions (Berger, Goulding, and Rice 2014). We argue that illicit actors living in counties with a large community banks presence and high drug-related problems are less prone to participate in the traditional financial market given the bank's overreliance on soft information. As a result, such actors will transition to a more market-based lending setting. To see if this transition from soft to hard is allowing such actors to more actively and frequently participate in the lending market, we split our sample based on whether the number of community banks in problem areas is below or above the yearly median.[16] Table 4 indicates that HIDTA counties with a high presence of community banks will experience a higher amount of demand based on the amount requested (6.10%) and number of requests (4.91%) when compared with counties who do not experience such problems. Simultaneously, high drug-activity counties with a low number of community banks tend to have a higher P2P demand in both amount (10.66%) and count (4.63%) compared with counties who do not experience such problems.

It is important to not only consider the number of community banks in the area but consider the percentage of community banks as a percentage of total banks operating in the counties. For this reason, we split our sample based on whether the percentage of community banks operating in problem areas is below or above the yearly median. The results of Table 5 indicate that high drug trafficking counties with higher percentage of community banks request a higher amount of P2P loans (16.93%) and higher number of P2P loans (3.74%) compared with counties not designated as high intensity drug trafficking areas. On the other hand, high intensity drug trafficking counties with a lower percentage of community banks operating in the area tend to request only 4.58% and 3.63% more, respectively, compared to non-HIDTA counties. Based on these results, we infer that there is a strong possibility of individuals taking advantage of this shift in type of information to make credit decisions because the only requirement is to look good on paper.

To ensure that our results are robust, we use two alternative measures of drug-related activities. First, we use a county's rate of drug overdose deaths, $Overdoses_{i,s,t}$, measured as the death rate of drug overdoses per 100,000 population. Like Martinez, Rosenfeld, and Mares (2008), we argue that drug consumption happens in the same area or in a very close vicinity to where the illegal substance is either produced or distributed. Figure 8 supports this argument. For example, the average rate of overdoses per 100,000 inhabitants is higher in counties with significant problems related to the production, manufacturing, importation, or distribution of illegal drugs (i.e., HIDTA county).

[16] Results are robust when we use the mean.

Table 3. P2P demand by HIDTA designation.

	P2P demand: Amount	P2P demand: Count	P2P demand: Average
HIDTA	0.0825***	0.0409**	0.0058
	(0.0185)	(0.0168)	(0.0058)
Poverty	-1.9582***	-2.8971***	0.2225*
	(0.2959)	(0.3980)	(0.1200)
GDP per capita	-0.0273	-0.1624***	0.0067
	(0.0242)	(0.0419)	(0.0078)
Unemployment	0.8183*	1.6062**	0.1881
	(0.4488)	(0.6822)	(0.1887)
Household income	0.5408***	0.2862***	0.2688***
	(0.0851)	(0.0940)	(0.0278)
Establishments	0.1692***	0.0424	0.0141
	(0.0444)	(0.0591)	(0.0143)
Population	0.8810***	1.0780***	0.0206*
	(0.0366)	(0.0533)	(0.0119)
Elderly	0.1786	-0.2027	0.0051
	(0.2844)	(0.3723)	(0.0913)
Foreign	0.0277**	0.0874***	0.0011
	(0.0123)	(0.0183)	(0.0051)
Language	-1.1243**	1.1805**	-0.2155
	(0.4936)	(0.5585)	(0.1787)
Education	0.0302	0.2519***	-0.0037
	(0.0723)	(0.0947)	(0.0264)
Minority (Black/African American)	0.4273***	0.4837***	0.0069
	(0.0747)	(0.0944)	(0.0295)
Minority (American Indian/Alaska Native)	0.0845	0.1370	0.0420
	(0.1548)	(0.1832)	(0.0689)
Minority (Asian)	-0.3613	-1.1505***	-0.1749*
	(0.4094)	(0.2600)	(0.0911)
Minority (Native Hawaiian/Other Pacific Islander)	7.3753**	11.7810**	0.1269
	(3.7048)	(5.4333)	(1.0195)
Minority (Hispanic)	0.2828**	-0.2199	-0.0178
	(0.1319)	(0.1680)	(0.0495)
Branches	0.0228	0.0153	-0.0228**
	(0.0237)	(0.0375)	(0.0093)
Fixed effects	Year State	Year State	Year State
Clustered S.E.	County	County	County
N	18066	18066	18066
R2	0.8925		0.1568

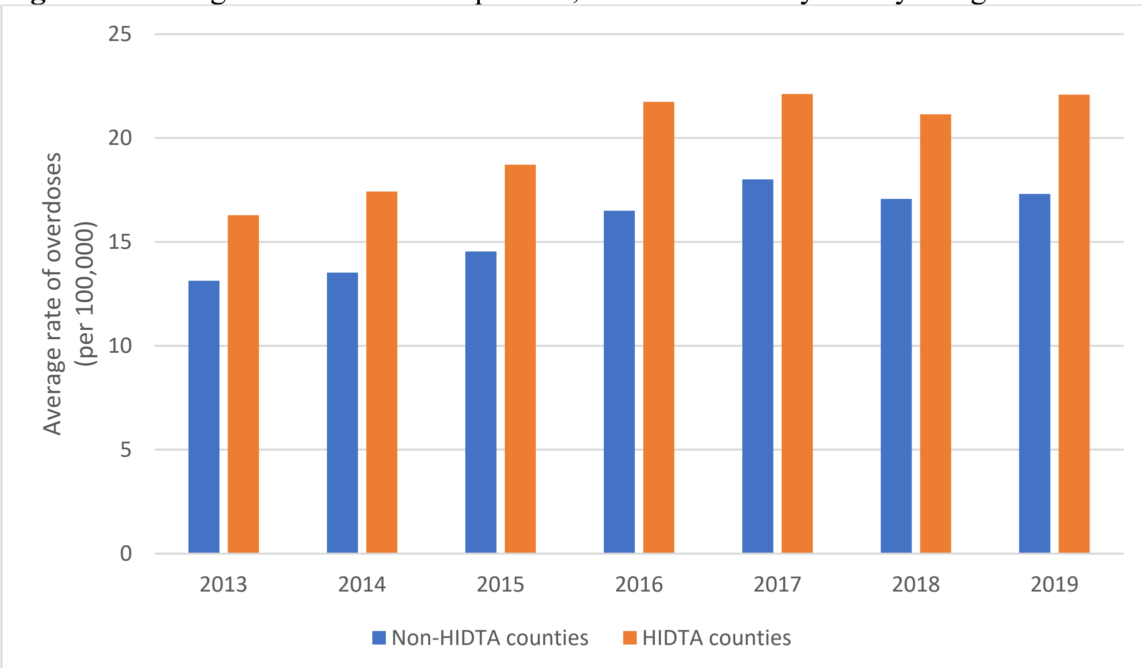
Table 4. HIDTA-designated P2P demand by number of community banks.

	P2P demand: Amount (Low CB)	P2P demand: Amount (High CB)	P2P demand: Count (Low CB)	P2P demand: Count (High CB)	P2P demand: Average (Low CB)	P2P demand: Average (High CB)
HIDTA	0.1013***	0.0592***	0.0453*	0.0479**	0.0122	0.0012
	(0.0299)	(0.0200)	(0.0264)	(0.0192)	(0.0099)	(0.0061)
Poverty	-1.5564***	-2.5497***	-2.5493***	-2.8728***	0.3012*	0.1712
	(0.3631)	(0.4692)	(0.4099)	(0.5206)	(0.1580)	(0.1479)
GDP per capita	0.0076	-0.1419***	-0.0785**	-0.1636***	0.0048	0.0089
	(0.0282)	(0.0367)	(0.0306)	(0.0591)	(0.0099)	(0.0115)
Unemployment	0.2529	2.0095***	0.7353	3.1788***	0.0328	0.8011***
	(0.5413)	(0.7753)	(0.7086)	(1.1619)	(0.2368)	(0.2826)
Household income	0.5227***	0.5119***	0.2266*	0.3631***	0.2897***	0.2645***
	(0.1097)	(0.1300)	(0.1219)	(0.1176)	(0.0397)	(0.0313)
Establishments	0.1824***	0.1366**	0.0880	0.0196	0.0213	0.0135
	(0.0541)	(0.0645)	(0.0587)	(0.0810)	(0.0185)	(0.0203)
Population	0.8240***	1.0693***	0.9186***	1.1751***	0.0253	0.0136
	(0.0475)	(0.0481)	(0.0548)	(0.0778)	(0.0159)	(0.0160)
Elderly	0.3662	-0.3642	-0.0238	-0.0362	0.0779	-0.0518
	(0.3574)	(0.3856)	(0.5102)	(0.4883)	(0.1197)	(0.1246)
Foreign	0.0151	0.0346	0.0606***	0.0837***	-0.0011	-0.0021
	(0.0152)	(0.0217)	(0.0177)	(0.0272)	(0.0068)	(0.0068)
Language	-0.8033	-1.4171	0.4371	1.4235**	-0.1891	-0.2919*
	(0.5745)	(0.9286)	(0.7019)	(0.5712)	(0.2360)	(0.1699)
Education	0.0198	0.1598	0.3339***	0.1782	-0.0237	0.0418
	(0.0919)	(0.1045)	(0.0920)	(0.1402)	(0.0349)	(0.0387)
Minority (Black/African American)	0.3111***	0.4568***	0.5213***	0.3518***	-0.0139	0.0448
	(0.0971)	(0.1117)	(0.0930)	(0.1251)	(0.0401)	(0.0318)
Minority (American Indian/Alaska Native)	-0.0155	0.4934	-0.0606	0.7265	0.0753	0.0001
	(0.1757)	(0.4172)	(0.1962)	(0.4550)	(0.0777)	(0.1838)
Minority (Asian)	0.8006	-0.4384	-0.0744	-1.2150***	0.0624	0.0391
	(0.6299)	(0.4374)	(0.5422)	(0.2856)	(0.1915)	(0.0837)
Minority (Native Hawaiian/Other Pacific Islander)	15.8398***	0.7109	7.6007**	16.0523**	0.1493	0.4274
	(6.0774)	(4.2953)	(2.9556)	(7.7424)	(1.8804)	(0.9857)
Minority (Hispanic)	0.1429	0.3481*	-0.1406	-0.2739	-0.0387	0.0548
	(0.1640)	(0.2097)	(0.2093)	(0.1975)	(0.0678)	(0.0490)
Branches	0.0233	0.0161	0.0669**	-0.0576	-0.0273**	-0.0163
	(0.0288)	(0.0461)	(0.0292)	(0.0622)	(0.0119)	(0.0151)
Fixed effects	Year State	Year State	Year State	Year State	Year State	Year State
Clustered S.E.	County	County	County	County	County	County
N	10795	7271	10795	7271	10795	7271
R2	0.8094	0.9343			0.1263	0.2611

Table 5. HIDTA-designated P2P demand by community bank market share.

	P2P demand: Amount (Low CB)	**P2P demand: Amount (High CB)**	**P2P demand: Count (Low CB)**	**P2P demand: Count (High CB)**	**P2P demand: Average (Low CB)**	**P2P demand: Average (High CB)**
HIDTA	0.0448**	0.1564***	0.0357*	0.0367*	-0.0001	0.0203*
	(0.0214)	(0.0312)	(0.0194)	(0.0223)	(0.0058)	(0.0115)
Poverty	-2.1291***	-1.8920***	-2.8474***	-1.8340***	0.4356***	-0.0168
	(0.3752)	(0.4381)	(0.4618)	(0.5389)	(0.1595)	(0.1915)
GDP per capita	-0.0385	-0.0270	-0.1360***	-0.2326***	-0.0036	0.0152
	(0.0367)	(0.0311)	(0.0508)	(0.0381)	(0.0101)	(0.0117)
Unemployment	0.9840*	0.8755	1.7181**	0.8672	0.0645	0.2626
	(0.5851)	(0.6989)	(0.7977)	(0.6325)	(0.2257)	(0.3264)
Household income	0.4961***	0.5734***	0.2923***	0.5274***	0.3162***	0.2236***
	(0.1080)	(0.1273)	(0.1065)	(0.1420)	(0.0342)	(0.0485)
Establishments	0.0342	0.2598***	-0.0317	0.3614***	0.0166	0.0108
	(0.0587)	(0.0615)	(0.0698)	(0.0525)	(0.0182)	(0.0215)
Population	0.9925***	0.7872***	1.1110***	0.8936***	0.0149	0.0260
	(0.0496)	(0.0511)	(0.0668)	(0.0492)	(0.0142)	(0.0186)
Elderly	0.0067	0.0054	-0.2284	-0.0509	-0.0367	0.0293
	(0.3538)	(0.4661)	(0.4222)	(0.4501)	(0.0966)	(0.1810)
Foreign	0.0432**	0.0153	0.0965***	0.0699***	0.0055	-0.0041
	(0.0181)	(0.0167)	(0.0232)	(0.0254)	(0.0067)	(0.0077)
Language	-0.0904	-2.3592***	1.3811**	-0.7036	-0.0586	-0.3490
	(0.5212)	(0.7415)	(0.6119)	(1.1376)	(0.1628)	(0.3494)
Education	0.0602	0.0392	0.2747**	0.2784**	-0.0229	0.0280
	(0.0942)	(0.1018)	(0.1159)	(0.1140)	(0.0315)	(0.0408)
Minority (Black/African American)	0.3594***	0.5000***	0.4427***	0.3276**	-0.0156	0.0531
	(0.0910)	(0.1188)	(0.1068)	(0.1619)	(0.0318)	(0.0552)
Minority (American Indian/Alaska Native)	-0.0670	0.1003	0.0501	0.5576**	-0.0311	0.1314
	(0.1971)	(0.2002)	(0.2219)	(0.2528)	(0.0773)	(0.1279)
Minority (Asian)	-1.0225**	1.8526	-1.2152***	-2.2118**	-0.1968**	-0.0667
	(0.4185)	(1.3144)	(0.2771)	(1.0299)	(0.0929)	(0.2896)
Minority (Native Hawaiian/Other Pacific Islander)	11.0481**	3.8646	12.9380**	2.2028	-0.4990	1.7785
	(5.5638)	(4.4698)	(5.9665)	(2.8356)	(1.2197)	(1.7405)
Minority (Hispanic)	0.0301	0.3858*	-0.3403*	0.4567*	-0.0282	-0.0030
	(0.1553)	(0.1994)	(0.1796)	(0.2551)	(0.0533)	(0.0884)
Branches	0.0675*	-0.0083	0.0247	-0.0170	-0.0206*	-0.0212
	(0.0349)	(0.0316)	(0.0493)	(0.0530)	(0.0120)	(0.0139)
Fixed effects	Year State	Year State	Year State	Year State	Year State	Year State
Clustered S.E.	County	County	County	County	County	County
N	9364	8702	9364	8702	9364	8702
R2	0.9186	0.8199			0.2109	0.1269

Figure 8. Average rate of overdoses per 100,000 inhabitants by county designation.



The second is drug-related violations, $Violations_{i,s,t}$, measured as the sum of drug equipment violations, defined as the count of violations related to "the unlawful manufacture, sale, purchase, possession, or transportation of equipment or devices utilized in preparing and/or using drugs or narcotics" (U.S. DOJ-FBI 2018) of county i of state s in year t, and drug violations, defined as the count of violations related to "the unlawful cultivation, manufacture, distribution, sale, purchase, possession, transportation, or importation of any controlled substance" (U.S. DOJ-FBI 2018) of county i of state s in year t.

Tables 6 and 7 show that our previous results are robust. An increase in overdoses is related to higher P2P demand. Furthermore, this increase in demand is in counties where community banks have a higher market presence. We must note that the overdose death rate is only used as an alternative measure of illicit drug activities because although Martinez, Rosenfeld, and Mares (2008) argue drug consumption happens in the same area or in a very close vicinity to where the illegal substance is either produced or distributed, it is difficult to disentangle supply and demand. In other words, we cannot separate a supplier's P2P loan demand, as a means to obtain liquidity for entrepreneurial purposes, or a drug user's P2P loan demand to finance their drug habits. We assume that individuals who supplied the product to the deceased live in the same county as where the overdose death happened.

The second alternative measure of drug-related activities is the sum of drug-related violations disclosed to the FBI via the NIBRS database. Table 8 shows that P2P demand, both in amount and count, increases in counties who experience higher than the yearly median drug-related violations. When we split our sample based on community bank's market share, as seen in Table 9, the results indicate that demand is more pronounced than in counties where the market share is below the yearly median.

Table 6. Relationship between drug overdose deaths and P2P demand.

	P2P demand: Amount	**P2P demand: Count**	**P2P demand: Average**
Overdoses	0.1473***	0.0116	0.0304***
	(0.0186)	(0.0229)	(0.0070)
Poverty	-1.9536***	-2.8728***	0.2145*
	(0.2924)	(0.3988)	(0.1197)
GDP per capita	-0.0349	-0.1704***	0.0047
	(0.0243)	(0.0425)	(0.0078)
Unemployment	0.6003	1.7606**	0.1151
	(0.4446)	(0.6924)	(0.1884)
Household income	0.6023***	0.2984***	0.2799***
	(0.0841)	(0.0919)	(0.0277)
Establishments	0.1701***	0.0574	0.0133
	(0.0442)	(0.0600)	(0.0143)
Population	0.8743***	1.0743***	0.0184
	(0.0364)	(0.0529)	(0.0120)
Elderly	0.0445	-0.2640	-0.0225
	(0.2822)	(0.3785)	(0.0927)
Foreign	0.0219*	0.0872***	0.0002
	(0.0122)	(0.0185)	(0.0051)
Language	-0.5840	1.2496**	-0.1082
	(0.4992)	(0.5766)	(0.1813)
Education	-0.0209	0.2185**	-0.0119
	(0.0714)	(0.0933)	(0.0265)
Minority (Black/African American)	0.6192***	0.5102***	0.0478
	(0.0774)	(0.0970)	(0.0306)
Minority (American Indian/Alaska Native)	0.0915	0.1157	0.0455
	(0.1552)	(0.1840)	(0.0678)
Minority (Asian)	-0.1270	-1.1451***	-0.1403
	(0.4253)	(0.2689)	(0.0897)
Minority (Native Hawaiian/Other Pacific Islander)	9.4920**	12.5670**	0.5915
	(3.7785)	(5.5026)	(1.0273)
Minority (Hispanic)	0.3396**	-0.2300	-0.0102
	(0.1348)	(0.1629)	(0.0499)
Branches	0.0367	0.0169	-0.0196**
	(0.0236)	(0.0371)	(0.0094)
Fixed effects	Year State	Year State	Year State
Clustered S.E.	County	County	County
N	18021	18021	18021
R2	0.8928		0.1574

Table 7. High drug overdose deaths and P2P demand by community bank market share.

	P2P demand: Amount (Low CB)	**P2P demand: Amount (High CB)**	**P2P demand: Count (Low CB)**	**P2P demand: Count (High CB)**	**P2P demand: Average (Low CB)**	**P2P demand: Average (High CB)**
Overdoses	0.1043***	0.1901***	-0.0072	0.0349	0.0215***	0.0417***
	(0.0220)	(0.0300)	(0.0257)	(0.0377)	(0.0073)	(0.0127)
Poverty	-2.0884***	-1.9083***	-2.7919***	-1.8683***	0.4419***	-0.0350
	(0.3690)	(0.4414)	(0.4651)	(0.5539)	(0.1583)	(0.1922)
GDP per capita	-0.0403	-0.0344	-0.1415***	-0.2363***	-0.0047	0.0131
	(0.0372)	(0.0309)	(0.0516)	(0.0381)	(0.0102)	(0.0117)
Unemployment	0.8651	0.4950	1.8845**	0.9412	0.0028	0.1509
	(0.5766)	(0.7034)	(0.8035)	(0.6413)	(0.2252)	(0.3287)
Household income	0.5577***	0.6187***	0.2978***	0.5475***	0.3279***	0.2318***
	(0.1065)	(0.1276)	(0.1032)	(0.1357)	(0.0339)	(0.0485)
Establishments	0.0364	0.2633***	-0.0122	0.3601***	0.0167	0.0106
	(0.0587)	(0.0617)	(0.0712)	(0.0533)	(0.0183)	(0.0214)
Population	0.9934***	0.7716***	1.1032***	0.8897***	0.0138	0.0214
	(0.0492)	(0.0515)	(0.0665)	(0.0509)	(0.0146)	(0.0188)
Elderly	-0.0903	-0.0353	-0.2718	-0.1142	-0.0542	0.0126
	(0.3501)	(0.4725)	(0.4300)	(0.4489)	(0.0981)	(0.1822)
Foreign	0.0360**	0.0137	0.0993***	0.0685***	0.0044	-0.0041
	(0.0181)	(0.0165)	(0.0237)	(0.0248)	(0.0068)	(0.0077)
Language	0.3296	-1.8617**	1.4164**	-0.5723	0.0416	-0.2539
	(0.5330)	(0.7348)	(0.6258)	(1.1655)	(0.1653)	(0.3491)
Education	0.0149	-0.0219	0.2436**	0.2773**	-0.0295	0.0168
	(0.0939)	(0.1005)	(0.1146)	(0.1143)	(0.0320)	(0.0406)
Minority (Black/African American)	0.4953***	0.7296***	0.4505***	0.3637**	0.0124	0.1070*
	(0.0928)	(0.1279)	(0.1103)	(0.1666)	(0.0325)	(0.0582)
Minority (American Indian/Alaska Native)	0.0018	-0.0398	0.0096	0.5047**	-0.0196	0.1103
	(0.1969)	(0.1940)	(0.2237)	(0.2531)	(0.0758)	(0.1264)
Minority (Asian)	-0.8548**	2.1595	-1.2519***	-2.1276*	-0.1747*	-0.0197
	(0.4353)	(1.3724)	(0.2863)	(1.0924)	(0.0935)	(0.2933)
Minority (Native Hawaiian/Other Pacific Islander)	13.1190**	6.8795	13.6911**	3.1223	0.0612	2.3999
	(5.5503)	(4.8058)	(6.0634)	(2.8655)	(1.2699)	(1.7582)
Minority (Hispanic)	0.0648	0.5074**	-0.3860**	0.4965*	-0.0274	0.0179
	(0.1605)	(0.2036)	(0.1730)	(0.2562)	(0.0546)	(0.0888)
Branches	0.0667*	0.0116	0.0197	-0.0035	-0.0205*	-0.0165
	(0.0348)	(0.0315)	(0.0491)	(0.0475)	(0.0122)	(0.0139)
Fixed effects	Year State	Year State	Year State	Year State	Year State	Year State
Clustered S.E.	County	County	County	County	County	County
N	9319	8702	9319	8702	9319	8702
R2	0.9187	0.8206			0.2114	0.1280

Table 8. Relationship between drug-related violations and P2P demand.

	P2P demand: Amount	**P2P demand: Count**	**P2P demand: Average**
High Violations	0.0611***	0.0542**	0.0103
	(0.0203)	(0.0221)	(0.0076)
Poverty	-1.3176***	-3.1667***	0.0066
	(0.4208)	(0.5305)	(0.1976)
GDP per capita	-0.0424	-0.2762***	-0.0088
	(0.0336)	(0.0496)	(0.0124)
Unemployment	0.6398	2.3350**	0.6314**
	(0.6728)	(1.1534)	(0.2970)
Household income	0.5870***	0.1937	0.2405***
	(0.1256)	(0.1273)	(0.0469)
Establishments	0.1444***	0.0587	0.0106
	(0.0531)	(0.0779)	(0.0205)
Population	0.9582***	1.1005***	0.0338*
	(0.0422)	(0.0522)	(0.0179)
Elderly	0.5002	-0.0386	-0.0192
	(0.3749)	(0.4139)	(0.1564)
Foreign	0.0166	0.1239***	-0.0013
	(0.0193)	(0.0204)	(0.0082)
Language	-1.1061	-0.6276	0.2254
	(0.9586)	(1.0628)	(0.3138)
Education	0.0675	0.3682***	-0.0399
	(0.0986)	(0.1167)	(0.0386)
Minority (Black/African American)	0.3929***	0.6703***	0.0454
	(0.1190)	(0.1292)	(0.0476)
Minority (American Indian/Alaska Native)	-0.1929	0.4798*	0.0945
	(0.1978)	(0.2532)	(0.1144)
Minority (Asian)	0.1707	0.0002	-0.3492*
	(0.8024)	(0.4909)	(0.2037)
Minority (Native Hawaiian/Other Pacific Islander)	-2.6883	0.7122	-1.5663
	(4.4004)	(2.9272)	(1.3794)
Minority (Hispanic)	0.2336	-0.1577	-0.0939
	(0.2569)	(0.2524)	(0.1050)
Branches	0.0172	0.0741*	-0.0118
	(0.0342)	(0.0422)	(0.0138)
Fixed effects	Year State	Year State	Year State
Clustered S.E.	County	County	County
N	8320	8320	8320
R2	0.8949		0.1523

Table 9. High drug-related violations and P2P demand by community bank market share.

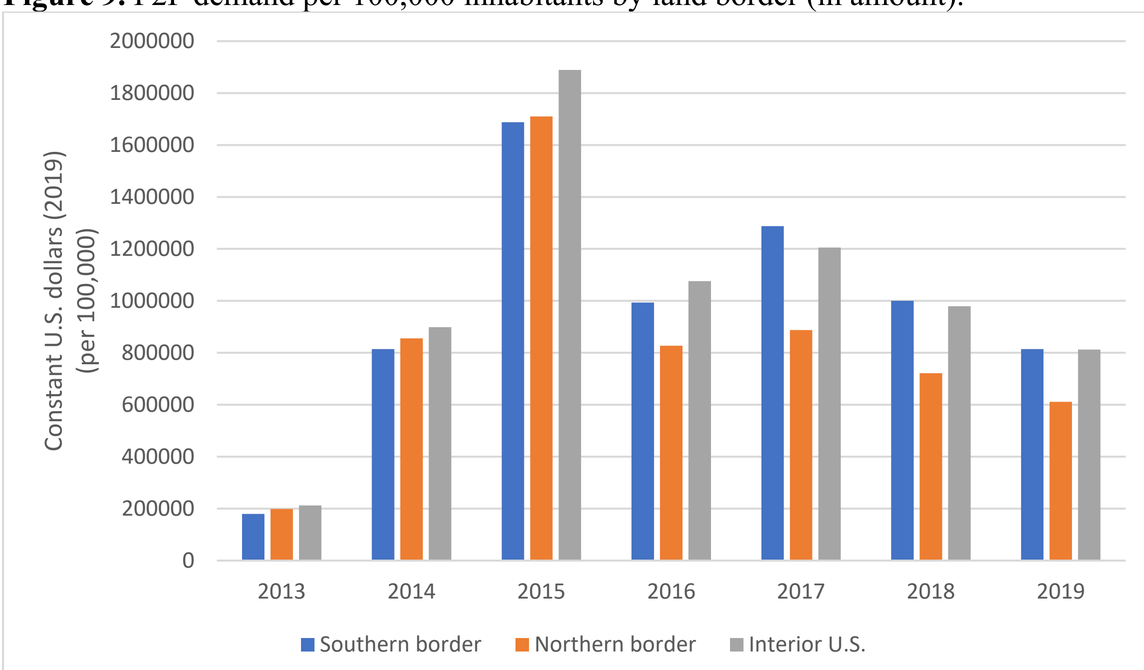
	P2P demand: Amount (Low CB)	**P2P demand: Amount (High CB)**	**P2P demand: Count (Low CB)**	**P2P demand: Count (High CB)**	**P2P demand: Average (Low CB)**	**P2P demand: Average (High CB)**
High Violations	0.0524*	0.0772***	0.0485*	0.0318	0.0094	0.0111
	(0.0288)	(0.0279)	(0.0261)	(0.0222)	(0.0095)	(0.0125)
Poverty	-1.6839***	-1.2232**	-3.1232***	-1.4140***	-0.0105	0.1160
	(0.6012)	(0.5998)	(0.6544)	(0.5148)	(0.2864)	(0.2853)
GDP per capita	-0.0738	-0.0286	-0.2338***	-0.2002***	-0.0121	-0.0054
	(0.0554)	(0.0438)	(0.0506)	(0.0455)	(0.0154)	(0.0186)
Unemployment	0.4717	1.2902	2.6763**	0.5275	0.1121	1.1228**
	(0.9107)	(0.9762)	(1.2717)	(0.7206)	(0.3712)	(0.4553)
Household income	0.4462**	0.6723***	0.2302	0.4518***	0.2195***	0.3178***
	(0.1806)	(0.1784)	(0.1589)	(0.1431)	(0.0626)	(0.0769)
Establishments	0.1194	0.1719**	-0.0633	0.2857***	0.0390	-0.0102
	(0.0734)	(0.0745)	(0.0829)	(0.0697)	(0.0254)	(0.0328)
Population	0.9947***	0.9187***	1.1702***	0.8891***	0.0195	0.0418
	(0.0624)	(0.0613)	(0.0636)	(0.0620)	(0.0185)	(0.0302)
Elderly	0.2169	0.3608	0.2994	-0.9120*	-0.1391	0.2347
	(0.4826)	(0.5718)	(0.4453)	(0.5050)	(0.1773)	(0.2722)
Foreign	0.0544**	-0.0088	0.1394***	0.0451**	-0.0046	-0.0022
	(0.0276)	(0.0268)	(0.0271)	(0.0229)	(0.0095)	(0.0127)
Language	0.0025	-1.7330	-0.8941	-2.1324*	0.1747	0.6217
	(1.0108)	(1.4891)	(0.9705)	(1.2615)	(0.3869)	(0.5862)
Education	0.2089	-0.0365	0.4488***	0.2893**	-0.0631	-0.0139
	(0.1413)	(0.1327)	(0.1447)	(0.1200)	(0.0424)	(0.0638)
Minority (Black/African American)	0.2126	0.4942***	0.4885***	0.5537***	0.0036	0.0711
	(0.1527)	(0.1832)	(0.1440)	(0.1485)	(0.0589)	(0.0786)
Minority (American Indian/Alaska Native)	-0.0971	-0.2121	1.3509***	0.2262	-0.1229	0.1763
	(0.4230)	(0.2037)	(0.4430)	(0.2465)	(0.1652)	(0.1453)
Minority (Asian)	-0.4557	0.5378	0.3229	-3.2987***	-0.1587	-0.2982
	(0.9990)	(1.6529)	(0.5014)	(0.6076)	(0.2341)	(0.5957)
Minority (Native Hawaiian/Other Pacific Islander)	-5.3682	-0.4912	-1.8355	3.2753	-3.2731	-0.0011
	(6.0133)	(5.8629)	(3.9503)	(2.8228)	(2.1044)	(1.6077)
Minority (Hispanic)	-0.4006	0.5289	-0.2385	0.5082*	-0.0537	-0.1553
	(0.3079)	(0.3890)	(0.2521)	(0.2612)	(0.1254)	(0.1851)
Branches	0.0307	0.0026	0.0893	0.0582	-0.0294*	0.0123
	(0.0539)	(0.0455)	(0.0547)	(0.0486)	(0.0161)	(0.0217)
Fixed effects	Year State	Year State	Year State	Year State	Year State	Year State
Clustered S.E.	County	County	County	County	County	County
N	4304	4016	4304	4016	4304	4016
R2	0.9161	0.8414			0.2080	0.1230

We must note that the results of Tables 8 and 9 must be taken with caution given that the violations dataset is not without its limitations (Doonan, Hamilton, and Johnson 2020). For example, although the FBI has referred to NIBRS as being "the crime dataset of the future" (Kaplan 2021), limited agencies have chosen to submit their crime data to NIBRS. Not until 2021 did the FBI require that all reporting agencies transition from the Uniform Crime Reporting (UCR) database to NIBRS. Prior to this mandate, a limited number of agencies reported to NIBRS with some states not being represented in the sample at all. For example, in 2019, only a little over 51% of all agencies that reported to the UCR database provided information to the NIBRS database (U.S. DOJ-FBI 2019) while in 2020, the percentage increased to 62.1% (FBI 2021).

Is P2P demand along the U.S. border different than the interior of the United States? Are illicit activities along the U.S. border influencing P2P demand?

It is important to compare the behavior of U.S. border counties in the context of P2P borrowing with those counties in the interior of the United States for multiple reasons. First, border communities, especially along the U.S.-Mexico border, are distinct from communities who do not share an international border. These communities have a higher probability of being influenced by their respective foreign neighbor through a shared history or economic relationship (Nugent 2012). Second, most drugs enter the United States through the land borders, thereby significantly causing drug-related problems. For example, in 2021, more than 56% of all drugs seized by U.S. Customs and Border Protection were at U.S. land borders (U.S. CBP 2021).

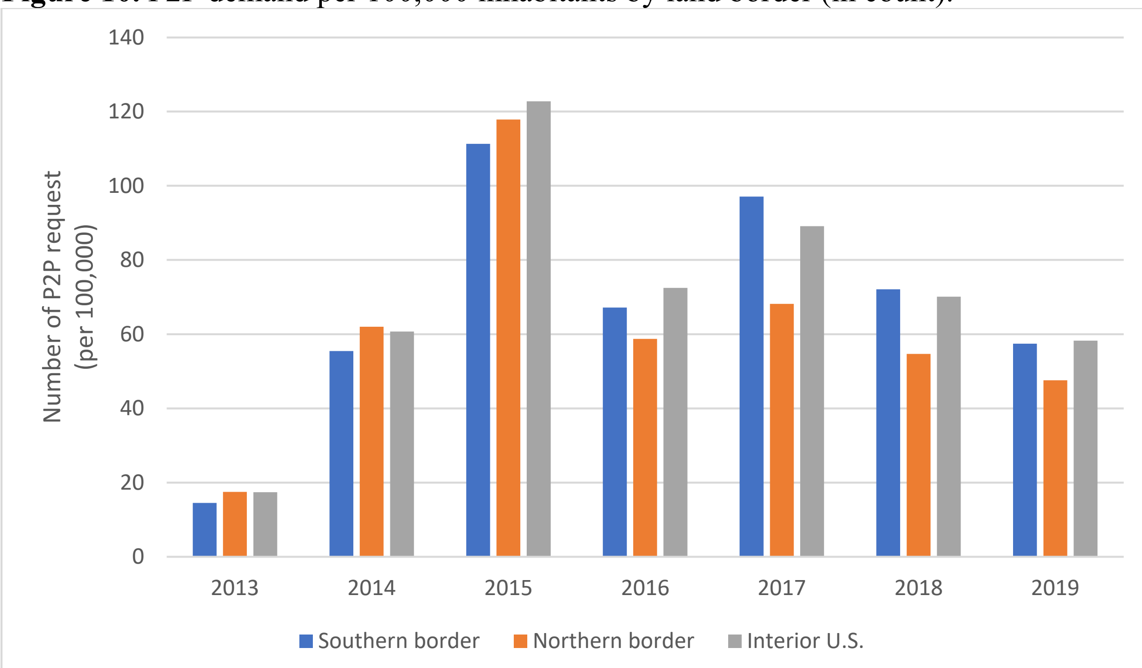
Figure 9. P2P demand per 100,000 inhabitants by land border (in amount).



A descriptive analysis shows P2P behavior of U.S. counties, based by their geographic location, is somewhat similar. Figure 9 illustrates the amount of P2P loans requested per 100,000 inhabitants. All three groups increased their P2P demand between the years 2013 through 2015 and decreased in subsequent years. Interestingly, P2P demand of southern border counties not only resembles those of interior counties but surpassed both northern border and non-border counties in the years 2017 through 2019.

Figure 10 illustrates the number of P2P requests per 100,000 inhabitants. Like Figure 9, this figure shows an increase in the number of requests from 2013 through 2015, with a decrease beginning in 2016. Once again, the data shows that the P2P demand of southern border counties closely resembles and at times surpasses the P2P demand of non-border counties.

Figure 10. P2P demand per 100,000 inhabitants by land border (in count).



For a more robust relational analysis, we use Equation 2 to analyze the relationship a border county has with P2P demand. Table 10 hints to the fact that border counties do not act any different than interior counties. We do not see that the demand in amount or count are any greater or less than interior counties. On the other hand, the average demand is 2% more than non-border counties at a 10% significance level.

Due to the two U.S. land borders being distinct from a social, demographic, and economic perspective, it is imperative we analyze the two borders separately. Table 11 compares the P2P demand of the U.S. land borders, in a disaggregate format, with counties within the interior of the United States. Overall, these results show that the amount of P2P demand of counties situated along the two U.S. land borders are not statistically different from those counties in the interior of the United States. These results can be interpreted in any of two ways. First, P2P demand is uniformed. Second, the differences in border communities (e.g., financially underserved, high minority population, high drug-related activities) do not influence the way such communities approach P2P borrowing.

Table 10. P2P demand by a border county.

	P2P demand: Amount	**P2P demand: Count**	**P2P demand: Average**
HIDTA	0.0839***	0.0497***	0.0053
	(0.0186)	(0.0173)	(0.0059)
Border	0.0562	-0.0200	0.0198*
	(0.0347)	(0.0264)	(0.0118)
Poverty	-2.0077***	-3.3503***	0.2632**
	(0.2972)	(0.4277)	(0.1200)
GDP per capita	-0.0255	-0.1870***	0.0078
	(0.0239)	(0.0439)	(0.0078)
Unemployment	1.0573**	1.7814***	0.2038
	(0.4455)	(0.6771)	(0.1852)
Household income	0.5073***	0.1292	0.2779***
	(0.0842)	(0.0943)	(0.0276)
Establishments	0.1718***	0.0263	0.0132
	(0.0440)	(0.0613)	(0.0143)
Population	0.8680***	1.0724***	0.0190
	(0.0362)	(0.0548)	(0.0118)
Elderly	0.1050	-0.5160	0.0065
	(0.2743)	(0.3470)	(0.0889)
Foreign	0.0277**	0.0899***	0.0010
	(0.0123)	(0.0187)	(0.0052)
Language	-1.2440**	0.9803*	-0.2415
	(0.4919)	(0.5911)	(0.1766)
Education	-0.0003	0.1231	-0.0051
	(0.0730)	(0.0950)	(0.0265)
Minority (Black/African American)	0.4120***	0.4705***	0.0026
	(0.0742)	(0.0964)	(0.0294)
Minority (American Indian/Alaska Native)	0.0750	0.1809	0.0358
	(0.1565)	(0.1814)	(0.0687)
Minority (Asian)	-0.1312	-1.0223***	-0.1510
	(0.4184)	(0.2626)	(0.0925)
Minority (Native Hawaiian/Other Pacific Islander)	7.1638*	11.7552**	0.1597
	(3.6573)	(5.6644)	(1.0111)
Minority (Hispanic)	0.2709**	-0.1975	-0.0233
	(0.1326)	(0.1659)	(0.0493)
Branches	0.0235	0.0613*	-0.0224**
	(0.0235)	(0.0367)	(0.0093)
Exchange (MEX/USA)	-0.3360***	-0.2539***	-0.0625***
	(0.0049)	(0.0079)	(0.0022)
Exchange (CAN/USA)	11.6842***	8.8062***	1.9583***
	(0.1096)	(0.1280)	(0.0539)
Fixed effects	State	State	State
Clustered S.E.	County	County	County
N	18066	18066	18066
R2	0.8699		0.1405

Table 11. P2P demand disaggregated by northern and southern border.

	P2P demand: Amount	**P2P demand: Count**	**P2P demand: Average**
HIDTA	0.0830***	0.0503***	0.0049
	(0.0184)	(0.0173)	(0.0059)
South	0.0900	-0.0630*	0.0358
	(0.0696)	(0.0380)	(0.0223)
North	0.0423	0.0353	0.0132
	(0.0405)	(0.0349)	(0.0140)
Poverty	-2.0191***	-3.3241***	0.2578**
	(0.2978)	(0.4234)	(0.1203)
GDP per capita	-0.0254	-0.1896***	0.0079
	(0.0239)	(0.0444)	(0.0078)
Unemployment	1.0486**	1.7458***	0.1997
	(0.4473)	(0.6676)	(0.1853)
Household income	0.5042***	0.1413	0.2764***
	(0.0843)	(0.0936)	(0.0277)
Establishments	0.1723***	0.0247	0.0135
	(0.0440)	(0.0618)	(0.0143)
Population	0.8664***	1.0785***	0.0182
	(0.0367)	(0.0561)	(0.0118)
Elderly	0.0933	-0.4958	0.0010
	(0.2756)	(0.3468)	(0.0893)
Foreign	0.0287**	0.0890***	0.0015
	(0.0125)	(0.0189)	(0.0052)
Language	-1.2854**	0.9772*	-0.2610
	(0.5070)	(0.5764)	(0.1788)
Education	0.0021	0.1152	-0.0040
	(0.0736)	(0.0951)	(0.0266)
Minority (Black/African American)	0.4141***	0.4657***	0.0036
	(0.0743)	(0.0960)	(0.0295)
Minority (American Indian/Alaska Native)	0.0818	0.1700	0.0390
	(0.1576)	(0.1804)	(0.0693)
Minority (Asian)	-0.1248	-1.0320***	-0.1480
	(0.4188)	(0.2596)	(0.0924)
Minority (Native Hawaiian/Other Pacific Islander)	7.1088*	12.0201**	0.1336
	(3.6610)	(5.6412)	(1.0100)
Minority (Hispanic)	0.2573*	-0.1680	-0.0297
	(0.1324)	(0.1697)	(0.0494)
Branches	0.0236	0.0594	-0.0223**
	(0.0235)	(0.0362)	(0.0093)
Exchange (MEX/USA)	-0.3360***	-0.2544***	-0.0625***
	(0.0049)	(0.0079)	(0.0022)
Exchange (CAN/USA)	11.6840***	8.8083***	1.9582***
	(0.1096)	(0.1280)	(0.0539)
Fixed effects	State	State	State
Clustered S.E.	County	County	County
N	18066	18066	18066
R2	0.8699		0.1405

Table 12. P2P demand disaggregated by northern and southern border when using overdose deaths as an alternative measure of drug-related activities.

	P2P demand: Amount	**P2P demand: Count**	**P2P demand: Average**
Overdoses	0.1764***	0.0277	0.0320***
	(0.0186)	(0.0234)	(0.0070)
South	0.1538**	-0.0533	0.0429*
	(0.0715)	(0.0390)	(0.0222)
North	0.0310	0.0361	0.0098
	(0.0395)	(0.0339)	(0.0138)
Poverty	-2.0604***	-3.2976***	0.2419**
	(0.2945)	(0.4264)	(0.1200)
GDP per capita	-0.0356	-0.2018***	0.0057
	(0.0239)	(0.0453)	(0.0078)
Unemployment	0.7546*	1.9228***	0.1264
	(0.4449)	(0.6736)	(0.1850)
Household income	0.5670***	0.1669*	0.2862***
	(0.0832)	(0.0916)	(0.0276)
Establishments	0.1728***	0.0431	0.0127
	(0.0438)	(0.0623)	(0.0143)
Population	0.8531***	1.0739***	0.0151
	(0.0365)	(0.0557)	(0.0119)
Elderly	-0.1041	-0.5898*	-0.0343
	(0.2721)	(0.3532)	(0.0907)
Foreign	0.0241*	0.0868***	0.0009
	(0.0124)	(0.0193)	(0.0052)
Language	-0.7320	1.0894*	-0.1594
	(0.5106)	(0.6031)	(0.1807)
Education	-0.0543	0.0784	-0.0123
	(0.0726)	(0.0939)	(0.0267)
Minority (Black/African American)	0.6493***	0.5114***	0.0469
	(0.0774)	(0.0983)	(0.0307)
Minority (American Indian/Alaska Native)	0.1061	0.1558	0.0442
	(0.1578)	(0.1813)	(0.0683)
Minority (Asian)	0.1470	-0.9932***	-0.1117
	(0.4361)	(0.2726)	(0.0907)
Minority (Native Hawaiian/Other Pacific Islander)	9.4084**	13.0054**	0.5777
	(3.7297)	(5.6969)	(1.0147)
Minority (Hispanic)	0.2937**	-0.1592	-0.0256
	(0.1341)	(0.1675)	(0.0499)
Branches	0.0423*	0.0649*	-0.0187**
	(0.0234)	(0.0359)	(0.0093)
Exchange (MEX/USA)	-0.3471***	-0.2552***	-0.0647***
	(0.0050)	(0.0077)	(0.0023)
Exchange (CAN/USA)	11.7100***	8.8214***	1.9652***
	(0.1098)	(0.1260)	(0.0541)
Fixed effects	State	State	State
Clustered S.E.	County	County	County
N	18021	18021	18021
R2	0.8704		0.1413

We rerun Equation 2 using the alternative measure of drug-related activities, $Overdoses_{i,s,t}$, as seen in Table 12. These results paint a different picture. Although the number of P2P loan requests are not statistically different from interior counties, the results indicate that the southern border increases P2P demand, in amount, by 19.29%. Once again, these results must be taken with caution given that demand and supply cannot be separated from this alternative measure.[17]

The U.S. southern border

The U.S. southern region makes for an interesting geographic area to study. Not only do U.S. southern border states share similar social, historical, and cultural similarities, but some border communities are, directly or indirectly, influenced by the economic development of their neighboring country.[18] Furthermore, the U.S.-Mexico border "is one of the most formidable and strategically important drug smuggling corridors" (South Texas HIDTA 2022). For example, in 2021, a little more than 48% of all drug seizures happened in southern bordering states (U.S. CBP 2021). To account for such similarities, indirectly control for the neighboring countries' economic development, and avoid any possible omitted variables due to the analysis of two distinct borders, we conduct a more detailed analysis by focusing only on U.S. southern border states.

To see if this transition from soft to hard information is allowing such actors to more actively and frequently participate in the lending market, we look at whether the P2P demand between HIDTA and non-HIDTA counties situated in U.S.-Mexico border states differ based on whether the percentage of community banks operating in problem areas is below or above the yearly median. Table 13 results indicate that the P2P demand is higher, both in amount and average requests, for HIDTA counties where community banks make up the largest market share. For example, HIDTA counties in the southwest tend to make requests that are 35.96% more than non-HIDTA counties.

The behavior of southern border states is quite distinct from those of northern border states. Table 14 shows that P2P demand, in count, is less in high intensity drug trafficking counties than in northern border states.

One possible argument may be that highly populated counties are driving such results given that some of the most populated counties are situated in these states.[19] To ensure this is not the case, we exclude all counties in the top ten most populated counties in the United States in each particular year of the sample period from our subsample. Table 15 indicates that these highly populated counties are not driving our results. In fact, the magnitude of the coefficients stays relatively similar. For example, in Table 15, HIDTA counties where community banks have a higher market share tend to request a higher amount (34.61%) and higher average (6.60%) of P2P loans.

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[17] We purposefully disregard the alternative measure of violations, $Violations_{i,s,t}$, because border communities, especially along the U.S. southern border, are severely underrepresented in the dataset.

[18] The economic development of U.S. neighboring countries vastly differs. As per the World Bank (2022), the U.S. northern neighbor, Canada, is a high-income country while the U.S. southern neighbor, Mexico, is considered an upper-middle income country.

[19] Six to seven counties are in the top ten most populated counties in the United States in each year of our sample period. These counties are Maricopa County, AZ, Los Angeles County, CA, Orange County, CA, San Diego County, CA, Dallas County, TX, and Harris County, TX.

Table 13. P2P demand of southern border states by community banks market share.

	P2P demand: Amount (Low CB)	P2P demand: Amount (High CB)	P2P demand: Count (Low CB)	P2P demand: Count (High CB)	P2P demand: Average (Low CB)	P2P demand: Average (High CB)
HIDTA	0.1513**	0.3072***	-0.0650	0.0227	0.0292**	0.0641**
	(0.0678)	(0.0864)	(0.0631)	(0.0936)	(0.0130)	(0.0251)
Poverty	-4.3499***	-2.9850**	-3.5245***	1.3943	-0.0486	0.2814
	(1.1750)	(1.3082)	(1.2727)	(2.4691)	(0.2582)	(0.5168)
GDP per capita	-0.0213	0.0152	-0.4233***	0.0448	0.0049	0.0088
	(0.0894)	(0.0577)	(0.0971)	(0.0756)	(0.0279)	(0.0183)
Unemployment	-2.3794*	-2.1063	-0.5686	-2.0598	-0.3007	-0.1952
	(1.2566)	(1.9810)	(2.0117)	(2.9094)	(0.2564)	(1.0510)
Household income	-0.5294	0.0822	-0.5674*	0.7565	0.1853***	0.2670**
	(0.4236)	(0.3489)	(0.3380)	(0.5357)	(0.0656)	(0.1308)
Establishments	-0.2160	0.3072**	-0.3143**	0.0100	-0.0146	0.0359
	(0.1773)	(0.1312)	(0.1444)	(0.2534)	(0.0254)	(0.0511)
Population	1.0179***	0.7864***	1.3484***	0.9752***	-0.0069	0.0658*
	(0.1402)	(0.0934)	(0.1771)	(0.1237)	(0.0290)	(0.0384)
Elderly	-2.1954**	1.1456	-2.8852***	1.7225*	0.1769	-0.2080
	(0.9006)	(0.9654)	(1.0346)	(0.9660)	(0.2289)	(0.3699)
Foreign	0.0589	-0.0249	0.1088	0.0208	0.0213	-0.0400
	(0.0698)	(0.0566)	(0.1093)	(0.0791)	(0.0208)	(0.0282)
Language	-0.0557	-1.5913	1.3995	0.2034	-0.1321	-0.2609
	(0.7979)	(1.1341)	(0.9563)	(1.4788)	(0.2127)	(0.5353)
Education	-0.4161	-0.2434	-0.1778	-0.1429	-0.1011	-0.0104
	(0.2546)	(0.2665)	(0.3005)	(0.3792)	(0.0803)	(0.0983)
Minority (Black/African American)	-0.2701	-0.4793	-0.3726	-1.0845	-0.0362	-0.1701
	(0.6030)	(0.6648)	(0.6246)	(0.7318)	(0.1219)	(0.2483)
Minority (American Indian/Alaska Native)	-0.5920*	-0.6164	-0.6931	0.5089	0.1145	3.6793***
	(0.3168)	(8.6431)	(0.4700)	(3.2603)	(0.0900)	(1.3656)
Minority (Asian)	-0.5293	7.1208**	-0.0887	3.1306	-0.0558	0.0069
	(0.8033)	(2.9371)	(0.5402)	(3.9079)	(0.1249)	(0.8316)
Minority (Native Hawaiian/Other Pacific Islander)	39.8079***	37.2640**	32.0681*	49.5411**	2.2635	-1.9108
	(13.5865)	(18.1739)	(18.6210)	(21.0605)	(2.9967)	(4.3000)
Minority (Hispanic)	-0.2457	0.0330	-0.9793***	-0.2611	0.0139	-0.0196
	(0.2517)	(0.3054)	(0.3431)	(0.3194)	(0.0572)	(0.1170)
Branches	0.1833*	-0.1541*	0.4013***	0.0851	-0.0108	-0.0718**
	(0.1051)	(0.0884)	(0.1282)	(0.1396)	(0.0250)	(0.0360)
Exchange (MEX/USA)	0.1337***	0.1203***	0.0855***	0.1275***	0.0027	0.0062
	(0.0090)	(0.0114)	(0.0078)	(0.0186)	(0.0026)	(0.0050)
Fixed effects	State	State	State	State	State	State
Clustered S.E.	County	County	County	County	County	County
N	1075	1163	1075	1163	1075	1163
R2	0.8800	0.6976			0.1336	0.0541

Table 14. P2P demand of northern border states by community banks market share.

	P2P demand: Amount (Low CB)	P2P demand: Amount (High CB)	P2P demand: Count (Low CB)	P2P demand: Count (High CB)	P2P demand: Average (Low CB)	P2P demand: Average (High CB)
HIDTA	-0.0648	-0.0210	-0.0780*	-0.3255***	-0.0061	0.0302
	(0.0552)	(0.0861)	(0.0437)	(0.0716)	(0.0137)	(0.0280)
Poverty	-2.7645***	-4.5206***	-4.5609***	-5.6801***	0.3141	-1.4074**
	(0.8543)	(1.5185)	(0.8271)	(1.5233)	(0.2766)	(0.6995)
GDP per capita	0.0804	0.1916**	-0.1963***	0.0957	-0.0079	0.0759**
	(0.0817)	(0.0971)	(0.0746)	(0.1076)	(0.0189)	(0.0376)
Unemployment	13.3621***	8.4863***	28.0765***	13.8261***	1.5147***	2.3424***
	(1.5952)	(1.8614)	(4.1811)	(2.7055)	(0.5622)	(0.8467)
Household income	0.3207	-0.0733	-0.0755	-0.2822	0.2710***	-0.0483
	(0.2315)	(0.3272)	(0.1767)	(0.3193)	(0.0628)	(0.1353)
Establishments	-0.1836	-0.2508	0.0834	0.1232	-0.0348	-0.0527
	(0.1338)	(0.1671)	(0.1334)	(0.1845)	(0.0378)	(0.0580)
Population	0.7883***	0.8352***	0.6862***	0.8080***	0.0217	-0.0277
	(0.1261)	(0.1175)	(0.0856)	(0.1313)	(0.0310)	(0.0466)
Elderly	-2.2372***	-3.2128***	-5.9293***	-4.3345***	-0.4060**	-0.9050**
	(0.6787)	(0.9337)	(0.9925)	(0.9798)	(0.2030)	(0.3832)
Foreign	0.1268***	0.0980*	0.0890**	0.1038*	0.0209	0.0170
	(0.0457)	(0.0580)	(0.0418)	(0.0587)	(0.0152)	(0.0274)
Language	3.1440*	-4.0519**	0.6109	-0.5520	0.3387	-1.1021*
	(1.6393)	(2.0233)	(1.3376)	(3.4459)	(0.5348)	(0.6047)
Education	-0.0353	0.2325	-0.9087***	1.0159***	-0.1418**	-0.0222
	(0.2437)	(0.2166)	(0.2464)	(0.2631)	(0.0660)	(0.0919)
Minority (Black/African American)	0.7362	0.7041	-0.2604	-0.2402	0.0519	0.0455
	(0.4595)	(0.8015)	(0.4085)	(0.5298)	(0.1553)	(0.2328)
Minority (American Indian/Alaska Native)	-1.2334***	-1.2762***	-1.4029***	-0.6702*	-0.3526**	0.1691
	(0.3770)	(0.3258)	(0.5160)	(0.3663)	(0.1373)	(0.2364)
Minority (Asian)	-1.2449	-0.9553	-0.3335	-3.5723	-0.4021	-0.3970
	(1.2778)	(2.3840)	(0.6636)	(2.9119)	(0.3415)	(0.6138)
Minority (Native Hawaiian/Other Pacific Islander)	18.7976	-6.2256	8.8295	-11.4761	0.4625	10.7394*
	(12.3049)	(14.5892)	(7.7900)	(20.1270)	(3.2789)	(6.2788)
Minority (Hispanic)	-1.4412***	-0.4540	-0.4288	0.6183	-0.2291	0.0125
	(0.5300)	(0.9154)	(0.2927)	(0.8942)	(0.1734)	(0.3202)
Branches	0.2740***	0.1687*	0.4656***	0.1176	0.0091	0.0104
	(0.0804)	(0.0870)	(0.0830)	(0.0979)	(0.0238)	(0.0327)
Exchange (CAN/USA)	4.9747***	5.1437***	5.6558***	4.8328***	0.7225***	0.8946***
	(0.2261)	(0.2741)	(0.4518)	(0.3086)	(0.0822)	(0.1254)
Fixed effects	State	State	State	State	State	State
Clustered S.E.	County	County	County	County	County	County
N	2436	1310	2436	1310	2436	1310
R2	0.8425	0.7987			0.1735	0.1211

Table 15. P2P demand of southern border states excluding highly populated counties.

	P2P demand: Amount (Low CB)	**P2P demand: Amount (High CB)**	**P2P demand: Count (Low CB)**	**P2P demand: Count (High CB)**	**P2P demand: Average (Low CB)**	**P2P demand: Average (High CB)**
HIDTA	0.1563**	0.2972***	0.0457	0.0223	0.0303**	0.0639**
	(0.0677)	(0.0862)	(0.0558)	(0.0973)	(0.0130)	(0.0253)
Poverty	-4.3391***	-2.9516**	-4.2318***	0.2509	-0.0430	0.2770
	(1.2007)	(1.3043)	(1.1766)	(2.2611)	(0.2605)	(0.5180)
GDP per capita	-0.0228	0.0161	-0.3617***	0.0291	0.0042	0.0086
	(0.0907)	(0.0577)	(0.0882)	(0.0705)	(0.0282)	(0.0183)
Unemployment	-2.3492*	-2.0342	-1.8221	-0.2276	-0.2840	-0.2009
	(1.2836)	(1.9914)	(2.1530)	(2.1709)	(0.2604)	(1.0527)
Household income	-0.5120	0.0955	-0.6076*	0.5724	0.1881***	0.2653**
	(0.4322)	(0.3459)	(0.3281)	(0.5304)	(0.0658)	(0.1317)
Establishments	-0.2209	0.3088**	-0.3643**	0.1842	-0.0190	0.0342
	(0.1778)	(0.1317)	(0.1780)	(0.1746)	(0.0257)	(0.0514)
Population	1.0175***	0.7845***	1.2648***	0.9291***	-0.0046	0.0674*
	(0.1411)	(0.0938)	(0.1469)	(0.1068)	(0.0300)	(0.0385)
Elderly	-2.2258**	1.2339	-2.2334**	2.1488**	0.1706	-0.2193
	(0.9096)	(0.9769)	(1.0960)	(1.0800)	(0.2301)	(0.3755)
Foreign	0.0621	-0.0261	0.2462**	-0.0059	0.0224	-0.0398
	(0.0704)	(0.0566)	(0.1140)	(0.0568)	(0.0207)	(0.0282)
Language	-0.1083	-1.5831	-0.8761	1.2304	-0.1562	-0.2676
	(0.8021)	(1.1474)	(1.0493)	(1.3329)	(0.2150)	(0.5357)
Education	-0.4360*	-0.2405	-0.2728	-0.1514	-0.1096	-0.0119
	(0.2612)	(0.2664)	(0.3430)	(0.3987)	(0.0839)	(0.0989)
Minority (Black/African American)	-0.3164	-0.5065	-0.7874	-0.5294	-0.0628	-0.1786
	(0.6289)	(0.6674)	(0.6372)	(0.6284)	(0.1251)	(0.2509)
Minority (American Indian/Alaska Native)	-0.5913*	-1.3779	0.0127	0.4408	0.1132	3.6920***
	(0.3247)	(8.5567)	(0.4138)	(2.3825)	(0.0916)	(1.3725)
Minority (Asian)	-0.5781	8.2584***	-0.0891	2.4887	-0.0552	-0.1120
	(0.8180)	(2.8023)	(0.4893)	(3.9669)	(0.1288)	(0.9297)
Minority (Native Hawaiian/Other Pacific Islander)	42.1100***	37.8464**	35.6118***	43.1173**	2.8873	-1.7138
	(14.2576)	(17.8513)	(12.7637)	(18.3275)	(3.0587)	(4.3395)
Minority (Hispanic)	-0.2528	0.0493	-0.6488**	-0.1470	0.0112	-0.0212
	(0.2554)	(0.3045)	(0.2953)	(0.3102)	(0.0573)	(0.1173)
Branches	0.1799*	-0.1510*	0.2428**	0.0190	-0.0114	-0.0727**
	(0.1068)	(0.0888)	(0.1230)	(0.1144)	(0.0253)	(0.0360)
Exchange (MEX/USA)	0.1339***	0.1201***	0.0824***	0.1167***	0.0025	0.0062
	(0.0092)	(0.0114)	(0.0083)	(0.0164)	(0.0027)	(0.0050)
Fixed effects	State	State	State	State	State	State
Clustered S.E.	County	County	County	County	County	County
N	1033	1159	1033	1159	1033	1159
R2	0.8582	0.6864			0.1299	0.0540

VI. Robustness Measures

A reasonable question is whether P2P demand is increasing because crime is driving out traditional consumer lending. We study this possibility further by analyzing the association between the amount of and change in consumer loans by traditional financial intermediaries in HIDTA and non-HIDTA counties. Table 16 indicates that, in fact, financial intermediaries in HIDTA counties tend to make 34.93% less consumer loans. On the other hand, there is no statistical difference when we analyze the change in consumer loans by traditional financial intermediaries from one year to the next.

Table 16. Relationship between high intensity drug trafficking areas and traditional consumer loans.

	Consumer loans	**Change in consumer loans**
HIDTA	-0.2996***	0.0391
	(0.1015)	(0.0494)
Poverty	0.0881	-1.6820
	(1.6276)	(1.4147)
GDP per capita	0.3251***	0.0427
	(0.1152)	(0.1169)
Unemployment	6.2366***	4.0968
	(2.3917)	(3.5746)
Household income	0.2121	0.2760
	(0.3998)	(0.1937)
Establishments	0.4665**	-0.2272
	(0.2121)	(0.1391)
Population	0.6677***	0.0892
	(0.1739)	(0.1531)
Elderly	-0.9262	-2.3569
	(1.3335)	(1.8758)
Foreign	0.2973***	0.1085
	(0.0667)	(0.1072)
Language	-5.6188**	0.4655
	(2.4337)	(0.7304)
Education	-0.3610	0.6322
	(0.3391)	(0.9193)
Minority (Black/African American)	-1.0861**	0.2560
	(0.4489)	(0.2529)
Minority (American Indian/Alaska Native)	0.3297	-0.4269
	(0.9074)	(0.3941)
Minority (Asian)	-10.8853***	1.1421
	(1.9280)	(0.9572)
Minority (Native Hawaiian/Other Pacific Islander)	-18.6729	7.6265
	(24.7225)	(8.7378)
Minority (Hispanic)	-1.8124**	-0.5928
	(0.8184)	(0.5036)
Branches	-0.3207**	-0.2537
	(0.1398)	(0.2168)
Fixed effects	Year State	Year State
Clustered S.E.	County	County
N	24359	24358
R2	0.5879	0.0042

Table 17. Relationship between high intensity drug trafficking areas and traditional consumer loans by border location.

	Consumer loans (Non-HIDTA)	**Consumer loans (HIDTA)**	**Change in consumer loans (Non-HIDTA)**	**Change in consumer loans (HIDTA)**
South	-0.6168	-1.9557***	0.5374	0.0338
	(0.4764)	(0.4778)	(0.3723)	(0.0380)
North	-0.2758	-0.5793**	0.1372	0.0138
	(0.3304)	(0.2469)	(0.2395)	(0.0152)
Poverty	0.8294	-1.5884	-0.8221	-0.0863
	(1.7868)	(3.4564)	(1.2201)	(0.2992)
GDP per capita	0.4859***	-0.2131	0.0315	0.0125
	(0.1275)	(0.2296)	(0.1354)	(0.0196)
Unemployment	2.9169	6.4155	3.4930	-0.5102
	(2.6016)	(4.2533)	(4.8103)	(0.7118)
Household income	0.0846	0.4644	0.4770**	0.1116
	(0.4436)	(0.6619)	(0.2360)	(0.1509)
Establishments	0.5637**	0.1282	-0.2468	-0.1111
	(0.2288)	(0.4548)	(0.1578)	(0.0700)
Population	0.4914**	0.7717**	0.0769	0.0685**
	(0.1960)	(0.3178)	(0.1985)	(0.0330)
Elderly	0.1919	0.4339	-2.9256	-0.0971
	(1.4393)	(2.3498)	(2.2070)	(0.2491)
Foreign	0.2467***	0.4154**	0.1317	-0.0204
	(0.0754)	(0.1655)	(0.1280)	(0.0244)
Language	-5.0028	-5.3535*	-0.3434	0.2488
	(3.9652)	(3.2081)	(1.2443)	(0.2548)
Education	-0.2740	-0.4635	0.7577	-0.0436
	(0.3658)	(0.8023)	(1.0678)	(0.0780)
Minority (Black/African American)	-0.7216	0.0257	-0.0423	0.0459
	(0.5183)	(0.6794)	(0.3088)	(0.0839)
Minority (American Indian/Alaska Native)	0.5778	1.5915	-0.6590	-0.1376
	(0.9932)	(1.5117)	(0.4811)	(0.1413)
Minority (Asian)	-6.8166**	-6.9173***	0.8298	-0.5758*
	(3.1365)	(1.6753)	(1.6236)	(0.3228)
Minority (Native Hawaiian/Other Pacific Islander)	0.1727	-11.6911	12.4887	-1.5018
	(31.2081)	(20.0259)	(14.2773)	(1.6174)
Minority (Hispanic)	-2.3347**	0.0155	-0.9435	-0.0023
	(1.0393)	(1.1207)	(0.7725)	(0.0704)
Branches	-0.1920	-0.1278	-0.3306	0.0617
	(0.1499)	(0.2974)	(0.2607)	(0.0606)
Exchange (CAN/USA)	0.5406***	1.1206***	1.6649*	-0.0887
	(0.1717)	(0.2826)	(0.9331)	(0.0683)
Exchange (MEX/USA)	-0.0020	0.0010	-0.1053	-0.0054
	(0.0102)	(0.0159)	(0.0666)	(0.0069)
Fixed effects	State	State	State	State
Clustered S.E.	County	County	County	County
N	19876	4483	19875	4483
R2	0.5512	0.6975	0.0042	0.0165

When we analyze the sample based on border location and divide the sample based on the HIDTA designation (Table 17), the results indicate that there is a negative relationship between drug-related activities and traditional consumer lending. Compared to interior counties, HIDTA counties in the southern and northern border experience a significant reduction in consumer loans. There is no statistical significance if the change in consumer lending is considered.

VII. Limitations and Future Research

Although the results support several of our hypotheses, we have not proven causation. First, the results put forth are only correlations between the variables of interest and, at this moment, we cannot establish causality. Our next step is to investigate external shocks to help explore the presence of causality. Second, all measures of drug-related activities are proxies which are not perfect measures. For example, we are unable to disentangle demand from supply when overdoses are used as a proxy for drug-related activities. Furthermore, the violations measure is weak given that there is limited disclosure of drug-related violations to the NIBRS database. Third, the analysis would be best served if the sample period increased. Although our sample period is driven by limitations in our current peer-to-peer dataset, it is possible to add six more years with an alternative peer-to-peer dataset. In the future, we plan to replicate our results with this new dataset. Lastly, the county designation approach is not without the possibility of misclassification. Although we are aware of this possibility, we think this is the best approach. We argue that the current county assignment approach reduces the possibility of making a high number of classification errors due to assumptions that we would not originally make. Furthermore, this approach reduces the time needed to classify each city by its designated county.

Moving forward this study would benefit in determining P2P demand based on banks' exposure to high intensity drug trafficking areas. For example, how much of their deposits are generated in areas with high drug-related problems.

VIII. Conclusion

The disruption to the consumer lending landscape by fintech platforms has allowed for more participation in the consumer credit market, but has it simultaneously allowed for illicit actors to more openly and frequently partake in this market? Borrowing from the theory of financial intermediation and soft information theory, we hypothesize that fintech's shift from soft information to hard information to gauge a borrower's risk and make credit decisions has allowed illicit actors to more openly and frequently participate in the peer-to-peer borrowing marketplace to possibly finance their illicit enterprises or supplement their income. We pay close attention to the two land borders given that U.S. border communities are inherently different and are influenced by their foreign neighbor in either a social and/or economic way.

We conduct a county-level analysis and find that counties with severe problems related to the production, manufacturing, importation, or distribution of illegal drugs request more P2P loans in both amount and count after controlling for social and economic factors. These results are amplified when we compare counties with a large community bank market share versus a low community bank market share. These results are robust to alternative measures of drug-related activities.

When we analyze the P2P demand of border counties, we do not find that border counties behave any different from interior U.S. counties based on their HIDTA designation, but P2P demand increases in the southern border if the overdose rate is used as a proxy for illegal drug-related activities. On the other hand, when we compare the border regions individually, we find that HIDTA counties do behave differently from non-HIDTA counties within the state. For example, border communities in the southern border have a significantly higher P2P demand as opposed to the northern border region.

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Appendix

A1. Description of the *fuzzy match* approach.

The purpose of the *fuzzy match* approach, as used in this study, is to string match (i.e., merge) two datasets with imperfect matches. The usefulness of this approach "lies in the ability to quantify the similarity between two strings in terms of string metrics" (Robinson, Bryan, and Elias 2020, 1). In other words, it is the distance based on how many operations are needed to transform one string into another.

The table below illustrates the different operation types used in string transformation. For example, assume the desired string is *"acb"* but the written string is *"ba"*. In this case, the distance to transform *"ba"* into *"acb"* is equal to two because the system must swap "*b"* with "*a"* in *"ba"* to produce *"ab"* and insert *"c"* in *"ab"* to produce *"acb"*. The system adds the number of operations completed to convert one string to the other to find the final distance.

Operation Type	**Original String**	**Desired String**
Substitution	boo	foo
Deletion	oo	foo
Insertion	floo	foo
Transportation	ofo	foo

Source: Reproduced from van der Loo (2014).

In the context of this study, assume there are three individuals from the city of Corpus Christi, TX requesting P2P loans. When completing their loan application, the customer must type in the city and select the state from a drop-down menu which he/she lives (as illustrated in the table below). Given that the application does not request county disclosure, it is the researcher's duty to assign the county to each observation.

borrower_city	**borrower_state**
corpus christi	TX
corpus cristi	TX
corpus chiristi	TX

As illustrated, the approach to showing an applicant's city is prone to errors due to typos, as in this example, and fictitious or use of colloquial names. Using a *fuzzy match* approach, we can merge based on the best approximation or highest degree of similarity. The tables below illustrate this approach.

P2P Application	
borrower_city	**borrower_state**
corpus christi	TX
corpus cristi	TX
corpus chiristi	TX

USPS City, County, State Listing	
city	**state**
corpus christi	TX

Fuzzy match results					
borrower_city	**borrower_state**	**city**	**state**	**county**	**distance**
corpus christi	TX	corpus christi	TX	nueces	0
corpus cristi	TX	corpus christi	TX	nueces	1
corpus chiristi	TX	corpus christi	TX	nueces	1

The table below illustrates another example we encountered when cleaning our data. This example relates not only to cities with typos but cities that expand multiple counties. When we analyze observations from the city of Dallas, TX, we observe several variations that may or may not pertain to the location of Dallas, TX. Furthermore, it was necessary to account for all four counties that the city belongs to.

borrower_city	borrower_state	city_match	state_match	county	distance
dallas	TX	dallas	TX	dallas	0
dallas	TX	dallas	TX	collin	0
dallas	TX	dallas	TX	denton	0
dallas	TX	dallas	TX	tarrant	0
dallaa	TX	dallas	TX	dallas	1
dallaa	TX	dallas	TX	collin	1
dallaa	TX	dallas	TX	denton	1
dallaa	TX	dallas	TX	tarrant	1
wallis	TX	dallas	TX	dallas	2
wallis	TX	dallas	TX	collin	2
wallis	TX	dallas	TX	denton	2
wallis	TX	dallas	TX	tarrant	2
far north dallas	TX	dallas	TX	dallas	NA
far north dallas	TX	dallas	TX	collin	NA
far north dallas	TX	dallas	TX	denton	NA
far north dalls	TX	dallas	TX	tarrant	NA

The *fuzzy match* approach allows us to assign all counties which are part of the city of Dallas, TX as well as allows us to either omit all observations that do not meet our minimum distance threshold or hand-check these observations.