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The Main Street Lending Program: Who Borrowed and How Have They Benefited?

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Abstract:
The Main Street Lending Program (MSLP) was established by the Federal Reserve to supply credit to small and, especially, midsize businesses so they could weather COVID-19–induced disruptions. This study uses Dun & Bradstreet (D&B) data on the financial condition and overall viability of firms to examine the characteristics of MSLP borrowers and their performance after receiving a loan relative to the performance of their peers. Estimates show that, even when differences in firms' industries and geographic regions are taken into account, a firm was more likely to borrow from the MSLP if it was larger, more active, had a good but not excellent risk score, was hit harder by the pandemic, had received a Paycheck Protection Program (PPP) loan early but was located in a county with a longer delay in PPP lending, operated in a nonessential industry, or was located in a county with fewer community banks. A nontrivial fraction of MSLP borrowers also received second-draw PPP loans in 2021, indicating that they were, in fact, in need of funding. Receiving an MSLP loan improved firms' financial condition progressively and significantly on average, even though it did not lead to significant increases in employment over the year following loan receipt.

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1 Introduction

As the COVID-19 pandemic and the public health measures implemented in response wreaked havoc on the US economy, Congress authorized the Paycheck Protection Program (PPP) to provide liquidity to small businesses through low-cost loans that essentially turned into grants. At the same time, the Federal Reserve launched unprecedented corporate bond purchase facilities, which proved to be effective liquidity backstops that stabilized the funding supply to large corporations. By comparison, midsize firms were initially in danger of falling through the cracks: They tended to be too small to access the corporate bond market and thus still bank-dependent, but some were too large to borrow under the PPP. The Federal Reserve therefore established the Main Street Lending Program (MSLP or Main Street) on April 9, 2020, to provide targeted credit support for these mid-market businesses as well as nonprofits and any small businesses that might need additional funding beyond what they could obtain from the PPP.

The MSLP was by far the most challenging of the Fed credit programs to administer because it "purchases interests in loans that are, by nature, bespoke agreements often with complex, borrower-specific terms and conditions," as Eric Rosengren, then president of the Federal Reserve Bank of Boston, noted in his congressional testimony on August 7, 2020. This inherent complexity makes it important to understand why certain firms became borrowers whereas other observationally comparable firms, such as those of similar size and operating in the same industry and the same geographic region, did not. In particular, were the borrowers more risky than other firms (controlling for size, industry, and location)? Did their financial situation deteriorate more over the few months after the COVID-19 pandemic hit and before they received an MSLP loan? As importantly, to what extent did the MSLP loans help these borrowers' performance, such as showing relatively greater improvement in financial health?

Such an analysis is difficult because virtually all of the firms that were eligible for the MSLP, along with their peers, are private companies about which limited information is available. We therefore turn to the Dun & Bradstreet (D&B) database, which offers the most comprehensive coverage of private US firms, especially those firms that have only a few employees.

The MSLP operated by purchasing participations in bank loans made to eligible borrowers, so whether a firm became an MSLP borrower was jointly determined by the firm's need for credit and a bank's decision to extend credit but only under the MSLP. For this outcome to be the bank's optimal decision, intuition suggests that the firm would more likely than not have been sufficiently viable to benefit from the injection of this funding but too risky to qualify for a private loan of comparable terms. Fully characterizing this joint optimization problem is clearly challenging and beyond the scope of this paper.

Instead, this study focuses on two aspects of this problem. It (1) examines which firm attributes, along with local economic and public health conditions, were associated with a higher likelihood that a firm borrowed from the MSLP, and (2) estimates how much the MSLP aided the borrowers, especially in shoring up their financial condition after they received a loan measured *relative to* the condition of their peer companies that had the same observable characteristics (and thus were also eligible for the MSLP based on the scale of their operation) but did not borrow. The answer to the first question can help evaluate whether the program reached the subset of businesses it was designed to target. Perhaps more importantly, it can provide useful clues about which program parameters might be altered to make it more suitable should a similar program be called for in the future. Answers to the second question serve as an evaluation of the efficacy of the MSLP in providing liquidity to alleviate financial strains on firms, which should subsequently help to support the recovery of real economic activity.

First, we find that, as intended by the design of the program, being midsize (that is, employing 250 to somewhat more than 500 workers) was the strongest predictor of a firm becoming an MSLP borrower. Firms with fewer than 10 employees were the least likely to borrow by a notable margin, consistent with the feedback that many firms considered the certification requirements too onerous. Interestingly, being an early recipient of a 2020 PPP loan increased the odds that a firm would borrow from the MSLP by a smaller but comparable magnitude, indicating the importance of preexisting banking relationships. It also suggests that these firms needed more funding than provisioned under the PPP. This conjecture is supported by the fact that a substantial subset of MSLP borrowers also received second-draw PPP loans in 2021, which further indicates that these firms suffered relatively large disruptions due to the pandemic.

By comparison, the influence of risk scores on the probability of borrowing was much more modest. Consistent with intuition, firms with good risk scores were the most likely to become borrowers, while those with the best scores were the least likely. Having experienced a larger improvement in risk scores over the year before the pandemic but a greater deterioration in risk scores after its onset was also associated with a stronger propensity to borrow. This indicates that borrowers tended to be firms that had better prospects but were more adversely affected by the pandemic. Local economic conditions mildly influenced the likelihood of MSLP borrowing. Greater economic vibrancy in a firm's county (proxied by a higher mobility index) and a larger presence of community banks in that county were associated with a lower likelihood of borrowing, as was operating in an essential industry. A longer delay in PPP lending in a firm's county raised the likelihood of a firm becoming an MSLP borrower. These relationships are largely consistent with intuition.

Our subsequent estimates of the MSLP's treatment effects show that the financial health of recipient firms improved progressively and significantly over the year following loan receipt. The reduction in credit risk reached nearly 18 percent four quarters after loan receipt when estimated using a staggered treatment effects estimator à la Callaway and Sant'Anna (2021). This suggests that the MSLP did achieve its objective of shoring up the liquidity position of firms that had promising prospects but were hit hard by the pandemic. By comparison, MSLP borrowers experienced slightly better recovery in employment over the year following loan receipt relative to their peers, but the difference was insignificant. This may be due in part to the imprecision of the employment data. Moreover, full recovery may require more time. To the extent that firms with more ample liquidity are better able to realize their real-growth goals, these borrowers should be in a good position to expand operations as the economy fully normalizes over the coming quarters.

Our analysis complements several existing studies of the MSLP. Arseneau et al. (2021) offer a comprehensive review of the MSLP—its goals and design, the characteristics of its borrowers and lenders, etc.[1] Bräuning and Paligorova (2021) find that the amount of credit extended by the MSLP reached about 60 percent of the volume of loans made by large banks to borrowers of comparable size and leverage. Bräuning et al. (2021) present evidence that the MSLP accomplished its key goal of directing more funds where and when they were most needed. Minoiu, Zarutskie, and Zlate (2022) find a positive spillover effect of the MSLP on participating banks' commercial and industrial (C&I) lending more generally, which, they argue, is because the MSLP served as a backstop. Unlike these previous studies, this paper is able to use data on MSLP borrowers and their peers to explore the treatment effects at the individual firm level.[2]

2 The Main Street Lending Program

Given the extensive reviews of the MSLP by studies such as Arseneau et al. (2021), we discuss only its key features pertaining to borrowers that are relevant for our analysis. First, only for-profit businesses that obtained MSLP loans are analyzed in this study.[3] This study

[1]Morgan and Clampitt (2021) provide an earlier review of the MSLP's main features and ultimate volume.

[2]It is closely related to Wang, Ballance, and Qing (2021), which also uses D&B data to understand the characteristics (particularly the financial condition) of MSLP borrowers relative to those of their peers before and after the COVID-19 outbreak in 2020.

[3]The Federal Reserve also established facilities within the MSLP to support nonprofit organizations. Those facilities, however, received only a few submissions and thus are omitted from this study.

compares borrowers with size-eligible non-borrowers, which are businesses with as many as 15,000 employees in the D&B database.[4]

Leverage limits set by the MSLP, which differ across the three loan facilities (New, Priority, and Expanded), cannot be considered because D&B provides no financial variables.[5] Instead, risk scores are used to gauge firms' riskiness. See Appendix B for more details about the Main Street program design.

3 Data Description

The primary data source for our study is the Dun & Bradstreet (D&B) database. It is the most comprehensive commercial database of private businesses in the United States.[6] The full "population" for our analysis includes all the US-domiciled employer establishments in the D&B database that were active as of January 2019 and employed one to 15,000 workers (which is the MSLP size limit).[7] Establishments with missing state and industry codes are also excluded, although they account for less than 1 percent of the firms.

D&B is aptly regarded as a credit bureau for businesses. It assigns credit scores to nearly all the businesses in its database based partly on their payment records. These scores are constructed to predict a firm's future credit performance (such as making timely repayment) and serve a role in business lending analogous to that of consumer credit scores in consumer lending. D&B scores are generally considered the leading scores used by a broad range of creditors (lenders and suppliers). For example, the primary credit score used by Bank of America for approving small-business loans is provided by D&B.[8] D&B updates the risk scores on an ongoing basis, based on the stream of signals it receives from a network of information providers (including landlords, lenders, utility companies, suppliers, postal services, secretaries of state, etc.). These risk scores thus enable us to adequately account for businesses' pre-pandemic financial health and commercial viability as perceived by lenders. Given that lenders had to retain 5 percent of the principal on an MSLP loan,

[4]According to the Main Street term sheets, businesses with no more than $5 billion in revenue were also eligible, but revenue is sparsely covered in the D&B data.

[5]Leverage is capped at four times adjusted 2019 earnings before interest, tax, and depreciation (EBITDA) for loans purchased by the New Loan Facility (MSNLF), and six times EBITDA for the Priority and Expanded Loan Facilities (MSPLF and MSELF).

[6]For years now, every government contractor has been required to obtain a D&B identifier to be eligible to bid for contracts.

[7]The two-employee (equivalent to one-worker) lower bound is needed to obtain a sample of employer firms because D&B tends to count the proprietor as an employee (see Barnatchez, Crane, and Decker, 2017). This threshold also excludes sole proprietorships and establishments with zero reported employees.

[8]https://www.bankofamerica.com/smallbusiness/education/business-credit-score/. Many digital financial services platforms (such as Credit Karma and Brex) highlight the importance of D&B credit scores, especially for small businesses.

a business' creditworthiness would have been an important factor in a bank's decision on whether to issue a loan and whether to seek the Fed's participation in the loan. Furthermore, it is likely that the most visible near-term effect of the liquidity injection through an MSLP loan was to enable the borrowing firm to make more timely payments on its liabilities (owed to suppliers and creditors).[9] This should have, in turn, shored up a firm's credit score, all else being equal. The D&B data thus enable us to examine the impact of the MSLP on businesses' bill payment records and the evolution of their risk scores. Greater financial resources should, in principle, provide the wherewithal for businesses to expand their real activity once demand has recovered.

Given the tight near-term link between credit availability and firms' ability to pay bills punctually, we focus our analysis of firm risk on the D&B Commercial Credit Score (CCS). CCS is modeled to measure the risk of delinquency in the next 12 months.[10] Scores range from 101 to 670, with each 40-point increase halving the risk of delinquency. When interpreting our estimates, we use the following formula to convert a change in the CCS to a change in the delinquency probability: $\%\Delta Risk = \exp\{-\xi \cdot \Delta\text{CCS}\} - 1$, where $\xi \equiv \ln(2)/40$. For example, $\Delta\text{CCS} = 12$ maps to an approximately 18 percent reduction in risk. See Appendix A for more details about the risk scores and ratings, along with comparable statistics of the other risk scores.

In analyzing firms' MSLP uptake decisions as well as estimating the MSLP's treatment effects, we also consider the 2019 average D&B Viability Score (VS) bin (which smooths out monthly fluctuations in a small fraction of observations) as a control variable in some specifications. By definition, the VS provides a more comprehensive measure of a firm's overall commercial viability prior to the onset of the pandemic. VS bins are analogous to credit rating bins and likely more commonly used than the more granular VS Points by creditors in making lending decisions.[11]

[9]This effect was partly indirect since, with a few exceptions (see Appendix B for details), borrowers had to "refrain from repaying the principal balance of, or paying any interest on, any debt" until the MSLP loan was repaid in full. But the MSLP loan would substitute for internal funds that could then be directed to other uses. To this end, the deferral of interest (for one year) and principal repayment (for two years) further helped.

[10]Schematically speaking, D&B estimates the CCS using its proprietary model of firm payment outcomes on past payment behavior and an array of firm attributes (such as industry, location, age, size, etc.). The CCS thus predicts default probability in the future given data to date and can be regarded as the forward-looking counterpart to the better known D&B Paydex score, which is simply a summary statistic of a firm's past payment behavior.

[11]VS Points is the more continuous counterpart to VS, ranging from 101 to 800. The relationship between VS Points and VS bins is similar to the relationship between consumer credit scores and consumer risk profile categories, an example of which (according to the Consumer Financial Protection Bureau) consists of five categories: deep subprime, subprime, near-prime, prime, and super-prime. Lenders tend to treat consumers who have scores in the range of a given category as equally risky.

Although the D&B data are available monthly, analyses here, especially of the MSLP treatment effects, are mostly conducted at the quarterly frequency, because quarterly averages smooth out occasional transitory fluctuations from month to month in some risk-score variables. The event time is defined according to the timing of the MSLP operations: Event quarter $\tau = 0$ in our analysis corresponds to 2020:Q3, as the MSLP began operations on July 6, 2020, while the majority of loans were made in $\tau = 1$ because of the surge in participation in early December 2020. $\tau = -1$ corresponds to 2020:Q2, coinciding with the initial acute phase of the COVID-19 pandemic. Overall, our sample runs from 2019:Q1 ($\tau = -6$) through 2021:Q4 ($\tau = 6$).

Because the volume of the D&B data is impractically large, we conduct all the analysis at the firm level using a representative random sample drawn by strata of geography (state), industry (two-digit NAICS code), and size (range of employee count) from the population of US-domiciled firms in the D&B database that were active as of January 2019 and employed one to 15,000 workers.[12] Firm attributes are measured either as of March 2020, our baseline pre-pandemic period, or as 2019 averages to minimize idiosyncratic monthly noise for more volatile variables.[13] The final sample comprises 418,995 firms for the uptake propensity score regressions and from 172,000 to 179,000 matched peers for the MSLP firms for the dynamic treatment effects analysis.

We use several additional data sources to estimate the factors that influenced MSLP uptake. First, to measure the de facto level of social distancing and commercial activity in each county, we use the mobility indexes from Google's COVID-19 Community Mobility reports.[14] In addition, county-level COVID-19 statistics (deaths per million) are used to account for pandemic severity.[15] We use two indicators to measure the type and degree of impact from the pandemic by industry. The first indicates whether an industry was designated as essential, which would have allowed it to operate during a lockdown, according to the Cybersecurity and Infrastructure Security Agency.[16] The other involves classifications for the six-digit NAICS industries by the Chicago Fed indicating which were subject to

[12]More precisely, the unit of analysis is "enterprise," according to D&B—either standalone or headquarters (but not branch)—which we refer to as "firm" for short. Some variables, such as risk scores, are measured only at the firm level.

[13]As explained in Wang, Ballance, and Qing (2021), given the typical lag of updates in D&B data, March 2020 was the last pre-pandemic month, although using February 2020 values makes virtually no difference. Moreover, a firm had to be established by March 13, 2020, to be eligible for a Main Street loan.

[14]See Google COVID-19 Community Mobility Reports, `https://www.google.com/covid19/mobility/`, obtained from Opportunity Insights (see Chetty et al., 2021). These indexes were compiled using mobile phone tracking data, and they measure *percentage changes* in the number of visitors to and lengths of stay at categorized places relative to the baseline period of January 2 through February 6, 2020.

[15]The data were compiled by the *New York Times* and also obtained from Opportunity Insights.

[16]Data downloaded from https://www.cdc.gov/niosh/topics/coding/essentialworkers/.

moderate, severe, substantial, or basically no impact from the COVID-19 shock.

Since essentially all lending to (small) private businesses is local, to measure such firms' access to funding, we use the share of bank branches in a county that belongs to community banks. We computed the shares using the FDIC's 2019 annual Summary of Deposits (SOD) data, which provide the location of all branches (and deposit balance by branch) of all depository institutions that were operating in the United States as of June 2019. We aggregate the branch-level data from the SOD to the county level. Community banks are identified according to the FDIC's institution directory. This ratio was also found to be associated with more rapid access to the PPP by small businesses, as community banks were more active in PPP lending, especially early on (see Faulkender et al., 2021).

Given the unprecedented fiscal support provided to small businesses and households following the onset of the pandemic, the amount of public assistance received by each locality (relative to its pre–COVID-19 economic activity) should be accounted for when evaluating the effects of the MSLP. We use the volume of PPP loans received by small businesses within a county as a summary measure of the degree of public-sector assistance delivered to that county. This amount is normalized by the 2019 average monthly payroll of eligible firms (that is, those with 500 or fewer employees), which is derived using data from the US Census Bureau's County Business Patterns (CBP 2020) combined with data from the bureau's Statistics of US Businesses (SUSB 2017).[17] The PPP data are from the July 2021 data release by the Small Business Administration. These data are also used to identify which MSLP borrowers also obtained PPP loans.

Identifying MSLP Borrowers in the D&B Database

D&B's name-matching algorithm is the primary tool for identifying the MSLP borrowers in the D&B database by locating their Data Universal Numbering System (DUNS) numbers. Of the accepted MSLP borrowers recorded as of January 8, 2021, we are able to find with high confidence the DUNS number at the headquarters level for a total of 1,781 borrower firms. However, we lose around 270 borrowers from the statistical analysis either because there are no pre-pandemic records for them in the database or they lack peers (in the same state, industry, and age and size bins) needed to compute the treatment effects. See Appendix B for further details.

Defining Matched Peers for MSLP Borrowers

Because the MSLP borrowers operate at different scales and in different industries and

[17] We use 2019 payroll expenses for normalization to be consistent with the PPP rule that capped the size of a loan at 2.5 months of a firm's payroll or $10 million.

localities, it is important to compare these firms with their suitably matched peers to accurately assess the "treatment effects" of the program. Industry, locality, age, and size are the dimensions considered in most studies. Here, industry is classified by two-digit NAICS code and locality by state.[18] The employment size bins are defined as follows: (1) as many as 10 employees, (2) 11 to 50 employees, (3) 51 to 250 employees, (4) 251 to 500 employees, (5) 500-plus employees. Firm age bins are defined as follows: (1) less than 2 years old in 2020 (that is, in the database by March 2020 and started no earlier than 2019), (2) 2 to 10 years old (that is, started between 2011 and 2018), and (3) started no later than 2010.

4 Why Did Firms Borrow from the MSLP?

This section examines the factors, including firm characteristics and economic conditions, that influenced whether a firm obtained an MSLP loan. To set the stage, we first compare the pre-pandemic characteristics of MSLP borrowers with those of firms that were also eligible (based on employee count) but did not borrow. One notable difference is that the MSLP firms were much larger than the other firms (with an average of 102 employees versus 8, respectively), even when differences in location (state), industry (two-digit NAICS), firm-age bin, and the small-business indicator (defined as up to 500 employees) are accounted for, as is evident in the Appendix Table B.2. MSLP firms' higher average employee count was driven by the substantially larger size of those in the top fifth percentile. Nevertheless, the majority of these firms had fewer than 500 employees and thus would have qualified for the PPP. The MSLP firms were also somewhat more established (that is, older by about a year and a half) than the other firms. By contrast, the unconditional distribution of MSLP-borrower risk scores is highly similar to that of non-borrowers.

We next formally test whether MSLP firms had the same risk scores and payment records, on average, as non-borrower firms in terms of both pre–COVID-19 levels (that is, as of March 2020) and the changes over the months (March through June 2020) after the pandemic's onset until the MSLP began operations on July 6, 2020.[19] Table 1 reports these comparisons, equivalent to differences in means, for risk scores, payment records, and employment between MSLP borrowers and all the non-borrowers (in the random sample). Each set of mean comparisons is conditioned on several commonly used key firm attributes. For example, the differences in means reported in column (1) are computed among firms in the same state

[18] These two dimensions became particularly relevant for this episode because the pandemic struck certain industries more severely than others, and social-distancing rules were imposed to differing degrees and at different times across states. Two-digit NAICS codes are used to preserve the sample size of each peer group.

[19] As detailed in Wang, Ballance, and Qing (2021), it makes virtually no difference whether February or March 2020 values are used to measure firms' pre–COVID-19 condition.

as well as the same industry (two-digit NAICS), whereas the mean differences in column (4) are conditioned on all the attributes (that is, being in the same state, industry, age bin, employment-size bin, and 2019 average Viability Score bin, and being a PPP borrower or not).[20]

The MSLP firms had significantly higher CCS scores in March 2020 compared with non-MSLP firms in the same state, industry, age bin, and employment-size bin, with a 17-point higher score mapping into nearly 30 percent lower delinquency risk over the next 12 months. This differential becomes insignificant once the MSLP firms are compared with non-borrowers that are also in the same 2019 average Viability Score bin. The score difference disappears entirely if the comparison is further conditioned on being a PPP borrower or not. Notably, even when conditioned along all these dimensions, the MSLP borrowers still exhibited a significantly larger decline in the CCS after the onset of the pandemic and before the start of the MSLP. This is consistent with the finding that MSLP firms' delinquency records (percentage of debt 31-plus days past due) in March 2020 were slightly better than those of other non-borrower firms when conditioned on all the attributes, but MSLP firms clearly fell behind on paying bills more than non-borrowers over the March–June 2020 period.[21] Likewise, as of March 2020, MSLP firms were much more viable overall, according to the Viability Scores, compared with non-borrower firms in the same state and industry, but that advantage more or less disappears once the comparison is further confined to firms in the same age bin, size bin, etc. MSLP firms showed slightly worse, albeit largely insignificant, deterioration in Viability Scores from March to June 2020 when compared with non-borrowers in the same state, industry, age bin, size bin, etc.

By comparison, MSLP firms displayed clearly greater financial distress risk (that is, a lower average Financial Stress Score (FSS)) before the pandemic compared with non-borrower firms matched along all six dimensions (same state, industry, etc., in column (4) of Table 1) but did not experience worse deterioration in their FSS after the COVID-19 outbreak. One likely explanation for MSLP borrowers' worse FSS is the finding reported in Arseneau et al. (2021) that these firms had higher pre–COVID-19 leverage than other comparable borrowers of the Y-14 banks (that is, those banks that have than $100 billion in total consolidated assets and are subject to the Dodd-Frank Act Stress Tests).

The essentially same overall pattern is confirmed (in Table B.3) if we further restrict the comparison group for each MSLP borrower to only those non-MSLP firms that are in the

[20]Specifically, the mean differences reported in column (1) are computed by first removing the mean value of each variable by state and then by industry.

[21]As defined, the CCS should be most correlated with delinquency records. This is confirmed for the MSLP firms in Wang, Ballance, and Qing (2021) and more generally for all the firms with delinquency data in Joaquim and Wang (2022).

same state and the same two-digit NAICS industry and have the same small-business status (that is, employ no more than 500 workers). With these matched peer firms, it is more natural to also compare the change in risk scores from March 2020 to the month when a borrower's loan was submitted to the MSLP; it is conceivable that the financial condition of MSLP firms that obtained their loans in later months continued to weaken beyond June 2020 relative to the condition of their peers. This conjecture is, in fact, borne out in the data: MSLP borrowers experienced significantly more severe deterioration in their risk profile and payment records over the months after COVID-19 broke out and before they obtained their MSLP loans (see Table B.3).

In sum, these estimates indicate that, on average, MSLP borrowers were in fairly sound condition on the whole before the pandemic, but they were later more adversely affected by the COVID-19 shock than peer firms comparable in terms of the attributes considered in most studies. In particular, the contrast between MSLP firms' FSS and their other two risk scores suggests these firms were commercially viable and able to service their liabilities in a timely manner, but perhaps they were able to finance these expenditures by being more heavily indebted. The cessation of income due to the pandemic would then be more detrimental to these firms, which is consistent with the observed greater deterioration in their risk scores after the COVID-19 outbreak. These findings for nearly all the MSLP firms confirm the findings presented in Arseneau et al. (2021) for a small subset of MSLP firms that also borrowed from the Y-14 banks.[22] This overall pattern is intuitively consistent with the outcome of these firms borrowing from the MSLP: Each was deemed adequately viable to be granted a bank loan but also sufficiently risky that it needed assistance from the MSLP to obtain better terms and perhaps a larger loan.

4.1 Which Factors Predict Firms' MSLP Uptake?

We now formally estimate which factors help predict whether a firm became a Main Street borrower. The patterns uncovered above imply that risky and more adversely affected but still fundamentally sound firms were more likely to seek credit from the MSLP. Guided by this conjecture, intuition suggests that the pandemic wreaked more havoc on these firms in part because of the nature of their operations, as some industries (especially those that rely more on in-person contact, such as leisure and hospitality) suffered more COVID-19–induced disruptions. In the initial phase of the pandemic, normal operations at firms outside the essential industries were relatively more disrupted because of government lockdown orders.

[22] Arseneau et al. (2021) find that Main Street borrowers had higher leverage and lower bank internal credit ratings than other comparable Y-14 borrowers, and their ratings declined more rapidly after their loans were originated.

We thus include indicators that measure whether a firm's industry was deemed essential or especially susceptible to COVID-19–induced disruptions. In addition, a firm's ability to operate could also be undermined by worse local public health conditions and the resulting restraint on economic activity from either mandatory containment measures or voluntary social distancing. We thus also consider indicators of pandemic severity and a broad measure of mobility, which captures the actual level of commercial activity (relative to the pre-pandemic baseline in January and February 2020), whether it was the result of a mandate or voluntary restraint.

Given that many MSLP borrowers were also eligible for the PPP, from which many MSLP firms obtained loans that were expected to be largely forgivable, we include indicators for PPP loan recipients depending on when a PPP borrower received that funding. In light of the analysis by Joaquim and Netto (2021) and Joaquim and Wang (2022), we classify the PPP borrowers into three groups: early (those that received loans before the initial funding ran out), middle (those that received loans after newly appropriated funding arrived on April 27 and through May 2, 2020, when the PPP lending volume slowed to a trickle), and late (all the rest).[23] The unprecedented fiscal support provided to small businesses and households in the wake of the COVID-19 outbreak means that the size of the stimulus received relative to the pre-pandemic size of the local economy likely also mattered for the overall economic condition in a locality. We use the total (normalized) cumulative volume of PPP loans received by July 1, 2020, by small businesses in a county as a summary measure of the level of public-sector assistance delivered to that county.[24] More PPP funding should have reduced the need for businesses to seek additional financing, controlling for local economic and public health conditions. To further capture the potentially differential impact of PPP credit even conditional on the overall volume, we also include the share of PPP funds that were delayed, as proposed in Doniger and Kay (2021), which relies on the volume of PPP loans made in the two days right after the exogenous 10-day window of funding delay from April 17 through April 26, 2020, relative to the two days right before it.[25]

Moreover, findings by previous studies suggest that the structure of the local banking market affects private firms' access to loan financing, particularly the access of small private firms. We thus include the (deposit-volume-weighted) share of bank branches in each county belonging to community banks, which enabled PPP funds to be disbursed more rapidly after

[23] The indicator for PPP eligibility is omitted because it coincides exactly with the above-500-employee indicator.

[24] This amount is normalized by the average monthly payroll expenses in 2019 because of the PPP rule that capped the size of a loan at 2.5 months of a firm's payroll or $10 million.

[25] In fact, Joaquim and Wang (2022) show that this delayed share is the only instrumental variable that retains its explanatory power after firms' pre–COVID-19 financial health is taken into account.

the onset of COVID-19 (as shown, for example, in Faulkender et al., 2021).

In sum, we estimate the following linear probability regression as the main specification:

$$Y_i = \alpha + \mathbf{X}_i\gamma + \mathbf{S}_{i0}\beta_1 + \Delta\mathbf{S}_i\beta_2 + \mathbf{X}_j\kappa + \mathbf{X}_c\theta + \mathbf{X}_{ppp,i}\lambda + \epsilon_i. \quad (1)$$

Y_i is the binary indicator equal to one if firm i was an MSLP borrower and zero otherwise. $\mathbf{X}_i$ refers to a vector of i's nonfinancial attributes, including binned values of its employment and age in March 2020. These and other firm attributes are mostly accounted for by using binned values to allow for potentially nonlinear effects nonparametrically. $\mathbf{S}_{i0}$ denotes a vector of dummy variables based on binned values of i's risk score as of March 2020 or 2019 average. We consider two risk scores in turn: the CCS because of the tight linkage between a firm's near-term delinquency risk and credit availability, and the more comprehensive Viability Score. $\Delta\mathbf{S}_i$ denotes the risk score's change from March to June 2020, measured by quartile-based dummy variables. $\mathbf{X}_j$ includes industry-based indicators: Essentially equal to one if i operated in an essential industry, and Impacted Industry equal to one if 75 percent or more of employment in i's three-digit NAICS industry was deemed substantially or severely impacted by COVID.[26]

$\mathbf{X}_c$ denotes the vector of county-level regressors. First is the Google mobility indexes based on time away from home or time at a workplace (measured as the change relative to January and February 2020), used to measure the de facto level of commercial activity after COVID-19 hit but before the MSLP commenced operations.[27] Missing county-level data are proxied with state-level values. Each index's monthly values from March to June 2020 enter the regression separately to allow for potentially dynamic effects of changes in mobility in a locality on firms' MSLP uptake decisions. Pandemic severity is accounted for by using the county-level COVID-19 death rates (number of new deaths per 1 million population in each month). This should be more accurate than case rates, which depend on the extent of testing. Test rates were low and highly uneven across localities early on in the pandemic. New death rates in each month from March through June 2020 likewise enter the regression separately. $\mathbf{X}_c$ also includes the 2019 community-bank-branch share in each county (CB_{share}).

The linear probability model is estimated using all 1,238 MSLP firms for which there are data along with the random sample of non-borrowers. Each non-borrower observation is thus scaled up to represent the full population of slightly more than 25 million firms in the D&B

[26] The Impacted Industry is a weighted average indicator that equals one if a six-digit NAICS industry was classified as subject to severe or substantial impact from the COVID-19 shock, and zero otherwise, summed up to the three-digit NAICS industry level. The weight is each six-digit NAICS industry's employment share within the three-digit NAICS industry.

[27] The two indexes at the state level have been found to be the most correlated with MSLP uptake (see Bräuning et al., 2021). Their values are highly correlated at the county level as well.

database in March 2020. Clearly, the mean probability of being a borrower is vanishingly small, hence the minuscule magnitude of the coefficient estimates. Like the linear model, Equation (1) is estimated using the rare-event logit regression. See Appendix C for details and output of the logit estimation. By and large, the logit estimates corroborate the linear estimates.

Table 2 reports the estimates of the uptake propensity described in Equation (1), with firms' financial health measured by their CCS.[28] Column (1) considers only the firm financial indicators, assuming that the lenders cared most about potential borrowers' credit risk. Firms with pre–COVID-19 CCS of 300 to 600 (roughly corresponding to the 5^th and 95^th percentiles, respectively) were more likely (by 3 basis points) to obtain MSLP loans than firms with lower (the omitted category) or higher CCS; the higher the CCS within this range, the lower the probability of obtaining an MSLP loan, albeit insignificantly so.[29] CCS changes over the year before the onset of the pandemic are used to gauge whether a firm's pre–COVID-19 trajectory influenced MSLP uptake. Firms that had experienced a 20-plus-point increase or decrease in their CCS (equal to a 25 percent change in delinquency risk) and, to a lesser degree, those that had seen moderately positive changes showed an additional propensity to borrow. But firms with moderately negative or zero changes (the omitted subset) in their CCS did not exhibit such a propensity.

By comparison, large CCS changes (more than 20 points in absolute value) from March to June 2020 were several times more important in boosting the odds of borrowing, while modest CCS changes during the pandemic raised the odds by a margin comparable to large pre–COVID-19 CCS changes. This bimodal pattern of large CCS changes, positive or negative, being associated with a higher probability of borrowing is likely because large changes are correlated with the (unobserved) firm property of being more commercially active and thus receiving larger score updates, as suggested by the correlation between an indicator of large CCS changes and being a relatively large firm and receiving a PPP loan early in the program's operation (see Table B.4 in the Appendix). Overall, however, the CCS-based indicators have rather small explanatory power.

Column (2) adds employment-bin and PPP-timing indicators, and many of them boosted the propensity to borrow much more than the CCS-based variables, the coefficients on which shrink noticeably as a result.[30] In particular, having more than 250 employees exerted the greatest influence, followed by having 51 to 250 employees and receiving a PPP loan early.

[28]Table D.1 in Appendix D presents the estimates using the 2019 average Viability Score to measure firm financial health. The coefficients are highly similar to those from estimates using the CCS.

[29]Separate coefficients for more granular bins are omitted for brevity.

[30]When the other indicators are added, having an excellent pre–COVID-19 CCS (above 600) lowered the odds of borrowing, while all lower scores had no effect on borrowing.

This demonstrates that the MSLP achieved the goal of targeting firms that were too large for the PPP or likely to find the PPP's funding cap binding. At the same time, having access to a PPP loan early, which depended almost entirely on having an existing relationship with at least one bank, further enhanced a firm's chances of receiving a Main Street loan. This highlights the importance of banking relationships in firms' access to government credit-support programs administered through private lenders, given the evidence that early PPP recipients tended to have more established relationships with banks (see, for example, Bartik et al., 2020). It is thus not surprising that firms that had 10 or fewer employees (the omitted category) or received a PPP loan late or not at all (the omitted category) in 2020 were the least likely to borrow from the MSLP.[31] These additional regressors also augment the overall fit of the model by an order of magnitude, although their collective explanatory power is still rather modest.

Column (3) adds the two industry indicators (measuring sensitivity to the pandemic), along with the local mobility index and COVID-19 death rates during the period of April through June 2020. Operating in an essential industry or a county with greater mobility (proxying for more active commerce) was associated with a slightly lower likelihood of MSLP uptake, whereas the industry-level severity of COVID-19's impact or county death rates were insignificant determinants of uptake.[32] Column (4) shows that a higher community-bank-deposit share in the county or a lower share of delayed PPP loans also reduced MSLP uptake.[33] Both indicators likely serve as proxies for the importance of early injection of PPP liquidity for small businesses' survival.[34] Perhaps not surprisingly, columns (3) and (4) also make clear that despite the relevance of several industry- or county-level indicators, they add little to the model's fit beyond the firm-level attributes' contribution.

Discrete-Time Hazard Model of MSLP Uptake

Main Street loans were granted over a six-month period. To account for the timing of each loan, we next estimate a discrete-time hazard model that explains the probability of

[31]Small firms found it more difficult to access the MSLP because of the certification requirement (see Arseneau et al., 2021). Few truly small businesses borrowed because the minimum loan size was reduced from $250,000 to $100,000 in October 2020, leaving little time for such firms to complete the underwriting process before the program's deadline.

[32]The sum of the coefficients on the mobility index is reported in the bottom portion of Table 2, while the (insignificant) sum of the coefficients on death rates is omitted to save space.

[33]We also added the normalized cumulative PPP loan amount through June 2020 but found that it was insignificant and therefore omitted it for space.

[34]Granja et al. (2020) show that community banks were crucial to PPP lending early on, while Doniger and Kay (2021) document the impact of delays in obtaining PPP loans on local employment.

a firm receiving a Main Street loan in a particular month (conditional on the firm having not borrowed until then), instead of just the cross-section probability of being an MSLP borrower, as in Equation (1). Specifically, we estimate the following linear model on suitably organized panel data of (the random sample of) the size-eligible firms:[35]

$$Y_{it} = \eta_t + \mathbf{S}_{i0}\beta_1 + \Delta\mathbf{S}_{i,t-1}\beta_2 + \mathbf{X}_j\gamma + \mathbf{X}_{c,t-1}\theta + \mathbf{X}_{ppp,i}\lambda + \epsilon_{it}. \tag{2}$$

$Y_{it} = 0$ if in month t firm i did not borrow; $Y_{it} = 1$ otherwise, which is also the last observation in the time series for a borrower, since it is the last period the firm was "at risk."[36] η_t traces out a nonparametric baseline hazard with t indexing the periods over which the event may occur, which in this setting spans July through December 2020. $\Delta\mathbf{S}_{i,t-1}$ denotes the (binned) change in i's risk score from March 2020 to the month before the MSLP loan submission, while $\mathbf{X}_{c,t-1}$ denotes the average economic or public health conditions over the same time period, again approximated using the mobility index and COVID-19 death rates, respectively. $\mathbf{S}_{i0}$, $\mathbf{X}_j$, and $\mathbf{X}_{ppp,i}$ are the same set of time-invariant regressors as defined in Equation 1.

Table 3 reports the estimates of the linear hazard model. The coefficients clearly exhibit patterns similar to those from the static probability model above, with just a few noteworthy differences. Firms with a pre-pandemic CCS of 300 to 400 (below the 5^{th} percentile) now show a small but statistically significant higher propensity to borrow. With the COVID-19–period CCS change measured from March 2020 to the month immediately before the loan submission, arguably the more relevant period for each borrower, only firms that suffered a CCS decline of more than 20 points were more likely to borrow. The new definition also boosts the collective explanatory power of the CCS-based regressors by a fair margin. Mobility in the county becomes insignificant, its explanatory power likely taken over by the COVID-19–period CCS change defined over the more relevant months.[37]

In sum, the probability models paint a consistent picture: Being a midsize firm and having prior banking relationships were the most important predictors of MSLP uptake. This signifies the success of Main Street's design to target firms in danger of falling through the cracks of the other public-support programs. It also highlights the importance of prior banking relationships along with the potential drawbacks of implementing a lending program through banks. Having poor to mediocre pre-pandemic risk scores and suffering a large

[35] As Allison (1982) shows, a logit probability regression using properly organized panel data can be interpreted as a discrete-time hazard model: For every subject, there are as many observations as there are number of periods when a unit is at risk of the event. A logit model corresponds to assuming a proportional odds ratio, and it closely approximates proportional hazards if the hazard is low.

[36] The probability of borrowing more than one loan is ignored given the exceedingly small fraction of such borrowers.

[37] The industry-level pandemic impact, COVID-19 death rates, and cumulative PPP loan amount through June 2020 remain insignificant.

increase in delinquency risk also contributed to the propensity to borrow. These results confirm that Main Street also succeeded in reaching firms that were more disrupted by the pandemic, but the program's design features, including a uniform interest rate and a relatively high ceiling on the leverage ratio, attracted more risky firms as well, which is consistent with the findings in Arseneau et al. (2021).

5 The MSLP Helped Shore Up Firm Financial Health

In this section, we document how receipt of an MSLP loan and the receipt's timing affected the borrower's financial condition. Precisely speaking, receipt of an MSLP loan in 2020 is a staggered treatment even at the quarterly frequency, since the MSLP operation spanned the last two quarters of 2020 (from July 6 through December 31). A burgeoning body of work demonstrates that the standard two-way fixed effects (TWFE) estimations applied to staggered treatments can potentially lead to nontrivial biases.[38] The cause of biases highlighted in this literature is likely minor in our setting because the never-treated group accounts for the overwhelming majority of the sample.

Nevertheless, we apply the method of Callaway and Sant'Anna (2021) to derive a more precise nonparametric estimate of the treatment effects of receiving MSLP loans. This enables us to not only account for the staggered design, but also provide a consistent aggregation of the coefficients estimated for firms receiving loans in different quarters. We specifically apply the doubly robust (dr) estimand as follows:[39]

$$ATT_{dr}(c,t) = \mathbb{E}\left[\left(\frac{G_c}{\mathbb{E}(G_c)} - \frac{\frac{p_c(X)N}{1-p_c(X)}}{\mathbb{E}\left[\frac{p_c(X)N}{1-p_c(X)}\right]}\right)\left(y_{f,t} - y_{f,c-1} - m^{nev}_{c,t}(X)\right)\right], \tag{3}$$

where $y_{f,t}$ is an outcome y of firm f in quarter t, and $y_{f,c-1}$ is its outcome in the quarter immediately before the treatment. G_c is an indicator equal to one if the firm was treated in quarter c and zero otherwise. The treatment quarter also defines the cohort: Cohort c

[38] The basic intuition is that, with staggered treatment, in some periods the comparison group for a newly treated cohort includes units that have been treated earlier, but this is not accounted for by the TWFE estimator, leading to biased estimates of treatment effects. See, for instance, Sun and Abraham (2021), Callaway and Sant'Anna (2021), and Baker et al. (2022). Roth et al. (2022) offer an excellent review of the literature.

[39] It is an adaptation of Equation (2.4) in Callaway and Sant'Anna (2021), which applies to settings with a never-treated group, under the assumption that there is no anticipation effect. This can be justified by the argument that firms could not take action in anticipation of receiving MSLP loans because not only was the approval uncertain, but also they could not pay their bills or employees (which would improve their CCS) until they received the funds. This doubly robust estimand is robust to misspecifications of either the propensity score or the conditional expectation of the outcome of the comparison group.

refers to all the constituent firms that received MSLP loans in quarter c. N is the indicator equal to one if the firm did not borrow (that is, never treated). $p_c(X)$ is the propensity score for being treated in quarter c, that is, $p_c(X) = P(G_c = 1|X, G_c = 1 or G_i = \infty)$. $m^{nev}_{c,t}(X) = \mathbb{E}[y_{f,t} - y_{f,c-1}|X, N = 1]$ denotes the mean change in outcome for non-borrower firms from quarter t to the pre-treatment quarter for cohort c. X denotes the vector of all the control variables, which enter as fixed effects here.

Empirical estimates of $ATT_{dr}(c,t)$, denoted $\widehat{ATT}_{dr}(c,t)$, are obtained in two steps. First, we estimate $p_c(X)$ with a parametric (logit) model and $m^{nev}_{c,t}(X)$ with a linear regression, both of which take X as the covariates.[40] The fully saturated specification includes these fixed effects in X: firm, state-time, industry-time, age-bin-time, employment-bin-time, time interacted with the firm's 2019 average Viability Score (VS), and the binned value of the VS Point change from March 2020 to the month just before the loan submission. Second, we plug the fitted values ($\hat{p}_c(X)$ and $\hat{m}^{nev}_{c,t}(X)$) into Equation (3) to derive the sample analog $\widehat{ATT}_{dr}(c,t)$. Note that for $\widehat{ATT}_{dr}(c,t)$ to identify the treatment effect of Main Street, we need only the assumption of a parallel trend in the *absence* of a treatment between the borrowers and the non-borrowers *after* the treatment quarter (that is, Assumption 4 in Callaway and Sant'Anna (2021)). It imposes no condition on the evolution of a variable for borrowers relative to non-borrowers *before* the treatment time. Hence, any non-parallel trend before the onset of the pandemic does not per se invalidate the treatment effect estimates. On the other hand, the presence of a parallel pre–COVID-19 trend provides supporting evidence for the assumption of a parallel (non-treatment) trend after the treatment time.

We present the dynamic treatment effects by the relative quarter (typically referred to as event time) τ with $\tau = t - c$, that is, indexed by the number of quarters after receipt of an MSLP loan. Figure 1 depicts the estimated $\widehat{ATT}_{c,\tau}$ for the CCS (panel (a)) and employment (panel (b)).[41] Panel (a) shows that both cohorts of Main Street borrowers exhibited an essentially parallel pre-pandemic CCS trend relative to non-borrowers, except for a noticeable decline in CCS in the quarter just before they received loans. Receiving an MSLP loan was then associated with progressive increases in CCS over the four quarters afterward, reaching 15 and 10 points higher after four quarters for the 2020:Q3 and 2020:Q4 cohorts of borrowers, respectively.[42] The CCS increases in the third and fourth post-borrowing quarters are significant for the 2020:Q4 cohort because of the much larger number of borrowers (due to

[40] $\mathbb{E}(Z) = n^{-1}\sum_{i=1}^{n} Z_i$ for any variable Z.

[41] All the estimates in this section are produced using the DiD package in R created by Brantly Callaway and Pedro Sant'Anna; see https://cran.r-project.org/web/packages/did/.

[42] These gains correspond to 23 and 16 percent reductions in delinquency risk, respectively. In the pre–COVID-19 period, the average within-firm standard deviation in CCS is 9. Thus, MSLP receipt is associated with a CCS increase that is 1.1 to 1.7 times the within-firm standard deviation.

the surge in December) and hence smaller standard errors, but the increase is only marginally significant for the 2020:Q3 borrowers in the fourth quarter after loan receipt.[43]

Likewise, Main Street also appears to have boosted both borrower cohorts' employment by noticeable margins in the third and fourth quarters after loan receipt, although none of the increases is statistically significant (shown in panel (b) of Figure 1). This lack of significance may stem in part from greater measurement errors in the employment data, which are exacerbated in changes over a relatively brief period.[44] It is also plausible that more time is needed for the effect of Main Street funding to manifest in employment since the economy was not yet fully recovered from the pandemic disruptions in 2021, including the shortfall in labor supply that has constrained employment growth. The labor shortage will likely take some time to abate. In principle, because the liquidity injection from Main Street put MSLP borrowers on sounder financial footing, they should be in a more advantageous position to exploit growth opportunities as the economy continues to normalize.

Estimates of $\widehat{ATT}_{c,\tau}$ for Viability Scores and FSS are presented in Appendix E. Main Street funding brought about improvement in these two financial indicators as well, albeit not as notably as for the CCS, consistent with our earlier conjecture that the liquidity injection would most likely manifest in better payment performance and hence lower borrowers' delinquency risk. In Appendix F, we also consider the Sun and Abraham (2021) estimator for staggered treatments to corroborate the findings using the Callaway-Sant'Anna estimator and to explore the relative contribution of firms' pre-MSLP-borrowing financial and nonfinancial attributes to the estimates. The overall finding is that these two estimators yield fairly similar estimates of Main Street's effects, although accounting for a firm's propensity to borrow is important for tight matching between borrowers and their most comparable non-borrowers to minimize different pre-trends between borrowers and their peers.

In sum, we find generally robust evidence that Main Street credit helped borrowers improve their financial health—reducing their delinquency risk in particular—over the four quarters after they received a loan. By comparison, there is only suggestive evidence that the program also enabled borrowers to recover their employment over the same period. So it appears that Main Street, at the very least, achieved its goal of bridging the COVID-19–induced liquidity gap and thus placed firms on more solid financial footing. All else being equal, the more adequate liquidity should enable these firms to take advantage of growth

[43]The average treatment effect $\widehat{ATT}_{dr}(\tau)$ across cohorts (c) in a given quarter τ is fairly close to that for the 2020:Q4 cohort because of its dominating sample size.

[44]See Appendix A and Wang, Ballance, and Qing (2021) for more details. Despite the inadequacies of D&B employment data, there is no strong reason to suspect that the data shortcomings should bias the estimates instead of just compromising the precision. Moreover, assessing the impact of Main Street on employment is an important element for analyzing the policy. We therefore choose to use the employment data.

opportunities in the coming years as the economy continues to recover from pandemic-induced dislocations.

6 Concluding Thoughts

Using a comprehensive database of businesses' financial condition, this study compares firms that borrowed from the Main Street Lending Program with their peers to understand which attributes and circumstances made it more likely for firms to seek Main Street credit and how the program benefited them afterward. The patterns that emerge are broadly consistent with the targeting and objective of the MSLP. In line with the program's targeting, midsize firms (those with 250 to somewhat more than 500 employees) exhibited the highest probability of becoming borrowers. On the other hand, several of the program's design elements appear to have made it notably harder for firms with fewer than 10 employees to borrow. Being an early recipient of a 2020 PPP loan raised the likelihood that a firm would borrow by a nontrivial margin, confirming the importance of preexisting banking relationships, as well as these firms' need for funding to weather the COVID-19 shock to their liquidity. This interpretation is further supported by the fact that a considerable fraction of MSLP borrowers also received second-draw PPP loans in 2021.

As conjectured, firms with moderately low risk just prior to the COVID-19 outbreak were more likely to borrow compared with riskier firms, while the safest firms were the least likely to borrow. Changes in risk scores reveal a pattern that MSLP borrowers tended to be firms with better prospects but that had suffered worse disruptions due to the pandemic. Local economic environments also exerted mild influence over a firm's probability of borrowing in ways consistent with intuition. Better county economic conditions and a larger presence of community banks reduced the odds of borrowing, as did operating in an essential industry. Having more PPP loans in a county delayed by the funding hiatus made it more likely for firms in that county to borrow from Main Street.

Based on a doubly robust estimator tailored to staggered treatments, Main Street is estimated to have led to progressive and significant improvement in recipient firms' financial health over the year after they received a loan. In particular, the reduction in their delinquency risk reached nearly 18 percent four quarters after loan receipt. This constitutes evidence that the MSLP achieved the objective of shoring up the liquidity position of firms that had promising prospects but were hit hard by the pandemic. By comparison, employment at MSLP firms recovered slightly better than at their peer firms over the same period after borrowing, but the difference was barely significant. Apart from the noise in the employment data, full recovery may require more time, especially considering the labor market tightness in general. To the extent that firms in a better liquidity position can more readily take advantage of growth opportunities, these borrowers should be able to expand operations more easily as the economy continues to normalize over the coming quarters.

The general pattern that emerges from the findings is that Main Street borrowers were, on average, more commercially active and viable before COVID-19 hit, but they were more adversely affected by the pandemic and thus suffered a worse short-term liquidity shortage. The combination of these conditions made these firms suitable recipients of Main Street loans. Their promising long-term prospects made the lending relationship valuable to their banks. The onset of the pandemic, however, rendered the firms more risky, at least temporarily. Therefore, the banks turned to the MSLP to fund the loans, as the program likely enabled them to offer lower rates or lend larger amounts, or both, than they would have had they used solely their own capital. For the firms that were eligible for the PPP but required more funding, Main Street helped make up for the shortfall. For those too large to qualify for the PPP, Main Street filled the gap, as intended. The additional credit or lower rates should enhance MSLP firms' odds of survival and a more robust recovery, enhancing the relationship value to the banks.

The analytical results here support the argument that, despite the various challenges, a program like the MSLP following major disruptions to the economy can confer substantial real economic benefits by providing the bridge funding to firms that have good prospects but are suffering from short-term liquidity shortages. More time is needed to assess the medium-term efficacy of Main Street, especially in terms of promoting real growth. In addition, more analysis remains necessary to gain a better understanding of the attributes that identify firms with greater growth potential and design a program accordingly to encourage their participation. This will reduce the chances of offering cheap credit to fundamentally nonviable firms that enables them to linger longer than they would otherwise, which could discourage the entry of new, more promising firms. Additional analysis of the MSLP can thus help make a similar lending program in the future more efficient in terms of funding and more effective in terms of providing an economic stimulus.

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Table 1: Comparison of Pre-COVID Characteristics: MSLP Borrowers versus All Non-Borrowers

Attribute	(1)	(2)	(3)	(4)	Min. Obs.
CCS Points (2020M3)	17.033	8.258	4.309	-0.198	485,378
	(0.001)	(0.031)	(0.153)	(0.944)	
CCS Change (2020M3–2020M6)	-5.557	-4.710	-4.545	-4.760	480,890
	(0.024)	(0.041)	(0.06)	(0.042)	
FSS Points (2020M3)	-0.918	-9.711	-11.629	-15.088	485,303
	(0.802)	(0.001)	(0)	(0)	
FSS Change (2020M3–2020M6)	-0.606	-0.159	-0.356	-0.911	480,829
	(0.536)	(0.859)	(0.715)	(0.327)	
Viability Points (2020M3)	20.057	2.473	3.267	-0.798	489,971
	(0)	(0.329)	(0.011)	(0.465)	
Viability Change (2020M3–2020M6)	-0.833	-0.571	-0.488	-1.236	485,529
	(0.038)	(0.176)	(0.462)	(0.057)	
% Debt 31+ Days Past Due (2020M3)	-0.003	-0.009	-0.023	-0.014	117,622
	(0.67)	(0.172)	(0.001)	(0.029)	
% Change Past Due (2020M3–2020M6)	0.038	0.036	0.034	0.036	107,792
	(0)	(0)	(0)	(0)	
Conditioning Variables	–	–	–	–	
State	Yes	Yes	Yes	Yes	
Industry	Yes	Yes	Yes	Yes	
Firm Age Bins	No	Yes	Yes	Yes	
Employement Bins	No	Yes	Yes	Yes	
Viability Score Bins (2019)	No	No	Yes	Yes	
PPP Indicator	No	No	No	Yes	

Note: This table compares the average value of firm attributes among MSLP borrowers versus all the other firms that were eligible (based on employee count) but did not borrow from the MSLP. The conditional mean differences are reported, along with the p values of the equal-mean test in parentheses. The mean difference for each attribute is computed by regressing that attribute on a set of binary indicators for the conditioning variables, along with the MSLP borrower indicator, whose coefficient then measures the mean difference between MSLP borrowers and the other firms while controlling for the conditioning variables. The conditioning variables for each set of mean comparisons (organized by column) are reported in the bottom block of the table. "Min. Obs." lists the minimum number of observations among the four sets of mean differences reported in each row, universally corresponding to column (4). There are generally around 5% more observations underlying results in columns (1) and (2). Source: D&B and author's calculations.

Table 2: Probability of Firm MSLP Uptake: Financial Health Based on CCS

	(1)	(2)	(3)	(4)
CCS Range (300,600]	0.0003***	−0.00001	0.00000	0.00001
	(0.0001)	(0.00005)	(0.00005)	(0.0001)
CCS >600	0.0001	−0.0004***	−0.0004***	−0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
CCS Change Pre <-20	0.0002***	0.00004	0.00005*	0.00005*
	(0.00005)	(0.00003)	(0.00003)	(0.00003)
CCS Change Pre [-20,0)	−0.00000	0.00001	0.00002*	0.00002**
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
CCS Change Pre (0,20]	0.0001***	0.0001***	0.0001***	0.0001***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
CCS Change Pre >20	0.0003***	0.0002***	0.0002***	0.0002***
	(0.0001)	(0.00004)	(0.00004)	(0.00004)
CCS Change Covid <-20	0.001***	0.0004***	0.0004***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
CCS Change Covid [-20,0)	0.0001**	0.00003	0.00003	0.00003
	(0.00003)	(0.00002)	(0.00002)	(0.00002)
CCS Change Covid (0,20]	0.0002***	0.00005***	0.00004***	0.00004**
	(0.00003)	(0.00002)	(0.00001)	(0.00001)
CCS Change Covid >20	0.001***	0.0002***	0.0002***	0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PPP Early		0.002***	0.002***	0.002***
		(0.0005)	(0.0005)	(0.0005)
PPP Mid		0.0004***	0.0004***	0.0004***
		(0.0001)	(0.0001)	(0.0001)
PPP Late		0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)
Emp. [11, 50]		0.001***	0.001***	0.001***
		(0.0002)	(0.0002)	(0.0002)
Emp. [51,250]		0.003***	0.003***	0.003***
		(0.001)	(0.001)	(0.001)
Emp. [251,500]		0.006***	0.006***	0.006***
		(0.002)	(0.002)	(0.002)
Emp. >500		0.005***	0.005***	0.005***
		(0.002)	(0.002)	(0.002)
Essential Industry			−0.0001*	−0.0001*
			(0.0001)	(0.0001)
COVID Impacted			0.0001	0.0001
			(0.0001)	(0.0001)
Community Bank Share				−0.0002*
				(0.0001)
PPP Loans Share Delayed				0.0005**
				(0.0002)
Sum mobility coefs (p val)	–	–	-0.002 (0.091)	-0.002 (0.081)
Observations	418,995	418,995	418,995	418,995
Adjusted R^2	0.0003	0.003	0.003	0.003

Note: This table reports coefficients from Equation (1). CCS Range and Employment (Emp.) bins: as of 2020:M3. CCS Change Pre: binned values of CCS change 2019:M3–2020:M3. CCS Change Covid: binned values of CCS change 2020:M3–2020:M6. PPP Early, Mid, Late: Indicator if a firm received PPP loans before April 16, April 27 to May 2, and after May 2, 2020, respectively. See text for the other variables' definitions. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Source: D&B and author's calculations.

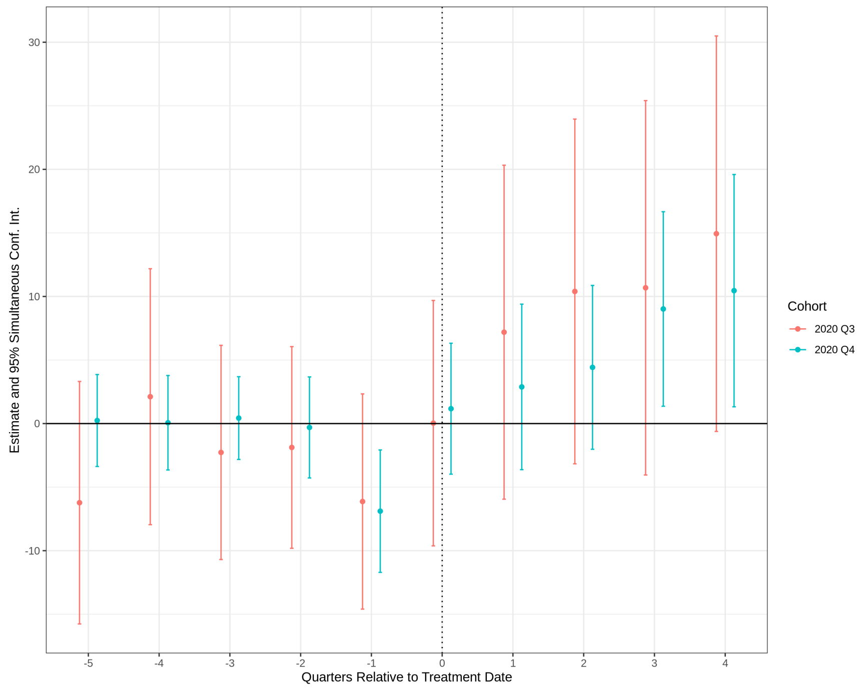
Table 3: Discrete-Time Hazard Model of Firm MSLP Uptake

	(1)	(2)	(3)	(4)
M3 CCS Range (300,400]	0.0004***	0.0001**	0.0001**	0.0001**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
M3 CCS Range (400,600]	0.0002***	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
M3 CCS >600	0.0001	−0.0004***	−0.0004***	−0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
CCS Change Pre <-20	0.0002***	0.0001*	0.0001**	0.0001**
	(0.0001)	(0.00003)	(0.00004)	(0.00004)
CCS Change Pre [-20,0)	0.00000	0.00002*	0.00002**	0.00002**
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
CCS Change Pre (0,20]	0.0001***	0.0001***	0.0001***	0.0001***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
CCS Change Pre >20	0.0003***	0.0002***	0.0002***	0.0002***
	(0.0001)	(0.00004)	(0.00004)	(0.00004)
CCS Change Covid <-20	0.001***	0.0003***	0.0003***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
CCS Change Covid [-20,0)	−0.00001	−0.00002	−0.00002	−0.00002
	(0.00001)	(0.00001)	(0.00002)	(0.00001)
CCS Change Covid (0,20]	0.0001***	−0.00003	−0.00003	−0.00004
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
CCS Change Covid >20	0.0004***	0.0001	0.0001*	0.0001
	(0.0001)	(0.00003)	(0.00003)	(0.00003)
PPP Early		0.002***	0.002***	0.002***
		(0.0005)	(0.0005)	(0.0005)
PPP Mid		0.0004***	0.0004***	0.0004***
		(0.0001)	(0.0001)	(0.0001)
PPP Late		0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)
Emp. [11,50]		0.001***	0.001***	0.001***
		(0.0002)	(0.0002)	(0.0002)
Emp. [51,250]		0.003***	0.003***	0.003***
		(0.001)	(0.001)	(0.001)
Emp. [251,500]		0.005***	0.005***	0.005***
		(0.002)	(0.002)	(0.002)
Emp. >500		0.005***	0.005***	0.005***
		(0.002)	(0.002)	(0.002)
Essential Industry			−0.0001*	−0.0001*
			(0.00005)	(0.00005)
Community Bank Share				−0.0004**
				(0.0002)
PPP Loans Share Delayed				0.001**
				(0.0002)
Observations	2,491,824	2,491,824	2,491,824	2,491,824
Adjusted R^2	0.001	0.003	0.003	0.003

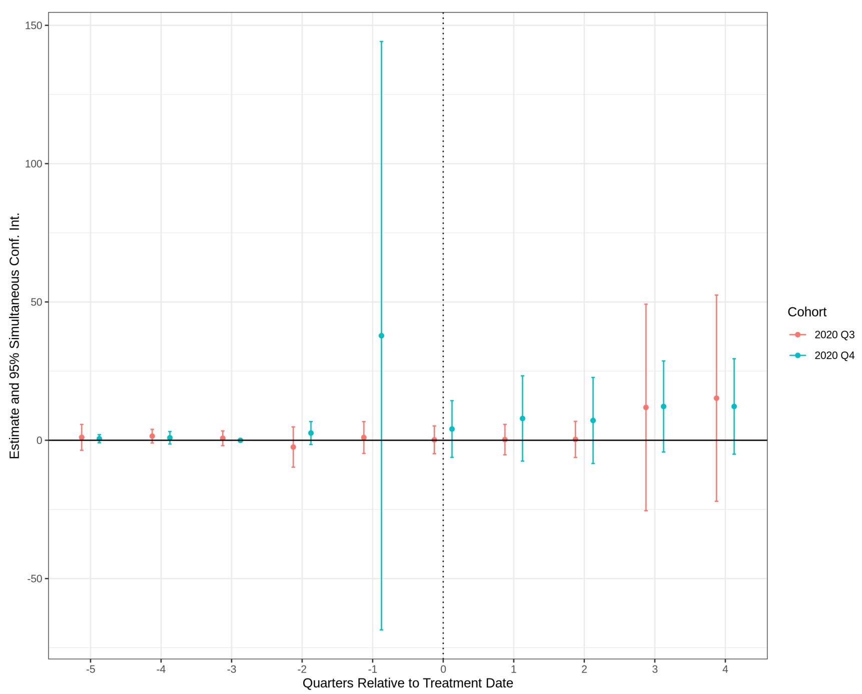
Note: This table reports coefficients from Equation (2). M3 CCS Range and Employment (Emp.) bins: as of 2020:M3. CCS Change Pre: binned values of CCS change 2019:M3–2020:M3. CCS Change Covid: binned values of CCS change 2020:M3–MSLP submission month. PPP Early, Mid, Late: Indicator if a firm received PPP loans before April 16, April 27 to May 2, and after May 2, 2020, respectively. See text for the other variables' definitions. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Source: D&B and author's calculations.

Figure 1: Effects of the MSLP on Firm Commercial Credit Score and Employment

(a) MSLP Effects on CCS



(b) MSLP Effects on Employment



Note: This figure depicts the dynamic effects of the staggered treatment of MSLP loans on borrowers' Commercial Credit Score (top panel) and employment (bottom panel), estimated using the doubly robust DiD estimator à la Callaway and Sant'Anna (2021). Source: D&B and author's calculations.

Part I

Online Appendix — Not For Publication

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A Dun & Bradstreet Database

Employment

D&B offers two types of data on firm employment: (1) actual employee count for a firm, either directly reported by the firm or gleaned from other sources, and (2) modeled (imputed) employment, which is estimated using D&Bs proprietary model along with other data items D&B collects on the firm. Around 25 percent of the firms report actual employment.[1] Note, however, that the actual employment data are updated only with a lag and often at different times for different firms, or even any given firm, depending on the arrival of new information. This means that the actual employment may be out of date to varying degrees across firms. The general pattern is that the smallest businesses (especially those with fewer than 10 employees) and young businesses (those established in 2017 or after) are more likely to have only estimated or modeled values for employment (as documented in Wang, Ballance, and Qing, 2021). To maximize the sample size, we thus use all the firms with any type of employment data in our baseline analysis. In unreported results, we compare estimates for firms with actual versus modeled employment and find that in general the former are more creditworthy but do not exhibit significantly different dynamics since COVID-19 hit.

As documented in Wang, Ballance, and Qing (2021), more than a third of the firms were ranked in the highest decile by employee count in March 2020 relative to other firms in the same state and three-digit NAICS industry. Also, compared with such peers as of March 2020, nearly a third of them were ranked in the lowest decile and another 20 percent in the second-lowest decile. Overall, nearly 40 percent of the firms have been established within the last 10 years. In the D&B population of firms, firm size and age are broadly positively correlated. So, it seems that, controlling for size just before the pandemic hit, a fraction of MSLP firms had experienced faster growth relative to their peers.

Risk Scores

We consider the three major risk scores compiled by D&B, all of which are modeled to be predictive indicators. The granular raw points for every score is structured as it is for consumer credit scores, so a higher value signifies lower risk. Among these, the most comprehensive are Viability Points, which range from 101 to 800. They assess a business's overall likelihood of going out of business (which includes becoming inactive or filing for bankruptcy) over the next 12 months. We use the Viability Points discretized counterpart—Viability Score—in most analyses because this is more widely used by creditors.[2] The Com-

[1] D&B makes no distinction between full- and part-time employees, and the data are best regarded as roughly full-time-equivalent employees.

[2] This score also contains descriptive components pertaining to the quantity of predictive data available

mercial Credit Score (CCS, also known as the Delinquency Score), ranging from 101 to 670, predicts the likelihood of a business having a severely delinquent account (91-plus days past due) over the next 12 months.[3] The Financial Stress Score (FSS, also known as the Failure Score), ranging from 1,001 to 1,875, predicts the likelihood over the next 12 months that a business will incur financial distress (such as ceasing operations, leaving unpaid obligations to creditors, or moving into receivership) or file for bankruptcy. As an example, Figure A.1 depicts the range of Viability Scores (from the 10th to the 90th percentiles) for MSLP borrowers from January 2020 onward. The figure shows that the scores generally peaked around March 2020 and then declined visibly among the top percentiles.[4]

Payment Records

The last set of variables record the degree of a business's payment delinquency, if any, over the past 3 to 24 months (depending on the variable). We focus on the more timely records over the past three months. We examine the portion of the total amount owed over the most recent three months that is 31-plus, 61-plus, or 91-plus days past due.[5] As shown in Wang, Ballance, and Qing (2021), the share of firms with bills 31-plus days past due rose after the March–April 2020 period and mostly peaked in July 2020, followed by a modest improvement (that is, a decline) in July among firms with visibly higher than average shares (whereas those with the most serious delinquency level had their portion of bills that were 31-plus days past due stuck at 1).[6]

As a sufficient statistic of these indicators for how punctually a business has been paying its bills, D&B compiles the Paydex score. The most commonly used version of Paydex is based on payment behavior over the past 24 months. A value of 80 or above means a firm pays on time, 70 equals 15 days beyond terms, 60 equals 22 days beyond terms, 50 equals

to make a reliable risk assessment, as well as the market segment for each firm based on its age, size, and quantity of data signals. These are not used because we apply our own grouping criteria.

[3] The marginal odds of being a good risk doubles for each 40-point increase. This also applies to the Financial Stress Score described next.

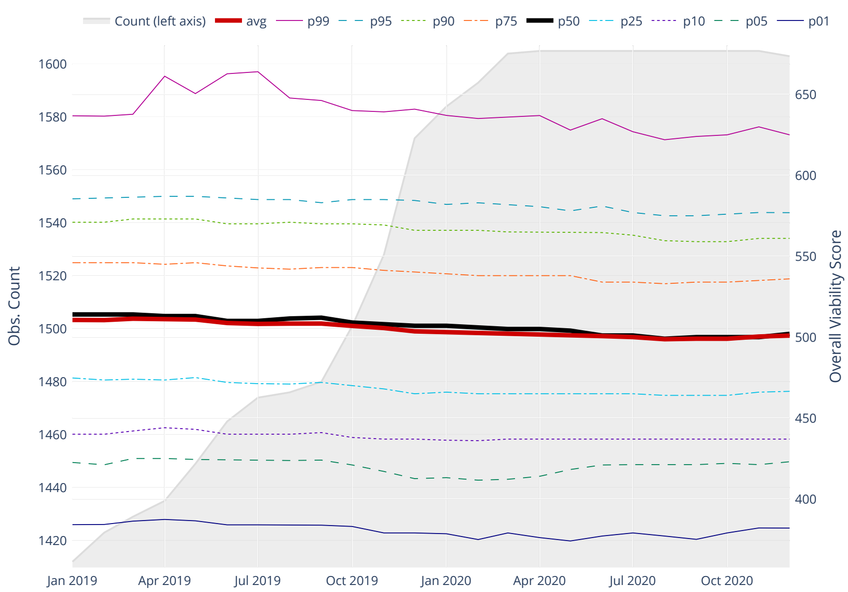
[4] The distributional patterns of the time series of these risk scores from January 2020 onward for all the firms in our internal D&B data are broadly similar. In fact, this holds for basically all the variables analyzed here. A few minor exceptions are the past due variables, where the highest percentiles of the distribution tend to take the value of one throughout the sample months.

[5] To supplement these near-term records that are based on the amount owed on bills that are due, in unreported results we also looked at a measure based on the number of accounts (the highest ratio of the cumulative number of accounts reaching 31-plus days past due divided by the cumulative total number of active accounts for the most recent month and three months prior) and how persistent a firm's trouble in paying bills had been (the portion of months over the last 12 months with reported data that contain a balance that is 31-plus or 61-plus days past due).

[6] The pattern is broadly similar for the portion of bills that were 61-plus and 91-plus days past due, although the share reporting zero is higher.

30 days beyond terms, 40 equals 60 days beyond terms, 30 equals 90 days beyond terms, 20 equals 120 days beyond terms, and 0 equals 180-plus days beyond terms. If a Paydex score is missing, it is due to an insufficient number of qualified trade experiences. This score thus is available for many more firms than the number of firms that have data for recent (over the past three months) payment records, even though it is less available than the three risk scores.[7] The 24-month Paydex is available for 90 percent or so of the firms since January 2020 in our downloaded data set, whereas payment records over the last three months are available for only about one-third of the firms. Unlike the forward-looking risk scores, the commonly referenced Paydex score is backward-looking, based on a firm's past payment records.

Figure A.1: Viability Score Points, MSLP Borrowers, 01/2019 to 12/2020



Note: Number of MSLP firms in the sample (light gray shading) on the left scale; monthly value at selected percentiles along with the mean value on the right scale. Source: D&B and author's calculations.

[7]The Paydex score is available only for firms with three or more payment experiences from at least two trade providers, and some firms do not satisfy this condition even over a 24-month period.

B Main Street Lending Program and Identifying Borrowers in the D&B Database

Main Street Lending Program

Several facilities were established under the MSLP to offer different parameters and loan features that would meet the diverse needs of small and midsize businesses. Secured or unsecured "new loans" with principal as high as $35 million were available for borrowers with an *adjusted* debt-to-EBITDA ratio (inclusive of the Main Street loan) as high as 4. "Priority loans" or "expanded loans" were available for borrowers with an adjusted debt-to-EBITDA ratio as high as 6 in amounts of as much as $50 million or $300 million, respectively, but these loan types came with more stringent security and bankruptcy priority requirements. Except for loans made under the Priority Loan Facility—and only at the time of origination—no MSLP loans could be used to refinance existing debt owed to lenders other than the MSLP lender. Moreover, borrowers had to "refrain from repaying the principal balance of, or paying any interest on, any debt" until the MSLP loan was repaid in full, "unless the debt or interest payment is mandatory and due." These covenants would not prohibit borrowers from repaying a line of credit, taking on and paying additional debt obligation in the normal course of business, or refinancing debt that was maturing in no more than 90 days.[8]

All the facilities featured an interest rate of LIBOR plus 300 basis points (bps) and a maturity of five years, as well as the deferral of principal payments and interest payments for two years and one year, respectively. The minimum loan size was initially set at $250,000 for all the facilities, but it was later lowered to $100,000 in October 2020 to better accommodate very small businesses. Moreover, all MSLP loans required the lender, which collected an origination fee and loan servicing fees, to retain 5 percent of the loan balance, while the Main Street Special Purpose Vehicle (SPV) purchased the remaining 95 percent at par.[9]

When the MSLP ended on January 8, 2021, it was the largest debt-purchase facility and the fastest growing in the second half of 2020 among all Federal Reserve debt-purchase facilities established in response to the COVID-19 pandemic (see Morgan and Clampitt, 2021). The program extended a total of $17.5 billion in credit to nearly 2,500 borrowers across virtually all the states. The volume of loans purchased by the MSLP grew more or less steadily over time through the end of November 2020, followed by a surge in the first half of December, after the US Treasury Secretary announced that the program would not

[8] See FAQs posted on the Federal Reserve Bank of Boston MSLP site https://www.bostonfed.org/-/media/Documents/special-lending-facilities/mslp/legal/frequently-asked-questions-faqs-post-termination.pdf.

[9] All vintages of the Main Street term sheets, which detail the parameters for each facility and their evolution over time, can be found on this official program page: https://www.federalreserve.gov/monetarypolicy/mainstreetlending.htm

Table B.1: Summary Statistics of Total Main Street Lending Activity

	Total Volume ($ Millions)	N. Loans	N. Borrowers	N. Lenders	Principal Loan Amount ($ Millions)							
					Mean	Min	p10	p25	p50	p75	p90	Max
All Facilities	17,459	1,830	1,815	319	9.5	0.1	0.7	1.5	4.0	10.6	25.0	300.0
MSELF	1,805	26	26	16	69.4	10.0	11.0	22.0	40.5	90.0	148.0	300.0
MSNLF	2,695	616	608	149	4.4	0.1	0.4	0.8	2.0	4.5	10.0	35.0
MSPLF	12,917	1,173	1,166	258	11.0	0.1	1.1	2.4	6.0	14.8	30.0	50.0
NONLF	42	15	15	13	2.8	0.2	0.4	0.6	2.5	5.0	5.0	8.5

Note: MSELF stands for Main Street Extended Loan Facility; MSNLF stands for Main Street New Loan Facility; MSPLF stands for Main Street Priority Loan Facility; and NONLF stands for Nonprofit Organization Loan Facilities (pooling loans in the New Loan and Extended Loan Facilities). Source: Main Street public-release data.

be renewed beyond December 31, 2020.[10]

Overall, the MSLP approved the participation requests for 1,830 loans totaling $17.5 billion. By far the most popular was the Priority Loan Facility—accounting for about 74 percent of the uptake (1,173 loans totaling $12.9 billion)—followed by the New Loan Facility (616 loans totaling $2.7 billion), and the Extended Loan Facility (26 loans totaling $1.8 billion). Loan sizes were generally concentrated in amounts substantially below the program's maximum loan-size limits, with a median loan size of $40.5 million in the Extended Loan Facility, $6 million in the Priority Loan Facility, and $2 million in the New Loan Facility. The loan-size distribution reveals that the vast majority of loans were much larger than the minimum requirement of $100,000. This is partly because the minimum requirement was lowered late in the program, leaving limited time for the smallest loans to be underwritten. This result is likely also an outcome of the MSLP's initial design goal of making the program appeal more to midsize firms.

The geographic coverage of the Main Street program was broad: Participation requests were submitted by borrowers from 49 states (all but Maine), the District of Columbia, and two territories (Puerto Rico and the US Virgin Islands).[11] Banks' participation was somewhat limited. About 600 banks registered for the program, but only about half originated loans that were subsequently sold to the Main Street Special Purpose Vehicle.

Identifying MSLP Borrowers in the D&B Database

We rely mostly on the D&B databases name-matching algorithm (Integration Manager or IM), supplemented with manual online searches, to identify the DUNS IDs for MSLP

[10] In fact, the program was closed to new submissions on December 15, 2020, but the volume of submissions in December was so large that it was not until January 8, 2021, that all the submissions (some of which had to be resubmitted due to missing documents) were processed.

[11] On the other hand, most of the uptake was concentrated in firms from Texas ($3.1 billion), Florida ($2.1 billion), and California ($2.1 billion). When the volume is scaled relative to the size of the state economy, the top three states by uptake per dollar of gross state product were Oklahoma, Arkansas, and Missouri.

borrowers.

Among the 1,813 accepted primary borrowers from the Main Street program recorded as of January 8, 2021, we are able to find DUNS matches for 1,796 directly through the IM based on the MSLP firm name and address.[12] Among these, we consider only the 1,516 borrowers matched by the IM with a confidence score of 8 or higher (which is deemed sufficiently precise).

To these, we are able to add 266 borrowers that initially matched with low confidence scores by improving their scores to 8 or higher with additional information obtained via manual searches. Likewise, we were also able to find matches for 13 of the 17 initially unmatched borrowers. On the other hand, 10 borrowers were incorrectly matched by the algorithm and were removed from our sample after manual inspection. Another four borrowers were dropped after we aggregated branches to their headquarters DUNS because several variables were not separately available at the branch level in the D&B database. In sum, our sample of matched borrowers totals 1,781, all corresponding to headquarters-level DUNS.

Subsequently, several borrowers were removed from our sample either because (1) they do not exist in the D&B database in the relevant period, (2) they cannot be assigned a peer group due to missing employment data, or (3) their status code changed (that is, a change to/from branch/headquarters) over the sample period.[13] In March 2020, for instance, 106 of these firms did not exist in the D&B database, another 49 had missing values for employment, and five had changed their status during the period used to compute changes in the variables of interest, from March 2020 to a firm's MSLP loan submission month. Thus there are 1,605 firms left for our analysis.

[12] For multi-borrower loans, which the MSLP started accepting in late September 2020, we consider only the primary borrower. All the counts reported here are based on the number of distinct DUNS unless otherwise noted. 1,813 DUNS correspond to 1,804 distinct tax IDs as reported by MSLP borrowers, some of which are mapped into more than one DUNS number.

[13] When a firm's status changes over a period, changes in many variables' values are likely to be subject to composition bias, and we therefore omit those firms.

Table B.2: Comparison of the Random Sample versus Full D&B Data Set versus MSLP Borrower

Variable	Data	N	Mean	Mean Diff (%)	5th Pctl.	25th Pctl.	50th Pctl.	75th Pctl.	95th Pctl.
CCS Points	Sample	179,452	503.02	0.02	395	473	496	551	606
	Full D&B	6,400,714	502.92		394	473	496	551	606
	MSLP Firms	1,506	506.08		416	474	500	554	603
FSS Points	Sample	179,452	1469.23	0.029	1394	1428	1471	1510	1550
	Full D&B	6,400,714	1468.81		1394	1425	1468	1510	1550
	MSLP Firms	1,506	1467.99		1387	1424	1470	1508	1550
Viability Points	Sample	179,452	495.77	-0.026	437	465	492	523	567
	Full D&B	6,400,714	495.90		437	465	492	523	569
	MSLP Firms	1,506	497.45		437	466	496	524	570
Viability Score	Sample	179,452	4.61	0.074	2	3	5	6	6
	Full D&B	6,400,714	4.61		2	3	5	6	6
	MSLP Firms	1,506	4.56		2	3	5	6	6
Firm Age	Sample	179,452	14.68	-0.745	2	6	10	17	42
	Full D&B	6,400,714	14.79		2	6	10	17	42
	MSLP Firms	1,506	16.30		3	6	10	19	47
Employment	Sample	179,452	7.18	-7.324	1	2	2	4	18
	Full D&B	6,400,714	7.72		1	2	2	4	18
	MSLP Firms	1,506	102.42		1	2	2	6	75

Note: This table presents the summary statistics of key characteristics of i) the MSLP borrowers, ii) the random sample of non-borrower peer firms matched on state, industry (3-digit NAICS), firm age bin, and small business indicator (defined as up to 500 employees), and iii) all non-borrower peer firms defined likewise in the full D&B dataset of active firms as of March 2020. The column "Mean Diff (%)" reports the percentage difference between mean value for the random sample versus the full D&B dataset. Source: D&B and author's calculations.

Table B.3: Comparison of Pre-COVID Characteristics: MSLP Borrowers versus Peers

Attribute	(1)	(2)	(3)	(4)	Min. Obs.
CCS Points (2020M3)	11.983	7.807	3.893	-1.245	179,578
	(0.01)	(0.046)	(0.198)	(0.622)	
CCS Change (2020M3–2020M6)	-5.207	-4.679	-4.551	-5.182	177,965
	(0.034)	(0.041)	(0.059)	(0.024)	
CCS Change (2020M3–MSLP Month)	-4.388	-3.136	-3.126	-6.475	176,398
	(0.125)	(0.184)	(0.197)	(0.009)	
FSS Points (2020M3)	-8.204	-8.602	-10.563	-13.263	179,554
	(0.035)	(0.002)	(0)	(0)	
FSS Change (2020M3–2020M6)	0.491	0.180	-0.097	-0.677	177,946
	(0.648)	(0.845)	(0.918)	(0.449)	
FSS Change (2020M3–MSLP Month)	-1.002	-1.314	-1.756	-3.195	176,367
	(0.404)	(0.129)	(0.084)	(0.005)	
Viability Points (2020M3)	11.821	3.081	3.489	-0.520	180,946
	(0.002)	(0.148)	(0.001)	(0.505)	
Viability Change (2020M3–2020M6)	-0.147	-0.305	-0.220	-0.778	179,353
	(0.712)	(0.446)	(0.73)	(0.174)	
Viability Change (2020M3–MSLP Month)	-0.503	0.409	0.129	-1.569	177,784
	(0.535)	(0.517)	(0.855)	(0.023)	
% Debt 31+ Days Past Due (2020M3)	0.000	-0.007	-0.022	-0.015	46,993
	(0.987)	(0.298)	(0.001)	(0.012)	
% Change Past Due (2020M3–2020M6)	0.038	0.033	0.031	0.033	43,364
	(0)	(0)	(0.001)	(0)	
% Change Past Due (2020M3–MSLP Month)	0.013	0.012	0.011	0.016	41,984
	(0.136)	(0.136)	(0.191)	(0.036)	
Conditioning Variables	–	–	–	–	
State	Yes	Yes	Yes	Yes	
Industry	Yes	Yes	Yes	Yes	
Firm Age Bins	No	Yes	Yes	Yes	
Employement Bins	No	Yes	Yes	Yes	
Viability Score Bins (2019)	No	No	Yes	Yes	
PPP Indicator	No	No	No	Yes	

Note: This table compares the average value of firm attributes among the MSLP borrowers versus their peer firms that are matched by state, 2-digit NAICS industry codes and whether a firm has no more than 500 employees. The conditional mean differences are reported, along with the p values of the equal-mean test in parentheses. The mean difference for each variable is computed by regressing it on a set of binary indicators for the conditioning variables, along with the MSLP borrower indicator, whose coefficient then measures the mean difference between MSLP borrowers and the other firms controlling for the conditioning variables. The conditioning variables for each set of mean comparison (organized by column) are reported in the bottom block of the table. "MSLP Month" refers to the month when a borrower's loan was submitted to the MSLP facilities. "Min. Obs." lists the minimum number of observations among the four sets of mean differences reported in each row, universally corresponding to column (4). There are generally around 5% more observations underlying results in columns (1) and (2). Source: D&B and author's calculations.

Table B.4: Score Change as An Active-Firm Indicator

	Abs. CCS Change Covid >5	Abs. Via Change Covid >5
	(1)	(2)
Emp. [11,50]	0.189***	0.062***
	(0.010)	(0.006)
Emp. [51,250]	0.227***	0.106***
	(0.012)	(0.009)
Emp. [251,500]	0.335***	0.134***
	(0.026)	(0.016)
Emp. >500	0.401***	0.108***
	(0.018)	(0.016)
PPP Early	0.232***	0.091***
	(0.008)	(0.005)
PPP Mid	0.219***	0.093***
	(0.008)	(0.005)
PPP Late	0.189***	0.080***
	(0.008)	(0.006)
Observations	2,491,824	2,491,824
Adjusted R^2	0.056	0.008

Note: This table reports correlation between having a change in CCS or Viability Score of at least 5 points and larger firm size and being more likely to receive PPP loans earlier. The dependent variable are indicators if the absolute value of a firm's CCS Change (column (1)) or Viability Score (column (2)) over 2020:M3–2020:M6 is 5 points or more. VS Change Covid: binned values of Via. Score change 2020:M3–2020:M6. Employment (Emp.) bins: as of 2020:M3. PPP Early, Mid, Late: Indicator if a firm received PPP loans before April 16, April 27 to May 2, and after May 2, 2020, respectively. See text for the other variable definitions. Source: D&B and author's calculations.

C Rare-Event Logit Model of MSLP Uptake Decision

Because MSLP firms constitute a vanishingly small fraction of all active firms in the D&B database as of January 2019, standard logistic regressions can sharply underestimate the probability of a rare event. We thus apply choice-based sampling to undersample non-borrower firms and arrive at a more balanced estimation sample (see Imbens, 1992). Specifically, we draw a small random sample of non-borrower firms that is approximately twice as large as the number of MSLP firms.[14] To also avoid selection on exogenous variables, this sample is drawn by a stratum of employment bins because MSLP firms are substantially larger than the other firms but have nearly the same distribution of risk scores and other attributes conditioning on size bins (see Table B.2). We then apply re-weighting in the estimation to account for the different sample versus population weights of MSLP firms.[15] We further adjust the coefficients to correct for the bias due to the extreme imbalance in the dependent variable.[16]

We estimate a rare-event logit model with the same set of regressors as those underlying Table 2. The coefficients are reported in Table C.1. Despite the much smaller sample (with non-borrowers massively undersampled), the same general pattern emerges. Having more than 250 employees and having received a PPP loan early were still the most significant predictors of a firm becoming a Main Street borrower. Firms with the best pre–COVID-19 CCS scores showed the least propensity to borrow, much lower than the firms with the worst CCS (the omitted category).[17] Firms that experienced a CCS increase in the year before the onset of the pandemic but a CCS decline afterward were more likely to borrow. Having a greater presence of community banks in the county or a lower share of PPP loans delayed were associated with a lower likelihood of borrowing from Main Street. In sum, the rare-

[14] According to Imbens (1992), equal-shares sampling is close to optimal in a large number of cases. But more data up to a point generally improve the efficiency of estimates; for example, King and Zeng (2001) advocate a number of observations of $y_i = 0$ that is two to five times that of $y_i = 1$. In unreported results, we verify that altering the ratio of non-borrowers to borrowers between 2 and 5 makes little difference to the coefficient estimates.

[15] Specifically, a weighted log likelihood function is estimated, with $\pi_i = Prob(y_i = 1)$, while $w_1 = \tau/\bar{y}$ and $w_0 = (1-\tau)/(1-\bar{y})$ denote the weights for $y_i = 1$ and $y_i = 0$, respectively, where τ and $\bar{y}$ are the fraction of units for which the dependent variable equal to one (which corresponds to being a borrower in this case) in the population and the sample, respectively. For more details, see King and Zeng (2001). In our application, τ is known.

[16] The bias adjustment formula is $(X'WX)^(-1)X'W\xi$. X is the regressor matrix, W is a $n \times n$ diagonal weight matrix with each element $w_i = \hat{\pi}_i(1-\hat{pi}_i)w_i^0$, where $\hat{\pi}_i$ denotes the fitted probability before the bias correction, and w_i^0 is the ratio of the population weight to the sample weight of observation i's class (either 0 or 1). ξ is a $n \times 1$ vector, with each element $\xi_i = 0.5Q_{ii}[(1+w_1)\hat{\pi}_i - w_1]$, with Q_{ii} being the diagonal elements of $Q = X(X'WX)^(-1)X'$ (for details, see King and Zeng, 2001).

[17] Coefficients on CCS in the range of 300 to 600 become insignificant once all the regressors are included and are thus omitted to save space.

event logit estimates confirm the findings from the linear probability estimate regarding the key factors that determined the odds of a firm becoming an MSLP borrower.

Table C.1: Logit Estimates of Firm MSLP Uptake Decision

	(1)	(2)	(3)	(4)
CCS >600	0.386	−0.780**	−0.846**	−0.752*
	(0.425)	(0.389)	(0.420)	(0.403)
CCS Change Pre <-20	0.816***	0.580***	0.590***	0.556***
	(0.103)	(0.194)	(0.180)	(0.186)
CCS Change Pre [-20,0)	0.077	0.362**	0.421**	0.394*
	(0.085)	(0.177)	(0.214)	(0.227)
CCS Change Pre (0,20]	0.662***	0.594**	0.730***	0.803***
	(0.105)	(0.246)	(0.256)	(0.259)
CCS Change Pre >20	1.067***	1.084***	1.321***	1.372***
	(0.060)	(0.219)	(0.223)	(0.165)
CCS Change Covid <-20	1.547***	0.960***	0.883***	0.843***
	(0.184)	(0.214)	(0.260)	(0.264)
CCS Change Covid [-20,0)	0.440***	0.466**	0.326	0.311
	(0.145)	(0.231)	(0.252)	(0.282)
CCS Change Covid (0,20]	0.895***	0.195	0.176	0.142
	(0.097)	(0.152)	(0.160)	(0.163)
CCS Change Covid >20	1.377***	0.762***	0.726**	0.754***
	(0.148)	(0.285)	(0.288)	(0.285)
PPP Early		2.534***	2.696***	2.772***
		(0.160)	(0.165)	(0.187)
PPP Mid		1.122***	1.172***	1.133***
		(0.197)	(0.179)	(0.181)
PPP Late		−0.801	−1.055	−0.939
		(0.610)	(0.704)	(0.653)
Emp. [11, 50]		1.305***	1.369***	1.374***
		(0.232)	(0.277)	(0.273)
Emp. [51,250]		2.356***	2.409***	2.528***
		(0.292)	(0.350)	(0.310)
Emp. [251,500]		3.276***	3.311***	3.429***
		(0.487)	(0.496)	(0.407)
Emp. >500		4.118***	3.775***	3.933***
		(0.412)	(0.469)	(0.438)
Community Bank Share				−1.538**
				(0.733)
PPP Loans Share Delayed				2.245**
				(1.119)
Observations	7,428	7,428	7,428	7,428
Log Likelihood	−1.722	−1.716	−1.712	−1.709

Note: This table reports coefficients from a rare-event logit model. CCS Range and Employment (Emp.) bins: as of 2020:M3. CCS Change Pre: binned values of CCS change 2019:M3–2020:M3. CCS Change Covid: binned values of CCS change 2020:M3–2020:M6. PPP Early, Mid, Late: Indicator if a firm received PPP loans before April 16, April 27 to May 2, and after May 2, 2020, respectively. See text for the other variables' definitions. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Source: D&B and author's calculations.

D Additional Estimates of Linear Model of MSLP Uptake

This section reports additional linear probability estimates of Main Street uptake. Instead of the CCS, these estimates use Viability Score bins to measure firms' pre–COVID-19 soundness. All the other explanatory variables remain the same as in the regressions underlying Table 2, which use the CCS as the financial indicator. These estimates reveal that the coefficients on the other regressors remain quite similar regardless of the financial variable used. We discuss the estimates from the regression with all the regressors, presented in column (4). Being a midsize firm and having prior banking relationships remain the most important predictors of MSLP uptake. Being in an industry less severely impacted by COVID or a county with greater mobility becomes associated with a slightly lower likelihood of uptake, whereas operating in an essential industry or county COVID-19 death rates each become an insignificant determinant.[18] In addition, a higher community bank deposit share in the county or a lower share of PPP loans delayed lower MSLP uptake.

At the same time, the coefficients on the VS bins confirm the pattern found using the CCS—firms with poor or mediocre risk scores were more likely to seek Main Street funding. Firms with an average 2019 Viability Score in the 7 to 8 range were most likely to borrow, followed by those with a VS in the 2 to 6 range, more so than those with the best VS (equal to 1, the omitted category). At the same time, firms that saw their VS Points increase over the year until March 2020, especially if the increase was more than 20 points, showed greater propensity to borrow. On the other hand, firms that suffered a decline in their VS Points after COVID-19 hit (March through June 2020), especially if the loss exceeded 20 points, were more likely to borrow.

[18] The sum of the coefficients on the mobility index is reported in the bottom portion of Table D.1, while the (insignificant) sum of the coefficients on death rates is omitted to save space.

Table D.1: Probability of MSLP Uptake: Financial Health Based on Viability Score

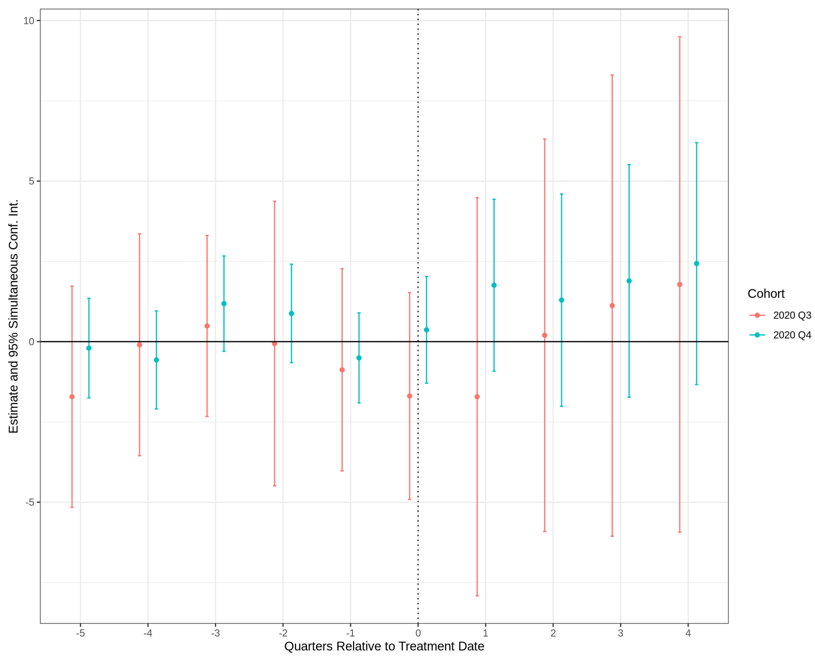
	(1)	(2)	(3)	(4)
Via. Score Range (1,6]	-0.0003^{*}	0.001^{***}	0.001^{***}	0.001^{***}
	(0.0002)	(0.0004)	(0.0004)	(0.0004)
Via. Score Range (6,8]	-0.0002	0.002^{***}	0.002^{***}	0.002^{***}
	(0.0002)	(0.0004)	(0.0004)	(0.0004)
VS Change Pre <-20	0.0001^{***}	0.00002	0.00003	0.00003
	(0.00004)	(0.00002)	(0.00002)	(0.00002)
VS Change Pre [-20,0)	0.0002^{***}	-0.00000	0.00001	0.00001
	(0.00004)	(0.00003)	(0.00003)	(0.00003)
VS Change Pre (0,20]	0.0002^{***}	0.0001^{**}	0.0001^{**}	0.0001^{**}
	(0.00005)	(0.00002)	(0.00003)	(0.00003)
VS Change Pre >20	0.0003^{***}	0.0001^{***}	0.0001^{***}	0.0001^{***}
	(0.0001)	(0.00003)	(0.00004)	(0.00004)
VS Change Covid <-20	0.0002^{***}	0.0001^{***}	0.0001^{***}	0.0001^{***}
	(0.0001)	(0.00004)	(0.00004)	(0.00004)
VS Change Covid [-20,0)	0.0002^{***}	0.0001^{**}	0.0001^{**}	0.0001^{**}
	(0.0001)	(0.00003)	(0.00003)	(0.00003)
VS Change Covid (0,20]	0.0003^{***}	0.0001^{***}	0.00005^{**}	0.00004^{*}
	(0.0001)	(0.00002)	(0.00002)	(0.00003)
VS Change Covid >20	0.0001^{***}	0.00004	0.00003	0.00002
	(0.00003)	(0.00003)	(0.00002)	(0.00002)
PPP Early		0.002^{***}	0.002^{***}	0.002^{***}
		(0.0005)	(0.0005)	(0.0005)
PPP Mid		0.0004^{***}	0.0004^{***}	0.0004^{***}
		(0.0001)	(0.0001)	(0.0001)
PPP Late		0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)
Emp. [11,50]		0.001^{***}	0.001^{***}	0.001^{***}
		(0.0002)	(0.0002)	(0.0002)
Emp. [51,250]		0.004^{***}	0.004^{***}	0.004^{***}
		(0.001)	(0.001)	(0.001)
Emp. [251,500]		0.006^{***}	0.006^{***}	0.006^{***}
		(0.002)	(0.002)	(0.002)
Emp. >500		0.005^{***}	0.005^{***}	0.005^{***}
		(0.002)	(0.002)	(0.002)
Essential Industry			-0.0001	-0.0001
			(0.0001)	(0.0001)
COVID Impacted			0.0001^{*}	0.0001^{*}
			(0.0001)	(0.0001)
Community Bank Share				-0.0002^{**}
				(0.0001)
PPP Loans Share Delayed				0.0005^{**}
				(0.0002)
Sum mobility coefs (p val)	–	–	-0.002 (0.065)	-0.002 (0.069)
Observations	418,995	418,995	418,995	418,995
Adjusted R^2	0.0001	0.002	0.003	0.003

Note: This table reports coefficients from Equation (1). Via. Score Range and Employment (Emp.) bins: as of 2020:M3. VS Change Pre: binned values of Via. Score change 2019:M3–2020:M3. VS Change Covid: binned values of Via. Score change 2020:M3–2020:M6. PPP Early, Mid, Late: Indicator if a firm received a PPP loan before April 16, April 27 to May 2, and after May 2, 2020, respectively. See text for the other variable definitions. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Source: D&B and author's calculations.

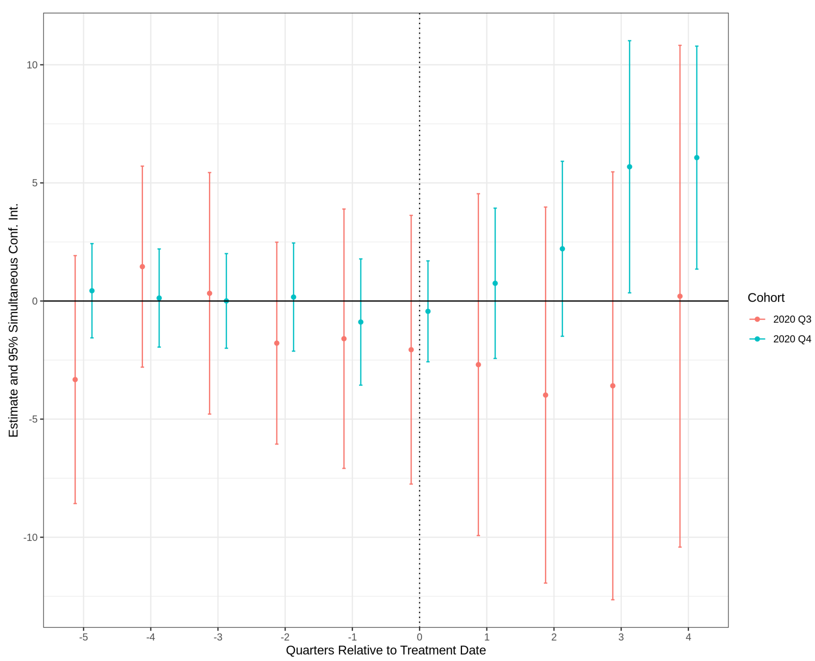
E Additional Callaway-Sant'Anna Estimates of MSLP's Effects

Figure E.1: Effects of Main Street on Firm Viability and Financial Stress Score

(a) MSLP Effects on Viability Score Points



(b) MSLP Effects on Financial Stress Score (FSS)



Note: This figure depicts the dynamic effects of the staggered treatment of MSLP loans on borrowers' Viability Score (top panel) and Financial Stress Score (bottom panel), estimated using the doubly robust DiD estimator à la Callaway and Sant'Anna (2021). Source: D&B and author's calculations.

F MSLP Treatment Effects Using Sun-Abraham Estimator

This section applies the estimator developed by Sun and Abraham (2021) (SA) to derive an alternative estimate of the treatment effects of receiving MSLP loans. Like the estimator by Callaway and Sant'Anna (2021), the SA estimator can also account for the staggered design and provide a consistent aggregation of the coefficients for firms receiving loans in different quarters. However, not being a doubly robust estimator by incorporating inverse-probability weighting, the SA estimator is susceptible to misspecification of the outcome regression. As will be shown, even with matching between the MSLP borrowers and their peers along as many dimensions as feasible given the data, the borrowers still display a different pre-trend compared with their non-borrower peers. On the other hand, the SA regression can be estimated rapidly using high-dimension fixed-effects estimators optimized for parallel computing. It is therefore suitable for estimating multiple specifications with different sets of regressors.[19] Hence, the results in this section are meant to explore the relative contribution of subsets of regressors, and to corroborate the estimates à la Callaway and Sant'Anna (2021).

Specifically, we estimate the following regression:

$$y_{f,t} = \sum_{\tau \neq -1} \sum_{c} \psi_{c,\tau} + \alpha_f + \gamma_t + \zeta_{s,t} + \eta_{n,t} + \theta_{a,t} + \kappa_{e,t} + \mu_t \times \mathrm{VS}_{f,2019} + \varepsilon_{f,t}, \tag{F.1}$$

where $y_{f,t}$ is an outcome y of firm f in quarter t, and $\psi_{c,\tau}$ are the coefficients on the interaction terms between indicators for cohort (c) and event time—defined as time relative to treatment—(τ). Each cohort is defined by the quarter in which the constituent firms received MSLP loans. The omitted category is firms that did not receive MSLP loans. $\psi_{c,\tau}$ is estimated while controlling for several sets of fixed effects. The fully saturated specification includes these fixed effects: firm (α_f), time (γ_t) (if the following time-interacted terms are not included), state-time ($\zeta_{s,t}$), industry-time ($\eta_{n,t}$), age-bin-time ($\theta_{a,t}$), employment-bin-time ($\kappa_{e,t}$), and time interacted with the firm's 2019 average Viability Score bin, $\mathrm{VS}_{f,2019}$.

Estimates of $\delta_{c,\tau}$ for the CCS and employment with fixed effects of only firms' nonfinancial attributes—state, industry (two-digit NAICS), age bin, employment bin, and the PPP indicators, all interacted with quarter indicators—are plotted in Figure F.1. Corresponding estimates of $\delta_{c,\tau}$ with fixed effects of all firm attributes (that is, adding indicators of pre–COVID-19 Viability Score bins and COVID-19–period change in Viability Score bins, again both interacted with quarter indicators) are depicted in Figure F.2.

[19] All the estimates in this section are produced using the fixest package in R (see https://cran.r-project.org/web/packages/fixest/).

Panel (a) of Figure F.2 reveals that, when compared with only non-borrower peers in the same state, industry, and small- or large-business category and controlling for all the firm attributes, the MSLP borrowers display a parallel trend of CCS before the pandemic, albeit at a higher level (on average better by 10 points, mapping into about 16 percent lower delinquency risk). Their CCS fell to the level of the peer firms after the pandemic hit, in the quarter before receiving the MSLP loan and the quarter of the loan.[20] The negative gap between $\delta^{CCS}_{c,-1}$ (normalized to zero here) and $\delta^{CCS}_{c,\tau}|_{\tau} < -1$ is qualitatively similar to the pattern observed in panel (a) of 1 (where the treatment effect for $\tau = -1$ is negative and not normalized to zero). This is corroborative evidence that Main Street borrowers likely suffered a more adverse effect on their cash flow due to the pandemic and thus had greater difficulty paying their bills. By comparison, MSLP borrowers display a slightly upward trend in employment (especially for the cohort of MSLP firms that borrowed in 2020:Q4) before the pandemic relative to their peers (panel (b) of F.2). This is suggestive evidence that they were likely regarded as having better growth prospects before the pandemic but were then more severely disrupted by it.

Borrowers experienced a relative recovery in their CCS scores, which grew progressively in magnitude over the four quarters after they received their loan and almost fully regained the ground they had lost to the CCS scores of borrowers' peers. The size of the estimated treatment effects for the 2020:Q4 borrower cohort is fairly similar to one found when using the Callaway-Sant'Anna estimator, although the SA estimates appear more significant because of the smaller standard errors.[21] Borrowers' employment also grew faster than at the peer firms over the post-MSLP year, especially in the last two quarters. These estimates are of similar magnitude as those from the CS estimator but appear more significant (especially for the 2020:Q4 borrowers) again due to the narrower confidence bands. All things considered, it is reassuring that the two somewhat different estimators for staggered treatments yield basically the same point estimates.[22] Using the more conservative simultaneous confidence band, we conclude that Main Street helped shore up borrowers' financial position by reducing delinquency risk (by 18 percent), but it did not boost employment significantly over the year after the loan disbursement.

Comparing the estimates in Figures F.1 and F.2 reveals that accounting for the VS-based financial variables hardly alters the estimates of Main Street's effects on the borrowers' CCS

[20]The horizontal axis depicts the event quarter—relative to the loan submission quarter—and the pre-event quarter ($\tau = -1$) is omitted (thus equivalent to being normalized to zero).

[21]The confidence bands from the SA estimator are generally narrower than those from the CS estimator because the former are point-wise while the latter are simultaneous bands for all the time periods used in the estimation and thus robust to multiple testing.

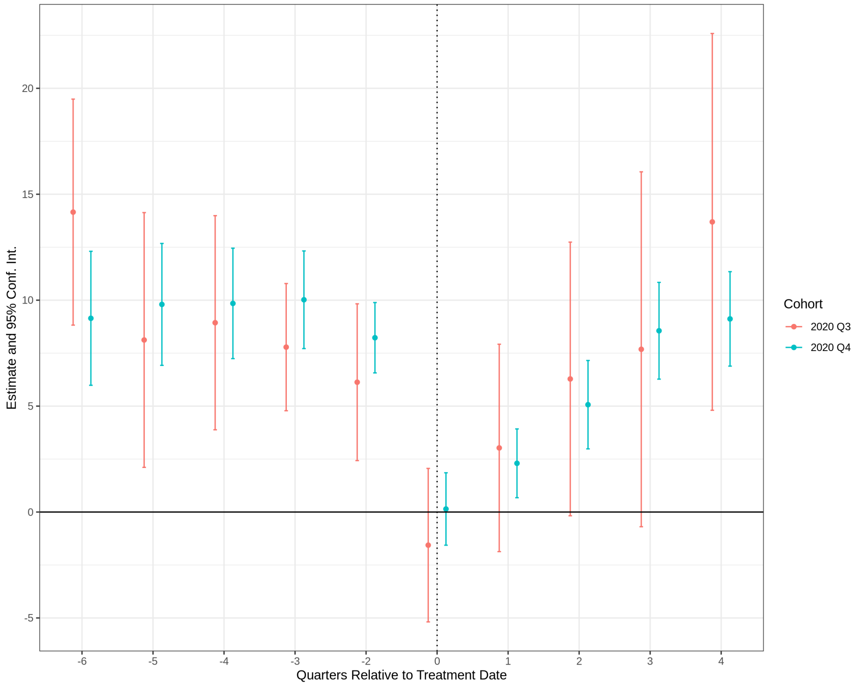
[22]The treatment effects estimates for the Viability Score and the FSS are also similar to those from the CS estimator, which are omitted here for brevity but are available upon request.

or employment. This is likely because the regression sample is already restricted to only those non-borrowers that belonged to the same broad pre–COVID-19 Viability Score bins as the borrowers.

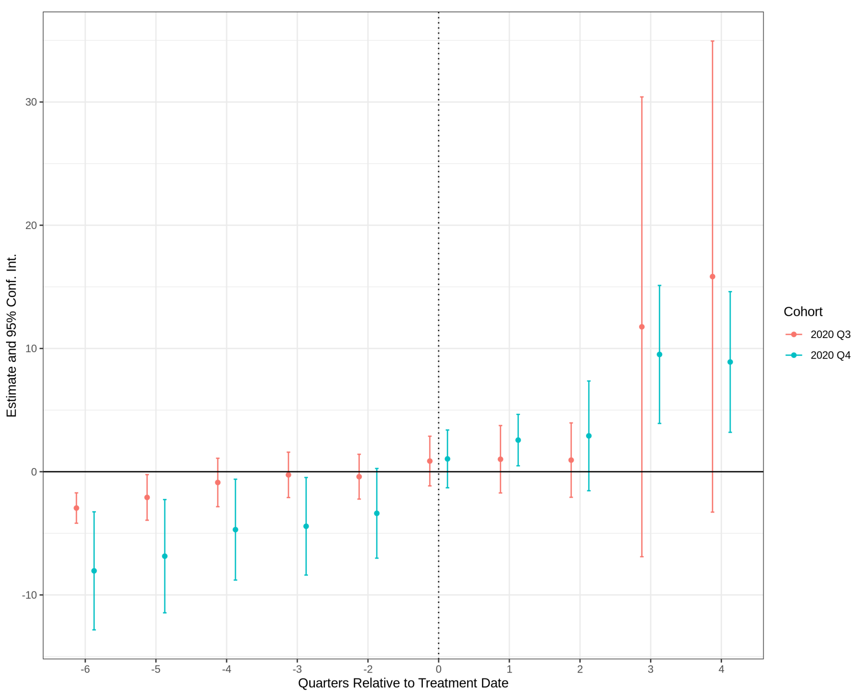
Figure F.3 plots the estimated effects of Main Street on borrowers' CCS for each cohort of borrowers grouped by the loan submission month. The broad picture is highly similar to the one in panel (a) of Figure F.2, although it also reveals some interesting patterns for firms that borrowed in different months. In particular, July 2020 borrowers exhibited the largest gain in CCS after receiving a loan, consistent with the interpretation that they tapped into the program early because their liquidity squeeze was the most severe and thus they also benefited the most. Not surprisingly, the effects on the December 2020 cohort are the most precisely estimated because of the much larger sample size.

Figure F.1: Effects of Main Street on Firm Commercial Credit Score and Employment (Fixed Effects of Only Nonfinancial Attributes)

(a) MSLP Effects on Commercial Credit Score



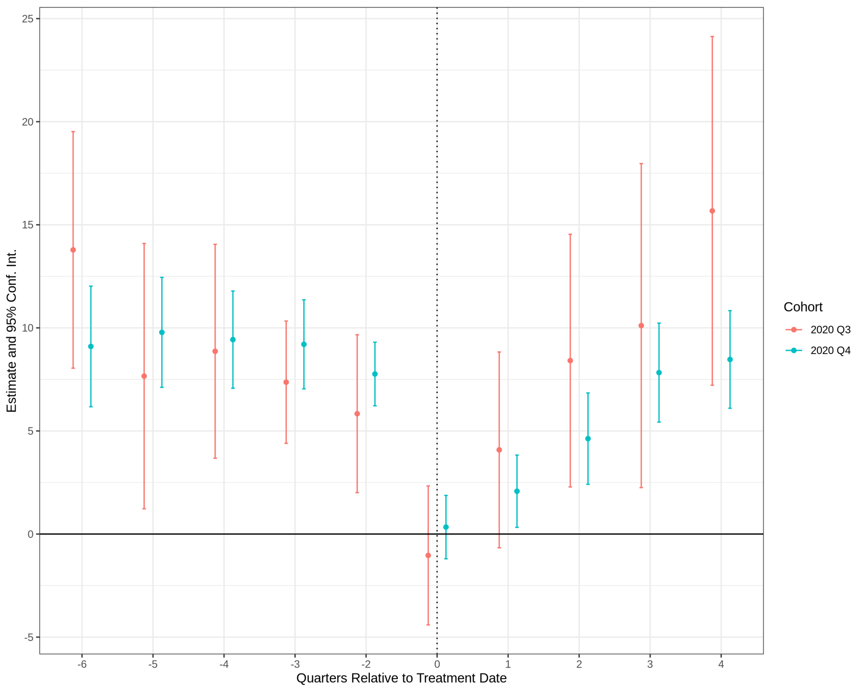
(b) MSLP Effects on Employment



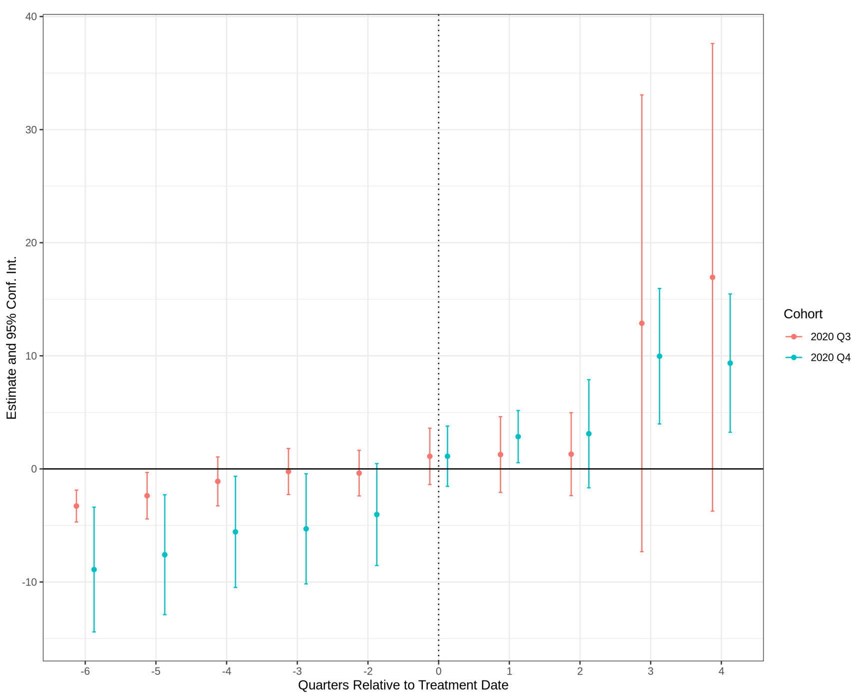
Note: This figure depicts the dynamic effects of the staggered treatment of MSLP loans on borrowers' Viability Score (top panel) and Financial Stress Score (bottom panel), estimated using the Sun-Abraham estimator as in Equation (F.1). Source: D&B and author's calculations.

Figure F.2: Effects of Main Street on Firm Commercial Credit Score and Employment (Fixed Effects of All Attributes)

(a) MSLP Effects on Commercial Credit Score

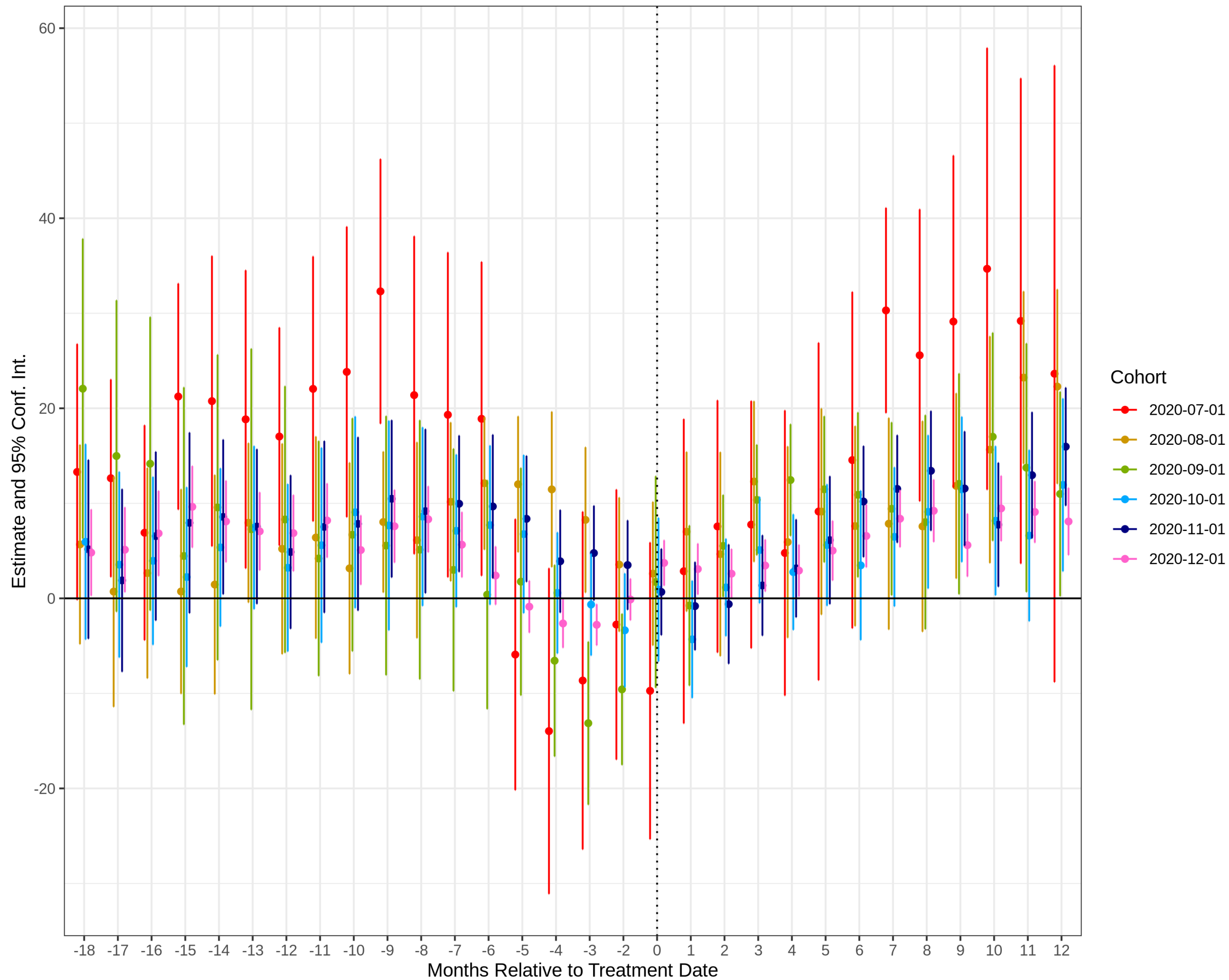


(b) MSLP Effects on Employment



Note: This figure depicts the dynamic effects of the staggered treatment of MSLP loans on borrowers' Viability Score (top panel) and Financial Stress Score (bottom panel), estimated using the Sun-Abraham estimator as in Equation (F.1). Source: D&B and author's calculations.

Figure F.3: Effects of Main Street on Firm Commercial Credit Score: Monthly Estimate



Note: This figure depicts the dynamic effects by month of the staggered treatment of MSLP loans on borrowers' Commercial Credit Score, estimated using the Sun-Abraham estimator as in Equation (F.1). Source: D&B and author's calculations.