Econometrica Supplementary Material

SUPPLEMENT TO "A DEMAND CURVE FOR DISASTER RECOVERY LOANS"

(*Econometrica*, Vol. 92, No. 3, May 2024, 713–748)

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APPENDIX B: HURRICANE HARVEY FACT SHEET

Date: 11/07/2017

U.S. Small Business Administration

U.S. SMALL BUSINESS ADMINISTRATION
FACT SHEET - DISASTER LOANS

TEXAS Declaration #15274 & #15275
(Disaster: TX-00487)
Incident: HURRICANE HARVEY

occurring: *August 23 through September 15, 2017*

*in the **Texas** counties of:* ***Aransas, Austin, Bastrop, Bee, Brazoria, Caldwell, Calhoun, Chambers, Colorado, DeWitt, Fayette, Fort Bend, Galveston, Goliad, Gonzales, Grimes, Hardin, Harris, Jackson, Jasper, Jefferson, Karnes, Kleberg, Lavaca, Lee, Liberty, Matagorda, Montgomery, Newton, Nueces, Orange, Polk, Refugio, Sabine, San Jacinto, San Patricio, Tyler, Victoria, Walker, Waller & Wharton;***
*for economic injury only in the contiguous **Texas** counties of:* ***Angelina, Atascosa, Brazos, Brooks, Burleson, Guadalupe, Hays, Houston, Jim Wells, Kenedy, Live Oak, Madison, Milam, San Augustine, Shelby, Travis, Trinity, Washington, Williamson & Wilson;***
*and for economic injury only in the contiguous **Louisiana** parishes of:* ***Beauregard, Calcasieu, Cameron, Sabine & Vernon***

Application Filing Deadlines:
Physical Damage: *November 30, 2017* **Economic Injury: *May 25, 2018***

If you are located in a declared disaster area, you may be eligible for financial assistance from the U.S. Small Business Administration (SBA).

What Types of Disaster Loans are Available?

- Business Physical Disaster Loans – Loans to businesses to repair or replace disaster-damaged property owned by the business, including real estate, inventories, supplies, machinery and equipment. Businesses of any size are eligible. Private, non-profit organizations such as charities, churches, private universities, etc., are also eligible.
- Economic Injury Disaster Loans (EIDL) – Working capital loans to help small businesses, small agricultural cooperatives, small businesses engaged in aquaculture, and most private, non-profit organizations of all sizes meet their ordinary and necessary financial obligations that cannot be met as a direct result of the disaster. These loans are intended to assist through the disaster recovery period.
- Home Disaster Loans – Loans to homeowners or renters to repair or replace disaster-damaged real estate and personal property, including automobiles.

What are the Credit Requirements?

- Credit History – Applicants must have a credit history acceptable to SBA.
- Repayment – Applicants must show the ability to repay all loans.
- Collateral – Collateral is required for physical loss loans over $25,000 and all EIDL loans over $25,000. SBA takes real estate as collateral when it is available. SBA will not decline a loan for lack of collateral, but requires you to pledge what is available.

What are the Interest Rates?

By law, the interest rates depend on whether each applicant has Credit Available Elsewhere. An applicant does not have Credit Available Elsewhere when SBA determines the applicant does not have sufficient funds or other resources, or the ability to borrow from non-government sources, to provide for its own disaster recovery. An applicant, which SBA determines to have the ability to provide for his or her own recovery is deemed to have Credit Available Elsewhere. Interest rates are fixed for the term of the loan. The interest rates applicable for this disaster are:

	No Credit Available Elsewhere	Credit Available Elsewhere
Business Loans	3.305%	6.610%
Non-Profit Organization Loans	2.500%	2.500%
Economic Injury Loans		
Businesses and Small Agricultural Cooperatives	3.305%	N/A
Non-Profit Organizations	2.500%	N/A
Home Loans	1.750%	3.500%

Amendment #8

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What are Loan Terms?

The law authorizes loan terms up to a maximum of 30 years. However, the law restricts businesses with credit available elsewhere to a maximum 7-year term. SBA sets the installment payment amount and corresponding maturity based upon each borrower's ability to repay.

What are the Loan Amount Limits?

- Business Loans – The law limits business loans to $2,000,000 for the repair or replacement of real estate, inventories, machinery, equipment and all other physical losses. Subject to this maximum, loan amounts cannot exceed the verified uninsured disaster loss.
- Economic Injury Disaster Loans (EIDL) – The law limits EIDLs to $2,000,000 for alleviating economic injury caused by the disaster. The actual amount of each loan is limited to the economic injury determined by SBA, less business interruption insurance and other recoveries up to the administrative lending limit. EIDL assistance is available only to entities and their owners who cannot provide for their own recovery from non-government sources, as determined by the U.S. Small Business Administration.
- Business Loan Ceiling – The $2,000,000 statutory limit for business loans applies to the combination of physical, economic injury, mitigation and refinancing, and applies to all disaster loans to a business and its affiliates for each disaster. If a business is a major source of employment, SBA has the authority to waive the $2,000,000 statutory limit.
- Home Loans – SBA regulations limit home loans to $200,000 for the repair or replacement of real estate and $40,000 to repair or replace personal property. Subject to these maximums, loan amounts cannot exceed the verified uninsured disaster loss.

What Restrictions are there on Loan Eligibility?

- Uninsured Losses – Only uninsured or otherwise uncompensated disaster losses are eligible. Any insurance proceeds which are required to be applied against outstanding mortgages are not available to fund disaster repairs and do not reduce loan eligibility. However, any insurance proceeds voluntarily applied to any outstanding mortgages do reduce loan eligibility.
- Ineligible Property – Secondary homes, personal pleasure boats, airplanes, recreational vehicles and similar property are not eligible, unless used for business purposes. Property such as antiques and collections are eligible only to the extent of their functional value. Amounts for landscaping, swimming pools, etc., are limited.
- Noncompliance – Applicants who have not complied with the terms of previous SBA loans may not be eligible. This includes borrowers who did not maintain flood and/or hazard insurance on previous SBA loans.

Note: Loan applicants should check with agencies / organizations administering any grant or other assistance program under this declaration to determine how an approval of SBA disaster loan might affect their eligibility.

Is There Help with Funding Mitigation Improvements?

If your loan application is approved, you may be eligible for additional funds to cover the cost of improvements that will protect your property against future damage. Examples of improvements include retaining walls, seawalls, sump pumps, etc. Mitigation loan money would be in addition to the amount of the approved loan, but may not exceed 20 percent of total amount of physical damage to real property, including leasehold improvements, and personal property as verified by SBA to a maximum of $200,000 for home loans. It is not necessary for the description of improvements and cost estimates to be submitted with the application. SBA approval of the mitigating measures will be required before any loan increase.

Is There Help Available for Refinancing?

- SBA can refinance all or part of prior mortgages that are evidenced by a recorded lien, when the applicant (1) does not have credit available elsewhere, (2) has suffered substantial uncompensated disaster damage (40 percent or more of the value of the property or 50% or more of the value of the structure), and (3) intends to repair the damage.
- Businesses – Business owners may be eligible for the refinancing of existing mortgages or liens on real estate, machinery and equipment, up to the amount of the loan for the repair or replacement of real estate, machinery, and equipment.
- Homes – Homeowners may be eligible for the refinancing of existing liens or mortgages on homes, up to the amount of the loan for real estate repair or replacement.

What if I Decide to Relocate?

You may use your SBA disaster loan to relocate. The amount of the relocation loan depends on whether you relocate voluntarily or involuntarily. If you are interested in relocation, an SBA representative can provide you with more details on your specific situation.

Are There Insurance Requirements for Loans?

To protect each borrower and the Agency, SBA may require you to obtain and maintain appropriate insurance. By law, borrowers whose damaged or collateral property is located in a special flood hazard area must purchase and maintain flood insurance. SBA requires that flood insurance coverage be the lesser of 1) the total of the disaster loan, 2) the insurable value of the property, or 3) the maximum insurance available.

For more information, contact SBA's Disaster Assistance Customer Service Center by calling (800) 659-2955, emailing *disastercustomerservice@sba.gov*, or visiting SBA's Web site at *https://www.sba.gov/disaster*. Deaf and hard-of-hearing individuals may call (800) 877-8339. Applicants may also apply online using the Electronic Loan Application (ELA) via SBA's secure Web site at *https://disasterloan.sba.gov/ela*.

Amendment #8

APPENDIX C: LIST OF DISASTERS IN WINDOWS

TABLE C.I

LIST OF DISASTERS IN WINDOWS.

Declaration Date	Number of Applicants	State	Disaster Type	Specific Disaster Name (if applicable)
2006-03-17	227	MO	Tornado	–
2006-03-17	103	IL	Tornado	–
2006-03-27	10	TX	Tornado	–
2006-04-06	175	TN	Tornado	–
2006-04-06	147	MO	Tornado	–
2006-04-06	28	KY	Tornado	–
2006-04-10	15	IN	Tornado	–
2006-04-13	114	AR	Tornado	–
2006-04-14	30	OK	Tornado	–
2006-06-19	1	IN	Tornado	–
2006-06-19	6	IA	Tornado	–
2006-06-26	752	OH	Storm / Flood	–
2006-06-26	10	MD	Storm / Flood	–
2006-06-29	38	DE	Storm / Flood	–
2006-06-29	14	CT	Storm / Flood	–
2006-07-01	2189	NY	Storm / Flood	–
2006-07-05	59	VA	Storm / Flood	–
2006-07-05	1353	PA	Storm / Flood	–
2006-07-07	68	NJ	Storm / Flood	–
2006-09-25	28	MO	Storm / Flood	–
2006-09-29	18	AK	Storm / Flood	–
2006-10-10	426	IN	Storm / Flood	–
2006-10-10	26	IN	Storm / Flood	–
2006-10-12	186	LA	Storm / Flood	–
2006-10-17	38	KY	Storm / Flood	–
2006-10-17	9	VA	Storm / Flood	–
2006-10-19	17	OH	Storm / Flood	–
2007-06-21	87	TX	Tornado	–
2007-06-29	8	CA	Fire	Angora Fire
2007-07-05	48	OK	Tornado	–
2007-07-05	36	KS	Storm / Flood	–
2007-07-10	1	PA	Storm / Flood	–
2007-07-17	3	VT	Storm / Flood	–
2007-09-26	64	IL	Storm / Flood	–
2007-10-24	6	CT	Storm / Flood	–
2007-10-24	471	CA	Storm / Flood	–
2008-03-17	14	GA	Tornado	–
2008-03-21	8	SC	Tornado	–
2008-03-21	176	AR	Tornado	–
2008-03-28	163	MO	Storm / Flood	–
2008-04-02	2	IL	Storm / Flood	–
2008-04-08	16	MS	Tornado	–
2008-04-09	2	TX	Storm / Flood	–
2008-04-14	14	MS	Tornado	–
2008-06-26	91	MO	Storm / Flood	–
2008-06-30	4	NE	Storm / Flood	–

(*Continues*)

TABLE C.I

Continued.

Declaration Date	Number of Applicants	State	Disaster Type	Specific Disaster Name (if applicable)
2008-07-21	7	OH	Fire	–
2008-07-23	574	TX	Hurricane	Hurricane Dolly
2008-07-23	4	CA	Storm / Flood	–
2008-07-23	16	CA	Fire	June 2008 Dry Lightning Wildfires
2009-03-26	241	ND	Storm / Flood	–
2009-03-31	21	IN	Tornado	–
2009-03-31	1	MS	Tornado	–
2009-04-07	79	MN	Storm / Flood	–
2009-04-08	26	GA	Tornado	–
2009-04-10	3	MS	Storm / Flood	–
2009-04-13	10	AL	Tornado	–
2009-04-13	5	TN	Tornado	–
2009-04-13	9	AR	Tornado	–
2009-04-13	3	OK	Fire	–
2009-04-14	4	AL	Tornado	–
2009-06-19	5	KY	Tornado	–
2009-06-25	29	PA	Storm / Flood	–
2009-07-07	79	WI	Storm / Flood	–
2009-07-07	10	WY	Storm / Flood	–
2009-07-14	1	FL	Storm / Flood	–
2009-07-16	1	PA	Fire	–
2010-03-18	673	NJ	Storm / Flood	–
2010-03-22	1693	RI	Storm / Flood	–
2010-03-30	319	CT	Storm / Flood	–
2010-03-31	14	ME	Storm / Flood	–
2010-03-31	11	NC	Tornado	–
2010-04-05	122	NY	Storm / Flood	–
2010-04-07	61	CA	Earthquake	Sierra El Mayor Earthquake
2010-09-20	597	WI	Tornado	–
2010-09-21	7	OH	Tornado	–
2010-09-22	55	TX	Hurricane	Remnants of Hurricane Karl
2010-09-27	133	MN	Storm / Flood	–
2010-10-04	125	NC	Storm / Flood	–
2011-03-14	41	OH	Storm / Flood	–
2011-03-14	3	NY	Storm / Flood	–
2011-03-17	22	IN	Storm / Flood	–
2011-03-21	5	HI	Tsunami	Honshu Tsunami
2011-03-22	3	CA	Fire	Center Fire
2011-04-04	14	FL	Tornado	–
2011-04-07	3	CA	Storm / Flood	March 2011 Statewide Storms
2011-04-11	2	VA	Tornado	–
2011-04-11	1	LA	Tornado	–
2011-09-13	1464	PA	Storm / Flood	Tropical Storm Lee
2011-09-14	10	DE	Hurricane	Hurricane Irene
2011-09-15	31	VA	Storm / Flood	Tropical Storm Lee
2011-10-07	31	MA	Storm / Flood	–
2012-06-18	4	FL	Storm / Flood	–
2012-06-28	56	CO	Storm / Flood	–
2012-06-29	615	FL	Storm / Flood	Tropical Storm Debby
2012-07-05	33	NJ	Storm / Flood	–

(*Continues*)

TABLE C.I

Continued.

Declaration Date	Number of Applicants	State	Disaster Type	Specific Disaster Name (if applicable)
2012-07-06	2	GA	Storm / Flood	–
2012-07-09	136	MN	Storm / Flood	–
2012-07-17	107	MN	Storm / Flood	–
2012-07-17	2	MT	Fire	Ash Creek Fire
2013-06-13	2	CA	Fire	Powerhouse Fire
2013-06-17	30	TX	Storm / Flood	–
2013-06-18	6	WV	Storm / Flood	–
2013-06-19	21	CO	Fire	Black Forest Fire
2013-06-21	6	NC	Storm / Flood	–
2013-07-01	27	NY	Storm / Flood	–
2013-07-05	13	NC	Storm / Flood	–
2013-07-08	9	AZ	Fire	Yarnell Hill Fire
2013-07-09	37	PA	Storm / Flood	–
2015-03-19	3	RI	Fire	–
2015-03-20	9	VA	Storm / Flood	–
2015-03-20	1	NY	Fire	–
2015-03-26	16	OK	Tornado	–
2015-04-10	129	KY	Tornado	–
2015-12-28	67	MS	Tornado	–
2015-12-28	38	TX	Tornado	–
2015-12-30	2	KS	Storm / Flood	–
2015-12-30	18	WA	Tornado	–
2015-12-31	56	AL	Storm / Flood	–
2016-01-04	7	CT	Fire	–
2016-01-04	269	MO	Tornado	–
2016-01-06	10	OR	Storm / Flood	–
2016-01-07	33	AR	Tornado	–
2016-01-14	8	OK	Storm / Flood	–
2016-01-15	8	FL	Tornado	–
2016-06-16	27	OK	Tornado	–
2016-06-24	634	WV	Storm / Flood	–
2016-06-24	20	CA	Fire	Erskine Fire
2016-07-01	19	WV	Storm / Flood	–
2016-07-07	4	PA	Storm / Flood	–
2016-07-08	10	KS	Tornado	–
2016-09-26	3	MS	Storm / Flood	–
2016-09-26	6	NC	Storm / Flood	–
2016-09-26	27	IA	Storm / Flood	–
2016-10-05	145	MN	Storm / Flood	–
2016-10-08	1219	SC	Hurricane	Hurricane Matthew
2016-10-11	1944	NC	Hurricane	Hurricane Matthew
2016-10-12	409	VA	Hurricane	Hurricane Matthew
2017-06-19	13	CO	Storm / Flood	–
2017-06-22	15	NE	Tornado	–
2017-06-30	259	MI	Storm / Flood	–
2017-07-07	34	TX	Storm / Flood	–
2017-07-11	3	NY	Storm / Flood	–
2017-07-12	11	TX	Storm / Flood	–
2017-07-17	2	CA	Fire	Wall Fire

APPENDIX D: LASSO ESTIMATION

IN OUR MAIN DEMAND ESTIMATION, we combine estimated demand responses from many different *windows* to stitch together a global demand curve. By combining windows we are assuming that, after including model controls, the below-market rate and market-rate recipients respond similarly to the same interest rate variation and can thus be combined into a single demand curve. Section 4 addresses this concern at the aggregate level through a separate identification strategy. However, it is also possible that the population who applies and is approved varies with the interest rate and the included controls insufficiently account for this variation. As a result, we include a more flexible set of controls as a robustness test. One potential option would be to finely discretize our controls to allow for any potential non-linearity. However, we would not have sufficient residual variation to identify the slope of the demand curve at most of our prices. As an alternative, we turn to Lasso estimation.

The least absolute shrinkage and selection operator (Lasso) is a model selection technique originally developed by Tibshirani (1996) as an improvement on step-wise regression. The technique has recently entered the econometrics literature.[36] The Lasso is a penalized linear regression where the sum of the absolute value of the coefficients is limited by a meta parameter. The Lasso allows us to account for (nearly) arbitrary nonlinearity in our control variables through the use of polynomial approximation. Rather than only including linear representations of our individual-level control variables, we include polynomial terms through the fifth power and then allow the Lasso to select the ones that are most predictive. Formally, our model is

First Stage:

$$\begin{aligned} &P(Accept_{i,t}) = f(rate_{i,t};\theta) + W_{i,t}\beta + F_{i,t}\alpha + X_i\gamma + L_i\delta + v_{i,t}, \\ &(\alpha,\beta,\gamma,\delta,\theta) = \operatorname{argmin}_{\alpha,\beta,\gamma,\delta,\theta}\Big\{\sum\big(P(Accept_{i,t}) \\ &\qquad\qquad - \big(f(rate_{i,t};\theta) + W_{i,t}\beta + F_{i,t}\theta + X_i\gamma + L_i\delta\big)\big)^2\Big\} \\ &\qquad\qquad \text{subject to } \|\delta\|_1 \le \lambda_1, \end{aligned} \tag{D.1}$$

Second Stage:

$$\begin{aligned} P(Accept_{i,t}) &= f(rate_{i,t};\theta) + W_{i,t}\beta + F_{i,t}\alpha + X_i\gamma + L_i^p\delta + v_{i,t}, \\ L_i^p &= (L_i \text{ such that } \delta \neq 0), \end{aligned} \tag{D.2}$$

Rate Specification:

$$f(rate_{i,t};\theta) = \sum_{j=1}^{J}\theta_j 1\{window_{j,t}\} * rate_{i,t} + \theta_0\left(1 - \prod_{j=1}^{J} 1\{window_{j,t}\}\right) * rate_{i,t},$$

[36]See Bai and Ng (2008), Caner (2009), Belloni, Chen, Chernozhukov, and Hansen (2012), Belloni, Chernozhukov, and Hansen (2014b), Belloni, Chernozhukov, and Hansen (2014a), Belloni, Chernozhukov, Hansen, and Kozbur (2016), and Chernozhukov, Hansen, and Spindler (2015) among others for general usage. See also Carson, Ellis, Hoyt, and Ostaszewski (2020) and Collier, Ellis, and Keys (2021) for a similar usage.

Controls:

$$\begin{aligned} W = \big(&\text{30-year Fixed Mort. Rate}, \text{30-year Fixed Mort. Rate}^2, \\ &\text{30-year Fixed Mort. Rate}^3, \text{Time}, \text{Time}^2, \text{Time}^3, \\ &\text{N. Loan Officers}, \text{Loan Officers per Applicant}\big), \\ X = (&\text{Credit Score}, \text{Income}, \text{Loss Amount}, \text{Monthly Fixed Debt}, \\ &\text{Home Value}, \text{Home Equity}, \text{Renter}), \\ F = (&\text{State}, \text{Year}), \\ L = \big\{&X^2, X^3, X^4, X^5, \log(X)\big\}, \end{aligned}$$

where W are our disaster-level controls; X are our individual level control variables; F are our fixed effects; and L is the polynomial representation of our individual level control variables up to the fifth power and logged.

In Equation (D.1), we estimate the penalized version of the model including the full set of L. In Equation (D.2), we then estimate an unpenalized version of the full model using all of the control variables whose coefficients were nonzero in the the first stage (Belloni et al. (2016)). The included variables and combinations of variables in L^p can be interpreted as the optimal polynomial form of the control variables that can be represented in a limited (via the choice of metaparameter λ) number of terms. λ is estimated prior to the main estimation, where we chose the value of λ that minimizes the out-of-sample root mean squared error in a 3-fold cross-validation procedure. We find that our linear set of controls was largely sufficient, with the Lasso procedure only adding 4 (out of a potential 32) new variables: log(Credit Score), Family Size^2, log(Loss Amount), and log(Monthly Fixed Debt).

APPENDIX E: ROBUSTNESS TESTS FOR CREDIT SCORE DISCONTINUITY

Figure E.1 shows the McCrary sorting test for the credit score discontinuity. We do not observe credit scores bunching at the discontinuity of 700.

APPENDIX F: WELFARE HETEROGENEITY BY DEBT-TO-INCOME

We split the sample at the median based on the household's debt-service-to-income (DTI) ratio at the time of application. The median value is 0.29 (Table VII). To estimate consumer surplus, we leverage the group-specific demand that we estimated in Section 3.3, adapting it to the consumer surplus approach described above, which measures aggregate demand in terms of total dollars loaned. Figure F.1 plots consumer surplus for each group. As described in Appendix A, we are limited in estimating willingness-to-pay (WTP) by the observed interest rate variation and calculate consumer surplus using the conservative assumption that the maximum WTP is the maximum observed interest rate. This conservative assumption likely approximates the true consumer surplus well if few households are willing to pay the maximum observed rate; however, a noteworthy feature of this figure is that a large share of the high DTI population would be willing to pay the maximum observed interest rate offered in the program. A key implication is that our consumer surplus estimates for high DTI households are a lower bound.

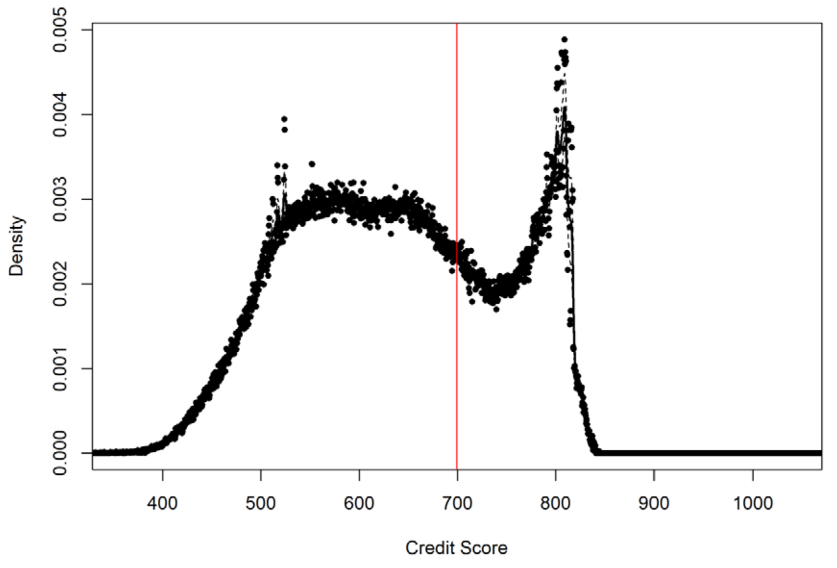

FIGURE E.1.—McCrary Sorting Test. *Note*: This figure presents the results of the McCrary (2008) Sorting Test. The p value for the test is .806, thus we fail to reject the null hypothesis that there is no sorting, and thus the data pass the test.

To estimate producer surplus, we allocate administrative and subsidy costs to each group. We divide administrative costs by total dollars loaned to each group. Low DTI households borrowed \$6.6 billion while high DTI households borrowed \$5.9 billion, so we assign 52% of administrative costs to the low DTI group. We divide subsidy costs by the share of dollars charged off due to non-repayment for each group. Approximately 54% of dollars charged off are for the low DTI group.[37] We also include a 30% cost based on the estimated administrative and subsidy costs for the marginal rate of taxation. Figure F.1 illustrates the producer surplus for each group.

APPENDIX G: SUPPORTING MATERIAL ON INCOME, INSURANCE, AND FEMA DISASTER GRANTS

G.1. *Comparing ZIP Codes With FDL Applicants to Other ZIP Codes*

Table G.I compares ZIP Codes that are represented in the FDL program data to ZIP Codes that are not. We use ZIP-by-year level demographic information from the Census Bureau's 5-year American Community Survey (ACS, Census Bureau (2018), Bureau, U.S. Census (2022)). The ACS data are from 2011 to 2017. The table shows that, compared to ZIP Codes not represented in the program, those containing FDL applicants have higher average income, differing by about \$6700 per year. FDL ZIP Codes also have more income inequality (Gini Coefficient), and a lower percentage of households who own their homes, identify as white, and have high school degrees. However, FDL ZIP Codes also have a slightly higher fraction of residents with college degrees.

[37]The low DTI group has a slightly higher charge-off rate per dollar loaned 11.2% versus 10.6%, possibly because low DTI borrowers take larger loans, which can increase repayment risks.

Panel A: Below-Median DTI | Panel B: Above-Median DTI

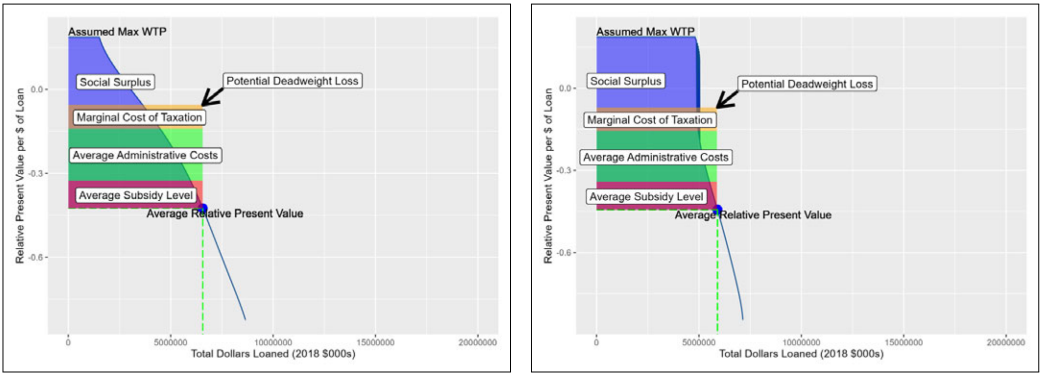

FIGURE F.1.—Welfare by Applicant Debt-Service-to-Income Ratio. *Note*: Panel A includes consumers with a DTI ratio below 29 at the time of application; Panel B includes consumers with DTI ratios at or above 29.

G.2. *Applicant Income, Insurance, and Grants*

We compare the incomes of applicants and borrowers relative to household incomes in their ZIP Code, in their MSA, and to incomes nationally. We focus on income relative to households in the same ZIP Codes because more aggregated data may overlook variation in risk (e.g., within an MSA, flood risks may be higher in lower income neighborhoods), though the results are similar when examining incomes relative to MSA or national levels). These analyses use the Census Bureau's 5-year ACS data and FDL applicants from years 2011 to 2017.

Table G.II shows the relative incomes of applicants. These analyses use the Census Bureau's 5-year ACS data and FDL applicants from years 2011 to 2017. The median applicant is at the 53rd percentile of the income distribution for its ZIP Code. The median *declined* applicant is at the 44th ZIP-level income percentile while the median *borrower*

TABLE G.I

ZIP CODE SUMMARY STATISTICS FOR ALL YEARS.

	All		In FDL Program		Not in FDL Program		Diff. Means	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Diff.	t
Mean Income ($000s)	67.528	30.099	71.032	32.079	64.320	27.779	6.712	48.795
Gini Coefficient	0.411	0.075	0.424	0.062	0.399	0.082	0.024	73.998
% Owner Occupied	0.733	0.174	0.716	0.163	0.749	0.183	−0.033	−42.673
% White	0.839	0.208	0.803	0.219	0.871	0.192	−0.068	−72.566
% High School	0.862	0.106	0.860	0.097	0.865	0.114	−0.005	−10.725
% Bachelors Degree	0.227	0.163	0.245	0.162	0.211	0.163	0.034	45.819
N	198,720		92,478		106,242		–	

Note: The table presents summary statistics for ZIP Codes in the 5-year American Community Survey (ACS) from 2011 to 2017. The first columns summarize all ZIP Codes by year observations. The second set of columns includes ZIP Code demographics for years in which at least one person in the ZIP Code applied to the FDL program. The remaining ZIP Code by year observations are represented in the third set of columns. The final columns provide two-way t-tests comparing the demographics of ZIP Codes that are represented in the program to those that are not.

TABLE G.II

APPLICANT INCOME PERCENTILE RELATIVE TO ZIP CODE, MSA, AND NATIONAL INCOMES.

Status	Mean	SD	Percentiles p1	p25	p50	p75	p99	Obs	NA
				ZIP Code					
Declined	0.46	0.24	0.02	0.27	0.44	0.63	0.99	219,883	17,319
Borrowed	0.60	0.21	0.14	0.44	0.61	0.77	0.98	133,094	227
Canceled	0.61	0.22	0.14	0.44	0.63	0.80	0.98	54,581	113
Total	0.53	0.24	0.03	0.34	0.53	0.72	0.98	407,558	17,659
				MSA					
Declined	0.43	0.22	0.03	0.27	0.41	0.57	0.98	219,883	74,536
Borrowed	0.59	0.20	0.18	0.44	0.59	0.75	0.97	133,094	34,516
Canceled	0.62	0.21	0.18	0.45	0.62	0.79	0.98	54,581	20,146
Total	0.51	0.23	0.04	0.34	0.50	0.68	0.98	407,558	129,198
				National					
Declined	0.42	0.23	0.03	0.26	0.39	0.56	0.97	219,883	16,761
Borrowed	0.59	0.21	0.18	0.43	0.59	0.76	0.98	133,094	2
Canceled	0.64	0.22	0.20	0.47	0.65	0.83	0.98	54,581	0
Total	0.51	0.24	0.04	0.33	0.49	0.69	0.98	407,558	16,763

Note: This table shows the income percentile of FDL applicants compared to the ZIP Code, MSA, and national level income distributions for all applications from 2011 to 2017. The measure of national relative income compares applicants to the national income distribution for the year in which they applied for a recovery loan. The MSA data use the Census Bureau's Core Based Statistical Areas, which includes metropolitan and micropolitan statistical areas.

is at the 61st percentile, a 17 pp difference. Applicants who are approved but cancel the loan have the highest income with a median at the 63rd percentile.

Panel A of Figure G.1 shows the ZIP-level results, plotting the income distributions as densities. If applicants of all incomes in the ZIP Code were equally likely to borrow from the program, it would result in a horizontal line at the density of 1.0 for borrowers. Borrowers, marked with triangles, overrepresent households between the 40th to 95th percentiles of the income distribution. Approved applicants who do not accept the loan, marked with squares, are mostly similar to borrowers, but include more high income applicants. Declined applicants, marked with circles, overrepresent households between the 20th to 70th percentiles of the income distributions in their ZIP Codes. The income differential in approval appears due to the program's underwriting rules, which rely on applicants' credit scores and DTIs. In the Supplemental Appendix G, we show that DTI and credit score, and especially the combination of the two, are strongly associated with the relative incomes of applicants. For the program's existing applicants, effectively any rule that determines loan approval based on *either* DTI or credit score thresholds would still result in a program that supplies recovery loans to the applicants with higher incomes.

We also examine the relationship between insurance claims payments and relative income of approved applicants. For approved applicants, our data indicate what relevant insurance policies the household has and the amount paid by each policy. The types of policies included are, in order of frequency, homeowners, flood, auto, wind, renters, and sewer backup.

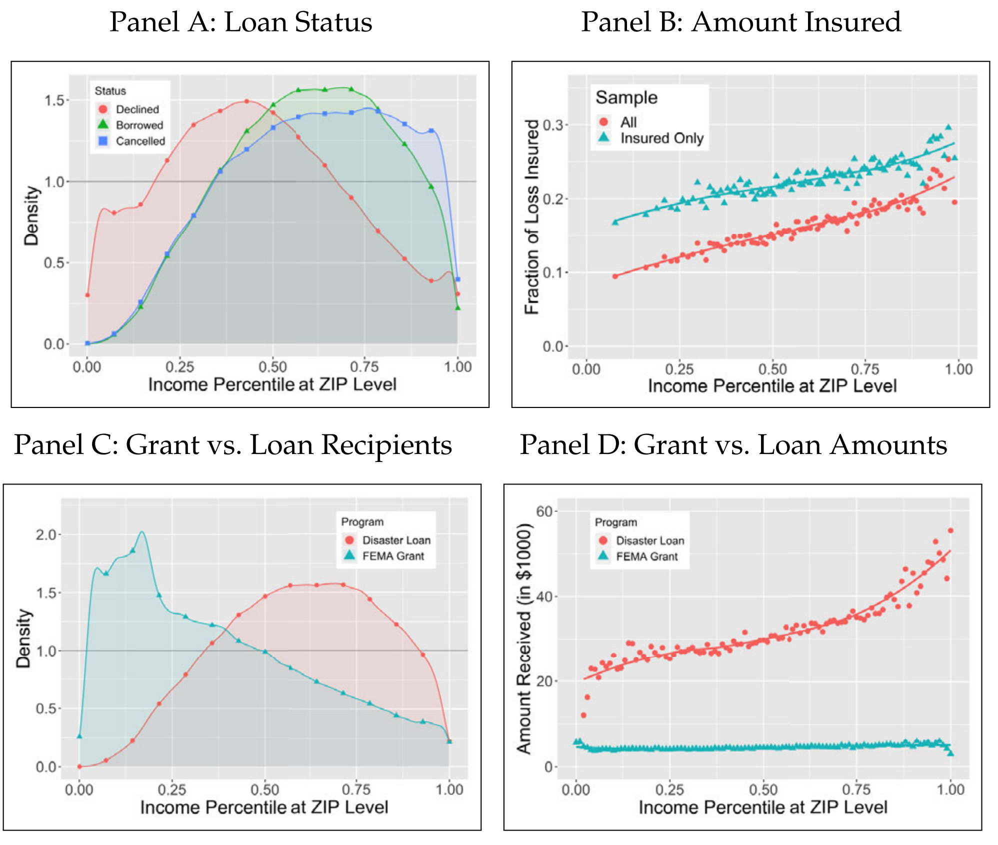

FIGURE G.1.—Relative Income and Its Correlates. *Note*: Panel A shows the income of applicants relative to other households in their ZIP Codes, using ACS data. “Canceled” were approved applicants who did not accept the loan. Panel B is similar but examines the fraction of a household’s loss that is insured. The circular points in panel B use data from both insured and uninsured households; the triangular points only include households who have some form of insurance. Panel C compares relative income of FEMA grant recipients to FDL borrowers. Panel D shows the average grant and loan amounts in thousands of dollars by relative income. The figures include completed applications from 2011 to 2017.

Panels B of Figure G.1 shows the insurance payments and income of approved applicants relative to other households in their ZIP Code. The green triangles represent only approved applicants who have insurance. The red dots in Panel B include all approved applicants and also include households who do not have insurance. Insurance coverage is positively associated with relative income. Around 10% of the losses of approved applicants with the lowest relative incomes are insured versus 20% of the losses of the approved applicants with the highest relative incomes.

Finally, we compare recovery loan borrowers to FEMA grant recipients to provide a more complete picture of our setting. FEMA grants can be used to repair or replace damaged property and for rental assistance. We obtained FEMA grant application data for our period of study, 2005 to 2018, through a Freedom of Information Act request. During this time, 13.7 million households applied for a grant. About 24% of applicants were approved with an average grant size of $4500. Only 9% of approved grants exceed $10,000.

Panel C of Figure G.1 shows the complementary allocation of grants and loans as the grant recipient overrepresent below-median-income households, especially those in the first quartile. Panel D shows the average amounts provided to grant recipients and loan recipients by income. Grants average \$4500 regardless of income. Loans are orders of magnitude larger, about 5 times larger for first quartile borrowers and 10 times larger for fourth quartile borrowers.

To summarize, approved applicants tend to have incomes above the median. They receive very little insurance payments for their property damages; however, applicants are most frequently affected by flood, which is a disaster against which many households are uninsured. Also, disaster loans are used by different, more affluent populations than users of a separate grant program.

G.3. *Estimating Households' Relative Income*

We describe the ZIP-level relative income calculation and similarly estimate MSA-level and national-level relative incomes. We develop point estimates for each household's income percentile in its ZIP Code. The ACS reports income by category, providing the number of households in a ZIP Code whose incomes are (1) below \$10,000, (2) between \$10,000 and \$14,999, (3) between \$15,000 and \$19,999, ..., and (16) \$200,000 or more. Let y_i represent the income of household i in ZIP Code j and $y_i \in [x, z]$ where x and z are the lower and upper endpoints of an ACS income category. Let F_j represent the continuous income distribution in ZIP Code j. The ACS data provide the percent of households in the ZIP Code with incomes below x, $F_j(x)$, and with incomes below z, $F_j(z)$, which create lower and upper bounds on the household's income percentile.

We use two approaches to convert the ACS data to an income percentile point estimate for the household. The first method, the one used in Section 4.2, is linear interpolation. It uses a weighted average of the distance between the household's income and each endpoint of the income bin. Let $\tau_i = (y_i - x)/(z - x)$ weight the distance of the household's income from each endpoint in the income category. Then $F_j(y_i) \approx (1 - \tau)F_j(x) + \tau F_j(z)$. For example, suppose that $\{x_i, y, z, F_j(x), F_j(z)\} = \{\$15{,}000, \$17{,}000, \$19{,}999, 0.2, 0.3\}$. Then $\tau_i = 0.4$ and $F_j(y) \approx 0.24 = (1-0.4) \times 0.2 + 0.4 \times 0.3$. For households in the bottom and top income categories (below \$10,000 and \$200,000 or more, respectively), we assign all households the middle percentile in the income bin. For example, if 96% of households in the ZIP Code have incomes below \$200,000, we would assign the 98th percentile to all households in the top category $(0.98 = (0.96 + 1.00)/2)$. About 3% of applicants are in each the bottom and top income categories.

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Co-editor Oriana Bandiera handled this manuscript.

Manuscript received 16 December, 2021; final version accepted 1 February, 2024; available online 6 February, 2024.