# Price Comparison Tools in Consumer Credit Markets

Erik **Berwart** Sean **Higgins** Sheisha **Kulkarni** Santiago **Truffa**  Comisión para el Mercado Financiero Northwestern University – Kellogg University of Virginia – McIntire Universidad de los Andes – ESE

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Lots of price dispersion

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- In our survey data, average within-consumer standard deviation in annual interest rate is 5.8 pp
  - Compared to an average interest rate of 15%

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Consumers who are unaware of this dispersion may shop less and take out more expensive loans than is optimal

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Mexican consumers pay 31% more (or 1% of income) due to borrowing on higher-APR card (Ponce Seira Zamarripa 2017)

#### Hard to compare prices

- Price shrouding and hidden fees (Campbell Jackson Madrian Tufano 2011; Alan Cemalcilar Karlan Zinman 2018)
- Complicated financial products that are cognitively costly to understand (Célérier Vallée 2017; Kulkarni Truffa Iberti 2023)

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#### High search costs

- Physical search across bank branches (Argyle Nadauld Palmer 2023)
- High rejection rates ⇒ higher search costs for less creditworthy (Agarwal Grigsby Hortaçsu Matvos Seru Yao 2022)

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#### Inaccurate expectations about prices

### **This Paper**

**Research question:** How do inaccurate priors about the distribution of interest rates affect search in consumer credit markets?

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Combine administrative and survey data to measure effects on:

- Expectations about interest rates
- Search behavior
- Whether they take out a loan
- Terms of the loan they eventually take out

#### **Consumers Tend to Underestimate Dispersion**



#### **Consumers Also Underestimate the Rate They Will Get**



## **Experimental Setting and Data**

### Sample

Chileans who Googled keywords related to consumer loans between November 2021 and June 2023 received an ad for our study

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Most popular search queries:

- "consumption loan"
- "apply for a loan online"
- "I need money urgently today"

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- "I need money urgently today"

Example ad:

Ad · www.eligemejortucredito.cl/credito

#### Choose Your Loan Better | Comisión Mercado Financiero

We give you tools to help you search for and evaluate loans in the market. Participate in this 10minute research study on the financial market.

### **Sample: Participation Funnel**



#### **Consumer Loans**

Consumer loans are unsecured loans

- Most commonly used to purchase durables (appliances, vehicles), pay off other debts, or make home improvements
- Median interest rate is 20.1%
- Median loan amount is \$4,582 USD
- Median maturity is 3.1 years

Administrative data from the CMF on loan and borrower characteristics for the universe of loans in Chile, merged with our RCT sample

- Loan type, loan amount, interest rate, maturity
- Borrower income, comuna (neighborhood) of borrower

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Baseline survey data immediately before and after treatment

More detail on next slides

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More detail on next slides

Follow-up phone surveys

### **Baseline Survey**



Paso 1. Por favor ingresa tus datos para comenzar:

Nombre (\*)

	 1.	1
RU	(*	J

Edad (\*)

Email (\*)



Teléfono (nueve díaitos) (\*)

Key: National ID number (RUT) is commonly used in Chile

- e.g., at grocery store; phone repair store
- This will allow us to merge with future administrative data on originated loans

Also collect contact information for follow-up surveys

### **Baseline Survey**

Sociodemographic characteristics

Current bank products they have and at which banks

Intended use of the loan

How they formed priors

Financial literacy and cognitive ability

Expectations about search

- How many banks
- Which bank first

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- How many banks
- Which bank first

#### Expectations about prices

Berwart (CMF), Higgins (Northwestern), Kulkarni (UVA), Truffa (ESE)

¿Cuál crees que es la tasa de interés que tú conseguirás por
este crédito?
(puedes utilizar decimales)

% -elige el período- 🗸

¿Cuál crees que es la tasa de interés <u>más baja</u> que un banco podría ofrecerte por este crédito? (puedes utilizar decimales)

% -elige el período- ~

¿Cuál crees que es la tasa de interés <u>más alta</u> que un banco podría ofrecerte por este crédito? (puedes utilizar decimales)



¿Cuál crees que es la tasa de interés <u>promedio</u> que personas como tú consiguen por un crédito como este?

# **Experimental Design**

#### **Treatment Arms**

Randomize whether participants are asked expectations about interest rates and search ("Elicit Priors" treatment)

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After completing the survey questions, participants are randomized into one of three groups:

- 1. Full price comparison tool
- 2. Simple tool with information on benefits of search
- 3. Control: view placebo video made by the CMF
  - Defines key terms related to credit

#### **Treatment Arms**

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- 3. Control: view placebo video made by the CMF
  - Defines key terms related to credit

After treatment, we ask again about their expectations about prices (if assigned to Elicit Priors treatment)

#### **Treatment 1: Full Price Comparison Tool**

Tutorial Video 
 Other comparison tools
Berwart (CMF), Higgins (Northwestern), Kulkarni (UVA), Truffa (ESE)

### **Treatment 2: Simple Tool**

Estimate personalized benefits of search based on simulations where we draw from their conditional distribution 
More details

Tell the user the expected benefit from searching at X additional banks

# Results

#### Full Tool $\Rightarrow$ Consumers Update Beliefs Upwards

 $\textit{Posterior}_i = \beta_0 + \beta_1 \textit{Prior}_i + \beta_2 \mathbb{1}(\textit{Simple Tool}) + \beta_3 \mathbb{1}(\textit{Full Tool}) + \varepsilon_i$ 

	Expected (Own)	Expected (Others)	Lowest	Highest	Dispersion
(Intercept)	27.850***	32.887***	22.063***	43.325***	19.403***
	(1.845)	(2.319)	(1.489)	(3.220)	(1.886)
Prior	0.806***	0.693***	0.794***	0.677***	0.517***
	(0.022)	(0.021)	(0.023)	(0.021)	(0.021)
Simple Tool	-0.265	-2.721***	0.467	0.921	-1.905**
	(0.860)	(1.056)	(0.698)	(1.463)	(0.803)
Full Tool	18.493***	20.179***	14.151***	37.953***	20.123***
	(1.552)	(1.910)	(1.235)	(2.920)	(1.768)
Observations	6751	6542	6693	6593	6215
# **Eliciting Priors Leads to More Search and Lower Rates**

			Survey Data			Administrative Data		
	N of inst. they searched	N of inst. they applied	N offers (unconditional)	N offers (if applied)	Log mean interest rate offered	Pr(take-up Ioan)	Log interest rate	
(Intercept)	3.325***	1.144***	0.508***	0.878***	2.226***	0.188***	3.174***	
	(0.043)	(0.036)	(0.022)	(0.032)	(0.068)	(0.002)	(0.005)	
Elicit Priors	0.140***	-0.012	0.000	0.008	-0.172**	-0.004	-0.011**	
	(0.052)	(0.042)	(0.026)	(0.038)	(0.077)	(0.003)	(0.006)	
Observations	4659	4503	4470	2566	1081	112066	21872	

▶ Balance tables

#### **Price Comparison Tool Leads to More Offers**

			Survey Data			Administrative Data		
	N of inst. they searched	N of inst. they applied	N offers (unconditional)	N offers (if applied)	Log mean interest rate offered	Pr(take-up Ioan)	Log interest rate	
(Intercept)	3.437***	1.067***	0.452***	0.771***	2.650***	0.194***	3.180***	
	(0.054)	(0.041)	(0.024)	(0.034)	(0.034) (0.093)		(0.007)	
Simple Tool	0.054	0.008	0.027	0.072	-0.133	0.009*	0.005	
	(0.079)	(0.058)	(0.035)	(0.050)	(0.138)	(0.005)	(0.010)	
Full Tool	-0.019	0.011	0.060*	0.094*	-0.132	0.009**	0.002	
	(0.079)	(0.057)	(0.035)	(0.049)	(0.129)	(0.005)	(0.010)	
Observations	2659	2573	2559	1489	455	46052	9321	

Balance tables

#### **Distribution of Interest Rate Offers**



Admin data CDF

# Next Steps

# Next Steps: Follow-Up Survey

Continue collecting phone surveys to increase sample size to measure:

- How do people form priors? (Friends, ads, bank simulators)
- Mechanisms behind the effect of eliciting priors on search (forming less diffuse priors vs. implementation intentions)
- Mechanisms behind the effect of the tool on taking out a loan (how are people searching better?)
- Better data on search histories, negotiating offers with banks, etc.

#### **Next Steps**

Scraping data from Google ads to understand if bank ads contribute to inaccurate priors

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Structural model of search in consumer credit market with incorrect priors

- Goal 1: quantify how much empirical search models overestimate search costs by assuming accurate priors
- Goal 2: counterfactuals such as search with correct priors, or correct about first moment but not second or vice versa
- Goal 3: supply side response to an aggregate improvement in priors

# Appendix

# **Balance Table: Elicit Priors administrative outcomes 1**

	Group	Mean			
	Control	Elicit Priors	Diff.	p-value	Ν
Personal characteristics					
Age	35.94	35.83	-0.11	0.119	112063
log(Income)	13.62	13.62	0	0.914	109667
Incomplete high-school	0.04	0.04	0	0.569	108811
Complete high-school	0.36	0.36	0	0.385	108811
Complete 2-year program	0.21	0.21	0	0.541	108811
Complete 5-year program or higher	0.39	0.39	0	0.905	108811
Financial products					
Bank account	0.68	0.68	0	0.566	106222
Any loan	0.71	0.7	-0.01	0.047	107130
F-test Elicit Priors				0.543	112066
Number of participants	28198	83868			
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# **Balance Table: Elicit Priors administrative outcomes 2**

	Group	Mean			
	Control	Elicit Priors	Diff.	p-value	Ν
Personal characteristics					
Age	35.13	35.11	-0.02	0.866	21872
log(Income)	14.04	14.04	0	0.696	21596
Incomplete high-school	0.01	0.01	0	0.996	21560
Complete high-school	0.21	0.21	0	0.562	21560
Complete 2-year program	0.2	0.2	0	0.687	21560
Complete 5-year program or higher	0.59	0.59	0	0.883	21560
Financial products					
Bank account	0.89	0.89	0	0.473	21557
Any loan	0.89	0.89	0	0.948	21632
F-test Elicit Priors				0.964	21872
Number of posticia anto	5504	16070			
Number of participants	5594	16278			
	Back				

#### Balance Table: Elicit Priors follow-up survey outcomes 1

	Group	Mean			
	Control	Elicit Priors	Diff.	p-value	Ν
Personal characteristics					
Age	36.65	36.35	-0.3	0.353	4659
Female	0.4	0.4	0	0.884	4268
log(Income)	13.62	13.64	0.02	0.554	4577
Incomplete high-school	0.03	0.03	0	0.905	4557
Complete high-school	0.34	0.33	-0.01	0.426	4557
Complete 2-year program	0.21	0.2	-0.01	0.621	4557
Complete 5-year program or higher	0.42	0.44	0.02	0.26	4557
Financial products					
Bank account	0.68	0.69	0.01	0.483	4467
Any loan	0.74	0.72	-0.02	0.258	4503
F-test Elicit Priors				0.514	4659
Number of participants	1313	3346			
	Back				

#### Balance Table: Elicit Priors follow-up survey outcomes 2

	Group	Mean			
	Control	Elicit Priors	Diff.	p-value	Ν
Personal characteristics					
Age	36.46	36.24	-0.22	0.492	4503
Female	0.4	0.4	0	0.89	4132
log(Income)	13.65	13.66	0.01	0.839	4428
Incomplete high-school	0.02	0.02	0	0.931	4408
Complete high-school	0.33	0.32	-0.01	0.563	4408
Complete 2-year program	0.21	0.2	-0.01	0.656	4408
Complete 5-year program or higher	0.44	0.46	0.02	0.348	4408
Financial products					
Bank account	0.69	0.7	0.01	0.475	4337
Any loan	0.75	0.74	-0.01	0.376	4369
F-test Elicit Priors				0.644	4503
Number of participants	1267	3236			
	Back				

#### Balance Table: Elicit Priors follow-up survey outcomes 3

	Group	Mean			
	Control	Elicit Priors	Diff.	p-value	Ν
Personal characteristics					
Age	36.75	36.46	-0.29	0.352	4918
Female	0.4	0.4	0	0.93	4499
log(Income)	13.61	13.62	0.01	0.701	4825
Incomplete high-school	0.03	0.03	0	0.958	4804
Complete high-school	0.35	0.34	-0.01	0.401	4804
Complete 2-year program	0.21	0.2	-0.01	0.403	4804
Complete 5-year program or higher	0.41	0.43	0.02	0.129	4804
Financial products					
Bank account	0.68	0.69	0.01	0.433	4703
Any loan	0.73	0.71	-0.02	0.263	4744
F-test Elicit Priors				0.375	4918
Number of participants	1390	3528			
	Back				

# **Balance Table: Tools administrative outcomes 1**

	Gr	roup Mea	n					
	Control	Simple Tool	Full Tool	ST-C diff.	p-value	FT-C diff.	p-value	Ν
Personal characteristics								
Age	35.77	35.83	35.63	0.06	0.623	-0.14	0.212	46051
log(Income)	13.46	13.46	13.46	0	0.763	0	1	44978
Incomplete high-school	0.04	0.04	0.04	0	0.358	0	0.607	44615
Complete high-school	0.43	0.42	0.42	-0.01	0.234	-0.01	0.183	44615
Complete 2-year program	0.22	0.22	0.23	0	0.348	0.01	0.206	44615
Complete 5-year program or higher	0.31	0.31	0.31	0	0.979	0	0.955	44615
Financial products								
Bank account	0.62	0.63	0.64	0.01	0.022	0.02	0.004	43272
Any loan	0.67	0.68	0.67	0.01	0.311	0	0.706	43675
Loan characteristics								
log(Loan Amount)	14.74	14.76	14.76	0.02	0.3	0.02	0.217	43775
log(Maturity (years))	1.32	1.33	1.32	0.01	0.236	0	0.706	40920
F-test FT vs C							0.279	30718
F-test ST vs C					0.207			30690
Number of participants	15357	15333	15361					
		Deels						

# **Balance Table: Tools administrative outcomes 2**

	Gr	oup Mea	n					
	Control	Simple Tool	Full Tool	ST-C diff.	p-value	FT-C diff.	p-value	Ν
Personal characteristics								
Age	35.09	35.1	35.05	0.01	0.964	-0.04	0.84	9321
log(Income)	13.9	13.92	13.93	0.02	0.296	0.03	0.116	9178
Incomplete high-school	0.01	0.01	0.01	0	0.673	0	0.691	9155
Complete high-school	0.24	0.23	0.23	-0.01	0.223	-0.01	0.371	9155
Complete 2-year program	0.21	0.22	0.22	0.01	0.26	0.01	0.232	9155
Complete 5-year program or higher	0.54	0.54	0.54	0	0.97	0	0.773	9155
Financial products								
Bank account	0.86	0.87	0.88	0.01	0.46	0.02	0.008	9155
Any loan	0.87	0.88	0.88	0.01	0.426	0.01	0.298	9190
Loan characteristics								
log(Loan Amount)	15.43	15.48	15.49	0.05	0.119	0.06	0.052	8893
log(Maturity (years))	1.43	1.45	1.47	0.02	0.173	0.04	0.014	8658
E to at ET up 0							0 10 1	6176
F-test FT vs C					0.075		0.104	61/6
F-test ST VS C					0.875			6162
Number of participants	3017	3145	3159					
		Back						

#### Balance Table: follow-up survey outcomes 1

	Group Mean							
	Control	Simple Tool	Full Tool	ST-C diff.	p-value	FT-C diff.	p-value	Ν
Personal characteristics								
Age	36.33	36.66	36.04	0.33	0.489	-0.29	0.534	2659
Female	0.39	0.39	0.38	0	0.948	-0.01	0.709	2418
log(Income)	13.56	13.57	13.52	0.01	0.798	-0.04	0.465	2620
Incomplete high-school	0.03	0.03	0.03	0	0.887	0	0.769	2600
Complete high-school	0.39	0.37	0.36	-0.02	0.461	-0.03	0.208	2600
Complete 2-year program	0.21	0.22	0.24	0.01	0.554	0.03	0.16	2600
Complete 5-year program or higher	0.38	0.39	0.38	0.01	0.778	0	0.885	2600
Financial products								
Bank account	0.63	0.66	0.65	0.03	0.13	0.02	0.305	2546
Any loan	0.68	0.7	0.73	0.02	0.462	0.05	0.014	2569
Loan characteristics								
log(Loan Amount)	14.97	15.02	15.03	0.05	0.451	0.06	0.331	2523
log(Maturity (years))	1.35	1.36	1.39	0.01	0.779	0.04	0.237	2405
F-test FT vs C							0.401	1745
F-test ST vs C					0.674			1793
Number of participants	879	914	866					
		Back						

# Balance Table: follow-up survey outcomes 2

	Group Mean							
	Control	Simple Tool	Full Tool	ST-C diff.	p-value	FT-C diff.	p-value	N
Personal characteristics								
Age	36.26	36.53	35.95	0.27	0.572	-0.31	0.51	2573
Female	0.4	0.39	0.38	-0.01	0.758	-0.02	0.425	2343
log(Income)	13.57	13.59	13.53	0.02	0.742	-0.04	0.512	2537
Incomplete high-school	0.02	0.02	0.02	0	0.912	0	0.976	2518
Complete high-school	0.38	0.36	0.35	-0.02	0.313	-0.03	0.167	2518
Complete 2-year program	0.21	0.22	0.24	0.01	0.494	0.03	0.144	2518
Complete 5-year program or higher	0.39	0.4	0.39	0.01	0.648	0	0.915	2518
Financial products								
Bank account	0.64	0.68	0.66	0.04	0.092	0.02	0.295	2477
Any loan	0.69	0.71	0.74	0.02	0.314	0.05	0.014	2497
Loan characteristics								
log(Loan Amount)	14.99	15.05	15.07	0.06	0.32	0.08	0.223	2443
log(Maturity (years))	1.35	1.36	1.39	0.01	0.646	0.04	0.186	2337
F-test FT vs C							0.315	1690
F-test ST vs C					0.428		0.010	1735
Number of participants	852	883	838					
		Back						

# Balance Table: follow-up survey outcomes 3

	Group Mean							
	Control	Simple Tool	Full Tool	ST-C diff.	p-value	FT-C diff.	p-value	Ν
Personal characteristics								
Age	36.53	36.68	36.18	0.15	0.755	-0.35	0.453	2823
Female	0.4	0.4	0.39	0	0.858	-0.01	0.756	2560
log(Income)	13.54	13.56	13.51	0.02	0.762	-0.03	0.544	2776
Incomplete high-school	0.03	0.03	0.02	0	0.698	-0.01	0.5	2755
Complete high-school	0.39	0.36	0.36	-0.03	0.171	-0.03	0.139	2755
Complete 2-year program	0.21	0.22	0.24	0.01	0.569	0.03	0.127	2755
Complete 5-year program or higher	0.37	0.39	0.38	0.02	0.306	0.01	0.685	2755
Financial products								
Bank account	0.63	0.67	0.65	0.04	0.079	0.02	0.397	2697
Any loan	0.68	0.7	0.72	0.02	0.417	0.04	0.041	2723
Loan characteristics								
log(Loan Amount)	14.91	15.02	15.01	0.11	0.09	0.1	0.115	2675
log(Maturity (years))	1.35	1.36	1.38	0.01	0.7	0.03	0.263	2541
F-test FT vs C							0.26	1861
F-test ST vs C					0.489			1902
Number of participants	940	962	921					
		Back						

#### **Distribution of Interest Rate Offers**



#### **Distribution of Interest Rates on Originated Loans**



▶ Back

#### Distribution of Interest Rates on Originated Loans (Tool)



▶ Back

#### Bank simulators vs. rates received



Berwart (CMF), Higgins (Northwestern), Kulkarni (UVA), Truffa (ESE)

#### Bank simulators vs. rates received



# Follow-Up Phone Survey

How do consumers searching for loans form expectations?

- How do people form priors about the distribution of rates and the rate they will get?
  - Previous searches
  - Advertisements
  - Information from friends and family
- Did they have a "strategy" for their loan search?
  - Search until get offers from X banks
  - Search until get an interest rate offer below y

# Follow-Up Phone Survey

Search history. For each institution where they searched:

- How did they search (online, by phone, in person)?
- Did they try to get a sense of probability of approval or interest rate before applying?
- Did they submit an application?
- Were they approved?
- What were the loan terms?

#### Negotiating

• Did they use quotes from another institution to negotiate a lower rate at their "home bank"?

#### **Google Search Terms**



#### **Recruit: Google Ad Campaign**

Decided on ad budget of \$120 USD per day to maximize number of treated participants per day.





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#### **Tutorial Video**

We ask participants to review whether their data is correct.

We summarize what the plot shows, and how lower rates translate into cheaper loans.

We summarize what the table shows: how different rates impact their monthly and total loan cost, and that they can play out with different rates.

# Other Comparison Tools: ComparaOnline

Compara		Seguros · Productos financieros · Blog ·	<b>&amp;</b> (56) 2 2581 4901	
Inicio > Crédito de Consun	о			
		Simula tu Crédito de		
		Consumo Online		
		Encuentra la mejor tasa de interés de crédito consumo y el menor costo asociado a tu prést bancario.	de amo	
	Crédito en Pesos	Cuotas Mensuales		
	1.500.000	12	CALCULAR	

#### **Other Comparison Tools: SERNAC**



#### Comparador de Créditos de Consumo

Información referencial obtenida de los sitios web de las instituciones financieras disponibles entre el 21/08/2023 y el 31/08/2023.

Esta herramienta permite comparar créditos de consumo de diferentes instituciones financieras. En caso de querer contratar un crédito, le recomendamos solicitar una cotización en al menos 3 de las instituciones más convenientes para que lo evalúen comercialmente.

#### ¿Cómo usar el comparador?



Berwart (CMF), Higgins (Northwestern), Kulkarni (UVA), Truffa (ESE)

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#### **More Details Button**

We explain how we calculate how much your monthly payments would be reduced by shopping at one additional bank.

"We use real data of loan rates granted to people similar to you, for loans similar to the one you are searching for. We simulate your search by choosing one of these rates as the first one you would get and another one as the second one. If the second rate is lower than the first one, we calculate how much your monthly payment would be reduced. If the second rate is higher than the first one, we assume you would keep choosing the first rate and then your monthly payment would not be reduced."

# **External Validity**

Consumer characteristics: similar to all borrowers; skew younger

Loan characteristics: similar Back



#### Loan maturity, descriptive data

Consumer loans (n = 1,985,185)



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# Time window (I), % population covered



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# Time window (II), number of data points per graph



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## Time window (III), differences in rate distributions



303 graphs used for mortgage loans (26.63% of population covered).

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Berwart (CMF), Higgins (Northwestern), Kulkarni (UVA), Truffa (ESE)

## **Priors about Prices**

## Perceptions of interest rates in the market Only people exclusively shopping for consumer loans are included.



Berwart (CMF), Higgins (Northwestern), Kulkarni (UVA), Truffa (ESE)

## **Planned Search Behaviour**

After treatment, not clear whether people planned to search at more banks

But planned search much higher than observed search

